Analyzing Home-Field Advantage in the NFL

In the world of professional sports, playing at home is often considered a key advantage for teams, especially in high-stakes leagues like the **NFL**(National Football League). **Home-field advantage** has become a central focus of debate, where teams seem to outperform when playing in their own stadium. This phenomenon raises questions: How much of an impact does playing at home truly have on **game outcomes**? What factors drive this advantage—could it be *travel fatigue* for the *opposing team*, *weather familiarity*, or the electrifying *support of home fans*?

In this project, I examine data from **57 NFL seasons** (1966-2023) to uncover the influence of **home-field advantage**. Through the use of *statistical analysis* and *visualizations*, I aim to quantify this advantage by exploring variables such as *team travel distances*, *weather conditions*, and *rivalries*. The goal is to move beyond anecdotal evidence and offer a comprehensive, data-driven perspective on how playing at home affects NFL teams' chances of winning.

Step 1: Load Data and look aroud

Skipping the real first step, finding the goal of the project.

For this project, I used **two main datasets**. The first one, from *ESPN*, includes detailed stats from over **14,000 NFL games** played between **1966 and 2023**. It covers information such as **team matchups, scores, locations, spreads**, and even **weather conditions**, which gave me a lot of important information to work with. The second dataset came from *nflfootballstadiums.com* and contains the **distances between all NFL stadiums**. This helped me look at how far teams had to travel and how that might affect their **performance**. Using both of these datasets allowed me to explore the factors that contribute to home-field advantage in the NFL.

In [66]:
```
import pandas as pd
import matplotlib.pyplot as plt
from scipy import stats

game_data = pd.read_csv('../raw_game_data.csv')
travel_distances = pd.read_csv('../raw_nfl_stadium_distances.csv')
```

Preview each dataset:

In [67]:
```
game_data.head()
```

Out [67]:

	schedule_date	schedule_season	schedule_week	schedule_playoff	team_home	s
0	9/2/1966	1966	1	False	Miami Dolphins	
1	9/3/1966	1966	1	False	Houston Oilers	
2	9/4/1966	1966	1	False	San Diego Chargers	
3	9/9/1966	1966	2	False	Miami Dolphins	
4	9/10/1966	1966	1	False	Green Bay Packers	

In [68]:

```
travel_distances.head()
```

Out [68]:

	Stadium 1	Stadium 2	Distance (miles)
0	AT&T Stadium	MetLife Stadium	1387.206289
1	AT&T Stadium	Arrowhead Stadium	458.379758
2	AT&T Stadium	SoFi Stadium	1229.436052
3	AT&T Stadium	Lambeau Field	945.215205
4	AT&T Stadium	Allegiant Stadium	1057.060692

Now check the **datatypes** of each dataset to see what we are working with.

In [69]:

```
print("Data types in Game Data:")
print(game_data.dtypes, "\n")
```

```
Data types in Game Data:
schedule_date           object
schedule_season          int64
schedule_week           object
schedule_playoff          bool
team_home               object
score_home             float64
score_away             float64
team_away               object
team_favorite_id        object
spread_favorite        float64
over_under_line         object
stadium                 object
stadium_neutral           bool
weather_temperature    float64
weather_wind_mph       float64
weather_humidity       float64
weather_detail          object
home_stadium            object
away_stadium            object
dtype: object
```

In [70]:
```
print("Data types in Travel Distances:")
print(travel_distances.dtypes, "\n")
```

```
Data types in Travel Distances:
Stadium 1           object
Stadium 2           object
Distance (miles)   float64
dtype: object
```

Step 2: Data Cleaning and Preprocessing

The first step is to check if there is any **missing data**.

In [71]:
```
print("Missing values in Game Data:")
print(game_data.isnull().sum(), "\n")
```

```
Missing values in Game Data:
schedule_date              0
schedule_season            0
schedule_week              0
schedule_playoff           0
team_home                  0
score_home               240
score_away               240
team_away                  0
team_favorite_id        2692
spread_favorite         2719
over_under_line         2729
stadium                    0
stadium_neutral            0
weather_temperature     1548
weather_wind_mph        1564
weather_humidity        5597
weather_detail         10946
home_stadium               0
away_stadium               0
dtype: int64
```

In [72]:
```
print("Missing values in Travel Distances:")
print(travel_distances.isnull().sum(), "\n")
```

```
Missing values in Travel Distances:
Stadium 1          0
Stadium 2          0
Distance (miles)   0
dtype: int64
```

Obtain all the game data of seasons **2023 and before**. (This is because the dataset includes partial data the 2024 season, which has not finished yet)

In [73]:
```
game_data = game_data[game_data['schedule_season'] <= 2023]
```

Round all the miles to **whole numbers**, so it is easier to work with.

In [74]:
```
travel_distances['Distance (miles)'] = travel_distances['Distance (miles)'].
```

Drop **unneccesary** columns

In [75]:
```
game_data = game_data.drop(columns=['weather_detail', 'team_favorite_id', 's
game_data.head()
```

Out[75]:

	schedule_date	schedule_season	schedule_week	schedule_playoff	team_home	s
0	9/2/1966	1966	1	False	Miami Dolphins	
1	9/3/1966	1966	1	False	Houston Oilers	
2	9/4/1966	1966	1	False	San Diego Chargers	
3	9/9/1966	1966	2	False	Miami Dolphins	
4	9/10/1966	1966	1	False	Green Bay Packers	

Rename the columns, as I will *merge* the datasets on these columns later.

In [76]:
```
travel_distances = travel_distances.rename(columns={
    'Stadium 1': 'home_stadium',
    'Stadium 2': 'away_stadium',
    'Distance (miles)': 'travel_distance'
})
```

Here I used **AI** to obtain a file of all the distances between NFL stadiums that are missing from my original dataset, and also add the data to itself, but in a reverse order so each pair of teams has two occurences, one where **Team A is home** and **Team B is away**, and one where **Team A is away** and **Team B is home**. I then read this file and set it as my *travel_distances* dataset.

In [77]:
```
travel_distances = pd.read_csv('../stadium_distances.csv')

travel_distances.head()
```

Out[77]:

	Unnamed: 0	home_stadium	away_stadium	distance
0	0	allegiant stadium	arrowhead stadium	1152
1	1	allegiant stadium	at&t stadium	1057
2	2	allegiant stadium	bank of america stadium	1958
3	3	allegiant stadium	caesars superdome	1492
4	4	allegiant stadium	empower field at mile high	626

I noticed the AI created an **uneeded index column**, so I **drop** it.

In [78]:
```
travel_distances = travel_distances.drop(travel_distances.columns[0], axis=1
travel_distances.head()
```

Out[78]:

	home_stadium	away_stadium	distance
0	allegiant stadium	arrowhead stadium	1152
1	allegiant stadium	at&t stadium	1057
2	allegiant stadium	bank of america stadium	1958
3	allegiant stadium	caesars superdome	1492
4	allegiant stadium	empower field at mile high	626

Clean the strings to make sure they are all in a **consistent format**.

In [79]:
```
game_data['home_stadium'] = game_data['home_stadium'].str.strip().str.lower(
game_data['away_stadium'] = game_data['away_stadium'].str.strip().str.lower(

travel_distances['home_stadium'] = travel_distances['home_stadium'].str.stri
travel_distances['away_stadium'] = travel_distances['away_stadium'].str.stri

travel_distances.head()
```

Out[79]:

	home_stadium	away_stadium	distance
0	allegiant stadium	arrowhead stadium	1152
1	allegiant stadium	at&t stadium	1057
2	allegiant stadium	bank of america stadium	1958
3	allegiant stadium	caesars superdome	1492
4	allegiant stadium	empower field at mile high	626

Let's preview our *game_data* dataset, just to see what we are working with.

In [80]:
```
game_data[['home_stadium', 'away_stadium']].head()
```

Out[80]:

	home_stadium	away_stadium
0	hard rock stadium	oakland coliseum
1	unknown stadium	empower field at mile high
2	qualcomm stadium	highmark stadium
3	hard rock stadium	metlife stadium
4	lambeau field	unknown stadium

I notice that in the **home_stadium** and **away_stadium columns**, some of the values are *"unknown stadium"*. This seems to be due to the fact that some NFL teams have changed their names over the years, so the mapping of a stadium to it's team caused an error.

To fix this, I will first I create a dictionary that **pairs the old names to the new names**. Then I use the **replace()** function to replace the teams in the dataset. Next, I will replace all of the *"unknown stadium"* values with the teams corresponding stadium, as defined in the **team_to_stadium** dictionary.

In [81]:
```
team_name_updates = {
    'San Diego Chargers': 'Los Angeles Chargers',
    'Oakland Raiders': 'Las Vegas Raiders',
    'Los Angeles Raiders': 'Las Vegas Raiders',
    'Washington Redskins': 'Washington Commanders',
    'Washington Football Team': 'Washington Commanders',
    'St. Louis Rams': 'Los Angeles Rams',
    'St. Louis Cardinals': 'Arizona Cardinals',
    'Houston Oilers': 'Tennessee Titans',
    'Tennessee Oilers': 'Tennessee Titans',
    'Baltimore Colts': 'Indianapolis Colts',
    'Boston Patriots': 'New England Patriots',
    'Phoenix Cardinals': 'Arizona Cardinals'
}

game_data['team_home'] = game_data['team_home'].replace(team_name_updates)
game_data['team_away'] = game_data['team_away'].replace(team_name_updates)
```

In [82]:
```
team_to_stadium = {
    'Arizona Cardinals': 'state farm stadium',
    'Atlanta Falcons': 'mercedes-benz stadium',
    'Baltimore Ravens': 'm&t bank stadium',
    'Buffalo Bills': 'highmark stadium',
    'Carolina Panthers': 'bank of america stadium',
    'Chicago Bears': 'soldier field',
    'Cincinnati Bengals': 'paycor stadium',
    'Cleveland Browns': 'firstenergy stadium',
    'Dallas Cowboys': 'at&t stadium',
    'Denver Broncos': 'empower field at mile high',
    'Detroit Lions': 'ford field',
    'Green Bay Packers': 'lambeau field',
    'Houston Texans': 'nrg stadium',
    'Indianapolis Colts': 'lucas oil stadium',
    'Jacksonville Jaguars': 'tiaa bank field',
    'Kansas City Chiefs': 'arrowhead stadium',
    'Las Vegas Raiders': 'allegiant stadium',
    'Los Angeles Chargers': 'sofi stadium',
    'Los Angeles Rams': 'sofi stadium',
    'Miami Dolphins': 'hard rock stadium',
    'Minnesota Vikings': 'u.s. bank stadium',
    'New England Patriots': 'gillette stadium',
    'New Orleans Saints': 'caesars superdome',
    'New York Giants': 'metlife stadium',
    'New York Jets': 'metlife stadium',
    'Philadelphia Eagles': 'lincoln financial field',
    'Pittsburgh Steelers': 'acrisure stadium',
    'San Francisco 49ers': "levi's stadium",
    'Seattle Seahawks': 'lumen field',
    'Tampa Bay Buccaneers': 'raymond james stadium',
```

```
    'Tennessee Titans': 'nissan stadium',
    'Washington Commanders': 'fedexfield'
}

game_data['home_stadium'] = game_data.apply(
    lambda row: team_to_stadium.get(row['team_home'], row['home_stadium']) i
    axis=1
)

game_data['away_stadium'] = game_data.apply(
    lambda row: team_to_stadium.get(row['team_away'], row['away_stadium']) i
    axis=1
)
```

Now let's see if we fixed the problem.

