BitByBit Team: Sports Data Notebook

From Data to Win: Bulding Predictive Models for Match Outcomes

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Intro

- Football is one of the most popular sports worldwide, that generates a vast amount of interest in betting and selecting winning teams. We will make predictions of which teams will win based on data from previous games results and data.

Data Description, Preciction Goals, Features as Predictors

- **Data Description:**
  The dataset we are using contains information for the National football League's bettings odds from 1979 up until 2013. The information in this dataset was collected from websites such as ESPN, NFL, Pro Football reference, while the weather information was collected from NOAA. Some of the information in this dataset includes columns with team scores, the location of the game, the style of the stadium, the weather during game day, and stadium capacity. The information contained in this dataset can help analyze trends to develop better betting strategies. We plan to add more features to the existing features. We can add win and loss columns based on the team's scores.

- **Prediction Goals:**
  Using our dataset we aim to build a predictive system for NFL games, this system will estimate the probability of winning or losing between two NFL teams when they face off. We will analyze historical performance, so our model can provide valuable insights into game outcomes.

- **Features as Predictors:**
  Our predictive system will use several features to enhance accuracy. We'll use team scores along with wins and losses , which will provide an overall record for each team. Additionally, we'll analyze wins against other teams, which will take into consideration the performance between different opponents. Also, we'll explore the relationship between team wins at home versus away games, along with the weather

of the stadium where they games are played. These features together will create great predictors.

Add Installs:

In [1]:
```
! if test -d ./CST383_SportsData; then \
echo "Data directory already exists"; \
else \
echo "Cloning data directory"; \
git clone https://github.com/nickleus27/CST383_SportsData.git; \
fi
```

```
Cloning data directory
Cloning into 'CST383_SportsData'...
remote: Enumerating objects: 35, done.
remote: Counting objects: 100% (35/35), done.
remote: Compressing objects: 100% (30/30), done.
remote: Total 35 (delta 10), reused 15 (delta 1), pack-reused 0
Receiving objects: 100% (35/35), 1.79 MiB | 2.61 MiB/s, done.
Resolving deltas: 100% (10/10), done.
```

Add Imports:

In [2]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
# add needed imports here
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.neighbors import KNeighborsClassifier
from sklearn.preprocessing import OneHotEncoder
from sklearn.tree import DecisionTreeClassifier, export_graphviz
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.ensemble import RandomForestClassifier
import graphviz
```

Defaults for Graphs

In [3]:
```
sns.set_context('talk')
plt.style.use('dark_background')
plt.rcParams['figure.figsize'] = (12, 8)
```

Read Data:

In [4]:
```
df = pd.read_csv("CST383_SportsData/archive/spreadspoke_scores.csv")
# add more data here
df.head()
```

Out[4]:

	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	

Overview of Data

In [5]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 13800 entries, 0 to 13799
Data columns (total 17 columns):
 #   Column               Non-Null Count  Dtype  
---  ------               --------------  -----  
 0   schedule_date        13800 non-null  object 
 1   schedule_season      13800 non-null  int64  
 2   schedule_week        13800 non-null  object 
 3   schedule_playoff     13800 non-null  bool   
 4   team_home            13800 non-null  object 
 5   score_home           13798 non-null  float64
 6   score_away           13798 non-null  float64
 7   team_away            13800 non-null  object 
 8   team_favorite_id     11319 non-null  object 
 9   spread_favorite      11319 non-null  float64
 10  over_under_line      11309 non-null  object 
 11  stadium              13800 non-null  object 
 12  stadium_neutral      13800 non-null  bool   
 13  weather_temperature  12420 non-null  float64
 14  weather_wind_mph     12404 non-null  float64
 15  weather_humidity     8474 non-null   float64
 16  weather_detail       3024 non-null   object 
dtypes: bool(2), float64(6), int64(1), object(8)
memory usage: 1.6+ MB
```

In [6]:
```
df.describe()
```

Out[6]:

	schedule_season	score_home	score_away	spread_favorite	weather_tempe
count	13800.000000	13798.000000	13798.000000	11319.000000	12420.(
mean	1996.636884	22.479852	19.797000	-5.373134	58.!
std	16.427953	10.523645	10.153181	3.439071	15.!
min	1966.000000	0.000000	0.000000	-26.500000	-6.(
25%	1983.000000	15.000000	13.000000	-7.000000	48.(
50%	1998.000000	22.000000	20.000000	-4.500000	62.(
75%	2011.000000	29.000000	27.000000	-3.000000	72.(
max	2023.000000	72.000000	62.000000	0.000000	97.(

Data Wrangling Prep

- **Convert schedule_date** to datetime
- **score_home, score_away** 2 missing data values
- **weather detail** lots of missing values
- **weather_humidity** missing data
- **weather_temperature** missing data
- **weather_wind_mph** missing data
- **over_under_line** missing data
- **spread_favorite** missing data
- **team_favorite** missing data

Covert datetime

In [7]:
```
df['schedule_date'] = pd.to_datetime(df['schedule_date'], format='%m/%d/%Y')
df['schedule_date']
```

Out[7]:
```
0        1966-09-02
1        1966-09-03
2        1966-09-04
3        1966-09-09
4        1966-09-10
            ...
13795    2024-01-20
13796    2024-01-21
13797    2024-01-21
13798    2024-01-28
13799    2024-01-28
Name: schedule_date, Length: 13800, dtype: datetime64[ns]
```

score_home & score_away

In [8]:
```
# Drop score rows with NaN
# dropping NaN in score_home should also take care of NaN score_away
df = df.iloc[df.score_home.dropna(axis=0).index]
pd.isna(df.score_away).sum()
```

Out[8]: 0

Manufacture Features

The First step we need to consider to have a realistic model is to drop old data from the data frame. Teams from the past should not have an influence on the odds of current teams winning or losing. So we will drop data before year 2010. This is an area we could continue to experiment with to find optimal results.

In [9]:
```
# drop old seasons. keep data only since 2010 to keep data from current team
df = df[df.schedule_season > 2010]
df.reset_index(drop=True, inplace=True)
df
```

Out[9]:

	schedule_date	schedule_season	schedule_week	schedule_playoff	team_home
0	2011-09-08	2011	1	False	Green Bay Packers
1	2011-09-11	2011	1	False	Arizona Cardinals
2	2011-09-11	2011	1	False	Baltimore Ravens
3	2011-09-11	2011	1	False	Chicago Bears
4	2011-09-11	2011	1	False	Cleveland Browns
...	...	...	...	...	...
3518	2024-01-15	2023	Wildcard	True	Tampa Bay Buccaneers
3519	2024-01-20	2023	Division	True	Baltimore Ravens
3520	2024-01-20	2023	Division	True	San Francisco 49ers
3521	2024-01-21	2023	Division	True	Buffalo Bills
3522	2024-01-21	2023	Division	True	Detroit Lions

3523 rows × 17 columns

Lets turn the teams scores into a column for wins and a column for losses. With this data feature we can continue to build features of teams win/loss ratios against other teams.

In [10]:
```
# add column for which teams won
def apply_fn(x):
  if x.score_home == x.score_away:
    return "Tie"
  elif  x.score_home > x.score_away:
    return x.team_home
  else:
    return x.team_away
df["winning_team"] = df.apply(apply_fn, axis=1)
```

In [11]:
```
# add column for which teams lost
def apply_fn(x):
  if x.score_home == x.score_away:
```

```
    return "Tie"
  elif  x.score_home > x.score_away:
    return x.team_away
  else:
    return x.team_home
df["losing_team"] = df.apply(apply_fn, axis=1)
```

Before realizing we should drop old data (not current seasons), we converted teams who had changed there name to all have the teams current name. We kept this in place even though it might not apply to all the current data. But it will still apply to recent team name changes, such as, the Raiders.

Questions?:

--- what should we do about teams that dont exist any more?

- ~~Oilers (drop?)~~
- ~~looks like oilers could be combined with current teams: wikipedia oilers~~
- added previous team names to current

--- what should we do about teams that have moved?

- ~~Raiders [LA, Oakland, Vegas] (combine?)~~
- combined teams

--- teams that changed names?

- ~~Washing Footbal Team, Commanders ?~~
- combined teams

There could be more...

In [12]:
```
cols_to_replace = ['winning_team', 'team_home', 'team_away', 'losing_team']
teams_to_replace = {'Oilers': 'Tennessee Titans', 'Raiders': "Las Vegas Raic
```

In [13]:
```
def replace_teams(data, cols, teams):
    for col in cols:
        for old_name, new_name in teams.items():
            mask = data[col].str.contains(old_name, case=False, na=False)
            data.loc[mask, col] = new_name
            print(f'Replaced {old_name} with {new_name} in {col}')
    return data
df = replace_teams(df, cols=cols_to_replace, teams=teams_to_replace)
```

```
Replaced Oilers with Tennessee Titans in winning_team
Replaced Raiders with Las Vegas Raiders in winning_team
Replaced Redskins with Washington Commanders in winning_team
Replaced Football with Washington Commanders in winning_team
Replaced Colts with Indianapolis Colts in winning_team
Replaced Patriots with New England Patriots in winning_team
Replaced Cardinals with Arizona Cardinals in winning_team
Replaced Chargers with Los Angeles Chargers in winning_team
Replaced Rams with Los Angeles Rams in winning_team
Replaced Oilers with Tennessee Titans in team_home
Replaced Raiders with Las Vegas Raiders in team_home
Replaced Redskins with Washington Commanders in team_home
Replaced Football with Washington Commanders in team_home
Replaced Colts with Indianapolis Colts in team_home
Replaced Patriots with New England Patriots in team_home
Replaced Cardinals with Arizona Cardinals in team_home
Replaced Chargers with Los Angeles Chargers in team_home
Replaced Rams with Los Angeles Rams in team_home
Replaced Oilers with Tennessee Titans in team_away
Replaced Raiders with Las Vegas Raiders in team_away
Replaced Redskins with Washington Commanders in team_away
Replaced Football with Washington Commanders in team_away
Replaced Colts with Indianapolis Colts in team_away
Replaced Patriots with New England Patriots in team_away
Replaced Cardinals with Arizona Cardinals in team_away
Replaced Chargers with Los Angeles Chargers in team_away
Replaced Rams with Los Angeles Rams in team_away
Replaced Oilers with Tennessee Titans in losing_team
Replaced Raiders with Las Vegas Raiders in losing_team
Replaced Redskins with Washington Commanders in losing_team
Replaced Football with Washington Commanders in losing_team
Replaced Colts with Indianapolis Colts in losing_team
Replaced Patriots with New England Patriots in losing_team
Replaced Cardinals with Arizona Cardinals in losing_team
Replaced Chargers with Los Angeles Chargers in losing_team
Replaced Rams with Los Angeles Rams in losing_team
```

