Final Project

1.Research Question

- How has the performance of NFL teams evolved over the past decade in terms of win percentages and offensive metrics?
- How have wins evolved over time for each conference in the NFL?
- What is the relationship between total yards, points, and wins? Which factor—yards or points—has a greater impact on winning?
- How do average points compare between the best and worst teams in the league?
- Which factor, turnover percentage or penalties, has a more significant impact on wins and point differential? What is the effect of turnover percentage on win percentage and point differential?
- Can a regression model be used to accurately predict wins in the NFL?
- What correlations exist between various NFL statistics? = How are passing yards and rushing yards related across teams?
- How do total snaps influence offensive outcomes? Investigate the relationship between total snaps and key metrics like yards gained, touchdowns, and total points.
- What is the impact of passing efficiency on team success? Explore the relationship between pass completion percentage and win percentage, total points, and yards gained.
- How does the frequency of rushing versus passing impact overall team performance? Compare teams that rely more heavily on rushing or passing in terms of win percentage, yards per snap (yps), and points per game.
- Does a higher number of turnovers (fumbles and interceptions) lead to a significant drop in win percentage? Analyze the impact of turnovers on win percentage and other success metrics like point differential.
- Which factors contribute most to a high points per game average? Identify the strongest predictors of points per game by exploring variables such as pass attempts, rushing yards, and touchdowns.
- Is there a relationship between receiving yards and points scored? Explore if teams with higher receiving yards tend to score more points or win more games.
- How does win percentage change over time across teams with different offensive strategies? Track how offensive strategies (e.g., passing-heavy, rushing-heavy) correlate with win percentage trends over multiple seasons.

2.Justification - why is this relevant? This project is especially relevant with the start of the new 2024 NFL season, as it will allow us to examine changes in team offenses over the past 10 years and provide insights into how teams' offenses have improved. These findings can also help fans anticipate trends and performances in the upcoming season.

3.Data Sources NFL dataset

- https://www.kaggle.com/datasets/philiphyde1/nfl-stats-1999-2022
- https://www.kaggle.com/datasets/nickcantalupa/nfl-team-data-2003-2023/code

4.Libraries Used

- pandas for data manipulation and analysis
- matplotlib and seaborn for visualization
- scikit-learn for any machine learning models or predictions

Introduction to Dataset and Summary Statistics

Dataset Overview

In [ ]:

```
# Import necessary libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import plotly.express as px
from IPython.display import display

# Load the dataset
df = pd.read_csv('..\Final Project\dataset\yearly_team_data.csv')


# Display the first few rows of the dataframe to get an overview
pd.set_option('display.max_columns', None) # Show all columns
# Clean the 'record' column by stripping leading/trailing whitespace and tabs
df['record'] = df['record'].str.strip()
df.head()
```

Out[ ]:

	team	season	total_snaps	yards_gained	touchdown	extra_point_attempt	field_goal_att
0	ARI	2012	1013	7595	28	25	
1	ARI	2013	1020	9855	37	37	
2	ARI	2014	983	9128	28	27	
3	ARI	2015	1005	11337	53	53	
4	ARI	2016	1080	10302	51	43	

In [ ]:

```
# Print random rows
df.sample(10).T
```

Out[ ]:

	174	152	4	45	29	111	183	33	155	96
team	JAX	HOU	ARI	BUF	BAL	DEN	KC	BAL	HOU	DAL
season	2018	2020	2016	2021	2017	2015	2015	2021	2023	2012
total_snaps	1001	932	1080	1125	1038	1047	945	1177	1078	1036
yards_gained	8261	10837	10302	10973	8140	9913	8810	10719	10404	11014
touchdown	23	44	51	57	38	35	41	43	40	42
extra_point_attempt	22	37	43	51	39	35	39	32	31	37
field_goal_attempt	23	27	21	28	34	30	30	35	34	29
total_points	229	382	412	477	369	335	375	395	373	376
td_points	138	264	306	342	228	210	246	258	240	252
xp_points	22	37	43	51	39	35	39	32	31	37
fg_points	69	81	63	84	102	90	90	105	102	87
fumble	24	18	25	19	15	13	12	19	16	14
fumble_lost	15	9	11	5	4	7	6	8	7	8
shotgun	690	771	529	822	517	675	608	1123	656	546
no_huddle	47	102	51	135	60	100	20	76	93	77
qb_dropback	645	660	692	733	599	656	577	745	660	703
pass_snaps_count	591	598	688	686	593	644	523	668	636	694
pass_snaps_pct	0.59	0.64	0.64	0.61	0.57	0.62	0.55	0.57	0.59	0.67
pass_attempts	523	537	626	639	551	582	466	586	578	636
complete_pass	329	383	383	415	363	368	310	396	372	434
incomplete_pass	194	154	243	224	188	214	156	190	206	202
air_yards	3777	4862	6204	5355	3842	5534	3167	5242	5180	5782
passing_yards	3431	4843	4425	4450	3235	4216	3493	4267	4578	4992
pass_td	16	34	30	36	22	22	21	24	28	32
interception	13	7	17	16	13	23	7	18	8	19
targets	523	537	626	639	551	582	466	586	578	636
receptions	329	383	383	415	363	368	310	396	372	434
receiving_yards	3423	4821	4425	4450	3235	4216	3493	4267	4578	4992
yards_after_catch	1825	1956	1747	1752	1506	1852	1936	1712	1982	1976
receiving_td	16	34	30	36	22	22	21	24	28	32

	174	152	4	45	29	111	183	33	155	96
pass_fumble	18	11	14	11	9	8	7	12	11	8
pass_fumble_lost	11	5	6	2	1	4	4	5	6	5
rush_snaps_count	410	334	392	439	445	403	422	509	442	342
rush_snaps_pct	0.41	0.36	0.36	0.39	0.43	0.38	0.45	0.43	0.41	0.33
qb_scramble	54	62	4	47	6	12	54	77	24	9
rushing_yards	1729	1476	1739	2229	1873	1727	2058	2487	1641	1287
run_td	7	10	21	20	15	13	20	19	10	8
run_fumble	6	7	11	8	6	5	5	7	5	6
run_fumble_lost	4	4	5	3	3	3	2	3	1	3
home_wins	3	2	4	6	5	6	6	5	6	4
home_losses	5	6	4	3	3	2	2	4	3	4
home_ties	0	0	1	0	0	0	0	0	0	0
away_wins	2	2	3	5	4	6	5	3	4	4
away_losses	6	6	5	3	4	2	3	5	4	4
away_ties	0	0	0	0	0	0	0	0	0	0
wins	5	4	7	11	9	12	11	8	10	8
losses	11	12	9	6	7	4	5	9	7	8
ties	0	0	1	0	0	0	0	0	0	0
win_pct	0.313	0.25	0.412	0.647	0.563	0.75	0.688	0.471	0.588	0.5
record	5-11-0	4-12-0	7-9-1	11-6-0	9-7-0	12-4-0	11-5-0	8-9-0	10-7-0	8-8-0
yps	8.25	11.63	9.54	9.75	7.84	9.47	9.32	9.11	9.65	10.63

Column Descriptions

Column Name	Data Type	Description	Example Values
team	Object	The name of the NFL team.	"NYG" New York Giants
season	Int	The year of the season.	2022
total_snaps	Int	Total number of plays (snaps) run by the team.	1200

Column Name	Data Type	Description	Example Values
yards_gained	Int	Total yards gained by the team during the season.	3500
touchdown	Int	Total touchdowns scored by the team.	25
extra_point_attempt	Int	Number of extra point attempts.	20
field_goal_attempt	Int	Number of field goal attempts made.	15
total_points	Int	Total points scored by the team.	275
td_points	Int	Points scored from touchdowns.	150
xp_points	Int	Points scored from extra point attempts.	20
fg_points	Int	Points scored from field goals.	45
fumble	Int	Total fumbles committed by the team.	10
fumble_lost	Int	Total fumbles lost by the team.	5
shotgun	Int	Number of plays run from a shotgun formation.	150
no_huddle	Int	Number of no-huddle plays run by the team.	75
qb_dropback	Int	Total dropbacks by the quarterback.	400
pass_snaps_count	Int	Total number of pass snaps taken.	300
pass_snaps_pct	Float	Percentage of snaps that were passing plays.	25.0
pass_attempts	Int	Total number of passing attempts.	500
complete_pass	Int	Total number of completed passes.	350
incomplete_pass	Int	Total number of incomplete passes.	150
air_yards	Int	Total air yards gained on passes.	2500
passing_yards	Int	Total passing yards gained.	3000
pass_td	Int	Total touchdown passes thrown.	20
interception	Int	Total interceptions thrown by the team.	10
targets	Int	Total targets for receivers.	400
receptions	Int	Total receptions made by receivers.	350
receiving_yards	Int	Total yards gained by receivers.	2800
yards_after_catch	Int	Total yards gained after catch by receivers.	800
receiving_td	Int	Total receiving touchdowns scored.	10

Column Name	Data Type	Description	Example Values
pass_fumble	Int	Total fumbles by the quarterback on pass plays.	5
pass_fumble_lost	Int	Total fumbles lost by the quarterback.	2
rush_snaps_count	Int	Total number of rush snaps taken.	200
rush_snaps_pct	Float	Percentage of snaps that were rushing plays.	15.0
qb_scramble	Int	Total times the quarterback scrambled.	25
rushing_yards	Int	Total rushing yards gained.	1500
run_td	Int	Total rushing touchdowns scored.	12
run_fumble	Int	Total rushing fumbles committed.	6
run_fumble_lost	Int	Total rushing fumbles lost.	3
home_wins	Int	Total wins at home.	6
home_losses	Int	Total losses at home.	2
home_ties	Int	Total ties at home.	0
away_wins	Int	Total wins away.	5
away_losses	Int	Total losses away.	3
away_ties	Int	Total ties away.	0
wins	Int	Total wins in the season.	11
losses	Int	Total losses in the season.	5
ties	Int	Total ties in the season.	0
win_pct	Float	Win percentage of the team.	0.688
record	Object	Win-loss-tie record of the team.	"5-11-0"
yps	Float	Yards per snap.	4.8

Summary Statistics

In [ ]:
```
summary_statistics = df.describe(include='all')  # Include all columns, numerical a
summary_statistics = summary_statistics.applymap(lambda x: f'{x:g}' if isinstance(x

# Display the summary statistics
print("Summary Statistics:")
display(summary_statistics)
```

```
Summary Statistics:
```

	team	season	total_snaps	yards_gained	touchdown	extra_point_attempt	field_goa
count	384	384	384	384	384	384	
unique	32	nan	nan	nan	nan	nan	
top	ARI	nan	nan	nan	nan	nan	
freq	12	nan	nan	nan	nan	nan	
mean	nan	2017.5	1024.26	9670.45	41.651	36.474	
std	nan	3.45656	52.2525	1050.13	9.11448	9.61419	
min	nan	2012	866	6761	21	16	
25%	nan	2014.75	989	8916.5	35	30	
50%	nan	2017.5	1018	9669.5	40	35	
75%	nan	2020.25	1060.25	10348.2	48	43	
max	nan	2023	1181	12913	74	75	