In [83]:
```
unknown_stadiums = game_data[(game_data['home_stadium'] == 'unknown stadium'

unknown_stadiums
```

Out[83]:

schedule_date	schedule_season	schedule_week	schedule_playoff	team_home	sc

Drop the **weather humidity** column and **schedule_week** column, as I won't be using these.

In [84]:
```
game_data = game_data.drop(columns=['weather_humidity', 'schedule_week'])
game_data.head()
```

Out[84]:

	schedule_date	schedule_season	schedule_playoff	team_home	score_home	scor
0	9/2/1966	1966	False	Miami Dolphins	14.0	
1	9/3/1966	1966	False	Tennessee Titans	45.0	
2	9/4/1966	1966	False	Los Angeles Chargers	27.0	
3	9/9/1966	1966	False	Miami Dolphins	14.0	
4	9/10/1966	1966	False	Green Bay Packers	24.0	

Now that everything is fixed, we can move on.

Step 3: Merging and Preparing the Datasets

Merge the datasets on the **home** and **away stadiums**.

In [85]:
```
merged_game_data = pd.merge(game_data, travel_distances, how='left', left_or
```

Now I want to see if the **merge** has worked, and if there are any rows in which the *distance* is **NaN**

In [86]:
```
rows_with_nan = merged_game_data[merged_game_data.isna().any(axis=1)]

rows_with_nan
```

Out[86]:

	schedule_date	schedule_season	schedule_playoff	team_home	score_home
44	10/2/1966	1966	False	Kansas City Chiefs	14.0
50	10/8/1966	1966	False	Buffalo Bills	10.0
52	10/8/1966	1966	False	Kansas City Chiefs	37.0
53	10/8/1966	1966	False	New York Jets	17.0
57	10/9/1966	1966	False	Las Vegas Raiders	21.0
...	...	...	...	...	...
14196	1/7/2024	2023	False	New England Patriots	3.0
14198	1/7/2024	2023	False	New York Giants	27.0
14199	1/7/2024	2023	False	San Francisco 49ers	20.0
14200	1/7/2024	2023	False	Tennessee Titans	28.0
14201	1/7/2024	2023	False	Washington Commanders	10.0

1450 rows × 13 columns

Since there is **missing data** in the *weather temperature* column, find the **average** of the temperature at **each stadium** and use that to fill it into the **missing values**

First Step: Find the *average temperature* by stadium

In [87]:
```
avg_temp_by_stadium = merged_game_data.groupby('home_stadium')['weather_temp
print(avg_temp_by_stadium)
```

```
home_stadium
acrisure stadium                    48.056723
allegiant stadium                   72.000000
arrowhead stadium                   50.643038
at&t stadium                        63.029787
bank of america stadium             58.507538
caesars superdome                   71.230435
empower field at mile high          48.015801
fedexfield                          54.217703
firstenergy stadium                 49.049875
ford field                          68.339869
gillette stadium                    50.194774
hard rock stadium                   76.185096
highmark stadium                    48.475490
lambeau field                       44.065574
levi's stadium                      57.809745
lincoln financial field             52.819905
los angeles memorial coliseum       62.459184
lucas oil stadium                   65.919588
lumen field                         62.348525
m&t bank stadium                    53.863636
mercedes-benz stadium               65.550976
metlife stadium                     53.027228
nissan stadium                      65.777228
nrg stadium                         72.260417
oakland coliseum                    58.570447
paycor stadium                      50.891688
qualcomm stadium                    64.519126
raymond james stadium               72.202857
sofi stadium                        67.568898
soldier field                       47.771635
state farm stadium                  63.518519
stubhub center                      73.625000
tiaa bank field                     69.363184
u.s. bank stadium                   62.553015
Name: weather_temperature, dtype: float64
```

Second Step: Fill it into the dataset

In [88]:
```
merged_game_data['weather_temperature'] = merged_game_data.apply(
    lambda row: avg_temp_by_stadium[row['home_stadium']] if pd.isna(row['wea
    axis=1
)
```

Third Step: Round all the *temperature values* to **whole numbers**.

In [89]:
```
merged_game_data['weather_temperature'] = merged_game_data['weather_temperat
```

Fourth Step: Check to see if there are any more **missing values**.

In [90]:
```
print(merged_game_data['weather_temperature'].isna().sum())
```

```
0
```

I will then check other related variables for this same thing.

```
In [91]: print(merged_game_data['weather_wind_mph'].isna().sum())
```

1449

I see the *weather_wind_mph* column has lots of **missing values**, so I will do the same process as before.

Step 1: Find the *average wind speed* by stadium.

```
In [92]: avg_wind_by_stadium = merged_game_data.groupby('home_stadium')['weather_winc
```

Step 2: Fill it into the dataset.

```
In [93]: merged_game_data['weather_wind_mph'] = merged_game_data.apply(
             lambda row: avg_wind_by_stadium[row['home_stadium']] if pd.isna(row['wea
             axis=1
         )
```

Step 3: Round all the values to **whole numbers**.

```
In [94]: merged_game_data['weather_wind_mph'] = merged_game_data['weather_wind_mph'].
```

Step 4: Check if there are any **missing values**.

```
In [95]: print(merged_game_data['weather_wind_mph'].isna().sum())
```

```
0
```

Here I turn the dataset into a file, so I have it saved on my computer as a **backup**.

```
In [96]: merged_game_data.to_csv('merged_dataset.csv')
```

Step 4: Exploratory Data Analysis and Engineering

Add a new column, the *home_win_margin*, to see how much the **home team wins** by in each game. Then add another column, showing **whether or not the home team won**. 1 for a win, 0 for a loss.

```
In [97]: merged_game_data['home_win_margin'] = merged_game_data['score_home'] - merge
         merged_game_data['home_team_won'] = (merged_game_data['home_win_margin'] > 0
         merged_game_data.head()
```

Out [97]:

	schedule_date	schedule_season	schedule_playoff	team_home	score_home	scor
0	9/2/1966	1966	False	Miami Dolphins	14.0	
1	9/2/1966	1966	False	Miami Dolphins	14.0	
2	9/3/1966	1966	False	Tennessee Titans	45.0	
3	9/4/1966	1966	False	Los Angeles Chargers	27.0	
4	9/9/1966	1966	False	Miami Dolphins	14.0	

Create **bins** so we can *categorize* how strong the wind was in each game.

In [98]:

```
merged_game_data['wind_category'] = pd.cut(
    merged_game_data['weather_wind_mph'],
    bins=[-1, 0, 10, 20, 100],
    labels=['none', 'low', 'moderate', 'high']
)

merged_game_data.head()
```

Out [98]:

	schedule_date	schedule_season	schedule_playoff	team_home	score_home	scor
0	9/2/1966	1966	False	Miami Dolphins	14.0	
1	9/2/1966	1966	False	Miami Dolphins	14.0	
2	9/3/1966	1966	False	Tennessee Titans	45.0	
3	9/4/1966	1966	False	Los Angeles Chargers	27.0	
4	9/9/1966	1966	False	Miami Dolphins	14.0	

Round all *scores* to **whole numbers**.

In [99]:

```
merged_game_data['score_home'] = merged_game_data['score_home'].round().asty
merged_game_data['score_away'] = merged_game_data['score_away'].round().asty
merged_game_data.head()
```

Out [99]:

	schedule_date	schedule_season	schedule_playoff	team_home	score_home	scor
0	9/2/1966	1966	False	Miami Dolphins	14	
1	9/2/1966	1966	False	Miami Dolphins	14	
2	9/3/1966	1966	False	Tennessee Titans	45	
3	9/4/1966	1966	False	Los Angeles Chargers	27	
4	9/9/1966	1966	False	Miami Dolphins	14	

I use this code below to see if there are any more **null values** in my dataset to so I can be done with **preprocessing**.

In [100…

```
null_values = merged_game_data.isnull().sum()
null_values
```

Out [100…

```
schedule_date          0
schedule_season        0
schedule_playoff       0
team_home              0
score_home             0
score_away             0
team_away              0
stadium                0
weather_temperature    0
weather_wind_mph       0
home_stadium           0
away_stadium           0
distance               0
home_win_margin        0
home_team_won          0
wind_category          0
dtype: int64
```

Next, I am going to create **travel bins**, so that I can **categorize** the **distances** teams have to *travel*. This is will help when we **visualize** the data.

In [101…

```
travel_bins = [1, 660, 1320, 1980, 2640, 3300]

bin_labels = ['very short', 'short', 'medium', 'long', 'very long']

merged_game_data['travel_distance_bin'] = pd.cut(
    merged_game_data['distance'],
    bins=travel_bins,
    labels=bin_labels,
    include_lowest=True
```

```
)
#This code is to expilcitiy set a bin with a distance of 0 to 'no travel' fo
merged_game_data['travel_distance_bin'] = merged_game_data['travel_distance_

merged_game_data.loc[merged_game_data['distance'] == 0, 'travel_distance_bir

merged_game_data[['distance', 'travel_distance_bin']].head()
```

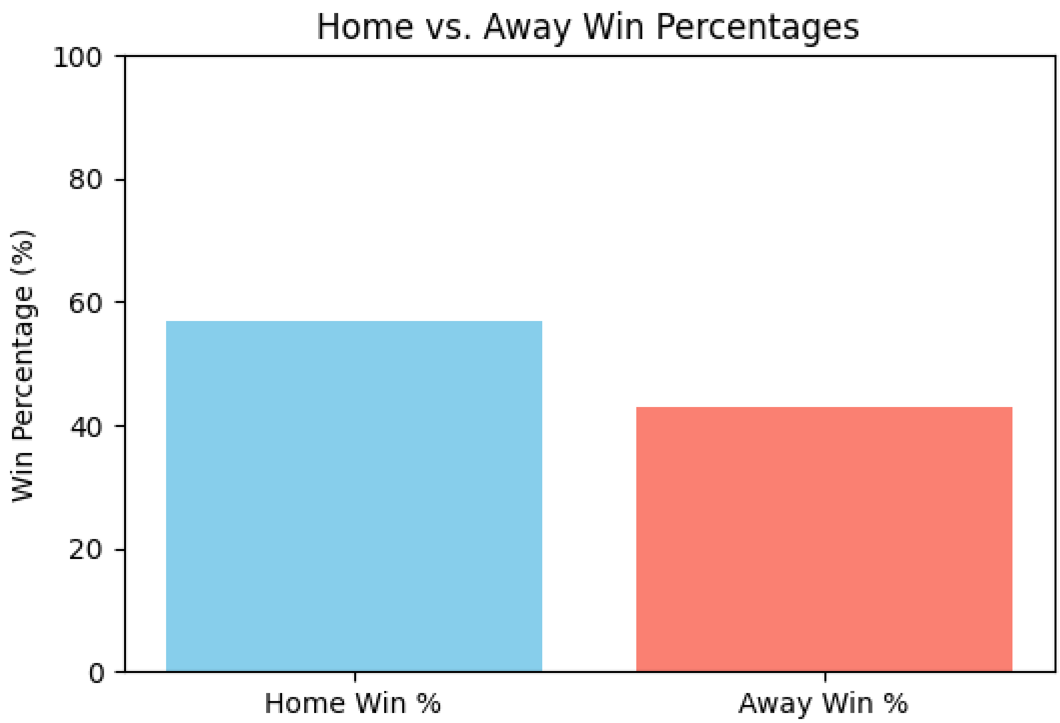
Out[101…

	distance	travel_distance_bin
0	3000	very long
1	2584	long
2	1016	short
3	2201	long
4	1087	short

I create a *win_rate_by_distance* variable that shows the **win rate percentage** at each categorical bin.