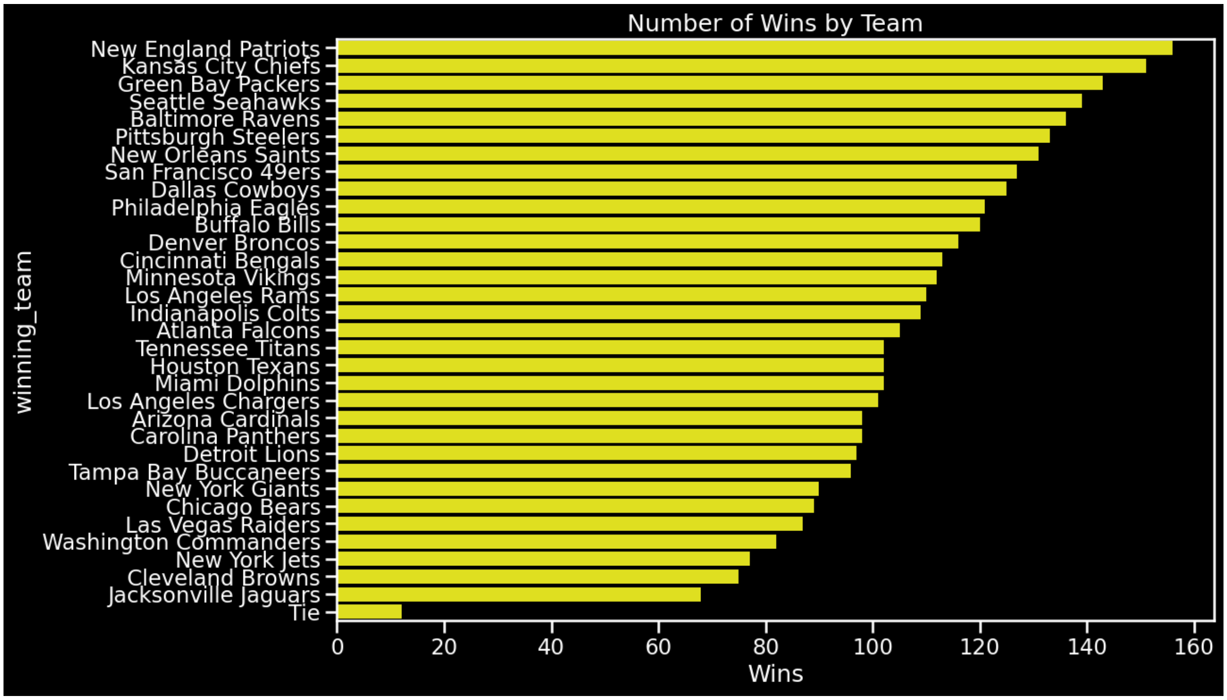
Lets take a look at how teams look as far as total wins. Lets get an idea from the data what teams we can expect to win often.

In [14]:

```
# plot which how many times each team won
df['winning_team'].value_counts()
sns.barplot(df['winning_team'].value_counts(), orient='h', color='yellow')
plt.title("Number of Wins by Team")
plt.xlabel("Wins")
```

Out[14]:

```
Text(0.5, 0, 'Wins')
```



Before we forget and move on, let try to mangle some of the data with missing values to make it usable

In [15]:

```
# filling in nans with mean
weather_mask = df['weather_temperature'].isna()
weather_wind_mask = df['weather_wind_mph'].isna()

weather_wind_mean = df['weather_wind_mph'].mean()
weather_mean = df['weather_temperature'].mean()

df.loc[weather_mask, "weather_temperature"] = weather_mean
df.loc[weather_wind_mask, 'weather_wind_mph'] = weather_wind_mean
```

Lets add one hot encoding for each team. That way we can keep track of what teams played in each row in a numerical format instead of a categorical format.

In [16]:

```
teams = df.team_home.unique()
oneHotTeams = pd.DataFrame(np.full((df.team_home.size, teams.size), -1.0), c
df = pd.concat([df, oneHotTeams], axis=1)
df
```

Out[16]:

	schedule_date	schedule_season	schedule_week	schedule_playoff	team_home
0	2011-09-08	2011	1	False	Green Bay Packers
1	2011-09-11	2011	1	False	Arizona Cardinals
2	2011-09-11	2011	1	False	Baltimore Ravens
3	2011-09-11	2011	1	False	Chicago Bears
4	2011-09-11	2011	1	False	Cleveland Browns
...	...	...	...	...	...
3518	2024-01-15	2023	Wildcard	True	Tampa Bay Buccaneers
3519	2024-01-20	2023	Division	True	Baltimore Ravens
3520	2024-01-20	2023	Division	True	San Francisco 49ers
3521	2024-01-21	2023	Division	True	Buffalo Bills
3522	2024-01-21	2023	Division	True	Detroit Lions

3523 rows × 51 columns

One hot encoding values in terms of wins and losses in order to gain percentages of wins per team

In [17]:

```
# One hot encoding goes here
for row in range(df.shape[0]):
  winner = df.loc[row, 'winning_team']
  loser = df.loc[row, 'losing_team']
  if winner == 'Tie' or loser == 'Tie':
    home = df.loc[row, 'team_home']
    away = df.loc[row, 'team_away']
    df.loc[row, home] = 0.5
    df.loc[row, away] = 0.5
  else:
    df.loc[row, winner] = 1
    df.loc[row, loser] = 0
df
```

Out[17]:

	schedule_date	schedule_season	schedule_week	schedule_playoff	team_home
0	2011-09-08	2011	1	False	Green Bay Packers
1	2011-09-11	2011	1	False	Arizona Cardinals
2	2011-09-11	2011	1	False	Baltimore Ravens
3	2011-09-11	2011	1	False	Chicago Bears
4	2011-09-11	2011	1	False	Cleveland Browns
...	...	...	...	...	...
3518	2024-01-15	2023	Wildcard	True	Tampa Bay Buccaneers
3519	2024-01-20	2023	Division	True	Baltimore Ravens
3520	2024-01-20	2023	Division	True	San Francisco 49ers
3521	2024-01-21	2023	Division	True	Buffalo Bills
3522	2024-01-21	2023	Division	True	Detroit Lions

3523 rows × 51 columns

Visualizations & Plots

Lets get an idea if it matters if a team is playing away or at home. Maybe it could help us in determine if a team will win or not.

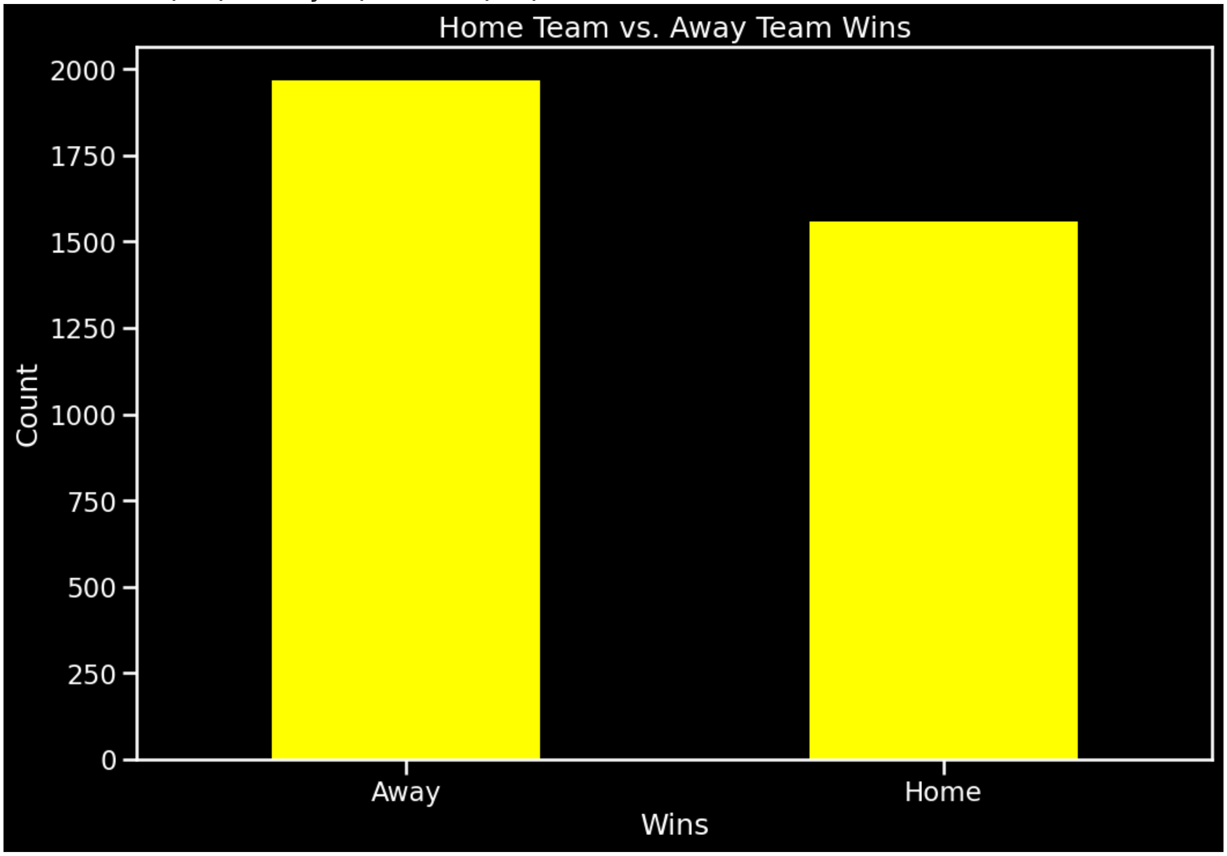
More teams win home than away this could indicate a home field advantage.