Check for missing data

In [ ]:

```
# Checking for missing values
missing_values = df.isnull().sum()
print("\nMissing Values:")
print(missing_values)
```

```
Missing Values:
team                  0
season                0
total_snaps           0
yards_gained          0
touchdown             0
extra_point_attempt   0
field_goal_attempt    0
total_points          0
td_points             0
xp_points             0
fg_points             0
fumble                0
fumble_lost           0
shotgun               0
no_huddle             0
qb_dropback           0
pass_snaps_count      0
pass_snaps_pct        0
pass_attempts         0
complete_pass         0
incomplete_pass       0
air_yards             0
passing_yards         0
pass_td               0
interception          0
targets               0
receptions            0
receiving_yards       0
yards_after_catch     0
receiving_td          0
pass_fumble           0
pass_fumble_lost      0
rush_snaps_count      0
rush_snaps_pct        0
qb_scramble           0
rushing_yards         0
run_td                0
run_fumble            0
run_fumble_lost       0
home_wins             0
home_losses           0
home_ties             0
away_wins             0
away_losses           0
away_ties             0
wins                  0
losses                0
ties                  0
win_pct               0
record                0
yps                   0
dtype: int64
```

Additional information on dataset

In [ ]:
```
# Additional dataset information (data types, non-null count, etc.)
print("\nDataset Info:")
df.info()
```

```
Dataset Info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 384 entries, 0 to 383
Data columns (total 51 columns):
 #   Column               Non-Null Count  Dtype  
---  ------               --------------  -----  
 0   team                 384 non-null    object 
 1   season               384 non-null    int64  
 2   total_snaps          384 non-null    int64  
 3   yards_gained         384 non-null    int64  
 4   touchdown            384 non-null    int64  
 5   extra_point_attempt  384 non-null    int64  
 6   field_goal_attempt   384 non-null    int64  
 7   total_points         384 non-null    int64  
 8   td_points            384 non-null    int64  
 9   xp_points            384 non-null    int64  
 10  fg_points            384 non-null    int64  
 11  fumble               384 non-null    int64  
 12  fumble_lost          384 non-null    int64  
 13  shotgun              384 non-null    int64  
 14  no_huddle            384 non-null    int64  
 15  qb_dropback          384 non-null    int64  
 16  pass_snaps_count     384 non-null    int64  
 17  pass_snaps_pct       384 non-null    float64
 18  pass_attempts        384 non-null    int64  
 19  complete_pass        384 non-null    int64  
 20  incomplete_pass      384 non-null    int64  
 21  air_yards            384 non-null    int64  
 22  passing_yards        384 non-null    int64  
 23  pass_td              384 non-null    int64  
 24  interception         384 non-null    int64  
 25  targets              384 non-null    int64  
 26  receptions           384 non-null    int64  
 27  receiving_yards      384 non-null    int64  
 28  yards_after_catch    384 non-null    int64  
 29  receiving_td         384 non-null    int64  
 30  pass_fumble          384 non-null    int64  
 31  pass_fumble_lost     384 non-null    int64  
 32  rush_snaps_count     384 non-null    int64  
 33  rush_snaps_pct       384 non-null    float64
 34  qb_scramble          384 non-null    int64  
 35  rushing_yards        384 non-null    int64  
 36  run_td               384 non-null    int64  
 37  run_fumble           384 non-null    int64  
 38  run_fumble_lost      384 non-null    int64  
 39  home_wins            384 non-null    int64  
 40  home_losses          384 non-null    int64  
 41  home_ties            384 non-null    int64  
 42  away_wins            384 non-null    int64  
 43  away_losses          384 non-null    int64  
 44  away_ties            384 non-null    int64  
 45  wins                 384 non-null    int64  
 46  losses               384 non-null    int64  
 47  ties                 384 non-null    int64  
 48  win_pct              384 non-null    float64
 49  record               384 non-null    object 
```

```
 50  yps                  384 non-null    float64
dtypes: float64(4), int64(45), object(2)
memory usage: 153.1+ KB
```

Additional Summary Statistics:

- Total Games Played: You can derive this from wins, losses, and ties.
- Average Points Per Game: Calculate as total_points / games_played.
- Average Yards Per Snap: Calculate as yards_gained / total_snaps.
- Turnover Ratio: Calculate as (fumble + interception) / total_snaps to understand how turnovers affect the game.
- Passing Efficiency: This could be measured as (passing_yards / pass_attempts) to see the effectiveness of the passing game.
- Rushing Efficiency: Similarly, rushing_yards / rush_snaps_count could be a valuable metric.

In [ ]:
```
df['games_played'] = df['wins'] + df['losses'] + df['ties']
df['avg_points_per_game'] = df['total_points'] / df['games_played']
df['avg_yards_per_snap'] = df['yards_gained'] / df['total_snaps']
df['turnover_ratio'] = (df['fumble'] + df['interception']) / df['total_snaps']
df['passing_efficiency'] = df['passing_yards'] / df['pass_attempts']
df['rushing_efficiency'] = df['rushing_yards'] / df['rush_snaps_count']

summary_statistics = df.describe(include='all')  # Include all columns, numerical a
summary_statistics = summary_statistics.applymap(lambda x: f'{x:g}' if isinstance(x

# Display the summary statistics
print("Summary Statistics:")
display(summary_statistics)
```

```
Summary Statistics:
```

	team	season	total_snaps	yards_gained	touchdown	extra_point_attempt	field_goa
count	384	384	384	384	384	384	
unique	32	nan	nan	nan	nan	nan	
top	ARI	nan	nan	nan	nan	nan	
freq	12	nan	nan	nan	nan	nan	
mean	nan	2017.5	1024.26	9670.45	41.651	36.474	
std	nan	3.45656	52.2525	1050.13	9.11448	9.61419	
min	nan	2012	866	6761	21	16	
25%	nan	2014.75	989	8916.5	35	30	
50%	nan	2017.5	1018	9669.5	40	35	
75%	nan	2020.25	1060.25	10348.2	48	43	
max	nan	2023	1181	12913	74	75	

In [ ]:

```
# Display the summary statistics
print("Summary Statistics:")
df.describe().T
```

```
Summary Statistics:
```

Out[ ]:

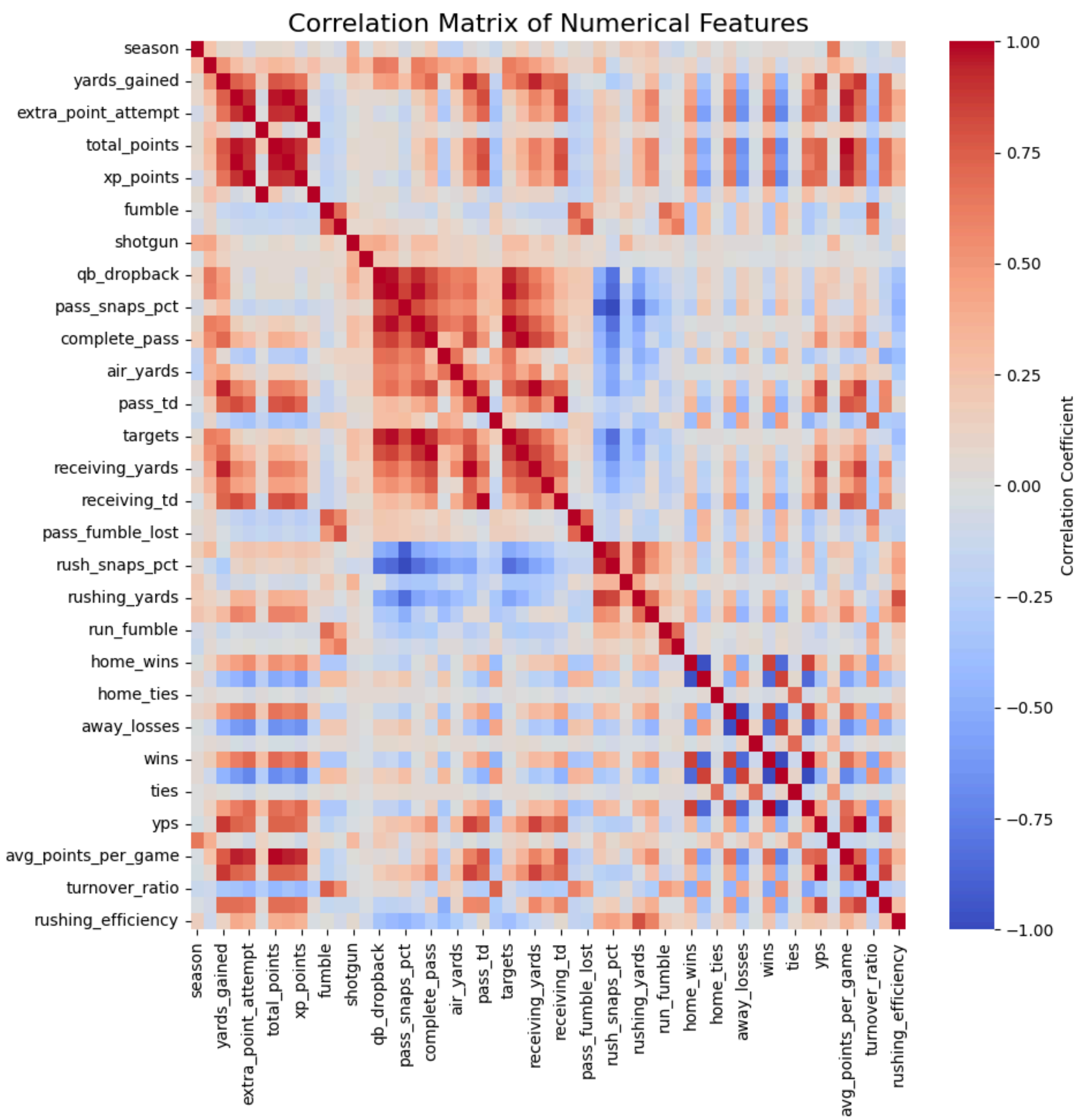
	count	mean	std	min	25%	50
season	384.0	2017.500000	3.456556	2012.000000	2014.750000	2017.5000
total_snaps	384.0	1024.260417	52.252549	866.000000	989.000000	1018.0000
yards_gained	384.0	9670.447917	1050.132630	6761.000000	8916.500000	9669.5000
touchdown	384.0	41.651042	9.114479	21.000000	35.000000	40.0000
extra_point_attempt	384.0	36.473958	9.614195	16.000000	30.000000	35.0000
field_goal_attempt	384.0	26.591146	5.581770	8.000000	23.000000	27.0000
total_points	384.0	366.153646	64.798179	227.000000	319.750000	361.0000
td_points	384.0	249.906250	54.686876	126.000000	210.000000	240.0000
xp_points	384.0	36.473958	9.614195	16.000000	30.000000	35.0000
fg_points	384.0	79.773438	16.745311	24.000000	69.000000	81.0000
fumble	384.0	16.937500	4.635120	6.000000	14.000000	17.0000
fumble_lost	384.0	8.028646	2.896241	1.000000	6.000000	8.0000
shotgun	384.0	642.085938	146.948830	228.000000	541.500000	638.0000
no_huddle	384.0	102.250000	102.215050	6.000000	45.000000	74.5000
qb_dropback	384.0	627.473958	58.060465	486.000000	587.750000	630.0000
pass_snaps_count	384.0	602.627604	59.866295	436.000000	560.000000	607.0000
pass_snaps_pct	384.0	0.588307	0.046670	0.450000	0.560000	0.5900
pass_attempts	384.0	548.174479	59.260220	361.000000	504.750000	551.5000
complete_pass	384.0	357.093750	46.231640	223.000000	324.750000	357.0000
incomplete_pass	384.0	191.080729	26.609275	131.000000	174.000000	191.0000
air_yards	384.0	4593.265625	647.379145	2898.000000	4116.250000	4571.0000
passing_yards	384.0	4032.023438	535.805255	2598.000000	3644.750000	4020.0000
pass_td	384.0	26.953125	7.403188	12.000000	22.000000	26.0000
interception	384.0	13.575521	4.494212	2.000000	10.000000	13.0000
targets	384.0	548.174479	59.260220	361.000000	504.750000	551.5000
receptions	384.0	357.093750	46.231640	223.000000	324.750000	357.0000
receiving_yards	384.0	4030.804688	535.789884	2589.000000	3643.500000	4018.0000
yards_after_catch	384.0	1851.658854	311.685690	1124.000000	1644.750000	1841.0000
receiving_td	384.0	26.953125	7.403188	12.000000	22.000000	26.0000
pass_fumble	384.0	10.028646	3.380440	2.000000	8.000000	10.0000