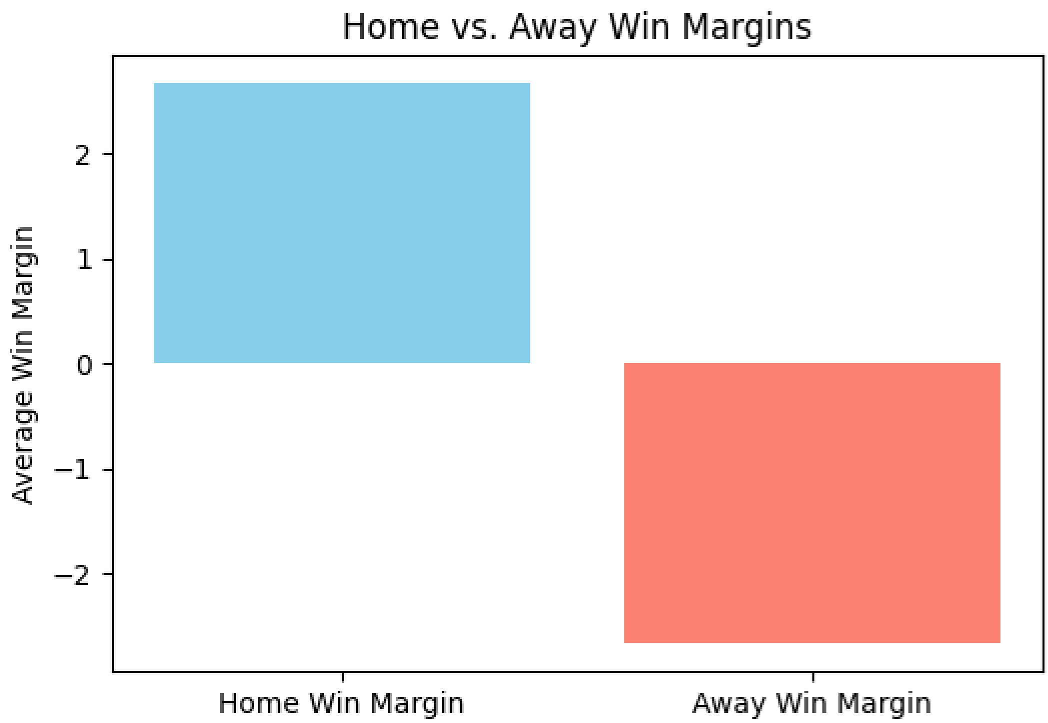
In [102…

```
home_win_percentage = merged_game_data['home_team_won'].mean() * 100
away_win_percentage = (1 - merged_game_data['home_team_won']).mean() * 100

win_percentages = [home_win_percentage, away_win_percentage]
labels = ['Home Win %', 'Away Win %']

plt.figure(figsize=(6, 4))
plt.bar(labels, win_percentages, color=['skyblue', 'salmon'])
plt.title('Home vs. Away Win Percentages')
plt.ylabel('Win Percentage (%)')
plt.ylim(0, 100)
plt.show()
```



In [103…

```
home_win_margin = merged_game_data['home_win_margin'].mean()
away_win_margin = (-merged_game_data['home_win_margin']).mean()

win_margins = [home_win_margin, away_win_margin]
labels = ['Home Win Margin', 'Away Win Margin']

plt.figure(figsize=(6, 4))
plt.bar(labels, win_margins, color=['skyblue', 'salmon'])
plt.title('Home vs. Away Win Margins')
plt.ylabel('Average Win Margin')
plt.show()
```



What does this tell us?

The charts above show that **home teams** win about **58%** of the time, while **away teams** win around **42%**, and **home teams** tend to win by a **larger margin** compared to **away teams**. The *average home win margin* is **over 2 points**, while away teams generally lose by a similar margin. These numbers clearly **support** the concept of **home-field advantage** in the NFL.

Next, I will conduct two separate **t-tests**; one for *win percentages* and one for *win margin*, to determine if the differences in the data are **statistically significant**.

In [104…

```
merged_game_data['away_win_margin'] = -merged_game_data['home_win_margin']

home_win_margins = merged_game_data['home_win_margin']
away_win_margins = merged_game_data['away_win_margin']

t_stat, p_value = stats.ttest_ind(home_win_margins, away_win_margins, nan_pc

print(f"Home vs. Away Win Margins - T-statistic: {t_stat}, P-value: {p_value
```

```
Home vs. Away Win Margins - T-statistic: 30.19324352068121, P-value: 3.77938
19620462044e-197
```

The **t-test** results for *home vs. away* **win margins** show a **T-statistic of 30.19** and a **P-value of 3.78e-197**, which is incredibly **small**. This means there's a huge difference between how much home and away teams win by. **Home teams** tend to win by much **larger margins**, and this difference isn't due to random chance. It really highlights just how big of a role **home-field advantage** plays in NFL games, not only in winning but also in the size of the victory.

In [105…

```python
merged_game_data['away_team_won'] = 1 - merged_game_data['home_team_won']

home_win_rates = merged_game_data['home_team_won']
away_win_rates = merged_game_data['away_team_won']

t_stat, p_value = stats.ttest_ind(home_win_rates, away_win_rates, nan_policy

print(f"Home vs. Away Win Rates - T-statistic: {t_stat}, P-value: {p_value}"
```

```
Home vs. Away Win Rates - T-statistic: 23.995525852025825, P-value: 5.551412
526859514e-126
```

The **t-test** above comparing *home vs. away* **win rates** in the NFL showed a **t-statistic** of **23.99** and a **p-value of 5.55e-126**, indicating a **significant** difference. This suggests that home teams tend to win **more often** than away teams, supporting the idea of **home-field advantage**. However, since the win rates are directly related (one team wins, the other loses), the extremely small p-value reflects this.

Below, I create a **bar graph** to see if there is a **correlation** between the *home team's win rate* and the *away team's travel distance*.

In [106…

```python
win_rate_by_distance = merged_game_data.groupby('travel_distance_bin')['home
win_rate_by_distance = (win_rate_by_distance * 100).round(1)
win_rate_by_distance.head(6)
```

```
/var/folders/hj/ss74h5m100j0j4b3f9n9tknh0000gn/T/ipykernel_30916/144600722.p
y:1: FutureWarning: The default of observed=False is deprecated and will be
changed to True in a future version of pandas. Pass observed=False to retain
current behavior or observed=True to adopt the future default and silence th
is warning.
  win_rate_by_distance = merged_game_data.groupby('travel_distance_bin')['ho
me_team_won'].mean()
```

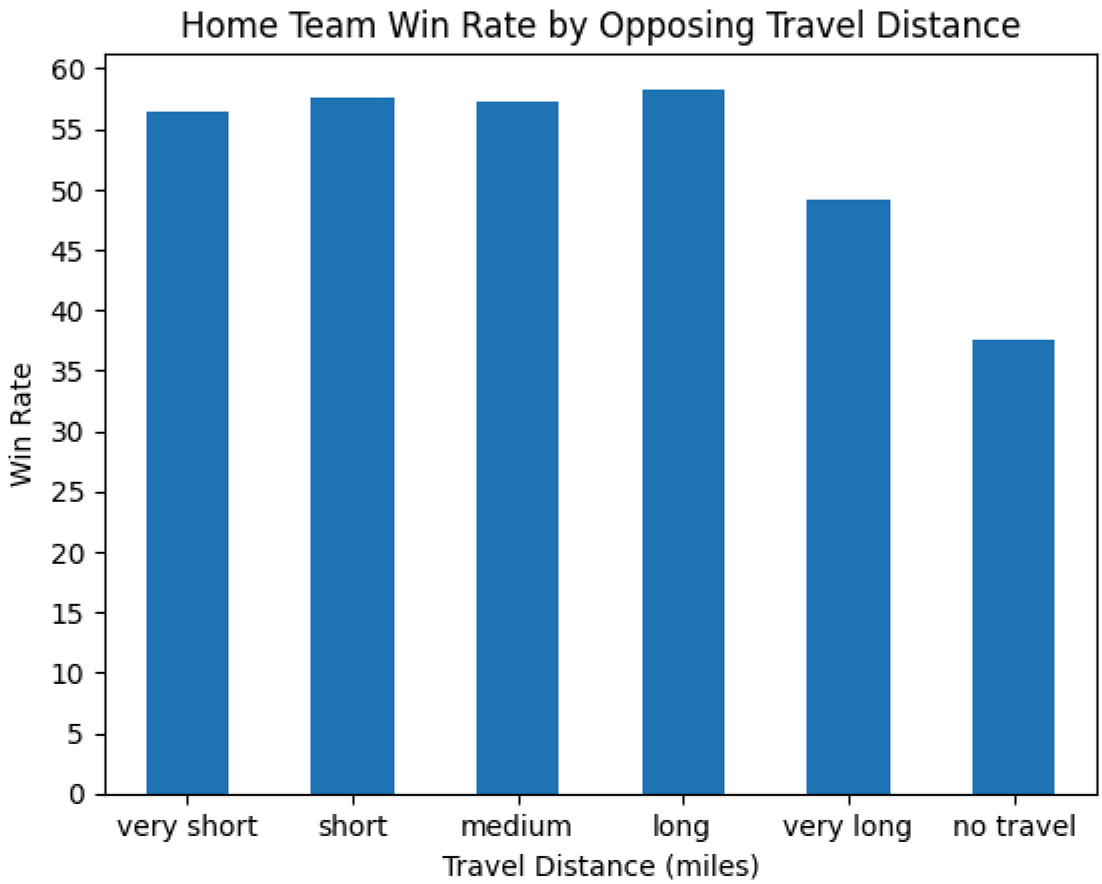
Out[106…

```
travel_distance_bin
very short    56.5
short         57.6
medium        57.3
long          58.3
very long     49.2
no travel     37.5
Name: home_team_won, dtype: float64
```

In [107…

```python
win_rate_by_distance.plot(kind='bar')
plt.title('Home Team Win Rate by Opposing Travel Distance')
plt.xlabel('Travel Distance (miles)')
plt.ylabel('Win Rate')

plt.yticks(range(0, int(win_rate_by_distance.max()) + 5, 5))

plt.xticks(rotation=0)
```

```
plt.show()
```



What we can gather from the graph:

The graph above illustrates that the *home team's win rate* is **consistently higher** when the away team **has** to travel, compared to instances where **no travel** is required. The only cases where the away team doesn't travel are when teams share the same home stadium, as seen with the Los Angeles Chargers and Los Angeles Rams.