In [18]:

```
# Home vs Away Scores/Wins
df['home_score_greater'] = df['score_home'] > df['score_away']
score_comparison_counts = (df['home_score_greater']).value_counts()
score_comparison_counts.plot(kind='bar', color='yellow')
plt.title("Home Team vs. Away Team Wins")
plt.xlabel("Wins")
```

```
plt.ylabel("Count")
plt.xticks(ticks=[0, 1], labels=["Away", "Home"], rotation=0)
```

Out[18]:
```
([<matplotlib.axis.XTick at 0x168c40ee0>,
  <matplotlib.axis.XTick at 0x168c40eb0>],
 [Text(0, 0, 'Away'), Text(1, 0, 'Home')])
```



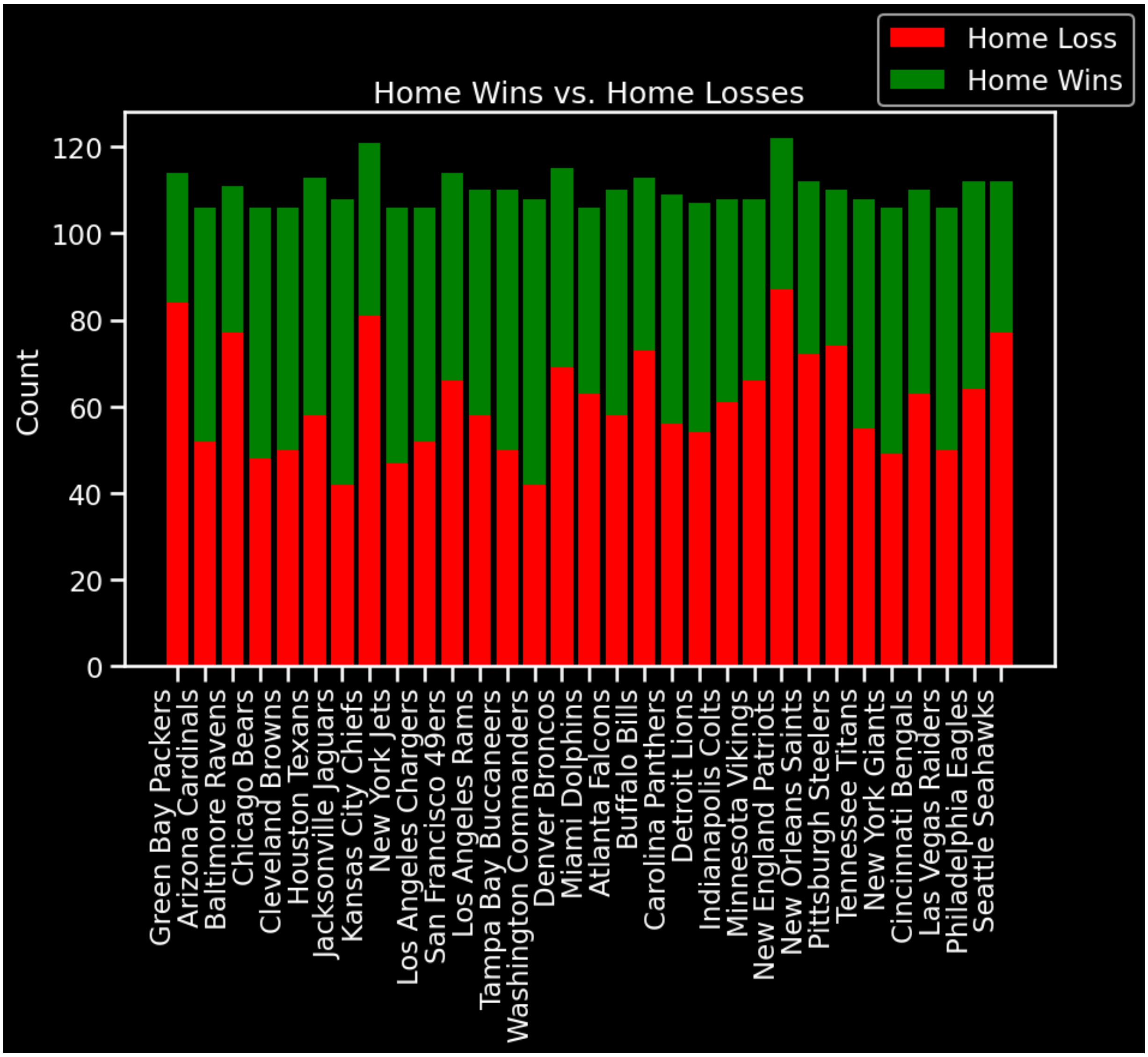
Invidual Teams Wins at Home vs Losses at Home

All teams win more games at home rather than away but there are some teams that do lose significantly more at home than others

In [19]:
```
team_names = df.columns[19:-2].tolist()

home_wins = {}
home_loss = {}

for team in team_names:
    dfh = df[df['team_home'] == team]
    home_wins[team] = dfh['score_home'] > dfh['score_away']
    home_loss[team] = ~home_wins[team]

plt.figure(figsize=(10, 6))

plt.bar(team_names, [home_wins[team].sum() for team in team_names], label='H
plt.bar(team_names, [home_loss[team].sum() for team in team_names], bottom=[
```

```
plt.title("Home Wins vs. Home Losses")
plt.ylabel("Count")
plt.xticks(rotation=90, ha='right')
plt.legend(bbox_to_anchor=(1.1, 1.2), loc='upper right')
```

Out[19]: <matplotlib.legend.Legend at 0x168d03010>

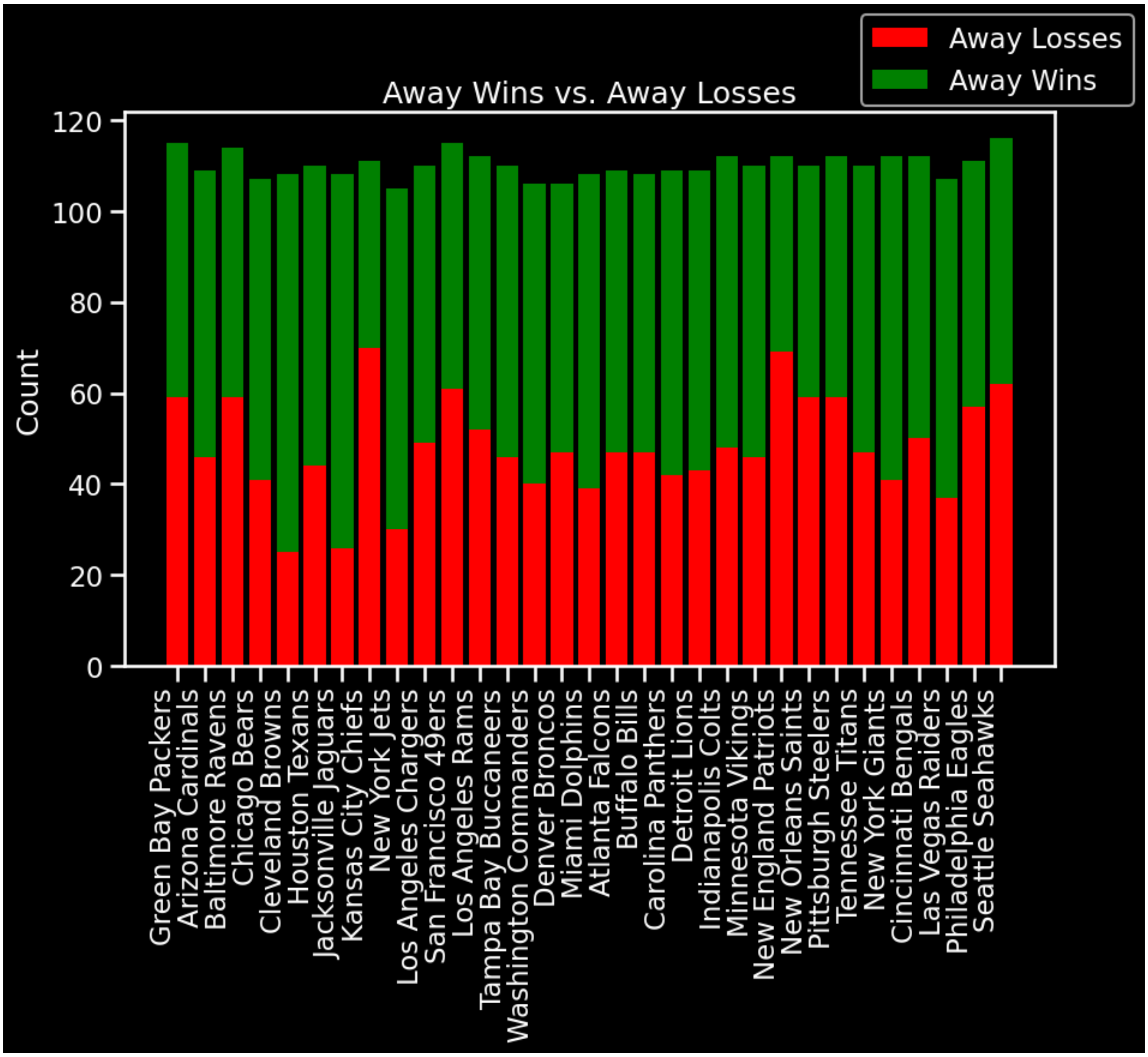


Invidual Teams Wins Away vs Losses Away

In [20]:
```
away_wins = {}
away_loss = {}

for team in team_names:
    dfh = df[df['team_away'] == team]
    away_wins[team] = dfh['score_home'] < dfh['score_away']
    away_loss[team] = ~away_wins[team]

plt.figure(figsize=(10, 6))
plt.bar(team_names, [away_wins[team].sum() for team in team_names], label='A
plt.bar(team_names, [away_loss[team].sum() for team in team_names], bottom=[
```

```
plt.title("Away Wins vs. Away Losses")
plt.ylabel("Count")
plt.xticks(rotation=90, ha='right')
plt.legend(bbox_to_anchor=(1.1, 1.2), loc='upper right')
```

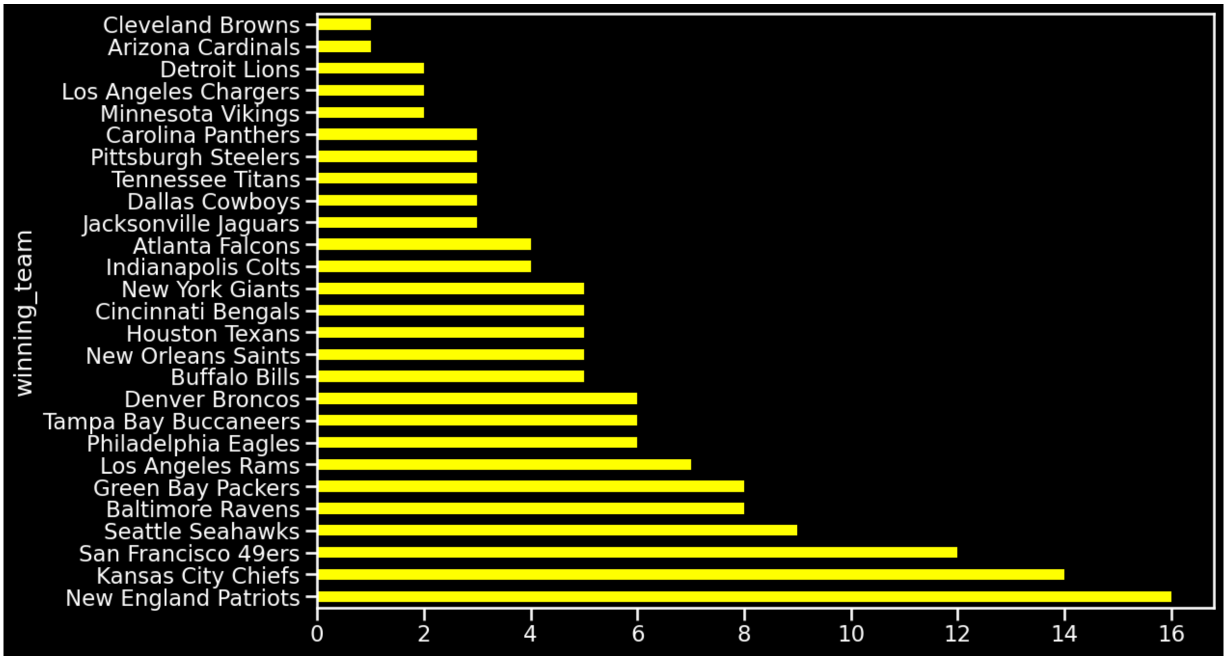
Out[20]: <matplotlib.legend.Legend at 0x168e99450>