	count	mean	std	min	25%	50
pass_fumble_lost	384.0	5.015625	2.247079	0.000000	3.000000	5.0000
rush_snaps_count	384.0	421.632812	49.809067	314.000000	386.000000	415.0000
rush_snaps_pct	384.0	0.411693	0.046670	0.310000	0.380000	0.4100
qb_scramble	384.0	24.875000	14.638195	1.000000	14.000000	22.0000
rushing_yards	384.0	1859.200521	348.128385	1168.000000	1616.500000	1820.0000
run_td	384.0	13.950521	5.111820	3.000000	10.000000	13.0000
run_fumble	384.0	6.908854	3.034962	0.000000	5.000000	7.0000
run_fumble_lost	384.0	3.013021	1.781054	0.000000	2.000000	3.0000
home_wins	384.0	4.500000	1.794974	0.000000	3.000000	5.0000
home_losses	384.0	3.622396	1.792243	0.000000	2.000000	4.0000
home_ties	384.0	0.031250	0.174220	0.000000	0.000000	0.0000
away_wins	384.0	3.591146	1.791195	0.000000	2.000000	4.0000
away_losses	384.0	4.531250	1.787412	0.000000	3.000000	5.0000
away_ties	384.0	0.031250	0.174220	0.000000	0.000000	0.0000
wins	384.0	8.091146	3.065776	0.000000	6.000000	8.0000
losses	384.0	8.153646	3.073484	1.000000	6.000000	8.0000
ties	384.0	0.062500	0.242377	0.000000	0.000000	0.0000
win_pct	384.0	0.496836	0.189440	0.000000	0.375000	0.5000
yps	384.0	9.439036	0.884055	7.100000	8.787500	9.3850
games_played	384.0	16.307292	0.494723	16.000000	16.000000	16.0000
avg_points_per_game	384.0	22.471291	4.024329	14.187500	19.500000	22.0900
avg_yards_per_snap	384.0	9.439060	0.884089	7.097806	8.784517	9.3833
turnover_ratio	384.0	0.029826	0.006805	0.012133	0.025218	0.0295
passing_efficiency	384.0	7.363735	0.664556	5.643478	6.881980	7.2915
rushing_efficiency	384.0	4.388807	0.450092	3.209135	4.080933	4.3804

Correlations

Heat Map

In [ ]:
```
# Create the heatmap

# Select numerical columns
numerical = df.select_dtypes(include=['float64', 'int64']).columns
plt.figure(figsize=(10,10))
sns.heatmap(df[numerical].corr(), cmap='coolwarm', cbar_kws={'label': 'Correlation

plt.title('Correlation Matrix of Numerical Features', fontsize=16)

# Save the plot
plt.savefig('..\Final Project\image\correlation_heatmap.png')

# Display the plot
plt.show()
```



From the correlation matrix, we can infer several important relationships between the numerical features:

1. **Strong Positive Correlations**:

    - **Passing Yards and Pass Attempts**: These variables are highly correlated, which makes sense since more pass attempts typically result in more passing yards.
    - **Total Points and Touchdowns (TD Points)**: There is a strong correlation here, indicating that touchdowns contribute significantly to the total points scored by a team.
    - **Wins and Win Percentage**: Naturally, these are closely tied, as more wins will result in a higher win percentage.

2. **Negative Correlations**:

    - **Fumbles and Wins**: There appears to be a negative correlation between fumbles (and fumbles lost) and wins, suggesting that teams that commit more fumbles are less likely to win games.
    - **Interceptions and Wins**: Similarly, a higher number of interceptions negatively correlates with wins.

3. **Interesting Relationships**:

    - **Pass Snaps Percent and Passing Yards**: Pass snaps percentage seems to have a moderate positive correlation with passing yards, which shows that teams that pass more frequently tend to gain more yards through the air.
    - **Rush Snaps Percent and Passing Yards**: Conversely, there's a slight negative correlation between rush snaps percent and passing yards, indicating that teams that run the ball more often tend to pass less and gain fewer passing yards.

This analysis helps identify which aspects of a team's offense are most closely associated with success (such as fewer turnovers and more passing yards). Further analysis could involve breaking down these relationships by season or team to explore trends over time.

Numerical features associated with a team's number of wins, sorted by descending

calculates the correlation between each numerical column in the dataset and the 'wins' column. The correlation indicates how strongly a particular feature is linearly related to the number of wins, with values ranging from -1 (strong negative correlation) to +1 (strong positive correlation). A correlation close to 0 would suggest little to no linear relationship.

In [ ]:
```
df[numerical].corrwith(df['wins']).abs().sort_values(ascending=False)
```

Out[ ]:
```
wins                    1.000000
win_pct                 0.996785
losses                  0.990168
home_wins               0.855220
away_wins               0.854557
away_losses             0.853642
home_losses             0.846679
extra_point_attempt     0.707368
xp_points               0.707368
total_points            0.697132
avg_points_per_game     0.691040
td_points               0.615691
touchdown               0.615691
turnover_ratio          0.538209
passing_efficiency      0.486535
interception            0.473396
yards_gained            0.464900
run_td                  0.458449
avg_yards_per_snap      0.450653
yps                     0.450540
pass_td                 0.449643
receiving_td            0.449643
rushing_yards           0.348181
rush_snaps_count        0.348170
pass_fumble             0.330539
incomplete_pass         0.327893
receiving_yards         0.307939
passing_yards           0.306810
pass_fumble_lost        0.300378
rush_snaps_pct          0.288886
pass_snaps_pct          0.288886
fumble                  0.288251
fumble_lost             0.284644
yards_after_catch       0.283803
field_goal_attempt      0.280789
fg_points               0.280789
rushing_efficiency      0.228822
total_snaps             0.165675
complete_pass           0.160574
receptions              0.160574
qb_dropback             0.157048
pass_snaps_count        0.145075
ties                    0.116612
away_ties               0.103114
run_fumble_lost         0.083898
run_fumble              0.072064
home_ties               0.059119
season                  0.051864
qb_scramble             0.030057
air_yards               0.027166
no_huddle               0.024402
shotgun                 0.023321
targets                 0.021961
pass_attempts           0.021961
games_played            0.011629
dtype: float64
```

In [ ]:
```
# List of columns to drop based on win correlation analysis
columns_to_drop = ['win_pct', 'losses', 'ties', 'home_wins', 'home_losses', 'home_t
                   'away_wins', 'away_losses', 'away_ties', 'season']

# Drop the unnecessary columns for win correlation analysis
df_reduced = df.drop(columns=columns_to_drop)

# Select only the numerical columns that remain in df_reduced
numerical_reduced = df_reduced.select_dtypes(include=['float64', 'int64']).columns

# Calculate the correlation of the remaining numerical columns with 'wins'
df_reduced[numerical_reduced].corrwith(df_reduced['wins']).sort_values(ascending=Fa
```

Out[ ]:
```
wins                    1.000000
extra_point_attempt     0.707368
xp_points               0.707368
total_points            0.697132
avg_points_per_game     0.691040
td_points               0.615691
touchdown               0.615691
passing_efficiency      0.486535
yards_gained            0.464900
run_td                  0.458449
avg_yards_per_snap      0.450653
yps                     0.450540
receiving_td            0.449643
pass_td                 0.449643
rushing_yards           0.348181
rush_snaps_count        0.348170
receiving_yards         0.307939
passing_yards           0.306810
rush_snaps_pct          0.288886
yards_after_catch       0.283803
field_goal_attempt      0.280789
fg_points               0.280789
rushing_efficiency      0.228822
total_snaps             0.165675
receptions              0.160574
complete_pass           0.160574
games_played           -0.011629
pass_attempts          -0.021961
targets                -0.021961
shotgun                -0.023321
no_huddle              -0.024402
air_yards              -0.027166
qb_scramble            -0.030057
run_fumble             -0.072064
run_fumble_lost        -0.083898
pass_snaps_count       -0.145075
qb_dropback            -0.157048
fumble_lost            -0.284644
fumble                 -0.288251
pass_snaps_pct         -0.288886
pass_fumble_lost       -0.300378
incomplete_pass        -0.327893
pass_fumble            -0.330539
interception           -0.473396
turnover_ratio         -0.538209
dtype: float64
```

From the correlation data, the following key points can be inferred about the relationship between various numerical features and the number of wins:

Strong Positive Correlations:

1. **Extra Point Attempts and XP Points**: Both extra point attempts and extra point (XP) points have a high positive correlation (~0.71) with wins. This suggests that teams that

score more touchdowns (leading to more extra point attempts) tend to win more games.