I then get the **average** *weather temp* and **wind speed** at each stadium. I add this to the *merged_game_data* dataset.

In [108…
```
normal_conditions_by_stadium = merged_game_data.groupby('home_stadium')[['we

merged_game_data = merged_game_data.merge(normal_conditions_by_stadium, on='
```

Here is where I add two columns called *temperature_familiary* and *wind_familiary* to my dataset which say whether or not the team is **used to the conditions** that were played at the game (**familiar** or **unfamiliar**).

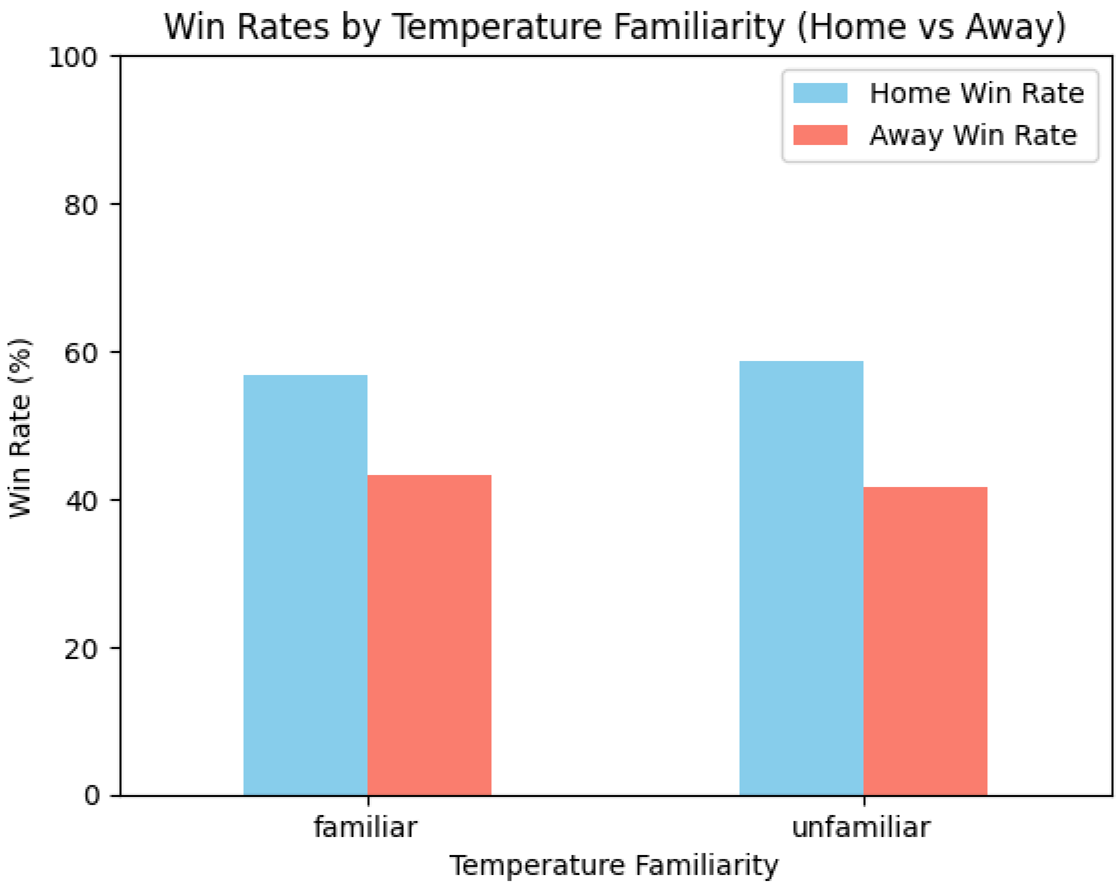
In [109…
```
merged_game_data['temperature_familiarity'] = merged_game_data.apply(
    lambda row: 'familiar' if abs(row['weather_temperature'] - row['weather_
```

```
    axis=1
)

merged_game_data['wind_familiarity'] = merged_game_data.apply(
    lambda row: 'familiar' if abs(row['weather_wind_mph'] - row['weather_wir
    axis=1
)
```

The cell below shows the *win rate* for the home team based off of their **familiarity** with the *temperature*.

In [110…

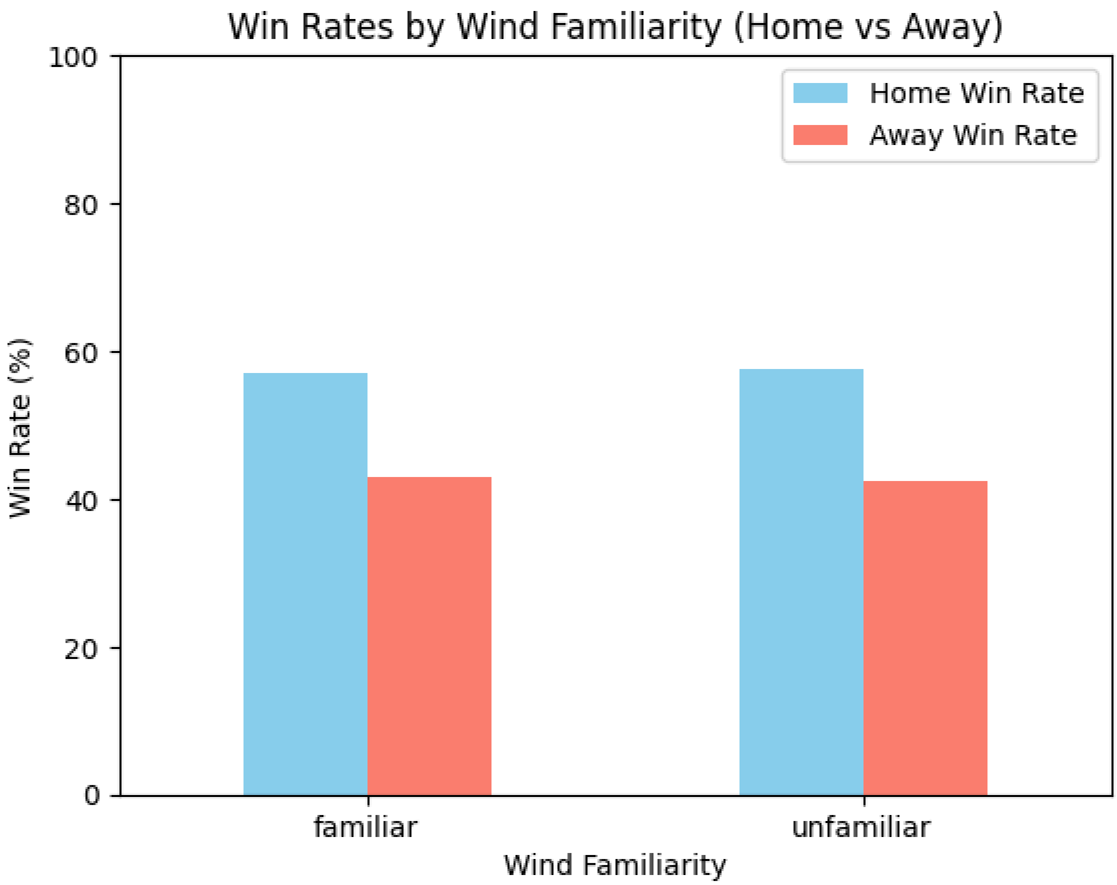
```
win_rate_by_temperature_familiarity = merged_game_data.groupby('temperature_

away_win_rate_by_temperature_familiarity = 100 - win_rate_by_temperature_fam

win_rates_by_temperature_familiarity = pd.DataFrame({
    'Home Win Rate': win_rate_by_temperature_familiarity,
    'Away Win Rate': away_win_rate_by_temperature_familiarity
})

win_rates_by_temperature_familiarity.plot(kind='bar', color=['skyblue', 'sal
plt.title('Win Rates by Temperature Familiarity (Home vs Away)')
plt.xlabel('Temperature Familiarity')
plt.ylabel('Win Rate (%)')
plt.xticks(rotation=0)
plt.ylim(0, 100)

plt.show()
```



The code below shows the same as above, but for *wind familiarity*.

In [111…

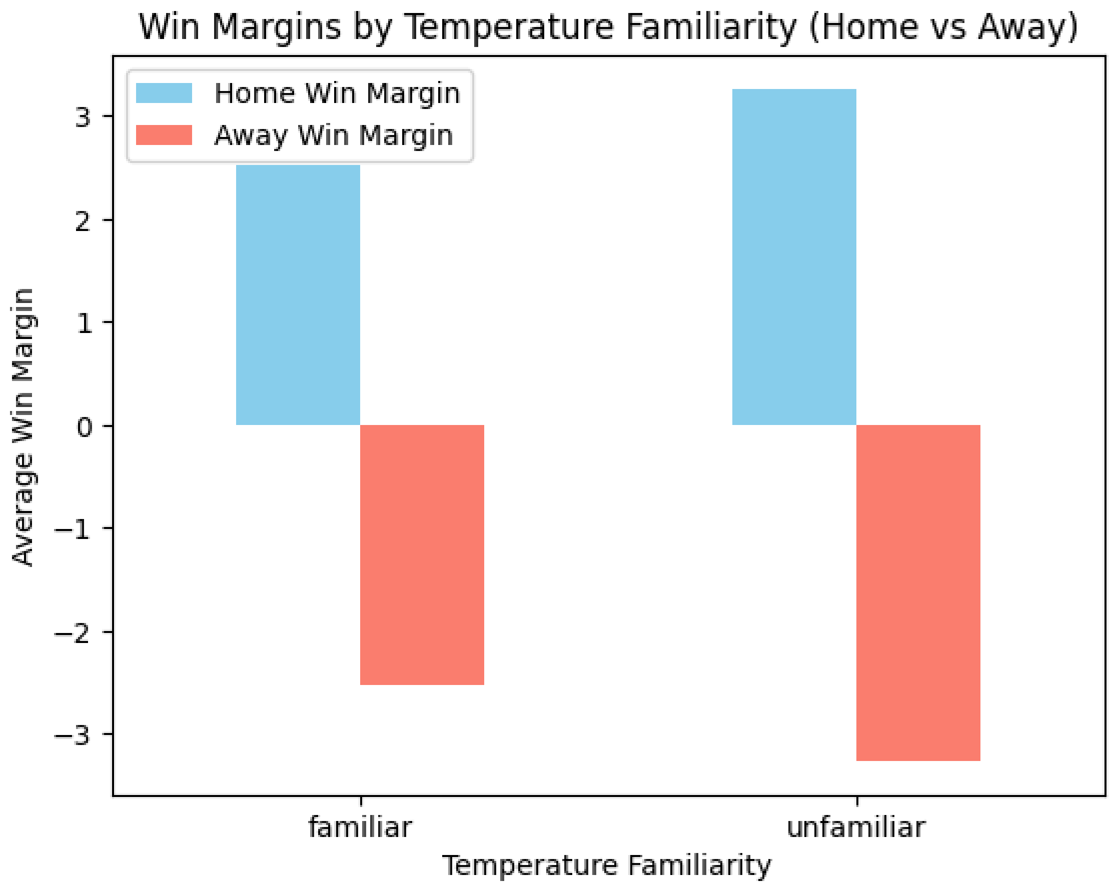
```
win_rate_by_wind_familiarity = merged_game_data.groupby('wind_familiarity')[

away_win_rate_by_wind_familiarity = 100 - win_rate_by_wind_familiarity

win_rates_by_wind_familiarity = pd.DataFrame({
    'Home Win Rate': win_rate_by_wind_familiarity,
    'Away Win Rate': away_win_rate_by_wind_familiarity
})

win_rates_by_wind_familiarity.plot(kind='bar', color=['skyblue', 'salmon'])
plt.title('Win Rates by Wind Familiarity (Home vs Away)')
plt.xlabel('Wind Familiarity')
plt.ylabel('Win Rate (%)')
plt.xticks(rotation=0)
plt.ylim(0, 100)

plt.show()
```



The code below calculates **how much the home team wins by** when they are faced with **familiar** and **unfamiliar conditions**.