- There is quite the difference in the amount of wins each team has in the playoffs this could indicate certain teams perform better under pressure, or some teams just dont make it playoff as much as other teams

In [21]:
```
df[df.schedule_playoff]['winning_team'].value_counts().plot.barh(color='yell
```

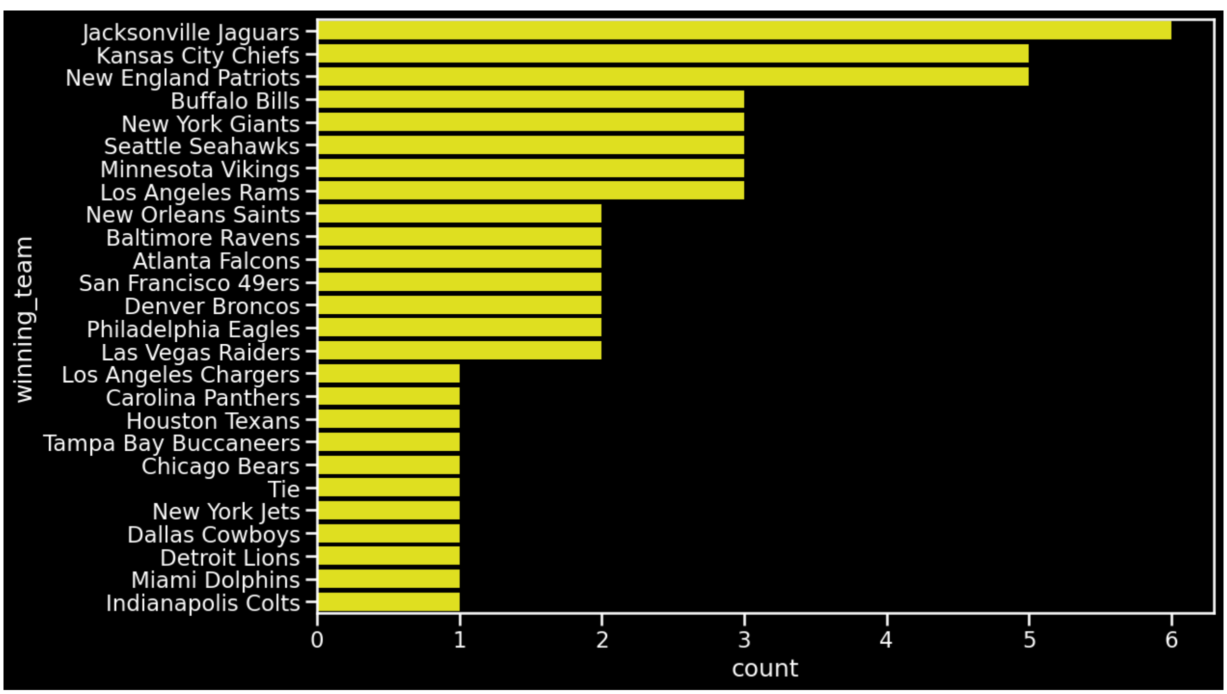
Out[21]: <Axes: ylabel='winning_team'>



This graph shows the amount of wins teams have on a neautral stadium. This could indicate some teams perform better when there is no home field advantage

In [22]:
```
neatrual_mask = df['stadium_neutral'] == True
wins_on_neatrual = df[neatrual_mask]['winning_team']
win_counts = wins_on_neatrual.value_counts().sort_values(ascending=False)
sorted_teams = win_counts.index

sns.countplot(y=wins_on_neatrual, order=sorted_teams, color='yellow')
```

Out[22]: <Axes: xlabel='count', ylabel='winning_team'>



Feature Building

Lets try to build features that will help us make predictions. We think the percentage a team wins or loses against another team could help us make predictions. Here we will build the aforementioned feature.

In [23]:
```
team_names = df.columns[19:-1].tolist()
team_names
```

Out[23]:
```
['Green Bay Packers',
 'Arizona Cardinals',
 'Baltimore Ravens',
 'Chicago Bears',
 'Cleveland Browns',
 'Houston Texans',
 'Jacksonville Jaguars',
 'Kansas City Chiefs',
 'New York Jets',
 'Los Angeles Chargers',
 'San Francisco 49ers',
 'Los Angeles Rams',
 'Tampa Bay Buccaneers',
 'Washington Commanders',
 'Denver Broncos',
 'Miami Dolphins',
 'Atlanta Falcons',
 'Buffalo Bills',
 'Carolina Panthers',
 'Detroit Lions',
 'Indianapolis Colts',
 'Minnesota Vikings',
 'New England Patriots',
 'New Orleans Saints',
 'Pittsburgh Steelers',
 'Tennessee Titans',
 'New York Giants',
 'Cincinnati Bengals',
 'Las Vegas Raiders',
 'Philadelphia Eagles',
 'Seattle Seahawks',
 'Dallas Cowboys']
```

Here we create a list of wins and losses each team has against each other

In [24]:
```
def wins_losses_per_team(df, list_teams):
  # loop through each team
  for x, team in enumerate(list_teams):
    # Make sure to grab all games not just home or away
    team_home = df['team_home'] == team
    team_away = df['team_away'] == team

    # Add team to list
    team_wins_losses['Team'].append(team)
    team_losses["Team"].append(team)
    for y, against in enumerate(list_teams):
      # Loop through all other teams and calculate amount of wins
```

```
      if ( y <= 32):
        wins = (df.loc[team_home | team_away, list_teams[y]] == 1).sum()
        losses = (df.loc[team_home | team_away, list_teams[y]] == 0).sum()

        team_wins_losses["Wins"].append(wins) # Append wins in order of list
        team_wins_losses["Against"].append(against) # Appends team in order

        team_losses['Losses'].append(losses)
        team_losses['Against'].append(against)
```

In [25]:
```
team_wins_losses = {'Team': [], "Wins": [], "Against": []}
team_losses = {'Team': [], 'Losses':[], 'Against': []}
wins_losses_per_team(df, team_names)
```

In [26]:
```
# Converting the wins list into 32 seperate list of win and loss records for
# each team
wins_per_team = [team_wins_losses['Wins'][i : i + 32] for i in range(0, len(
against_teams = [team_wins_losses['Against'][i : i + 32] for i in range(0, l

losses_per_team = [team_losses['Losses'][i : i + 32] for i in range(0, len(t
against_teams_losses = [team_losses['Against'][i : i + 32] for i in range(0,
```

In [27]:
```
team_wins_losses["Wins"] = wins_per_team
team_wins_losses["Against"] = against_teams

team_losses['Losses'] = losses_per_team
team_losses['Against'] = against_teams_losses
```

Here we are creating the dataframes for the amount of wins and losses in order to extract the percentages that each team either won or lost against one another

In [28]:
```
data = []

for team_idx, team in enumerate(team_wins_losses["Team"]):
  # Loop through entire list of teams
    wins = team_wins_losses["Wins"][team_idx] # Set wins to entire list of w
    opponents = team_wins_losses["Against"][team_idx] # set opponents to ent
    for win, opponent in zip(wins, opponents):
      # append a dictionary to data for each team, their oppponents, and the
        data.append({"Team": team, "Opponent": opponent, "Wins": win})

# convert to dataframe
team_df = pd.DataFrame(data)
```

In [29]:
```
data_losses = []
for team_idx, team in enumerate(team_losses['Team']):
  losses = team_losses["Losses"][team_idx]
  opponents = team_losses["Against"][team_idx]
  for loss, opponent in zip(losses, opponents):
    data_losses.append({"Team": team, "Opponent": opponent, "Losses": loss})

team_loss_df = pd.DataFrame(data_losses)
```

In [30]:
```
team_df.head(n=5)
```

Out[30]:

	Team	Opponent	Wins
0	Green Bay Packers	Green Bay Packers	143
1	Green Bay Packers	Arizona Cardinals	3
2	Green Bay Packers	Baltimore Ravens	1
3	Green Bay Packers	Chicago Bears	3
4	Green Bay Packers	Cleveland Browns	0

In [31]:
```
# Convert data into wide format
team_df = team_df.pivot(index="Team", columns="Opponent", values="Wins")
```

In [32]:
```
team_df.reset_index(inplace=True)
team_df.head()
```

Out[32]:

Opponent	Team	Arizona Cardinals	Atlanta Falcons	Baltimore Ravens	Buffalo Bills	Carolina Panthers	Chicago Bears	Cinci Ber
0	Arizona Cardinals	98	5	3	2	6	3	
1	Atlanta Falcons	3	105	3	2	10	4	
2	Baltimore Ravens	1	0	136	3	1	2	
3	Buffalo Bills	1	1	3	120	1	1	
4	Carolina Panthers	3	16	2	2	98	5	

5 rows × 33 columns

In [33]:
```
team_losses_df = team_loss_df.pivot(index="Team", columns="Opponent", values
```

In [34]:
```
team_losses_df.reset_index(inplace=True)
team_losses_df.head()
```

Out[34]:

Opponent	Team	Arizona Cardinals	Atlanta Falcons	Baltimore Ravens	Buffalo Bills	Carolina Panthers	Chicago Bears	Cinci Ber
0	Arizona Cardinals	115	3	1	1	3	2	
1	Atlanta Falcons	5	114	0	1	16	2	
2	Baltimore Ravens	3	3	89	3	2	1	
3	Buffalo Bills	2	2	3	101	2	2	
4	Carolina Panthers	6	10	1	1	119	1	

5 rows × 33 columns

In [35]:

```
team_names = team_df.columns[1:]
```

In [36]:

```
total_games_df = team_df.loc[:, team_names] + team_losses_df.loc[:, team_nam
```

In [37]:

```
win_percentage_df = team_df.loc[:, team_names] / total_games_df
win_percentage_df.replace([np.inf, -np.inf], 0, inplace=True)
win_percentage_df.index = team_names

loss_percentage_df = team_losses_df.loc[:, team_names] / total_games_df
loss_percentage_df.replace([np.inf, -np.inf], 0, inplace=True)
loss_percentage_df.index = team_names
```