2. **Total Points and Touchdown Points**: Total points (0.697) and touchdown points (0.615) also show strong positive correlations with wins, indicating that scoring more points is highly related to winning games.
3. **Touchdowns (0.615)**: Unsurprisingly, touchdowns themselves are strongly correlated with wins. Teams that score more touchdowns tend to have more victories.
4. **Yards Gained (0.465)**: Total yards gained is positively correlated with wins, showing that teams that accumulate more offensive yards tend to win more games.
5. **Run Touchdowns (0.458) and Yards per Snap (YPS) (0.451)**: Rushing touchdowns and yards per snap also positively correlate with wins, reinforcing the importance of effective offense for success.
6. **Receiving and Passing Touchdowns (~0.45)**: Both receiving and passing touchdowns contribute to more wins, with a moderate positive correlation, emphasizing balanced offensive strength.

Moderate to Low Positive Correlations:

1. **Rushing Yards (0.348) and Rush Snap Count (0.348)**: These metrics have moderate positive correlations with wins, indicating that while rushing is important, its impact is somewhat less than that of passing and total points scored.
2. **Receiving Yards (0.308) and Passing Yards (0.307)**: These stats show a moderate positive correlation with wins, suggesting that a team's ability to move the ball downfield via the passing game is beneficial, but not as strongly related to winning as points scored.
3. **Field Goal Attempts and Points (~0.28)**: Field goals also contribute to winning, but their impact is less than touchdowns.

Negative Correlations (Hindering Wins):

1. **Interceptions (-0.473)**: Interceptions have the strongest negative correlation with wins, showing that turnovers have a highly detrimental effect on winning.
2. **Pass Fumble (-0.33) and Fumbles (-0.288)**: Fumbles and lost fumbles, particularly during passing, negatively impact wins, highlighting the importance of ball security.
3. **Incomplete Passes (-0.328)**: This negative correlation shows that incomplete passes can hinder a team's ability to win by stalling offensive drives.
4. **Other Negative Correlations (e.g., Pass Snaps Percentage, Pass Fumbles Lost)**: Various passing-related metrics such as pass fumbles lost and pass snaps percentage also have a negative correlation, further emphasizing the downside of turnovers and inefficient passing plays.

Insights:

- Scoring more points (total points, touchdowns, extra points) is the strongest indicator of success in winning games.
- Yardage (both passing and rushing) is important but secondary compared to actual scoring.
- Turnovers, particularly interceptions and fumbles, have a highly negative impact on a team's ability to win.
- Balanced offensive production (both passing and rushing touchdowns) correlates well with winning, but minimizing turnovers is crucial.

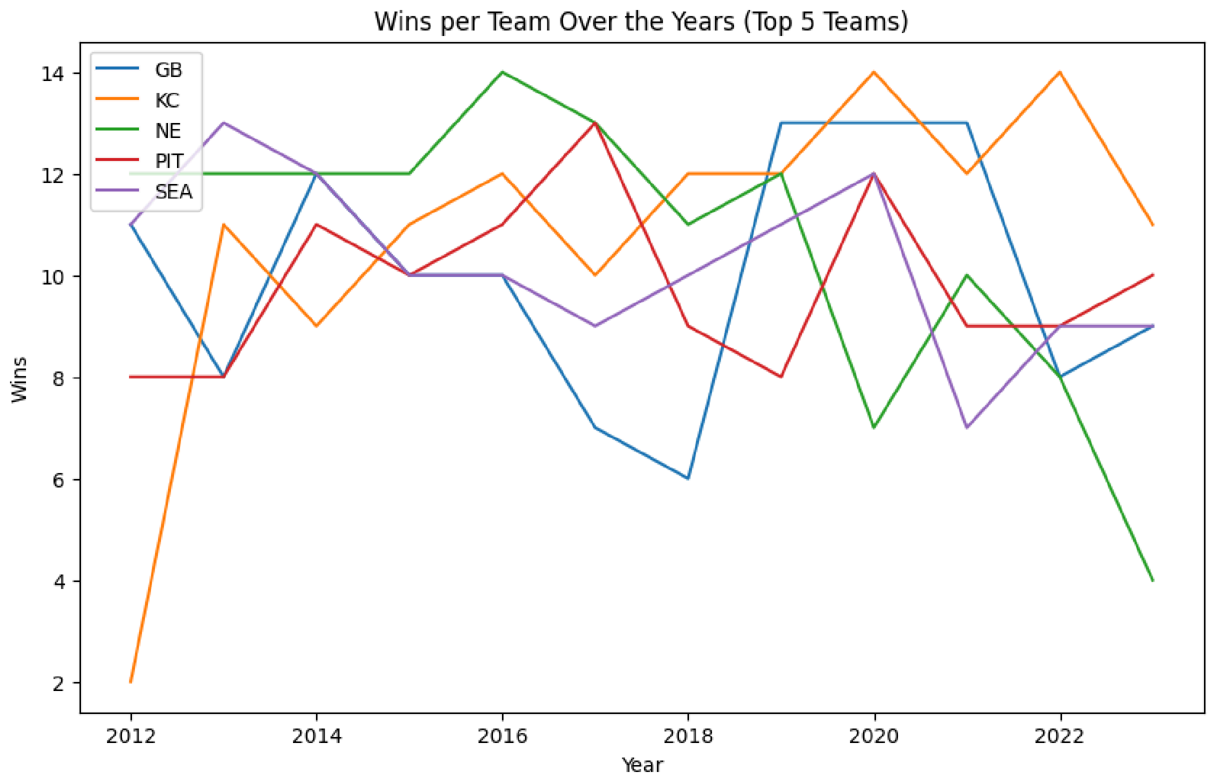
In summary, efficient scoring and minimizing turnovers are key drivers of winning in the NFL, with strong offenses contributing to more victories while turnovers can severely hinder success.

EDA & Plot

Top 5 teams based on total wins and bottom 5 teams based on total loses (line plot)

In [ ]:
```
# Top 5
top_teams = df.groupby('team')['wins'].sum().nlargest(5).index

# Filter
filtered_df = df[df['team'].isin(top_teams)]

# Grafics
filtered_df.groupby(['season', 'team']).sum()['wins'].unstack().plot(kind='line', f
plt.title('Wins per Team Over the Years (Top 5 Teams)')
plt.xlabel('Year')
plt.ylabel('Wins')
plt.legend(loc='upper left')
plt.show()
```

```
C:\Users\Kai\AppData\Local\Temp\ipykernel_35336\2387830812.py:8: FutureWarning: The
default value of numeric_only in DataFrameGroupBy.sum is deprecated. In a future ver
sion, numeric_only will default to False. Either specify numeric_only or select only
columns which should be valid for the function.
  filtered_df.groupby(['season', 'team']).sum()['wins'].unstack().plot(kind='line',
figsize=(10, 6))
```



The line chart depicts the performance of five NFL teams (GB, KC, NE, PIT, SEA) from 2012 to 2023 in terms of their number of wins each season.

Key Observations:

1. **Kansas City Chiefs (KC)**: The Chiefs show a consistent upward trend starting from 2013, peaking around 2020 with the most wins among the teams, before slightly declining in 2023.
2. **Green Bay Packers (GB)**: They exhibit fluctuations with strong performance between 2014 and 2021, but their performance declined sharply in 2022 and 2023.
3. **New England Patriots (NE)**: NE dominated between 2012 and 2019, maintaining consistent high wins, but their performance significantly declined after 2020.
4. **Pittsburgh Steelers (PIT)**: They maintain a relatively consistent but moderate performance, with some fluctuations over the years.
5. **Seattle Seahawks (SEA)**: SEA shows a generally declining trend, particularly in recent years, with their highest performance around 2014-2015.

General Insights:

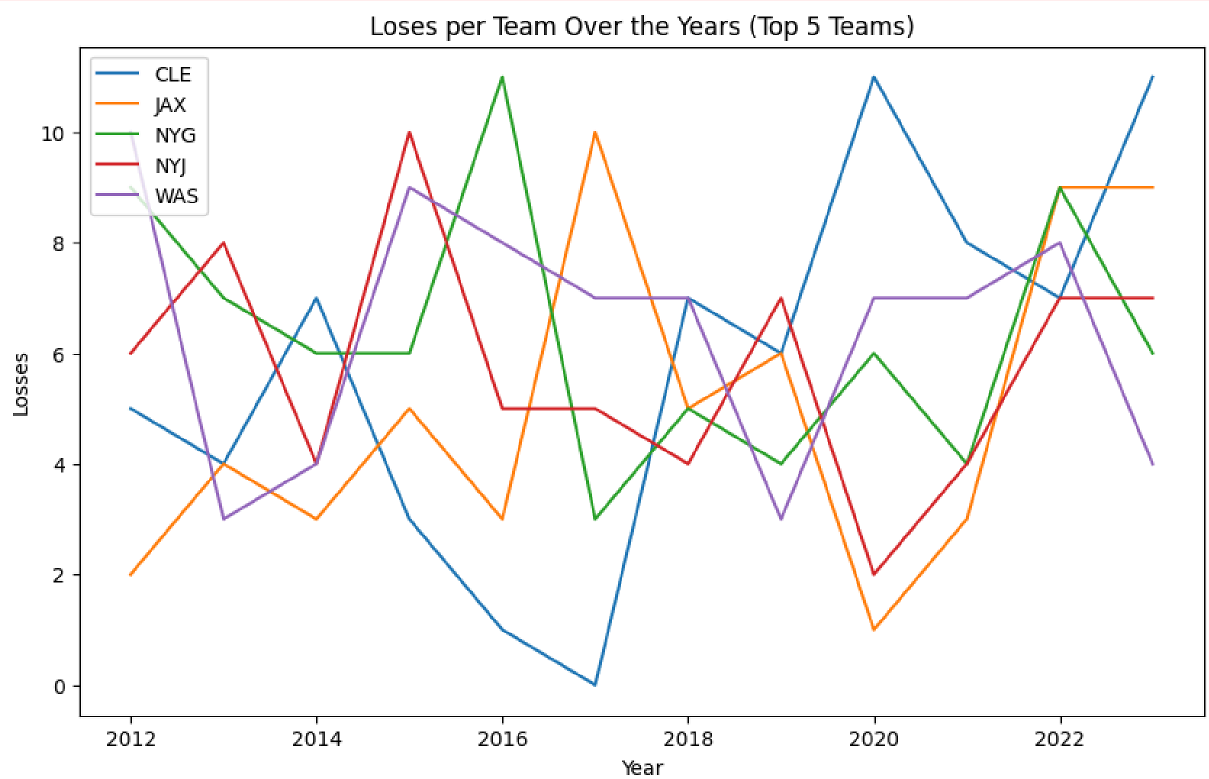
- **New England Patriots** and **Kansas City Chiefs** demonstrate dominance for most of the period, with the Chiefs' peak coming more recently, while the Patriots' dominance declines post-2020.
- **Seattle Seahawks** and **Green Bay Packers** have experienced notable declines in recent years.

- The chart highlights the varying consistency across teams, with some like the Chiefs steadily improving while others show more volatility.