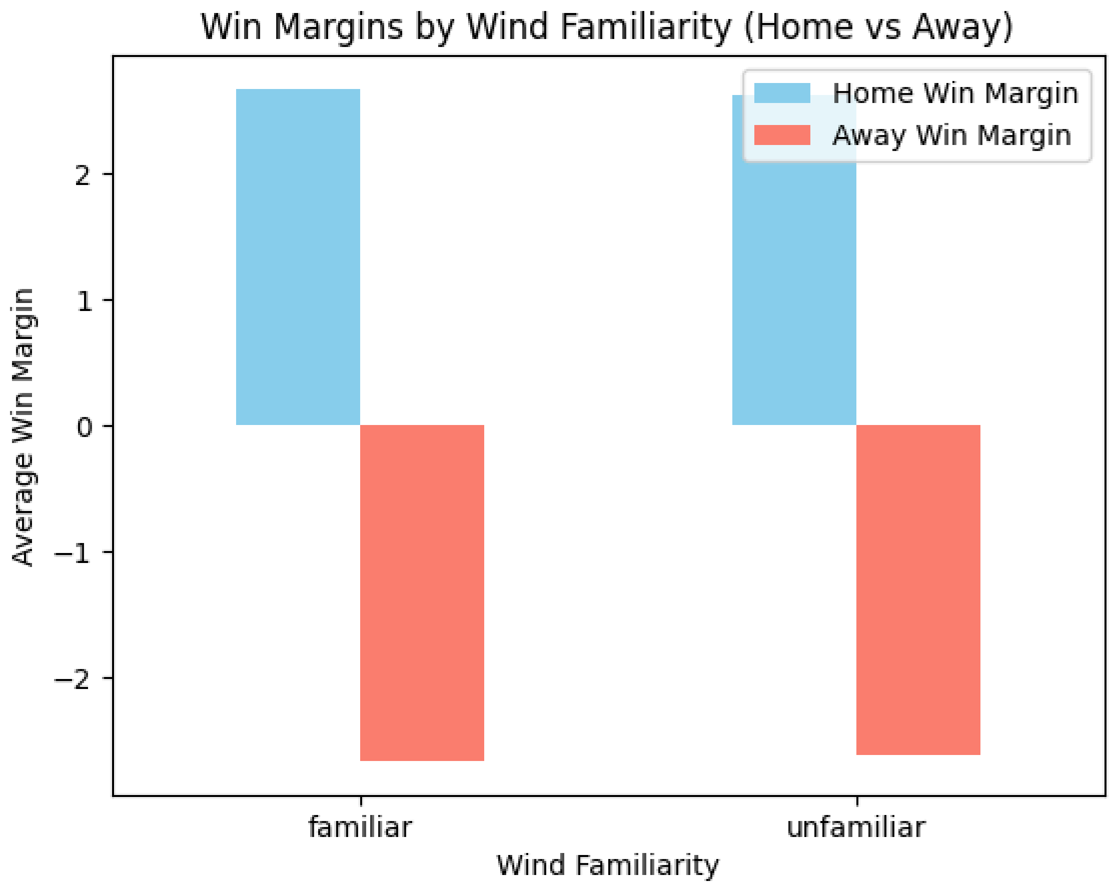
In [112…

```
win_margin_by_temp_familiarity = merged_game_data.groupby('temperature_famil

away_margin_by_temp_familiarity = -win_margin_by_temp_familiarity

win_margins_by_temp_familiarity = pd.DataFrame({
    'Home Win Margin': win_margin_by_temp_familiarity,
    'Away Win Margin': away_margin_by_temp_familiarity
})

win_margins_by_temp_familiarity.plot(kind='bar', color=['skyblue', 'salmon']
plt.title('Win Margins by Temperature Familiarity (Home vs Away)')
plt.xlabel('Temperature Familiarity')
plt.ylabel('Average Win Margin')
plt.xticks(rotation=0)
plt.show()
```



In [113…

```
win_margin_by_wind_familiarity = merged_game_data.groupby('wind_familiarity'

away_margin_by_wind_familiarity = -win_margin_by_wind_familiarity

win_margins_by_wind_familiarity = pd.DataFrame({
    'Home Win Margin': win_margin_by_wind_familiarity,
    'Away Win Margin': away_margin_by_wind_familiarity
})

win_margins_by_wind_familiarity.plot(kind='bar', color=['skyblue', 'salmon']
plt.title('Win Margins by Wind Familiarity (Home vs Away)')
plt.xlabel('Wind Familiarity')
plt.ylabel('Average Win Margin')
plt.xticks(rotation=0)
plt.show()
```



What this indicates:

We can see from the four graphs above that a team's **familiarity** with *weather conditions* has **no effect** on the outcome of the game. In all graphs, the home team has a consistently *higher win rate* and *win margin*, even if the away team is familiar with the weather conditions. We can conclude that the home team performs better **regardless** of *weather conditions*.

Next I do the same as I did previously and conduct two **t-tests**, one for *temperature* and one for *wind speed*.

In [114…

```
familiar_temp_margins = merged_game_data[merged_game_data['temperature_famil
unfamiliar_temp_margins = merged_game_data[merged_game_data['temperature_fam

t_stat_temp, p_value_temp = stats.ttest_ind(familiar_temp_margins, unfamilia

print(f"Temperature Familiarity - T-statistic: {t_stat_temp}, P-value: {p_va

familiar_wind_margins = merged_game_data[merged_game_data['wind_familiarity'
unfamiliar_wind_margins = merged_game_data[merged_game_data['wind_familiarit

t_stat_wind, p_value_wind = stats.ttest_ind(familiar_wind_margins, unfamilia

print(f"Wind Familiarity - T-statistic: {t_stat_wind}, P-value: {p_value_wir
```

```
Temperature Familiarity - T-statistic: -2.3694661915336828, P-value: 0.01782
7063127151925
Wind Familiarity - T-statistic: 0.06351968475148594, P-value: 0.949353577850
7926
```

The analysis reveals that temperature familiarity **significantly impacts** *home team performance*, as unfamiliar temperature conditions are associated with a smaller win margin for the home team **(p-value = 0.0178)**. On the other hand, *wind familiarity* shows **no significant effect** on *win margins*, with almost identical results in familiar and unfamiliar wind conditions **(p-value = 0.9494)**. This suggests that while temperature plays a role in home-field advantage, *wind conditions* may **not** have the same level of influence on the outcome of NFL games.

The next few sections of code are about the **type of game** that is being played (playoff or regular season game). It compares the **outcome** of the game with **home** and **away teams** based on whether or not it is a **regular season game** or **playoff game**.

Why?

Home-field advantage in the **playoffs** can be more severe than in **regular-season games** due to the **increased pressure** on away teams and the impact of a **loud, engaged home crowd**. The stakes are higher, amplifying the **psychological pressure** on visiting teams, while the home crowd's energy can **disrupt the away team's communication** and **lead to mistakes**. Having a **bigger home fan base** can also **boost morale**, causing increased **confidence** and **energy**.

In [115…

```python
merged_game_data['away_win_margin'] = -merged_game_data['home_win_margin']
```

In [116…

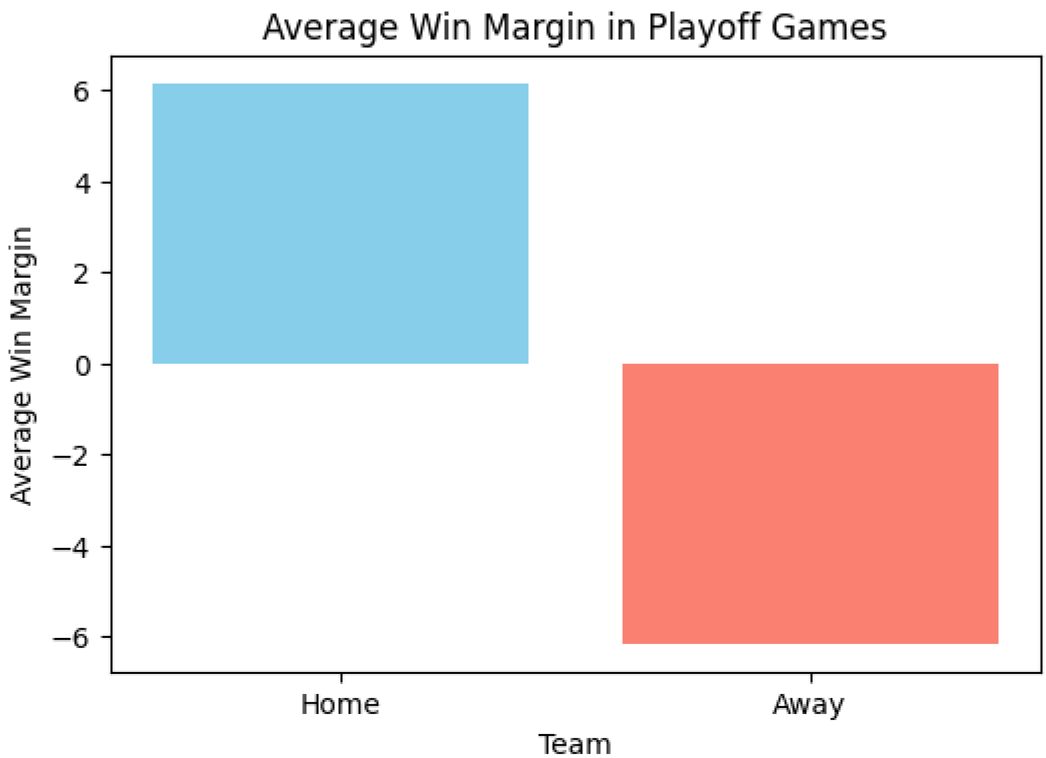
```python
playoff_games = merged_game_data[merged_game_data['schedule_playoff'] == Tru
regular_season_games = merged_game_data[merged_game_data['schedule_playoff']]

avg_home_win_margin_playoff = playoff_games['home_win_margin'].mean()
avg_away_win_margin_playoff = playoff_games['away_win_margin'].mean()

avg_home_win_margin_regular = regular_season_games['home_win_margin'].mean()
avg_away_win_margin_regular = regular_season_games['away_win_margin'].mean()

print(f'Average Home Win Margin (Playoff Games): {avg_home_win_margin_playof
print(f'Average Away Win Margin (Playoff Games): {avg_away_win_margin_playof
print(f'Average Home Win Margin (Regular Season Games): {avg_home_win_margir
print(f'Average Away Win Margin (Regular Season Games): {avg_away_win_margir
```