In [38]:

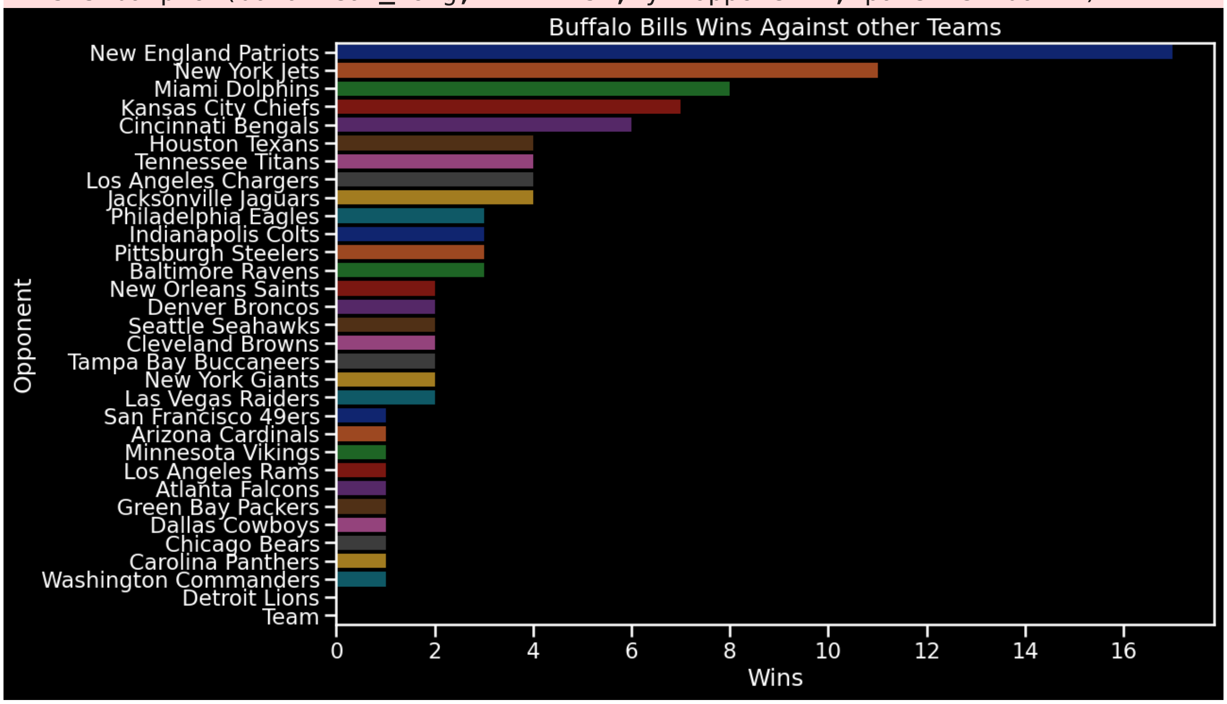
```
def plot_team_wins(team_name):
  # plotting team wins
  team = team_df["Team"] == team_name
  team = team_df[team]
  team = team.drop(columns=team_name)

  # Convert data into long format
  team_long = pd.melt(team, var_name='Opponent', value_name='Wins')
  team_long['Wins'] = pd.to_numeric(team_long["Wins"], errors='coerce')
  team_long = team_long.sort_values(by="Wins", ascending=False)

  sns.barplot(data=team_long, x='Wins', y="Opponent", palette='dark')
  plt.title(f"{team_name} Wins Against other Teams")
```

Plot of Buffalo Bills Wins Against Other Teams

By plotting the amount of wins each team has against each other we can gain more insight when creating our model and the predictions it makes. A team that normally wins against another should be a good indicator in the outcome of those teams playing against each other

In [39]:
```
plot_team_wins("Buffalo Bills")
```

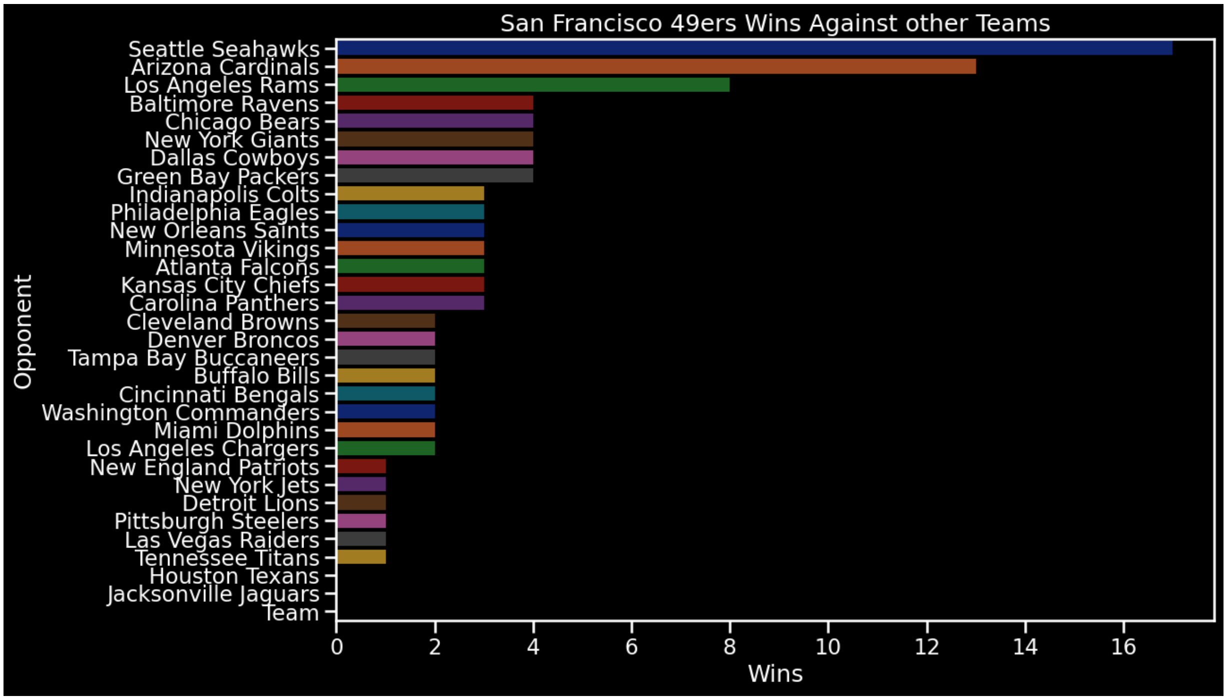
```
/var/folders/w6/tr1493cj7zd3sj7s4qyp_nwh0000gn/T/ipykernel_76728/4179918728.
py:12: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed
in v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the
same effect.

  sns.barplot(data=team_long, x='Wins', y="Opponent", palette='dark')
```



Plot of San Francisco 49ers Wins Against Other Teams

In [40]:
```
plot_team_wins("San Francisco 49ers")
```

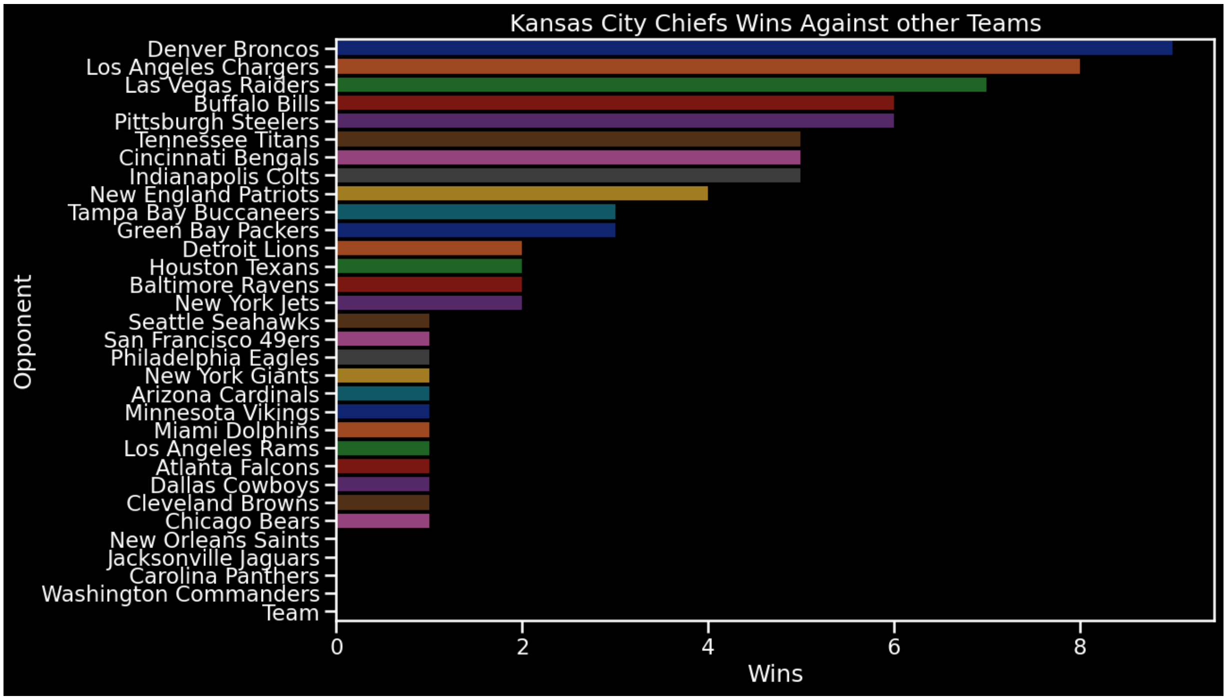
```
/var/folders/w6/tr1493cj7zd3sj7s4qyp_nwh0000gn/T/ipykernel_76728/4179918728.
py:12: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed
in v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the
same effect.

  sns.barplot(data=team_long, x='Wins', y="Opponent", palette='dark')
```