This chart effectively visualizes how some NFL teams have risen or fallen over the past decade in terms of wins.

```
In [ ]: # Top 5
top_teams = df.groupby('team')['losses'].sum().nlargest(5).index

# Filter
filtered_df = df[df['team'].isin(top_teams)]

# Grafics
filtered_df.groupby(['season', 'team']).sum()['wins'].unstack().plot(kind='line', f
plt.title('Loses per Team Over the Years (Top 5 Teams)')
plt.xlabel('Year')
plt.ylabel('Losses')
plt.legend(loc='upper left')
plt.show()
```

```
C:\Users\Kai\AppData\Local\Temp\ipykernel_35336\1070455082.py:8: FutureWarning: The default value of numeric_only in DataFrameGroupBy.sum is deprecated. In a future version, numeric_only will default to False. Either specify numeric_only or select only columns which should be valid for the function.
  filtered_df.groupby(['season', 'team']).sum()['wins'].unstack().plot(kind='line', figsize=(10, 6))
```



The second line chart visualizes the number of losses for five NFL teams (CLE, JAX, NYG, NYJ, WAS) from 2012 to 2023. Here are the key observations:

Key Observations:

1. **Cleveland Browns (CLE)**: Their number of losses fluctuates greatly, with a sharp spike in 2017 when they experienced the most losses. They show improvement around 2020 but see another increase in losses by 2023.
2. **Jacksonville Jaguars (JAX)**: JAX displays significant volatility. They had high losses in 2013 and 2020, but also periods of improvement, particularly around 2017 and 2022.
3. **New York Giants (NYG)**: The Giants' losses have remained moderately high, with consistent fluctuations, showing no dramatic improvement or decline.
4. **New York Jets (NYJ)**: NYJ has maintained a consistently high level of losses throughout the period, with occasional dips, but they seem to have been more stable in their struggles.
5. **Washington Football Team (WAS)**: WAS has fluctuated significantly, with notable dips in losses in 2015 and 2021 but more losses in recent years.

General Insights:

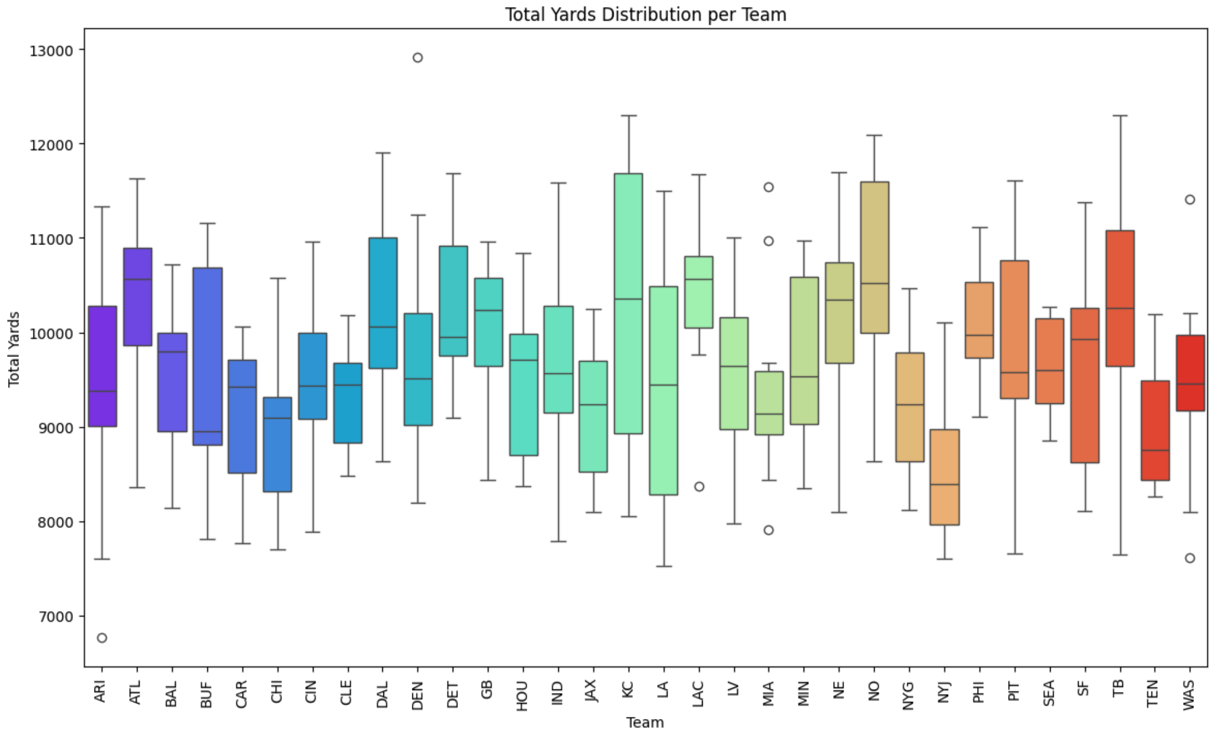
- **Cleveland Browns** stand out for their significant fluctuations, experiencing high losses in certain years (notably 2017) but improving in others.
- **Jacksonville Jaguars** also experience strong volatility, particularly peaking in losses during 2013 and 2020.
- **New York Giants** and **New York Jets** show relatively consistent poor performance with high losses over the years.
- **Washington Football Team** experiences more noticeable ups and downs but manages to avoid the consistent losing seasons seen by the Giants and Jets.

This chart highlights teams that have struggled the most with losses over the years, showcasing volatility and inconsistency in some teams' performance while others remain consistently poor in terms of results.

Total yards of each team (Box plot)

In [ ]:
```
# Plotting total yards distribution per team
plt.figure(figsize=(14,8))
sns.boxplot(x='team', y='yards_gained', data=df, palette='rainbow')
plt.xticks(rotation=90)
plt.title('Total Yards Distribution per Team')
plt.xlabel('Team')
plt.ylabel('Total Yards')
plt.show()
```

```
C:\Users\Kai\AppData\Local\Temp\ipykernel_35336\76092322.py:3: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.1
4.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.boxplot(x='team', y='yards_gained', data=df, palette='rainbow')
```



From the boxplot, which shows the distribution of total yards per team, we can infer several things:

1. **Spread and Variation**: Teams with wider boxes (e.g., Kansas City (KC), New Orleans (NO)) tend to have more variability in their total yards over the years, whereas teams with smaller boxes (e.g., Houston (HOU), Detroit (DET)) have more consistent yardage performance.

2. **Median Performance**: The middle line in each box represents the median total yards. Teams like Kansas City (KC) and New Orleans (NO) have higher median total yards compared to teams like Arizona (ARI) and Houston (HOU), indicating consistently higher offensive yardage.

3. **Outliers**: Some teams show outliers, represented by the dots outside the whiskers of the box. For example, Arizona (ARI) and Washington (WAS) have lower outlier values, which might indicate particularly poor performance in certain seasons.

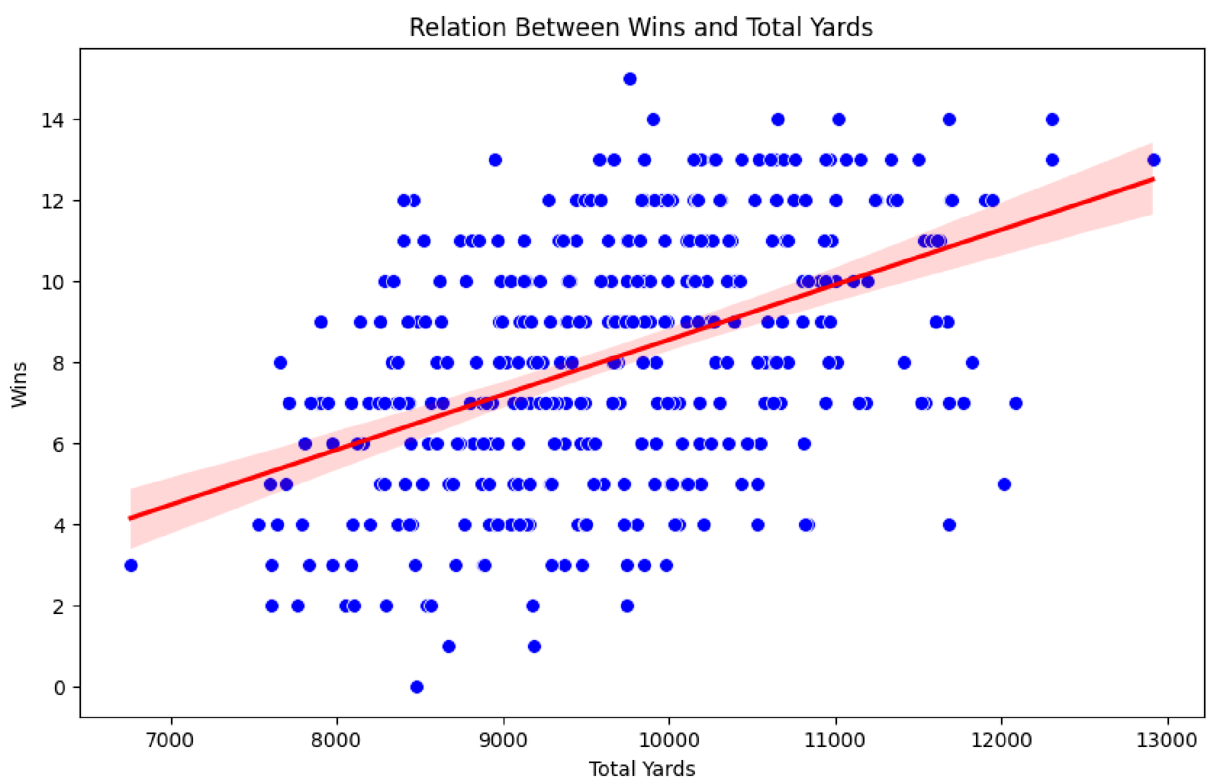
4. **Top Performers**: Teams like Kansas City (KC) and New Orleans (NO) are among the top performers in terms of both median total yards and the spread of their performance, consistently reaching higher yard totals over the years.

5. **Teams with Low Yardage**: Teams like Arizona (ARI), Houston (HOU), and Washington (WAS) show lower overall yardage, with smaller interquartile ranges and lower median values, indicating these teams tend to struggle more offensively.

This boxplot visually demonstrates which teams are consistently performing at a higher level offensively and which teams have more variability or struggle to maintain high yardage totals.