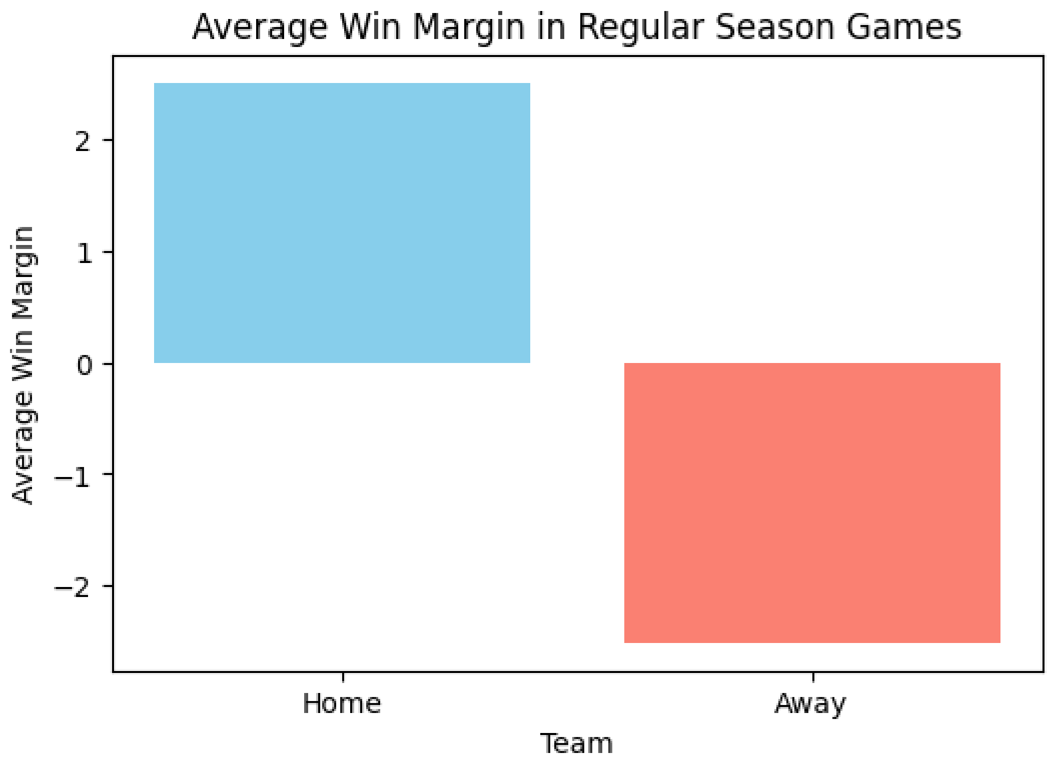
```
Average Home Win Margin (Playoff Games): 6.155143338954469
Average Away Win Margin (Playoff Games): -6.155143338954469
Average Home Win Margin (Regular Season Games): 2.5107163828537873
Average Away Win Margin (Regular Season Games): -2.5107163828537873
```

In [117…

```python
playoff_margins = [avg_home_win_margin_playoff, avg_away_win_margin_playoff]
labels = ['Home', 'Away']
```

```
plt.figure(figsize=(6, 4))
plt.bar(labels, playoff_margins, color=['skyblue', 'salmon'])
plt.title('Average Win Margin in Playoff Games')
plt.xlabel('Team')
plt.ylabel('Average Win Margin')
plt.show()

regular_margins = [avg_home_win_margin_regular, avg_away_win_margin_regular]
labels = ['Home', 'Away']

plt.figure(figsize=(6, 4))
plt.bar(labels, regular_margins, color=['skyblue', 'salmon'])
plt.title('Average Win Margin in Regular Season Games')
plt.xlabel('Team')
plt.ylabel('Average Win Margin')
plt.show()
```





In [118…

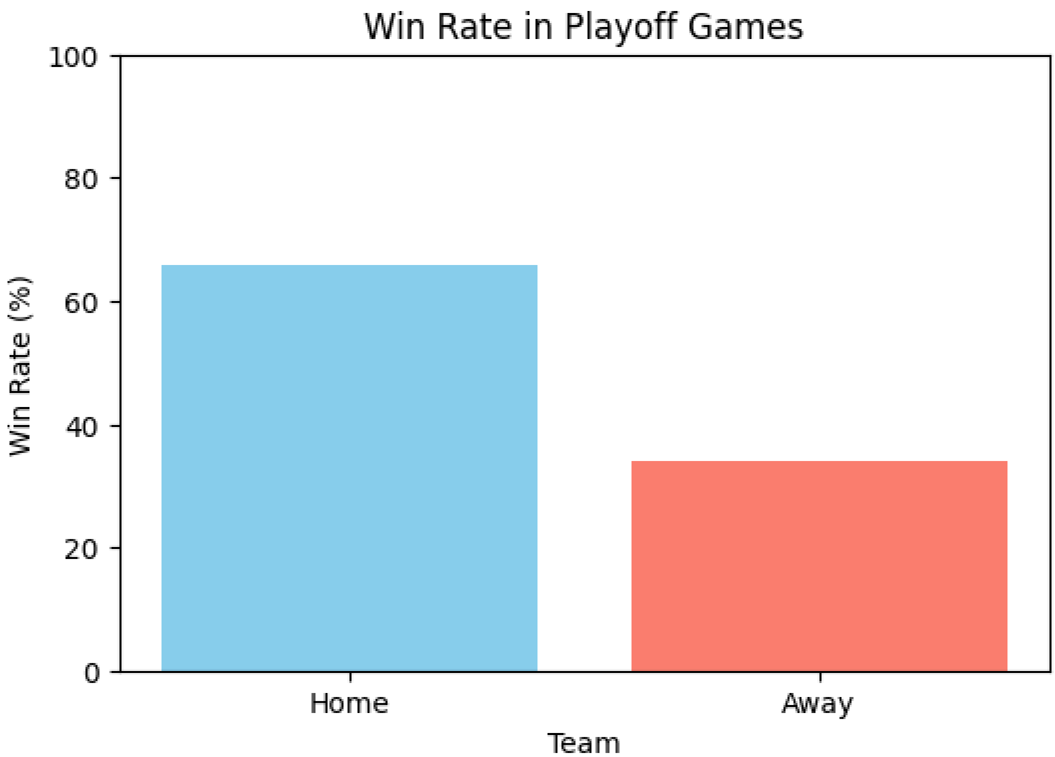
```
home_win_rate_playoff = (playoff_games['home_team_won'].mean()) * 100
home_win_rate_regular = (regular_season_games['home_team_won'].mean()) * 100

away_win_rate_playoff = 100 - home_win_rate_playoff
away_win_rate_regular = 100 - home_win_rate_regular

print(f'Home Win Rate (Playoff Games): {home_win_rate_playoff}%')
print(f'Away Win Rate (Playoff Games): {away_win_rate_playoff}%')
print(f'Home Win Rate (Regular Season Games): {home_win_rate_regular}%')
print(f'Away Win Rate (Regular Season Games): {away_win_rate_regular}%')
```

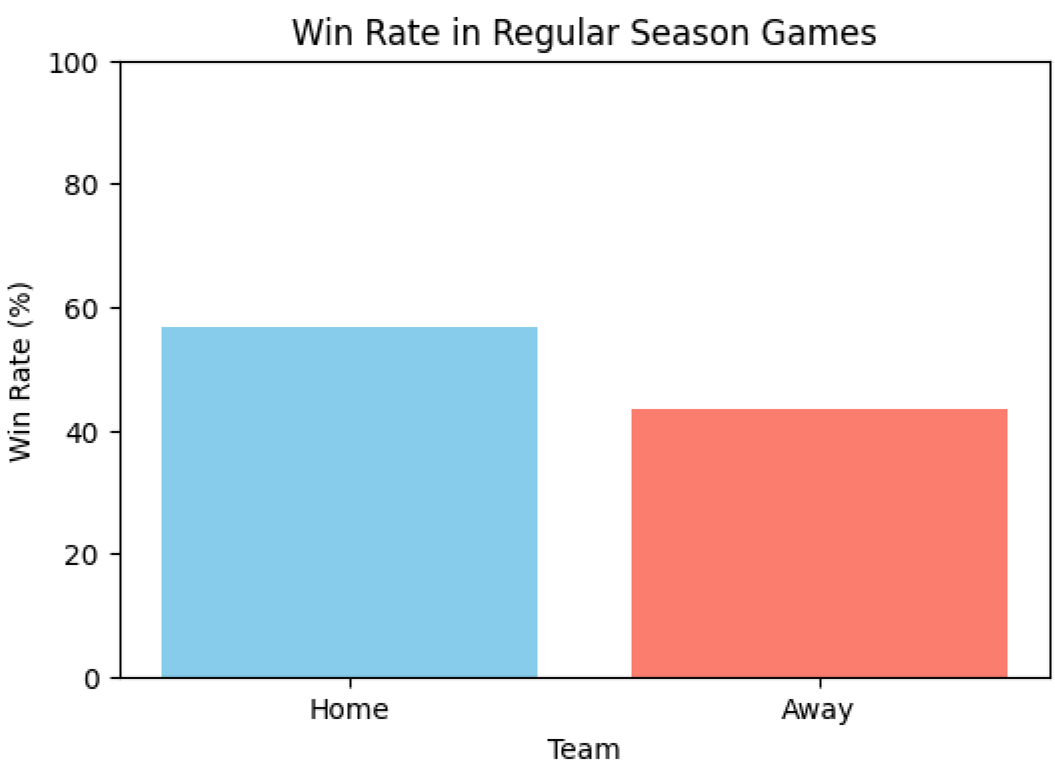
```
Home Win Rate (Playoff Games): 65.93591905564924%
Away Win Rate (Playoff Games): 34.06408094435076%
Home Win Rate (Regular Season Games): 56.657369348209045%
Away Win Rate (Regular Season Games): 43.342630651790955%
```

In [119…

```
playoff_win_rates = [home_win_rate_playoff, away_win_rate_playoff]
labels = ['Home', 'Away']

plt.figure(figsize=(6, 4))
plt.bar(labels, playoff_win_rates, color=['skyblue', 'salmon'])
plt.title('Win Rate in Playoff Games')
plt.xlabel('Team')
plt.ylabel('Win Rate (%)')
plt.ylim(0, 100)
plt.show()

regular_win_rates = [home_win_rate_regular, away_win_rate_regular]
labels = ['Home', 'Away']

plt.figure(figsize=(6, 4))
plt.bar(labels, regular_win_rates, color=['skyblue', 'salmon'])
```

```
plt.title('Win Rate in Regular Season Games')
plt.xlabel('Team')
plt.ylabel('Win Rate (%)')
plt.ylim(0, 100)
plt.show()
```





What the visualizations tell us:

After analyzing **regular season** and **playoff games**, the visualizations show that the **home team consistently outperforms** the away team in terms of *win rate* and *win margin*, regardless of the game type. Furthermore, both the *average win margin* and *win rate* are **higher** for the home team in **playoff games** compared to **regular season matchups**. These findings **strongly support** the concept of *home-field advantage*.