Plot of Kansas City Chiefs Wins Against Other Teams

In [41]:
```
plot_team_wins("Kansas City Chiefs")
```

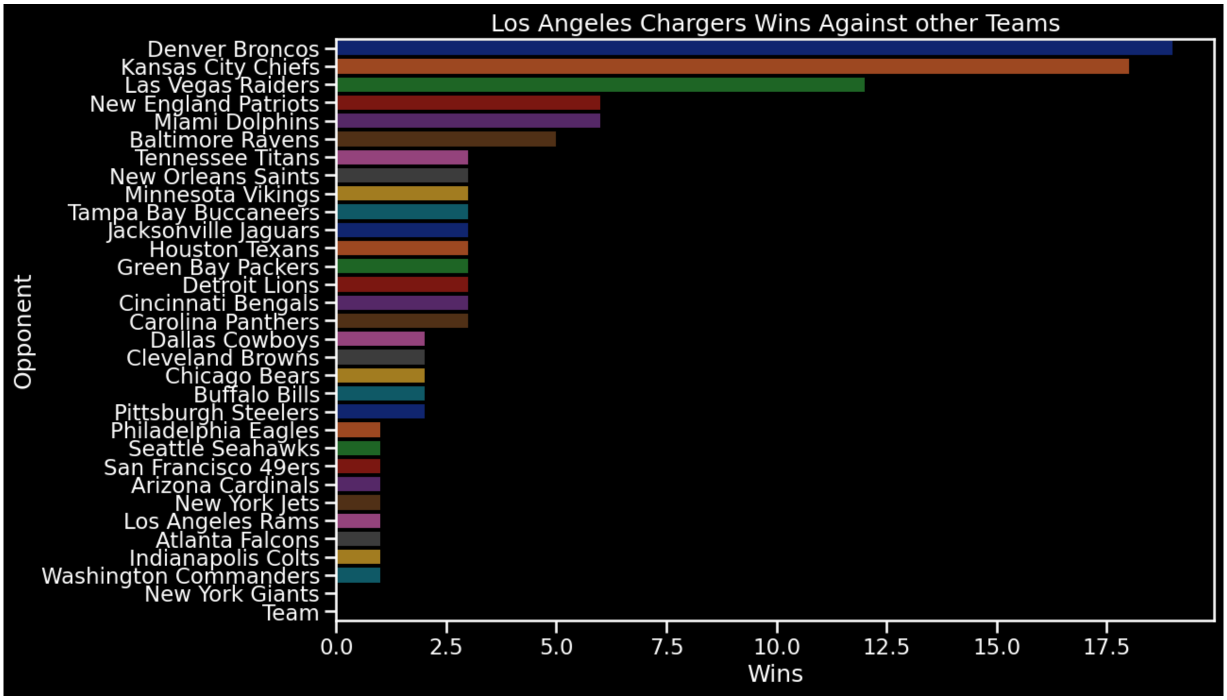
```
/var/folders/w6/tr1493cj7zd3sj7s4qyp_nwh0000gn/T/ipykernel_76728/4179918728.
py:12: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed
in v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the
same effect.

  sns.barplot(data=team_long, x='Wins', y="Opponent", palette='dark')
```



Bar Plot of LA Chargers Wins vs Other Teams

In [42]:
```
plot_team_wins("Los Angeles Chargers")
```

```
/var/folders/w6/tr1493cj7zd3sj7s4qyp_nwh0000gn/T/ipykernel_76728/4179918728.
py:12: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed
in v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the
same effect.

  sns.barplot(data=team_long, x='Wins', y="Opponent", palette='dark')
```



Machine Learning

Prepare data for training a model, and design a system for tuning the best possible model

---

First step is to add in our feature win loss ratio we manufactured earlier

In [43]:
```
def apply_win_feat(x):
  team_home = x['team_home']
  team_away = x['team_away']
  win_ratio = win_percentage_df.loc[team_home, team_away]
  loss_ratio = 1 - win_ratio
  return pd.Series([win_ratio, loss_ratio])
```

Now it is time to prepare the features we want to use for our model. Here we will one hot encode the teams into home or away columns. In each row we know what two teams are playing due to the teams column marked with a 1 for either home or away team.

In [44]:
```
encoder = OneHotEncoder(sparse_output=False)
team_home_encoded = encoder.fit_transform(df[['team_home']])
team_home_feature_names = encoder.get_feature_names_out(input_features=['tea

encoder = OneHotEncoder(sparse_output=False)
team_away_encoded = encoder.fit_transform(df[['team_away']])
team_away_feature_names = encoder.get_feature_names_out(input_features=['tea

team_home_df = pd.DataFrame(team_home_encoded, columns=team_home_feature_nam
team_away_df = pd.DataFrame(team_away_encoded, columns=team_away_feature_nam

df_encoded = pd.concat([df.reset_index(drop=True), team_home_df, team_away_c
```

```
df_encoded[["win_ratio", "loss_ratio"]] = df_encoded.apply(apply_win_feat, a
df_encoded
```

Out[44]:

	schedule_date	schedule_season	schedule_week	schedule_playoff	team_home
0	2011-09-08	2011	1	False	Green Bay Packers
1	2011-09-11	2011	1	False	Arizona Cardinals
2	2011-09-11	2011	1	False	Baltimore Ravens
3	2011-09-11	2011	1	False	Chicago Bears
4	2011-09-11	2011	1	False	Cleveland Browns
...	...	...	...	...	...
3518	2024-01-15	2023	Wildcard	True	Tampa Bay Buccaneers
3519	2024-01-20	2023	Division	True	Baltimore Ravens
3520	2024-01-20	2023	Division	True	San Francisco 49ers
3521	2024-01-21	2023	Division	True	Buffalo Bills
3522	2024-01-21	2023	Division	True	Detroit Lions

3523 rows × 118 columns

Adding Our Features Here

- One Hot Encoded Team Away vs Team Home
- Weather Temperature
- Weather Wind MPH
- Teams Win / Loss ratio

In [45]:

```
ohe = df_encoded.columns[51:].values.tolist()
ohe.insert(0, 'weather_temperature')
ohe.insert(0, 'weather_wind_mph')
ohe.remove("home_score_greater")
ohe
```

Out[45]:
```
['weather_wind_mph',
 'weather_temperature',
 'team_home_Arizona Cardinals',
 'team_home_Atlanta Falcons',
 'team_home_Baltimore Ravens',
 'team_home_Buffalo Bills',
 'team_home_Carolina Panthers',
 'team_home_Chicago Bears',
 'team_home_Cincinnati Bengals',
 'team_home_Cleveland Browns',
 'team_home_Dallas Cowboys',
 'team_home_Denver Broncos',
 'team_home_Detroit Lions',
 'team_home_Green Bay Packers',
 'team_home_Houston Texans',
 'team_home_Indianapolis Colts',
 'team_home_Jacksonville Jaguars',
 'team_home_Kansas City Chiefs',
 'team_home_Las Vegas Raiders',
 'team_home_Los Angeles Chargers',
 'team_home_Los Angeles Rams',
 'team_home_Miami Dolphins',
 'team_home_Minnesota Vikings',
 'team_home_New England Patriots',
 'team_home_New Orleans Saints',
 'team_home_New York Giants',
 'team_home_New York Jets',
 'team_home_Philadelphia Eagles',
 'team_home_Pittsburgh Steelers',
 'team_home_San Francisco 49ers',
 'team_home_Seattle Seahawks',
 'team_home_Tampa Bay Buccaneers',
 'team_home_Tennessee Titans',
 'team_home_Washington Commanders',
 'team_away_Arizona Cardinals',
 'team_away_Atlanta Falcons',
 'team_away_Baltimore Ravens',
 'team_away_Buffalo Bills',
 'team_away_Carolina Panthers',
 'team_away_Chicago Bears',
 'team_away_Cincinnati Bengals',
 'team_away_Cleveland Browns',
 'team_away_Dallas Cowboys',
 'team_away_Denver Broncos',
 'team_away_Detroit Lions',
 'team_away_Green Bay Packers',
 'team_away_Houston Texans',
 'team_away_Indianapolis Colts',
 'team_away_Jacksonville Jaguars',
 'team_away_Kansas City Chiefs',
 'team_away_Las Vegas Raiders',
 'team_away_Los Angeles Chargers',
 'team_away_Los Angeles Rams',
 'team_away_Miami Dolphins',
 'team_away_Minnesota Vikings',
 'team_away_New England Patriots',
```

```
 'team_away_New Orleans Saints',
 'team_away_New York Giants',
 'team_away_New York Jets',
 'team_away_Philadelphia Eagles',
 'team_away_Pittsburgh Steelers',
 'team_away_San Francisco 49ers',
 'team_away_Seattle Seahawks',
 'team_away_Tampa Bay Buccaneers',
 'team_away_Tennessee Titans',
 'team_away_Washington Commanders',
 'win_ratio',
 'loss_ratio']
```

Add our y value to predict (If the home team won)

In [46]:
```
df_encoded['home_team_win'] = df_encoded['score_home'] > df_encoded['score_a
df_encoded['home_team_win'] = df_encoded['home_team_win'].replace({False: 0,
```

Store our features in X and our values to predict in y

In [47]:
```
y = df_encoded['home_team_win'].values
X = df_encoded[ohe].values
```

Split Our Data and Try a Practice Run with KNN Classifier

In [48]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=42, t
scaler = StandardScaler()

X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

In [49]:
```
knn = KNeighborsClassifier()
knn.fit(X_train, y_train)
preds_train = knn.predict(X_train)
preds_test = knn.predict(X_test)

print(f"Train score: {(preds_train == y_train).mean()}  Test Score: {(preds_
```

```
Train score: 0.7262773722627737  Test Score: 0.6017029328287606
```

Optimize System Design for KNN Classifier

Lets see if we can optimize our KNN model to perform better, and potentially run the best that it can. We will start by producing graphs that will help us see the optimal value for different hyperparameters.

We will start at looking at optimal values of K and training data sizes.