Relation between wins and total yards (Scatter Plot)

In [ ]:
```
# Plotting the relationship between wins and total yards
plt.figure(figsize=(10, 6))
sns.scatterplot(x='yards_gained', y='wins', data=df, color='blue', s=50)

# Adding a regression line to understand the trend
sns.regplot(x='yards_gained', y='wins', data=df, scatter=False, color='red')

# Adding labels and title
plt.title('Relation Between Wins and Total Yards')
plt.xlabel('Total Yards')
plt.ylabel('Wins')

# Show plot
plt.show()

# Calculate the correlation between wins and total yards
correlation = df['wins'].corr(df['yards_gained'])
print(f'Correlation between Wins and Total Yards: {correlation:.2f}')
```



```
Correlation between Wins and Total Yards: 0.46
```

From the scatter plot and the correlation value of 0.46, we can infer the following:

1. **Moderate Positive Relationship**: A correlation of 0.46 indicates a moderate positive relationship between total yards and wins. This suggests that, in general, teams that gain more total yards tend to win more games, but the relationship is not very strong or absolute.

2. **Not a Perfect Predictor**: While more total yards are associated with more wins, it is clear from the scatter plot that many teams with high total yards still end up with fewer wins, and some teams with lower total yards can also have a decent number of wins. This implies that while yards are important, other factors (like defense, turnovers, penalties) also play a significant role in determining the number of wins.

3. **Wide Distribution**: The points are spread across a wide range, especially for teams with total yards between 8000 to 11000. This indicates variability, where similar yardage can correspond to a different number of wins depending on other circumstances.

4. **Regression Line Insight**: The upward trend of the regression line confirms that as total yards increase, wins generally increase too. However, the points deviate from the line quite a bit, further emphasizing the role of other variables beyond total yards in influencing team success.

In summary, while accumulating more yards contributes to winning games, it is not the sole factor, and the data shows variability that suggests teams must excel in other areas to consistently convert yards into wins.

In [ ]:
```python
# Group by team and sum wins
team_wins = df.groupby('team')['wins'].sum().reset_index()

# Sort by wins to get the top and bottom teams
top_5_wins = team_wins.sort_values(by='wins', ascending=False).head(5)
bottom_5_wins = team_wins.sort_values(by='wins', ascending=True).head(5)

# Display the results
print("Top 5 teams with most wins:")
print(top_5_wins)

print("\nBottom 5 teams with least wins (most losses):")
print(bottom_5_wins)


# Group by team and sum the total yards
team_yards = df.groupby('team')['yards_gained'].sum().reset_index()

# Sort by total yards to get the top and bottom teams
top_5_teams = team_yards.sort_values(by='yards_gained', ascending=False).head(5)
bottom_5_teams = team_yards.sort_values(by='yards_gained', ascending=True).head(5)

# Display the results
```

```
print("\nTop 5 teams with most total yards:")
print(top_5_teams)

print("\nBottom 5 teams with least total yards:")
print(bottom_5_teams)
```

```
Top 5 teams with most wins:
   team  wins
15   KC   130
21   NE   127
27  SEA   123
11   GB   120
26  PIT   118

Bottom 5 teams with least wins (most losses):
   team  wins
14  JAX    60
24  NYJ    69
7   CLE    70
23  NYG    76
31  WAS    77

Top 5 teams with most total yards:
   team  yards_gained
22   NO        128263
17  LAC        124460
1   ATL        123595
29   TB        122988
8   DAL        122958

Bottom 5 teams with least total yards:
   team  yards_gained
24  NYJ        102415
5   CHI        107564
30  TEN        107618
4   CAR        109575
14  JAX        110248
```

From this data, we can infer the following relationships between total yards gained and wins:

1. Teams with High Wins vs. High Yards:

- **Top 5 teams with most wins (KC, NE, SEA, GB, PIT)** are notably absent from the list of teams with the most total yards. This suggests that while total yards are important, other factors like defensive performance, special teams, and overall game strategy play a significant role in achieving a high number of wins.
- Teams like **DAL** (Dallas) appear on both the top wins and top total yards lists, showing a strong offensive presence likely contributing to their success.

2. Teams with High Yards but Fewer Wins:

- Teams like **NO** (New Orleans Saints), **LAC** (Los Angeles Chargers), and **ATL** (Atlanta Falcons) appear in the top 5 for total yards but are not in the top 5 for wins. This suggests that these teams may be good at moving the ball but are either inefficient in converting yards to points, or they may have weaknesses in other areas like defense, turnovers, or special teams that prevent them from winning more games.

3. **Teams with Low Wins and Low Yards:**

- Teams like **NYJ** (New York Jets) and **JAX** (Jacksonville Jaguars) rank at the bottom in both wins and total yards, confirming that weak offensive performance likely contributes to poor win records. These teams struggle to accumulate yards, which directly correlates with their struggles in winning games.

4. **Teams with Low Yards but More Wins:**

- Interestingly, **KC** (Kansas City Chiefs), **NE** (New England Patriots), **SEA** (Seattle Seahawks), **GB** (Green Bay Packers), and **PIT** (Pittsburgh Steelers), despite not appearing in the top total yards, have been very successful in terms of wins. This suggests these teams may compensate for fewer yards with factors like efficient red zone offense, strong defenses, or better turnover margins, highlighting that yards alone are not the sole predictor of success.

5. **Bottom Yards vs Bottom Wins:**

- **NYJ** appears at the bottom of both wins and total yards lists, reinforcing the idea that poor offensive production significantly impacts their ability to win games. However, teams like **JAX** and **CHI** appear at the bottom in both lists as well, further emphasizing that low yardage often correlates with fewer wins.

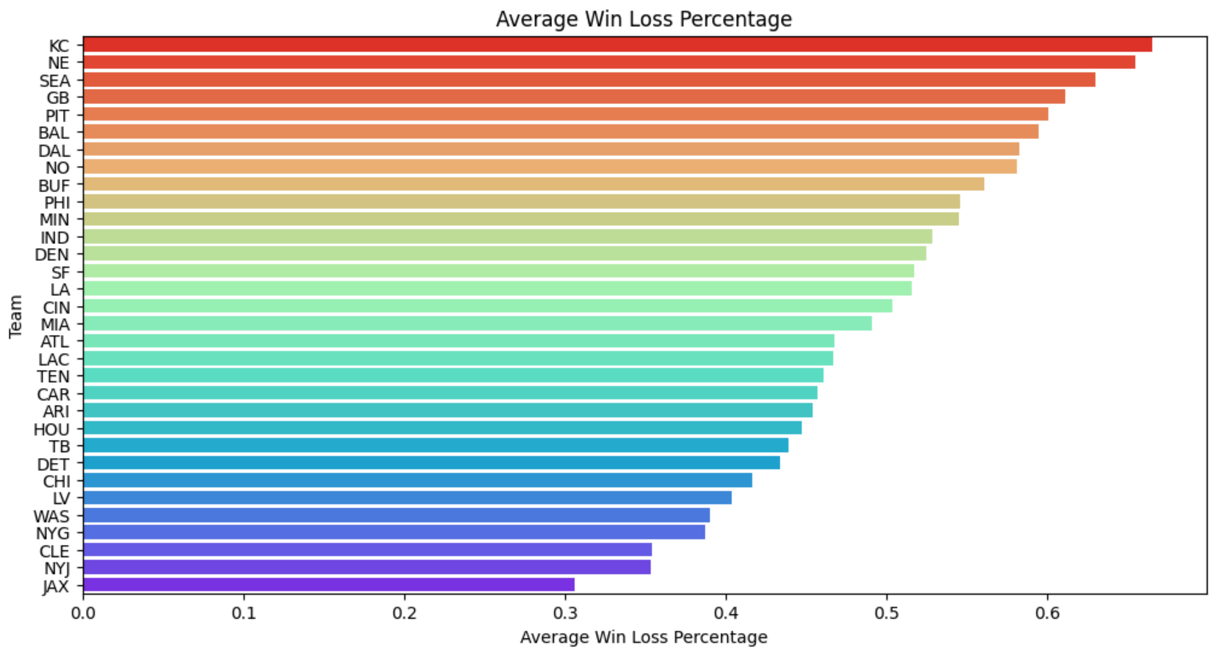
Conclusion:

While accumulating a lot of total yards tends to help a team's chances of winning, it is not a guaranteed formula for success. Other factors like defense, turnovers, and situational football (such as converting yards into points) can significantly influence a team's win-loss record. Teams with fewer yards can still win games by excelling in these other areas, whereas teams with high yardage may struggle if they lack balance.

Average Win Loss Percentage

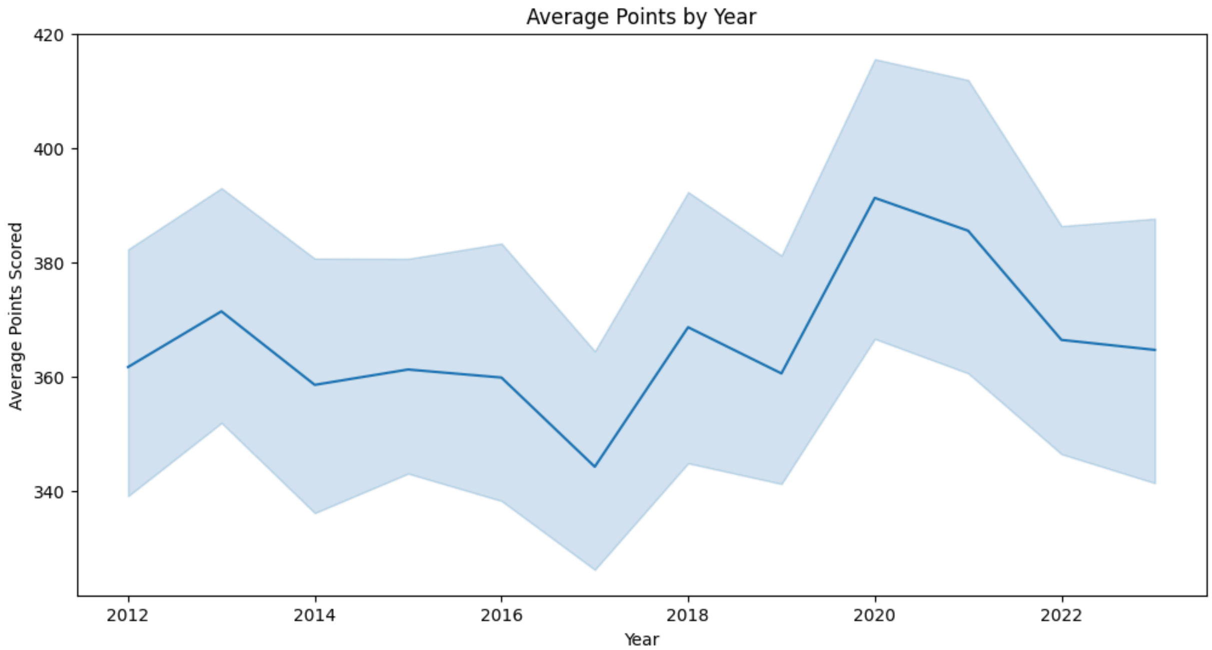
In [ ]:
```
plt.figure(figsize=(12,6))
topWinLoss = df.groupby("team")["win_pct"].mean().sort_values(ascending=False)

# Create the rainbow color palette with red starting at the top
rainbow_colors = sns.color_palette("rainbow", len(topWinLoss))

# Reverse the colors so that red is at the top
```

```
rainbow_colors = rainbow_colors[::-1]

# Assign the 'y' variable to 'hue' and set legend to False
sns.barplot(x=topWinLoss, y=topWinLoss.index, hue=topWinLoss.index, palette=rainbow

plt.title("Average Win Loss Percentage")
plt.xlabel("Average Win Loss Percentage")
plt.ylabel("Team")
plt.show()
```