Below I conduct a **t-test** with the *win margins* of **playoff versus regular season games** to see if this is **statistically significant**.

In [120…

```
playoff_margins = merged_game_data[merged_game_data['schedule_playoff'] == T
regular_margins = merged_game_data[merged_game_data['schedule_playoff'] == F

t_stat_playoff, p_value_playoff = stats.ttest_ind(playoff_margins, regular_m

print(f"Playoffs vs. Regular Season - T-statistic: {t_stat_playoff}, P-value
```

```
Playoffs vs. Regular Season - T-statistic: 5.848919543924191, P-value: 5.056
490425172657e-09
```

There is a **highly significant difference** between *win margins* in **playoff games** versus **regular season games**, with **home teams** performing **much better** in terms of *win margin* during playoffs. This finding **supports** the idea that home-field advantage is even more pronounced in high-stakes playoff games compared to regular season games.

The next piece of data I start analyzing are **rivalries**. Rivalry games create a unique home-field advantage due to **larger, louder crowds** that **boost** the home team's **energy** and **morale** while *throwing off* the away team. The emotional intensity and history behind these games push the **home team to perform better**, especially with increased media attention and higher stakes to defend their turf. The home team can often gain a mental edge, feeling more confident and comfortable in front of their fans. Special traditions also fuel the home crowd, making the atmosphere even more intense and difficult for the away team to handle. This can also sway the refs to make calls a certain way.

Below I create a dictionary of all of the rivalries in the NFL.

Source: https://www.espn.com

In [121…

```
rivalries = {
    'Buffalo Bills': ['New England Patriots', 'Miami Dolphins'],
    'Miami Dolphins': ['New England Patriots'],
    'New England Patriots': ['Buffalo Bills', 'New York Jets', 'Indianapolis
    'New York Jets': ['New England Patriots', 'Miami Dolphins'],

    'Baltimore Ravens': ['Pittsburgh Steelers'],
    'Cincinnati Bengals': ['Pittsburgh Steelers'],
    'Cleveland Browns': ['Pittsburgh Steelers'],
```

```
    'Pittsburgh Steelers': ['Baltimore Ravens', 'Cincinnati Bengals'],

    'Houston Texans': ['Indianapolis Colts'],
    'Indianapolis Colts': ['New England Patriots', 'Houston Texans'],
    'Jacksonville Jaguars': ['Tennessee Titans'],
    'Tennessee Titans': ['Indianapolis Colts'],

    'Denver Broncos': ['New England Patriots', 'Kansas City Chiefs'],
    'Kansas City Chiefs': ['Denver Broncos'],
    'Las Vegas Raiders': ['Denver Broncos'],
    'Los Angeles Chargers': ['Las Vegas Raiders'],

    'Dallas Cowboys': ['Washington Commanders', 'New York Giants', 'Philadel
    'New York Giants': ['Dallas Cowboys'],
    'Philadelphia Eagles': ['Dallas Cowboys'],
    'Washington Commanders': ['Dallas Cowboys'],

    'Chicago Bears': ['Green Bay Packers'],
    'Detroit Lions': ['Green Bay Packers'],
    'Green Bay Packers': ['Chicago Bears', 'Minnesota Vikings'],
    'Minnesota Vikings': ['Green Bay Packers'],

    'Atlanta Falcons': ['New Orleans Saints'],
    'Carolina Panthers': ['Atlanta Falcons'],
    'New Orleans Saints': ['Atlanta Falcons'],
    'Tampa Bay Buccaneers': ['Atlanta Falcons'],

    'Arizona Cardinals': ['Seattle Seahawks'],
    'Los Angeles Rams': ['San Francisco 49ers'],
    'San Francisco 49ers': ['Seattle Seahawks'],
    'Seattle Seahawks': ['Arizona Cardinals', 'San Francisco 49ers']
}

def is_rivalry_game(home_team, away_team, rivalries):
    if home_team in rivalries and away_team in rivalries[home_team]:
        return True
    return False

merged_game_data['is_rivalry'] = merged_game_data.apply(lambda row: is_rival

merged_game_data[['team_home', 'team_away', 'is_rivalry']].tail()
```

Out[121…

	team_home	team_away	is_rivalry
14212	Detroit Lions	Tampa Bay Buccaneers	False
14213	Baltimore Ravens	Kansas City Chiefs	False
14214	Baltimore Ravens	Kansas City Chiefs	False
14215	San Francisco 49ers	Detroit Lions	False
14216	Kansas City Chiefs	San Francisco 49ers	False

This calculates the average amount the home team wins by in both rivalry and non-rivalry games.

In [122…
```
rivalry_games = merged_game_data[merged_game_data['is_rivalry'] == True]
non_rivalry_games = merged_game_data[merged_game_data['is_rivalry'] == False

avg_win_margin_rivalry = rivalry_games['home_win_margin'].mean()
avg_win_margin_non_rivalry = non_rivalry_games['home_win_margin'].mean()

print(f'Average Home Win Margin (Rivalry Games): {avg_win_margin_rivalry}')
print(f'Average Home Win Margin (Non-Rivalry Games): {avg_win_margin_non_riv
```

```
Average Home Win Margin (Rivalry Games): 1.7475130270014212
Average Home Win Margin (Non-Rivalry Games): 2.8223195109862877
```

Add a column to our dataset which contains the **amount of points the away team won by in each game**. Mathematically, this is just the opposite of the *home_win_margin*.

In [123…
```
merged_game_data['away_win_margin'] = -merged_game_data['home_win_margin']
```

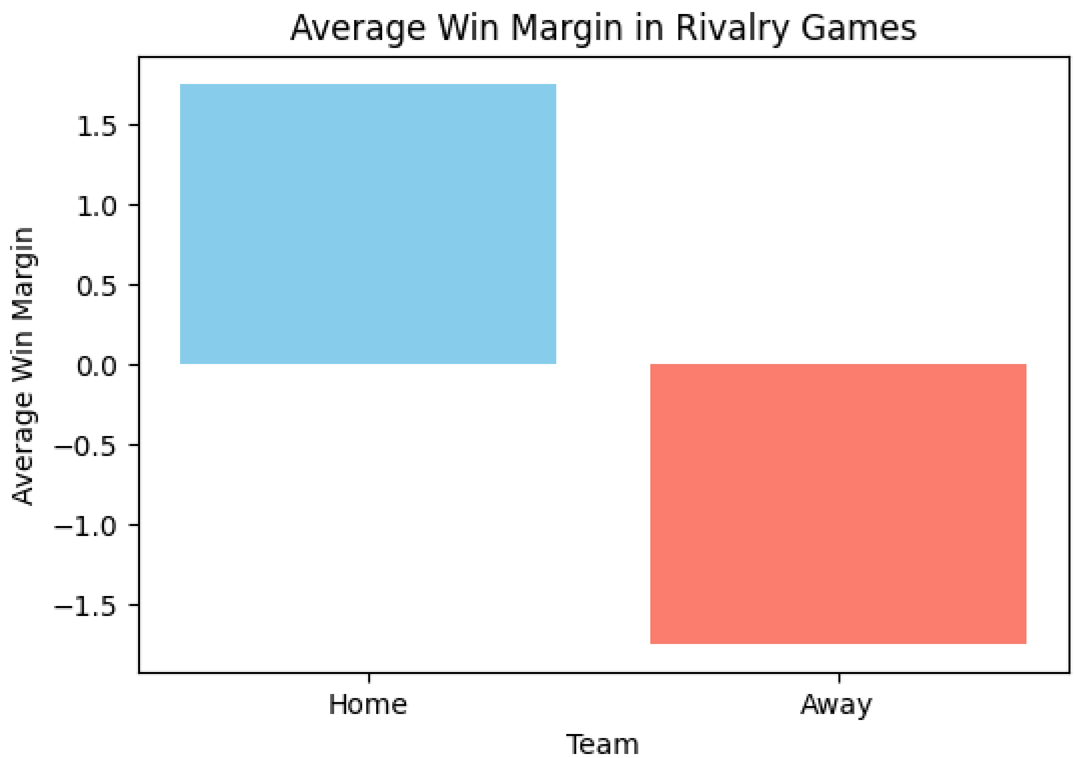
In [124…
```
rivalry_games = merged_game_data[merged_game_data['is_rivalry'] == True]
non_rivalry_games = merged_game_data[merged_game_data['is_rivalry'] == False

avg_home_win_margin_rivalry = rivalry_games['home_win_margin'].mean()
avg_away_win_margin_rivalry = rivalry_games['away_win_margin'].mean()

avg_home_win_margin_non_rivalry = non_rivalry_games['home_win_margin'].mean(
avg_away_win_margin_non_rivalry = non_rivalry_games['away_win_margin'].mean(

print(f'Average Home Win Margin (Rivalry Games): {avg_home_win_margin_rivalr
print(f'Average Away Win Margin (Rivalry Games): {avg_away_win_margin_rivalr
print(f'Average Home Win Margin (Non-Rivalry Games): {avg_home_win_margin_nc
print(f'Average Away Win Margin (Non-Rivalry Games): {avg_away_win_margin_nc
```

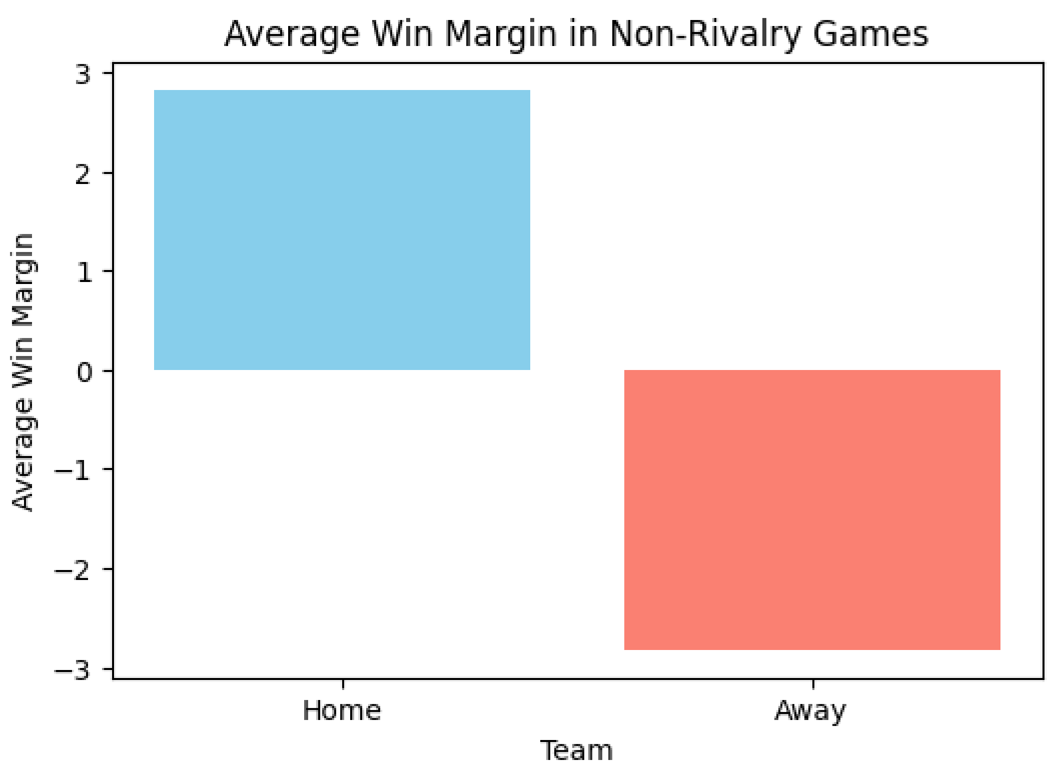
```
Average Home Win Margin (Rivalry Games): 1.7475130270014212
Average Away Win Margin (Rivalry Games): -1.7475130270014212
Average Home Win Margin (Non-Rivalry Games): 2.8223195109862877
Average Away Win Margin (Non-Rivalry Games): -2.8223195109862877
```

I create a graph to show the **average win margin** for both **home** and **away** teams in **rivalry** games, then the same for **non-rivalry** games.