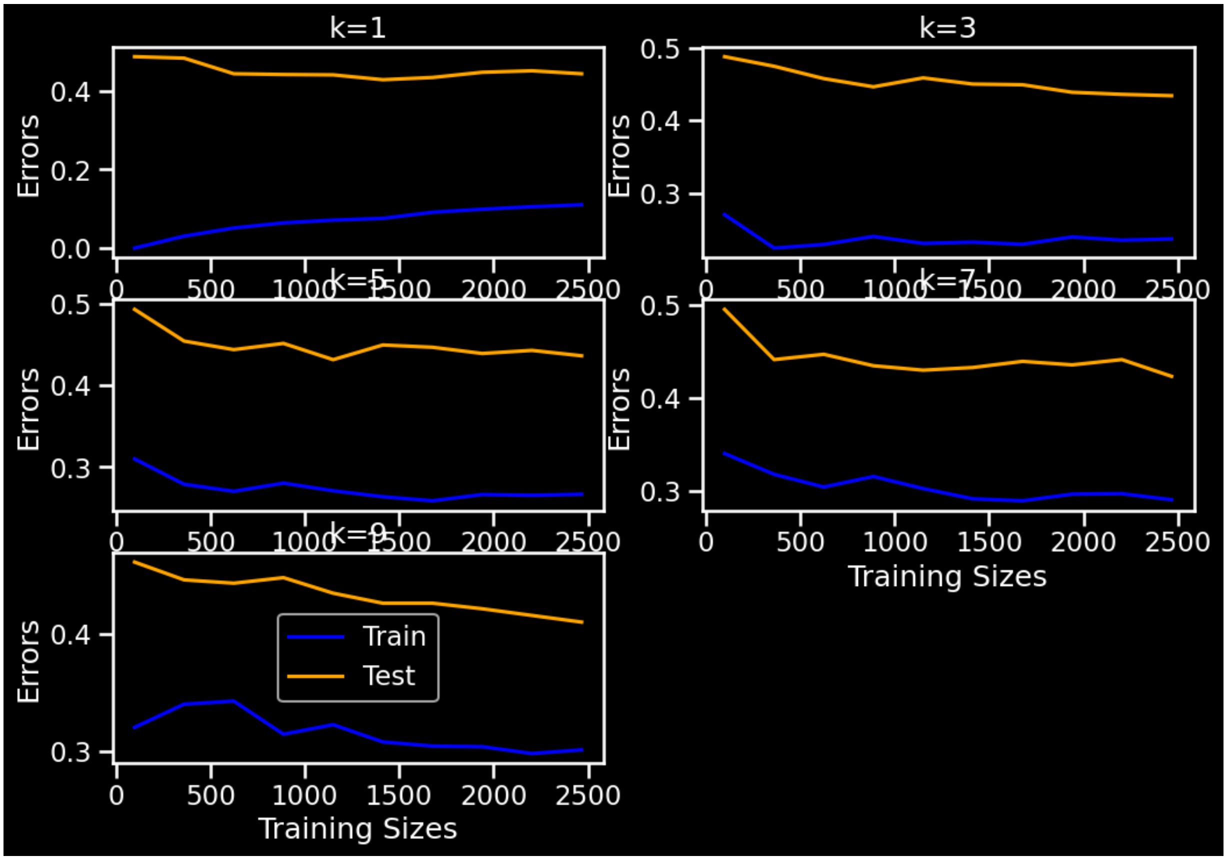
In [50]:
```
def optimize_knn_classifer(X, y, max_k, test_size, random_state):
  X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=test_s
  i = 0
```

```
  for k in range(1, max_k+1, 2):
      i +=1
      te_errs = []
      tr_errs = []
      tr_sizes = np.linspace(100, X_train.shape[0], 10).astype(int)
      knn = KNeighborsClassifier(n_neighbors=k)
      for tr_size in tr_sizes:
        X_train1 = X_train[:tr_size,:]
        y_train1 = y_train[:tr_size]

        # train model on a subset of the training data
        knn.fit(X_train1, y_train1)

        # error on subset of training data
        tr_predicted = knn.predict(X_train1)
        err = (tr_predicted != y_train1).mean()
        tr_errs.append(err)

        # error on all test data
        te_predicted = knn.predict(X_test)
        err = (te_predicted != y_test).mean()
        te_errs.append(err)
      plt.subplot(3, 2, i)
      plt.plot(tr_sizes, tr_errs, color="blue", label="Train")
      plt.plot(tr_sizes, te_errs, color="orange", label="Test")
      plt.xlabel("Training Sizes")
      plt.ylabel("Errors")
      plt.title("k={}".format(k))
  plt.legend()
  plt.show()
```

Print out graphs to show us how the value of k and test sizes affects the model.

We found that kNN model will not work well with our data. For all values of k it seems we are overfitting, the model performs well on training data but not test data, and there is a high variance.

In [51]:
```
optimize_knn_classifer(X, y, 9, .3, 0)
```



In [52]:
```
knn = KNeighborsClassifier(n_neighbors=7)
knn.fit(X_train, y_train)
preds_train = knn.predict(X_train)
preds_test = knn.predict(X_test)

print(f"Train score: {(preds_train == y_train).mean()}  Test Score: {(preds_
```

```
Train score: 0.7100567721005677  Test Score: 0.6026490066225165
```

Decision Tree Model

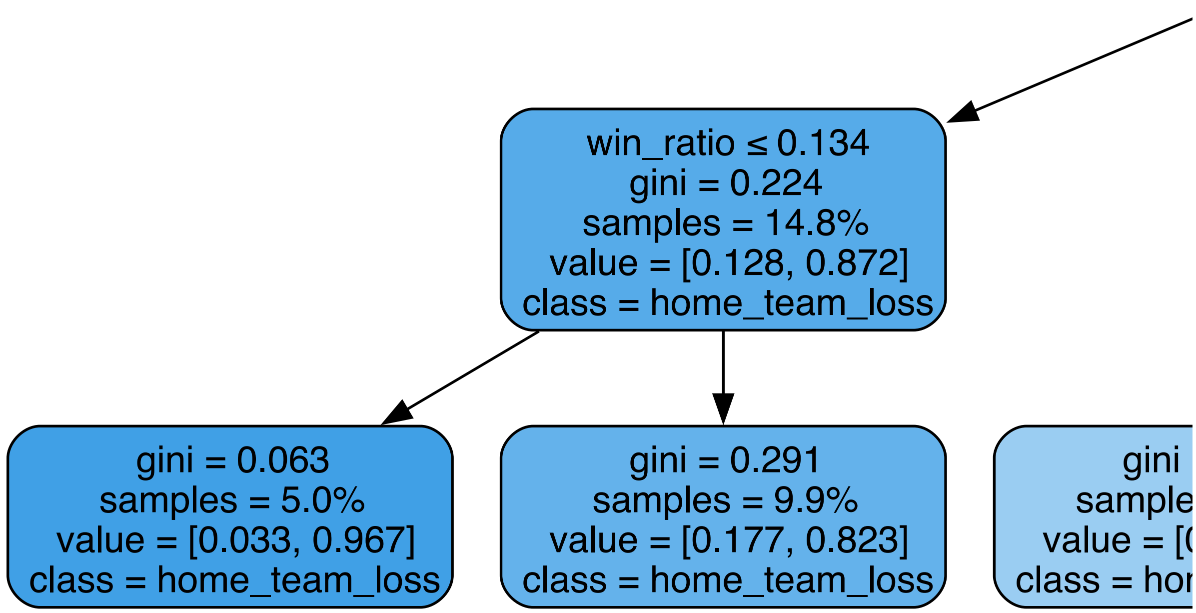
Lets try setting up a decision tree classifier and see how it compares to the KNN model we just optimized.

Here we set up an initial decision tree model to see how it works. We will also print out the tree. Being able to visualize the model will help us optimize as we continue.

In [53]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.30, ra

clf = DecisionTreeClassifier(max_depth=3, random_state=0)
clf.fit(X_train, y_train)

target_names = ['home_team_win','home_team_loss']
dot_data = export_graphviz(clf, precision=3,
                           feature_names=ohe,
                           proportion=True,
                           class_names=target_names,
```

```
                                filled=True, rounded=True,
                                special_characters=True)

graph = graphviz.Source(dot_data)
graph
```

Out[53]:



Okay, lets see how accurate the model is predicting.

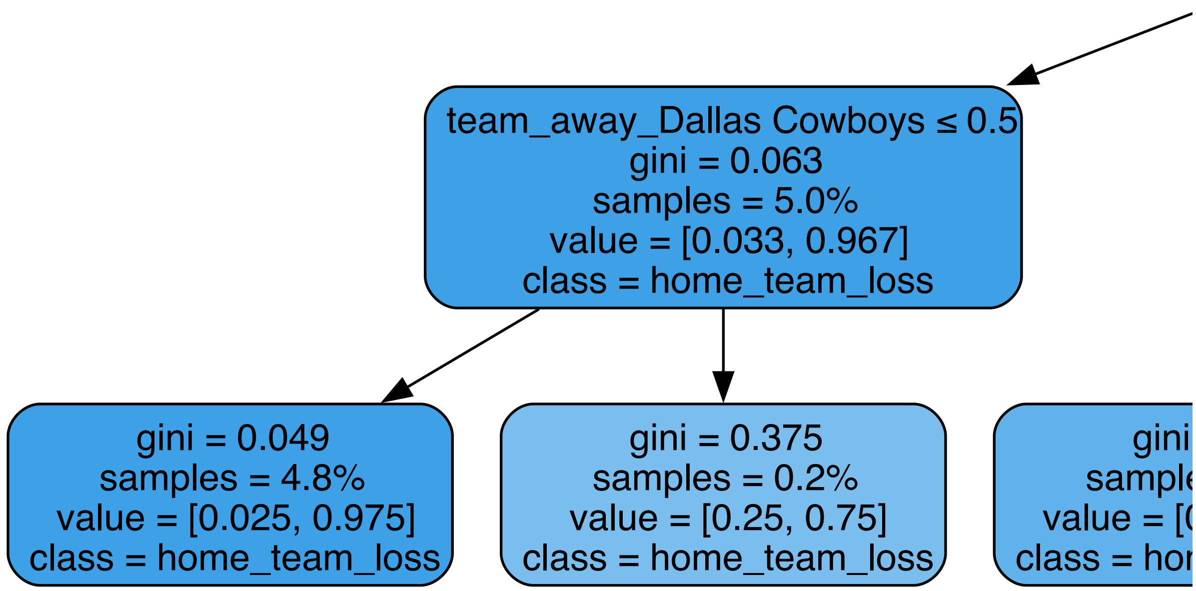
In [54]:
```
y_predict= clf.predict(X_test)
(y_predict == y_test).mean()
```

Out[54]: 0.6783349101229896

In [55]:
```
clf = DecisionTreeClassifier(max_depth=4, random_state=0)
clf.fit(X_train, y_train)
target_names = ['home_team_win','home_team_loss']
dot_data = export_graphviz(clf, precision=3,
                                feature_names=ohe,
                                proportion=True,
```

```
                                class_names=target_names,
                                filled=True, rounded=True,
                                special_characters=True)

graph = graphviz.Source(dot_data)
graph
```

Out[55]:



In [56]:
```
y_predict = clf.predict(X_test)
y_predict_train = clf.predict(X_train)
```

```
print("Test:", (y_predict == y_test).mean())
print("Train:", (y_predict_train ==  y_train).mean())
```