Average points per year

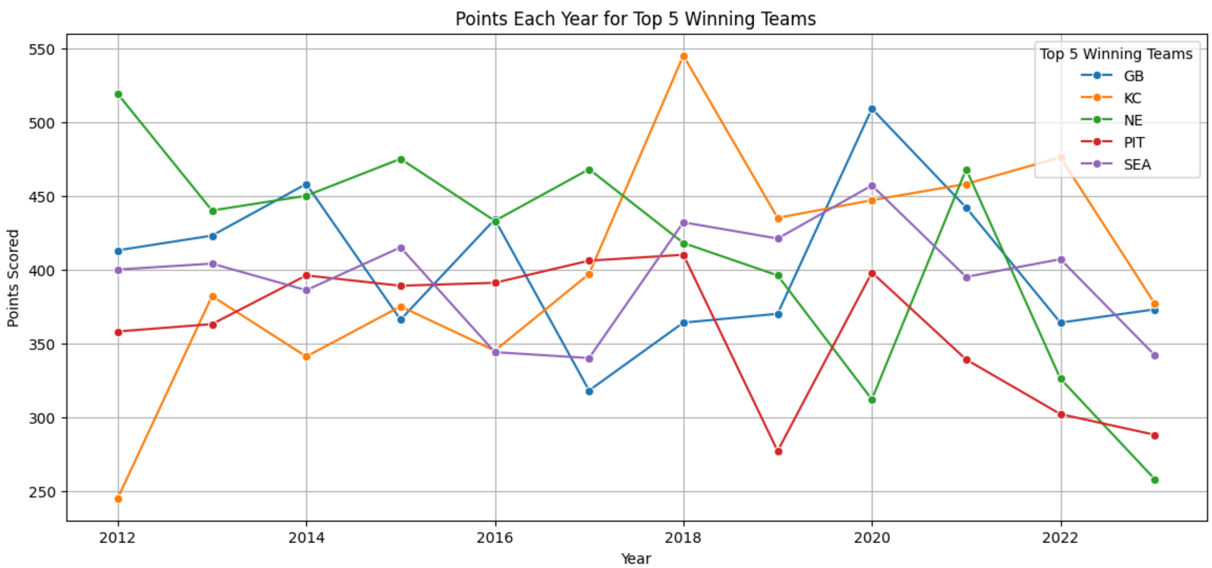
In [ ]:
```
plt.figure(figsize=(12,6))
sns.lineplot(x=df["season"], y=df["total_points"], estimator="mean")
plt.title("Average Points by Year")
plt.xlabel("Year")
plt.ylabel("Average Points Scored")
plt.show()
```

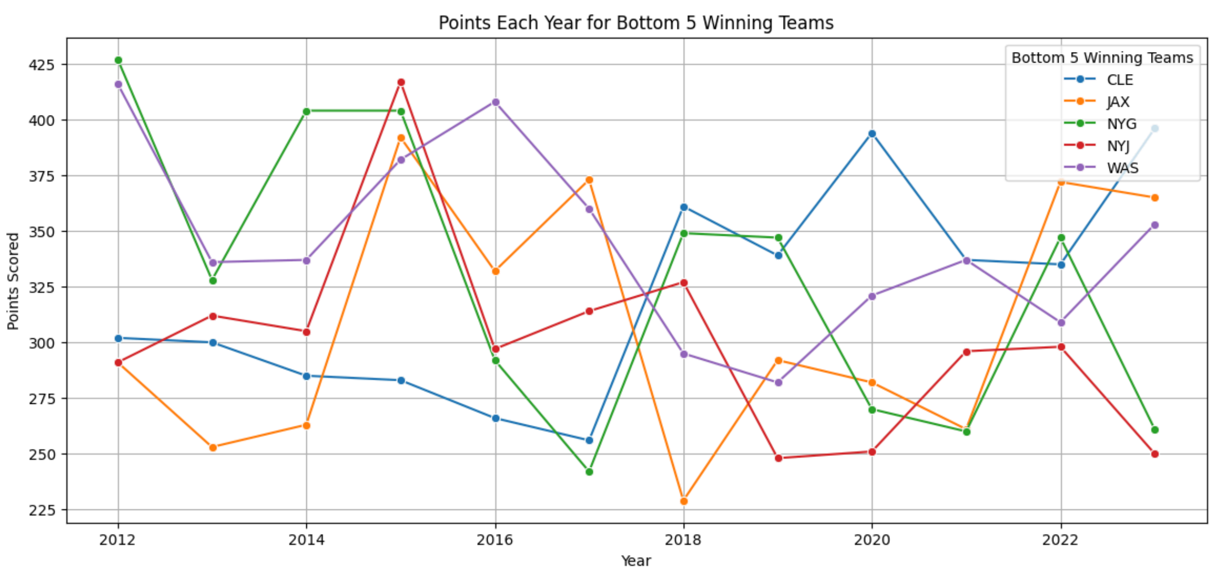


Points each year of the top 5 teams and bottom 5 teams

In [ ]:
```
# Group by team and calculate average win percentage for each team
top_5_teams_by_wins = df.groupby('team')['win_pct'].mean().sort_values(ascending=Fa

# Filter the dataframe to only include the top 5 winning teams
top_5_winning_teams = df[df['team'].isin(top_5_teams_by_wins)]

# Plotting points scored by the top 5 winning teams over the years
plt.figure(figsize=(14,6))
sns.lineplot(data=top_5_winning_teams, x='season', y='total_points', hue='team', ma

# Adding title and labels
plt.title('Points Each Year for Top 5 Winning Teams')
plt.xlabel('Year')
plt.ylabel('Points Scored')

# Displaying legend and grid
plt.legend(title='Top 5 Winning Teams')
plt.grid(True)

# Show the plot
plt.show()


# Group by team and calculate the average win percentage for each team
bottom_5_teams_by_wins = df.groupby('team')['win_pct'].mean().sort_values(ascending

# Filter the dataframe to only include the bottom 5 winning teams
bottom_5_winning_teams = df[df['team'].isin(bottom_5_teams_by_wins)]

# Plotting points scored by the bottom 5 winning teams over the years
```

```
plt.figure(figsize=(14,6))
sns.lineplot(data=bottom_5_winning_teams, x='season', y='total_points', hue='team',

# Adding title and labels
plt.title('Points Each Year for Bottom 5 Winning Teams')
plt.xlabel('Year')
plt.ylabel('Points Scored')

# Displaying legend and grid
plt.legend(title='Bottom 5 Winning Teams')
plt.grid(True)

# Show the plot
plt.show()
```





From the two charts showing points scored each year for both the top 5 and bottom 5 winning teams, here are some observations:

General Trends:

- The points scored by the top 5 teams are generally higher and more consistent than the bottom 5 teams.
- There are noticeable spikes for certain teams (e.g., **Kansas City (KC)** around 2018-2019), indicating standout offensive seasons.
- Teams like **New England (NE)** and **Seattle (SEA)** maintain relatively stable point totals over the years, although NE experienced a decline after 2018.
- The scoring trend appears to fluctuate but stays within the 350–500 point range, with occasional dips below 350 points for **Pittsburgh (PIT)** and **Seattle (SEA)**.
- **Top Teams** maintain a higher floor for points scored, rarely dropping below 300 points in a season.

What is the average and minimum points needed for a winning season?

In [ ]:
```
# Filter teams that had more wins than losses (positive season)
positive_season_teams = df[df['wins'] > df['losses']]

# Calculate the average points scored by teams with positive seasons
average_points_positive_season = positive_season_teams['total_points'].mean()

# Find the minimum points scored by a team with a positive winning season
min_points_positive_season = positive_season_teams['total_points'].min()

# Print results
print(f"Average points scored for a positive season: {average_points_positive_seaso
print(f"Minimum points scored for a positive season: {min_points_positive_season}")
```

```
Average points scored for a positive season: 405.3463687150838
Minimum points scored for a positive season: 277
```

Based on the data:

- The **average points scored** by teams that had a positive season (more wins than losses) is approximately **405.35 points**.
- The **minimum points scored** by a team with a positive season is **277 points**.

Interpretation:

- Teams generally need to score **around 405 points** on average in a season to have a winning record.
- The lowest number of points scored by a team that still had a winning record was **277 points**, meaning that it is possible to win more games than lose with fewer points, but it's less common.

In practical terms, aiming for a total of **405 points** or more over the season seems to increase a team's chances of having a positive winning record based on historical data.

Additional analysis:

- Draw up average and minimum points needed to be the first seed in each conference

Value of touchdown points, field goal points, and extra points to winning

1. Understanding the Data

First, we need to gather the relevant columns for:

- **Touchdowns (TD)**: Representing the number of touchdowns scored.
- **Field Goals (FG)**: Representing the number of successful field goals.
- **Extra Points (XP)**: Representing the number of extra points made after touchdowns.
- **Wins**: Representing the total number of wins for a team in a season.

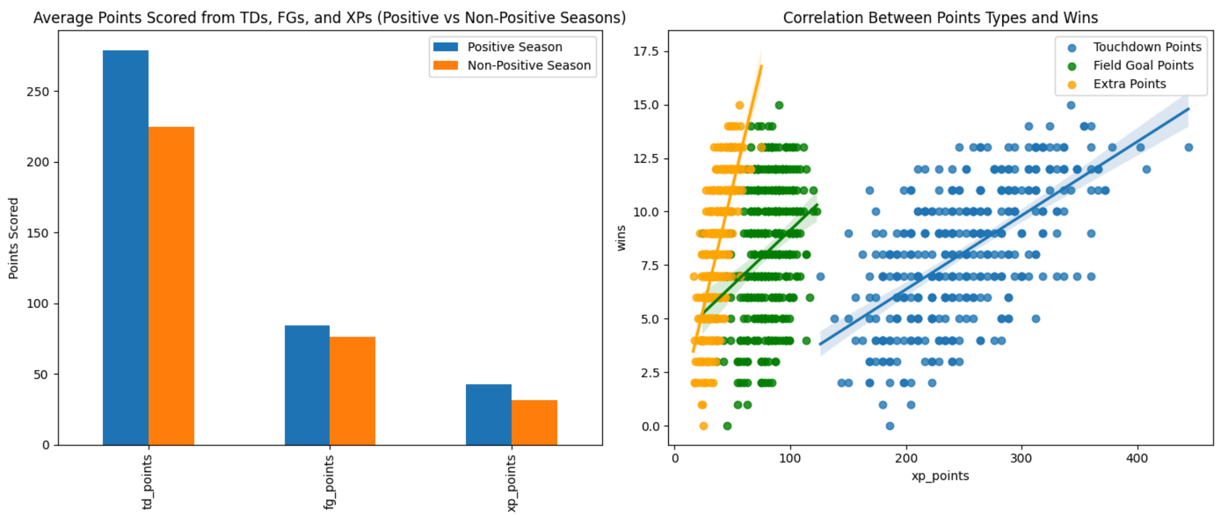
From this, we can calculate:

- **Touchdown Points** = TD * 6
- **Field Goal Points** = FG * 3
- **Extra Points** = XP * 1

The total score for a team in a season is the sum of all these values, and we'll evaluate their impact on the number of wins.