In [125…
```
rivalry_margins = [avg_home_win_margin_rivalry, avg_away_win_margin_rivalry]
labels = ['Home', 'Away']

plt.figure(figsize=(6, 4))
plt.bar(labels, rivalry_margins, color=['skyblue', 'salmon'])
plt.title('Average Win Margin in Rivalry Games')
plt.xlabel('Team')
plt.ylabel('Average Win Margin')
plt.show()

non_rivalry_margins = [avg_home_win_margin_non_rivalry, avg_away_win_margin_
labels = ['Home', 'Away']
```

```
plt.figure(figsize=(6, 4))
plt.bar(labels, non_rivalry_margins, color=['skyblue', 'salmon'])
plt.title('Average Win Margin in Non-Rivalry Games')
plt.xlabel('Team')
plt.ylabel('Average Win Margin')
plt.show()
```





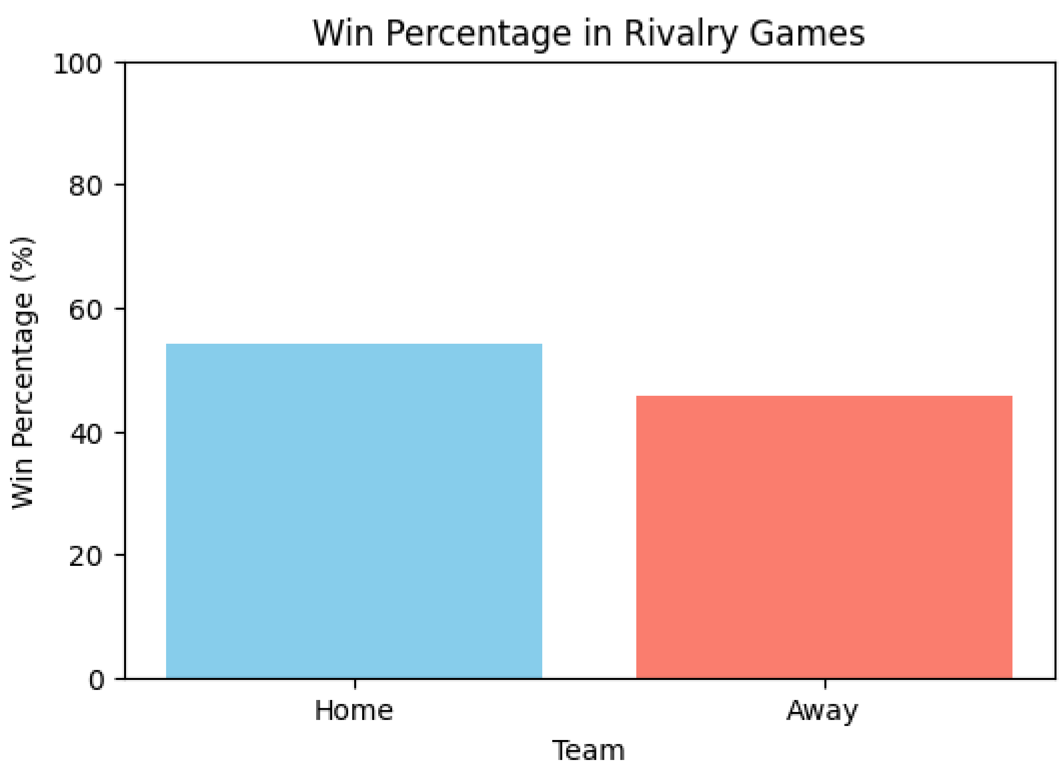
I do the same below, just with **win percentages** instead of **win margin**.

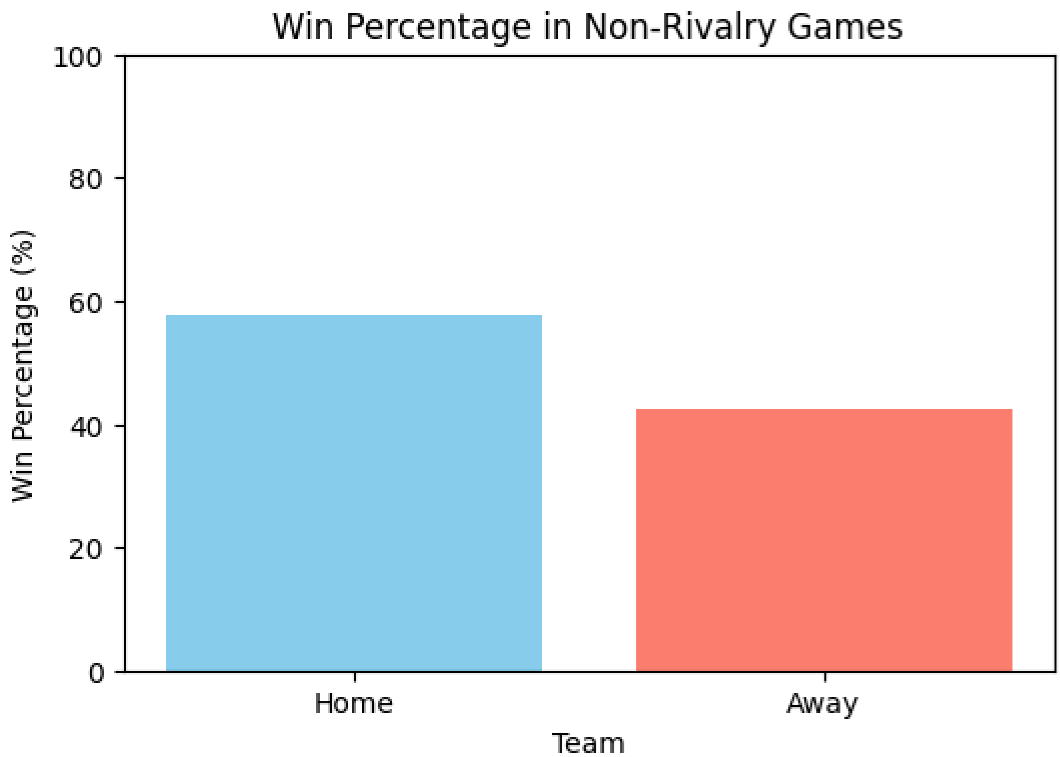
In [126…

```
home_win_percentage_rivalry = (rivalry_games['home_team_won'].mean()) * 100
home_win_percentage_non_rivalry = (non_rivalry_games['home_team_won'].mean()

away_win_percentage_rivalry = 100 - home_win_percentage_rivalry
away_win_percentage_non_rivalry = 100 - home_win_percentage_non_rivalry
```

In [127…

```
rivalry_win_percentages = [home_win_percentage_rivalry, away_win_percentage_
labels = ['Home', 'Away']

plt.figure(figsize=(6, 4))
plt.bar(labels, rivalry_win_percentages, color=['skyblue', 'salmon'])
plt.title('Win Percentage in Rivalry Games')
plt.xlabel('Team')
plt.ylabel('Win Percentage (%)')
plt.ylim(0, 100)
plt.show()

non_rivalry_win_percentages = [home_win_percentage_non_rivalry, away_win_per
labels = ['Home', 'Away']

plt.figure(figsize=(6, 4))
plt.bar(labels, non_rivalry_win_percentages, color=['skyblue', 'salmon'])
plt.title('Win Percentage in Non-Rivalry Games')
plt.xlabel('Team')
plt.ylabel('Win Percentage (%)')
plt.ylim(0, 100)
plt.show()
```





What can be drawn from this:

The visualizations above suggest that rivalry matchups tend to be closer games, with smaller win margins compared to non-rivalry games. However, the data still **supports** the concept of **home-field advantage**, as home teams win by an average of 15% more than away teams in non-rivalry matchups and by 5% more in rivalry games. In every graph, the home team consistently outperforms the away team on average, further **reinforcing** the idea of **home-field advantage**.

To **statistically validate** these visual observations, I conducted two **t-tests** to determine if the differences in *win margins* and *win percentages* between **rivalry** and **non-rivalry games** are **significant**. This will help us confirm whether the trends shown in the graphs are due to chance or reflect a meaningful pattern.

In [128…

```
rivalry_margins = merged_game_data[merged_game_data['is_rivalry'] == True]['
non_rivalry_margins = merged_game_data[merged_game_data['is_rivalry'] == Fal

t_stat_rivalry, p_value_rivalry = stats.ttest_ind(rivalry_margins, non_rival

print(f"Rivalry vs. Non-Rivalry Games - T-statistic: {t_stat_rivalry}, P-val
```

```
Rivalry vs. Non-Rivalry Games - T-statistic: -3.065229399285348, P-value: 0.
002179108878479995
```

This result shows that **home teams** tend to win by **smaller margins** in **rivalry games** compared to **non-rivalry games**. The intensity and competitiveness of rivalry games likely contribute to **closer matchups**, making it harder for the **home team** to win by a large margin.

In [129…

```
rivalry_win_rates = merged_game_data[merged_game_data['is_rivalry'] == True]
non_rivalry_win_rates = merged_game_data[merged_game_data['is_rivalry'] == F

t_stat_win_rivalry, p_value_win_rivalry = stats.ttest_ind(rivalry_win_rates,

print(f"Rivalry vs. Non-Rivalry Win Rates - T-statistic: {t_stat_win_rivalry
```

```
Rivalry vs. Non-Rivalry Win Rates - T-statistic: -2.8693584943215797, P-valu
e: 0.004119115185911054
```

The **t-test** comparing **win rates** in *rivalry* vs. *non-rivalry* games resulted in a **T-statistic of -2.87** and a **P-value of 0.0041**, indicating a **statistically significant difference**. The *negative t-statistic* suggests that home teams win **less** often in **rivalry games** compared to **non-rivalry games**. This shows that rivalry games tend to be **more competitive**, making it **harder** for home teams to secure a win, even though they typically have the home-field advantage.