```
Test: 0.67360454115421
Train: 0.6889699918896999
```

Lets optimize by cross validating with a grid search over a parameter grid. GridSearchCV is a very convenient function to help us find our optimum hyper parameters. We will find the optimum max depth, minimum samples split, and minimum samples leaf in the cell below.

In [57]:
```
# Define parameter grid
param_grid = {
    'max_depth': [None, 2, 4, 6, 8, 10, 12, 14, 32, 64],
    'min_samples_split': [2, 5, 10, 16, 32],
    'min_samples_leaf': [1, 2, 4, 8, 12, 26, 32]
}

clf = DecisionTreeClassifier(random_state=0)
grid_search = GridSearchCV(estimator=clf, param_grid=param_grid, cv=5, scori

grid_search.fit(X_train, y_train)

best_params = grid_search.best_params_
best_score = grid_search.best_score_
best_model = grid_search.best_estimator_

print("Best Params: ", best_params)
print("Best Score: ", best_score)
```

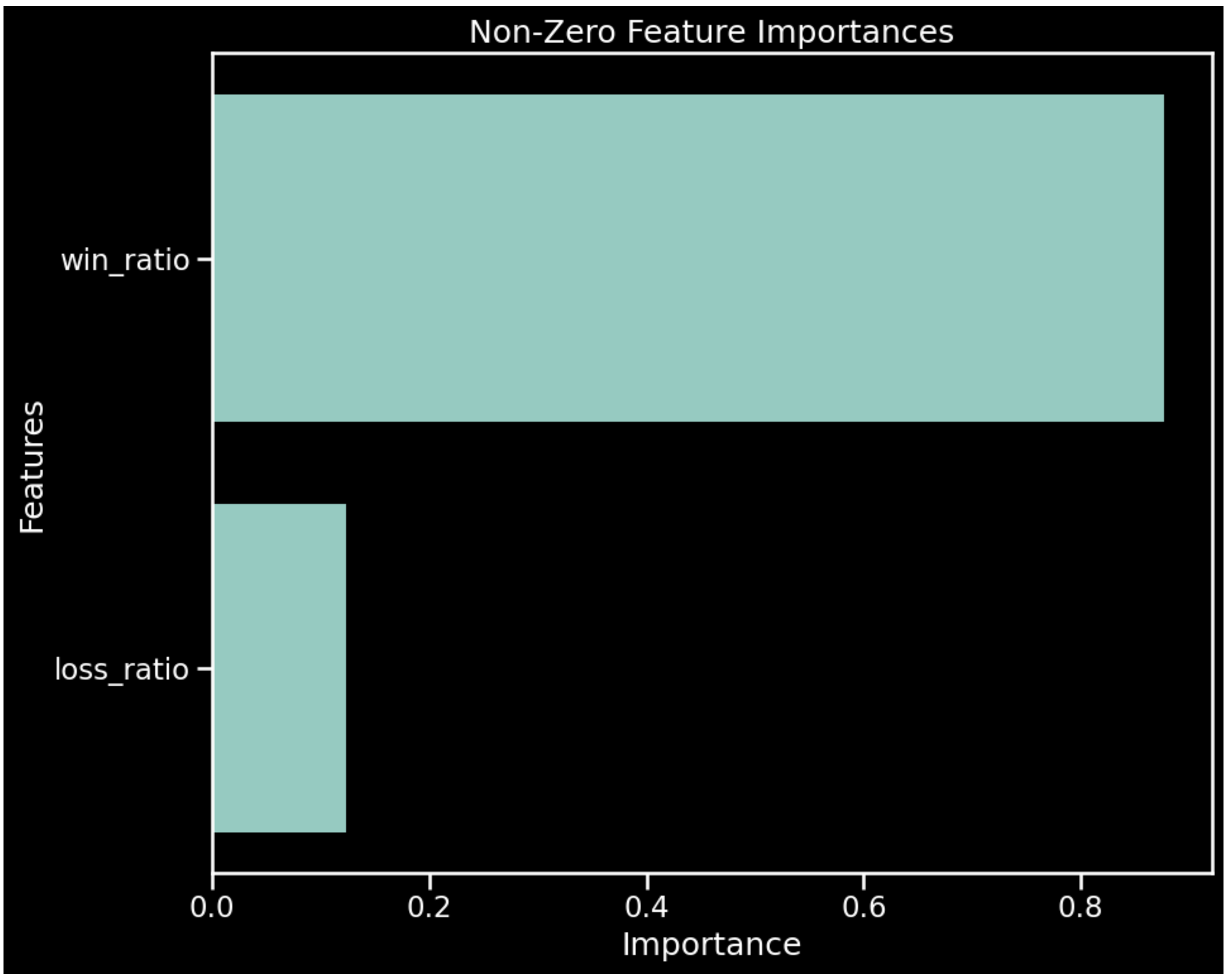
```
Best Params:  {'max_depth': 2, 'min_samples_leaf': 1, 'min_samples_split':
2}
Best Score:  0.6865435941233955
```

Feature Importances

- We had one-hot-encoded each team as some of our features but they had 0 importance on our model, along with our weather_wind_mph and weather_temperature.
- The main features our model was using to determine the outcome of matches are win and loss ratio.
- We were unable to use other features that we thought were going to be good predictors due to having more than 50% of it missing.
- We can see that the win ratio weighs heavy on our model when determining the outcome.

In [58]:
```
best = grid_search.best_estimator_
features = best.feature_importances_
```

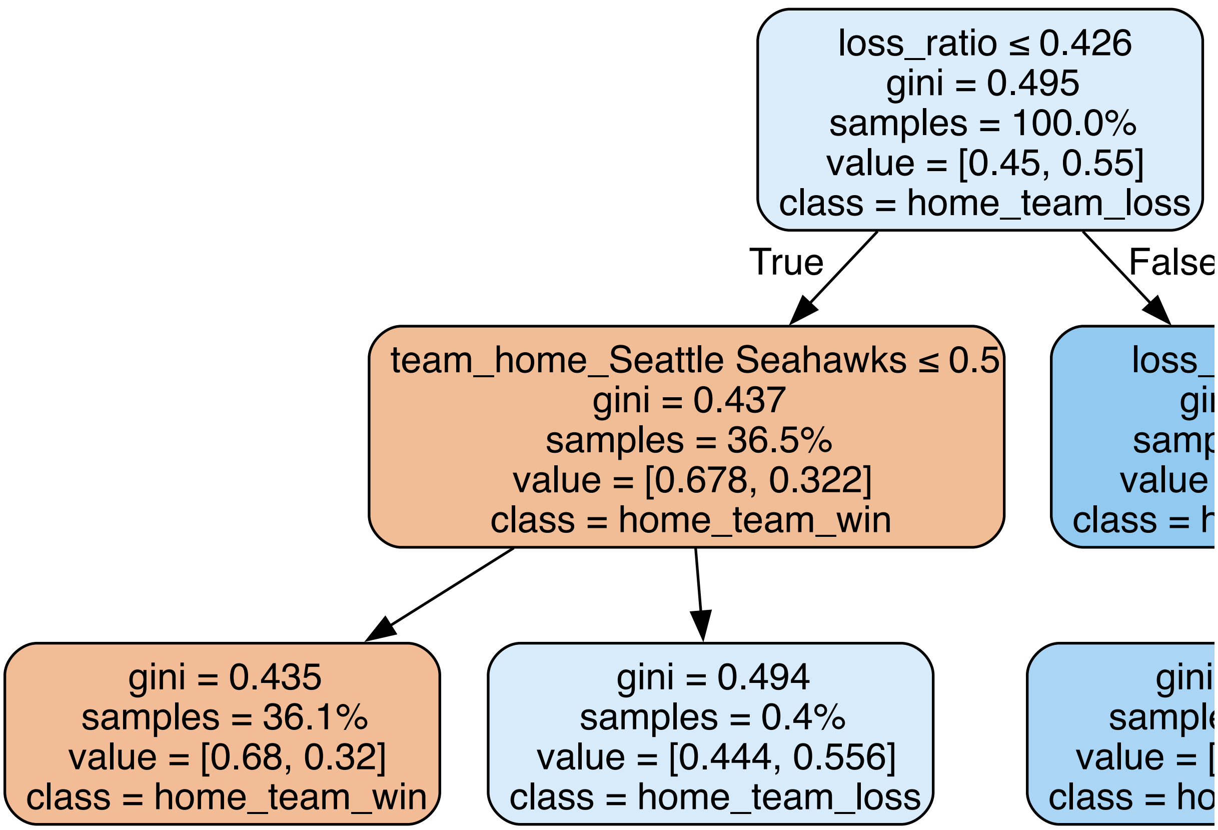
In [59]:
```
non_zero_importances = [importance for importance in features if importance
non_zero_features = [feature for feature, importance in zip(ohe, features) i

df_non_zero = pd.DataFrame({
    'Feature': non_zero_features,
    'Importance': non_zero_importances
})

df_non_zero_sorted = df_non_zero.sort_values(by='Importance', ascending=Fals

plt.figure(figsize=(10, 8))
sns.barplot(x='Importance', y='Feature', data=df_non_zero_sorted)

plt.title('Non-Zero Feature Importances')
plt.xlabel('Importance')
plt.ylabel('Features')
plt.tight_layout()

plt.show()
```



Randon Tree Classifier

Lets see if the random tree classifier performs with better accuracy than the decision tree.

In [60]:
```
rfclf = RandomForestClassifier(max_depth=2, random_state=0)
rfclf.fit(X_train, y_train)
target_names = ['home_team_win','home_team_loss']
dot_data = export_graphviz(rfclf.estimators_[0], precision=3,
                          feature_names=ohe,
                          proportion=True,
                          class_names=target_names,
                          filled=True, rounded=True,
                          special_characters=True)

graph = graphviz.Source(dot_data)
display(graph)
```



In [61]:
```
y_predict= rfclf.predict(X_test)
(y_predict == y_test).mean()
```

Out[61]: 0.6773888363292336

Lets try optimizing the hyperparameters of the random forest classifier with GridSearchCV like we did with the decision tree classifier. After running the cell, it looks like both the random forest and decision tree classifier have equivalent prediction accuracy, and either would be a good choice.

In [62]:
```
# Define parameter grid
param_grid = {
    'max_depth': [None, 2, 4, 6, 8, 10, 12, 14, 32, 64],
    'min_samples_split': [2, 5, 10, 16, 32],
    'min_samples_leaf': [1, 2, 4, 8, 12, 26, 32]
}

grid_search = GridSearchCV(estimator=rfclf, param_grid=param_grid, cv=5, scc

grid_search.fit(X_train, y_train)

best_params = grid_search.best_params_
best_score = grid_search.best_score_
best_model = grid_search.best_estimator_

print("Best Params: ", best_params)
print("Best Score: ", best_score)
```

```
Best Params:  {'max_depth': 6, 'min_samples_leaf': 1, 'min_samples_split': 1
6}
Best Score:  0.6857338775242053
```

Best model

Decision Tree

- Our best model was the Decision Tree model
- With a test score of 67.36% and a train score of 68.89%
- After tuninig our model this was the best accuracy we were able to achieve

Suggestions

- Adding more features to our predictors could've helped with our predictions
- More data was needed other than just historical data to predict outcomes of matches
- It is possible to predict whether a team is going to win, but there are many other factors not present in our data the could potentially allow us to create a better model.
- Some could be injuries, more weather data ie. rain, fog, and humidity, amount of starters playing, and coach information
- Overall we concluded that with the data we chose it would've been more suitable for a linear regression problem predicting how much points a team was going to score.