In [ ]:
```
# Filter relevant columns for the analysis
columns_of_interest = ['td_points', 'fg_points', 'xp_points', 'wins', 'win_pct']
data = df[columns_of_interest]

# Check for any missing values
data.isnull().sum()

# A. Summary statistics for teams with a positive winning season (more than 8 wins)
positive_season = data[data['wins'] > 8]
non_positive_season = data[data['wins'] <= 8]

# Calculate mean values for positive and non-positive seasons
avg_positive = positive_season[['td_points', 'fg_points', 'xp_points']].mean()
avg_non_positive = non_positive_season[['td_points', 'fg_points', 'xp_points']].mea

# B. Correlation matrix between points types and wins
correlation = data[['td_points', 'fg_points', 'xp_points', 'wins']].corr()

# C. Visualization

# Bar chart for comparison between positive and non-positive seasons
fig, ax = plt.subplots(1, 2, figsize=(14, 6))

avg_comparison = pd.DataFrame({'Positive Season': avg_positive, 'Non-Positive Seaso
```

```
avg_comparison.plot(kind='bar', ax=ax[0])
ax[0].set_title('Average Points Scored from TDs, FGs, and XPs (Positive vs Non-Posi
ax[0].set_ylabel('Points Scored')

# Scatter plots to show correlation with Wins
sns.regplot(x='td_points', y='wins', data=data, ax=ax[1], label='Touchdown Points')
sns.regplot(x='fg_points', y='wins', data=data, ax=ax[1], label='Field Goal Points'
sns.regplot(x='xp_points', y='wins', data=data, ax=ax[1], label='Extra Points', col
ax[1].legend()
ax[1].set_title('Correlation Between Points Types and Wins')

plt.tight_layout()
plt.show()

# Print correlation matrix
print("Correlation Matrix:")
print(correlation)
```




```
Correlation Matrix:
           td_points  fg_points  xp_points      wins
td_points   1.000000  -0.060086   0.897915  0.615691
fg_points  -0.060086   1.000000   0.003620  0.280789
xp_points   0.897915   0.003620   1.000000  0.707368
wins        0.615691   0.280789   0.707368  1.000000
```

1. Bar Chart: Points Comparison (Positive vs Non-Positive Seasons)

- **Touchdown Points (td_points)**: Teams with positive seasons (more than 8 wins) scored significantly more touchdown points compared to teams with non-positive seasons. This suggests that touchdowns are a crucial factor for a team's success.
- **Field Goal Points (fg_points)**: The difference in field goal points between positive and non-positive seasons is less pronounced, indicating that while field goals contribute to scoring, they may not be as strongly associated with achieving a winning season.
- **Extra Points (xp_points)**: Extra points, which are typically scored following touchdowns, also show a noticeable difference between positive and non-positive seasons, further reinforcing the importance of touchdowns for winning seasons.

2. **Scatter Plot: Correlation Between Point Types and Wins**

- **Touchdown Points** (blue): There is a clear positive correlation between touchdown points and wins, with more touchdown points leading to more wins. The upward trendline shows that teams with higher touchdown scores tend to have more wins.
- **Field Goal Points** (green): There is a weaker positive correlation between field goal points and wins. Although field goals contribute to overall scoring, their impact on winning appears less significant compared to touchdowns.
- **Extra Points** (orange): Extra points are highly correlated with wins, as they are directly tied to touchdowns. Teams with more extra points tend to have more wins, although the correlation is somewhat weaker than touchdown points.

3. **Correlation Matrix**

- **Touchdown Points (td_points)** have a correlation of **0.615** with wins, showing a moderately strong positive relationship. This means that touchdowns are a key contributor to winning games.
- **Field Goal Points (fg_points)** have a correlation of **0.280** with wins, which is relatively weak. While field goals contribute to scoring, they are less impactful than touchdowns for winning.
- **Extra Points (xp_points)** have a correlation of **0.707** with wins, which is even stronger than touchdowns. This is because extra points directly follow touchdowns, so they accumulate in proportion to touchdown success.
- **Touchdown Points and Extra Points** have a very high correlation (**0.897**), which is expected since extra points typically follow touchdowns.

Key Takeaways:

- **Touchdowns are the most impactful type of scoring** for a team's success, as evidenced by both the bar chart and the correlation of touchdown points with wins.
- **Extra points**, while directly tied to touchdowns, are also strongly correlated with winning, indicating that teams scoring many touchdowns naturally accumulate extra points.
- **Field goals** play a role in scoring but are less significant for determining whether a team has a winning season.

In summary, touchdowns are the biggest factor in a team's success, with extra points closely following, while field goals have a more moderate effect.

Regression model to calculate touchdown points needed to have a winning season

In [ ]:
```python
import statsmodels.api as sm
# Selecting relevant columns for touchdown points and wins
data = df[['td_points', 'wins']].dropna()

# Fitting a linear regression model to predict wins based on touchdown points
X = data['td_points']
y = data['wins']

# Adding constant for intercept
X = sm.add_constant(X)

# Performing the regression
model = sm.OLS(y, X).fit()

# Predicting the number of touchdown points required for 9 wins (a winning season)
touchdown_points_for_winning = (9 - model.params['const']) / model.params['td_point

touchdown_points_for_winning, model.summary()
```

Out[ ]:
```
(276.23767536749216,
 <class 'statsmodels.iolib.summary.Summary'>
 """
                            OLS Regression Results
 ==============================================================================
 Dep. Variable:                   wins   R-squared:                       0.379
 Model:                            OLS   Adj. R-squared:                  0.377
 Method:                 Least Squares   F-statistic:                     233.2
 Date:                Fri, 01 Nov 2024   Prob (F-statistic):           1.95e-41
 Time:                        14:24:10   Log-Likelihood:                -883.07
 No. Observations:                 384   AIC:                             1770.
 Df Residuals:                     382   BIC:                             1778.
 Df Model:                           1
 Covariance Type:            nonrobust
 ==============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
 ------------------------------------------------------------------------------
 const         -0.5346      0.578     -0.925      0.356      -1.671       0.602
 td_points      0.0345      0.002     15.271      0.000       0.030       0.039
 ==============================================================================
 Omnibus:                       14.978   Durbin-Watson:                   1.636
 Prob(Omnibus):                  0.001   Jarque-Bera (JB):                8.089
 Skew:                          -0.159   Prob(JB):                       0.0175
 Kurtosis:                       2.364   Cond. No.                     1.20e+03
 ==============================================================================

 Notes:
 [1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
 [2] The condition number is large, 1.2e+03. This might indicate that there are
 strong multicollinearity or other numerical problems.
 """)
```

From the OLS regression results, we can interpret the following about the relationship between touchdown points and the number of wins:

1. **Model Performance**:

   - The **R-squared value** is 0.379, meaning approximately 37.9% of the variance in wins is explained by the number of touchdown points. While this suggests a moderate relationship, there are other factors not captured in this model that also influence wins.
   - The **Adjusted R-squared** is 0.377, which is close to the R-squared value, indicating that the model doesn't lose much explanatory power even after accounting for the number of predictors.

2. **Coefficient (td_points)**:

   - The coefficient for **td_points** is **0.0345**. This means that for every additional touchdown point a team scores, the number of wins increases by 0.0345 on average.
   - So, for example, scoring an extra 100 touchdown points could increase a team's win count by approximately 3.45 wins (100 * 0.0345).

3. **Constant (Intercept)**:

   - The **intercept (const)** is **-0.5346**, but it is not statistically significant (p-value = 0.356). This implies that without scoring any touchdown points, the model does not provide a meaningful prediction for wins.

4. **Statistical Significance**:

   - The **P-value** for the touchdown points coefficient is **0.000**, meaning the relationship between touchdown points and wins is highly significant.
   - The **F-statistic** of 233.2 and the extremely low p-value (1.95e-41) further indicate that touchdown points significantly explain the variance in wins.

Insights:

- Touchdown points have a positive and significant impact on the number of wins a team can achieve.

- The model indicates that increasing touchdown points is strongly associated with an increase in wins, although the relationship is not the sole factor (as shown by the R-squared value).

- To calculate how many touchdown points are needed to achieve a specific number of wins, you can use the regression equation:

  $$\text{Wins} = 0.0345 \times \text{Touchdown Points} - 0.5346$$

If you want a specific number of wins (like 9 for a positive season), you can solve this equation for the number of touchdown points needed.

Example calculation

To determine the required number of touchdowns per game and total touchdowns for a winning season (defined as having more wins than losses, typically 9 or more wins in a 17-game NFL season), we can use the regression equation derived from the analysis.

The equation for wins is:

$$\text{Wins} = 0.0345 \times \text{Touchdown Points} - 0.5346$$

For a winning season (let's assume at least 9 wins):

$$9 = 0.0345 \times \text{Touchdown Points} - 0.5346$$

Step 1: Solve for the required Touchdown Points

We solve for the total touchdown points needed:

$$9 + 0.5346 = 0.0345 \times \text{Touchdown Points}$$

$$9.5346 = 0.0345 \times \text{Touchdown Points}$$

$$\text{Touchdown Points} = \frac{9.5346}{0.0345} \approx 276.37$$

So, approximately **276 touchdown points** are needed to achieve 9 wins.

Step 2: Convert Touchdown Points to Total Touchdowns

Since each touchdown is worth 6 points, we can find the number of touchdowns required by dividing the total touchdown points by 6:

$$\text{Total Touchdowns} = \frac{276.37}{6} \approx 46.06$$

This means a team would need to score **around 46 touchdowns** in total to have a winning season.

Step 3: Calculate Touchdowns Per Game

Since the NFL regular season consists of 17 games, the average touchdowns per game needed are:

$$\text{Touchdowns per Game} = \frac{46.06}{17} \approx 2.71$$

Step 4: Calculate Touchdown Points Per Game

To calculate the **touchdown points per game**, take the total touchdown points needed (276.37) and divide by the 17-game NFL season. Here's the calculation:

$$\text{Touchdown Points per Game} = \frac{276.37}{17} \approx 16.26$$

So, the team would need to average approximately **16.26 touchdown points per game** to reach 9 wins.

Summary:

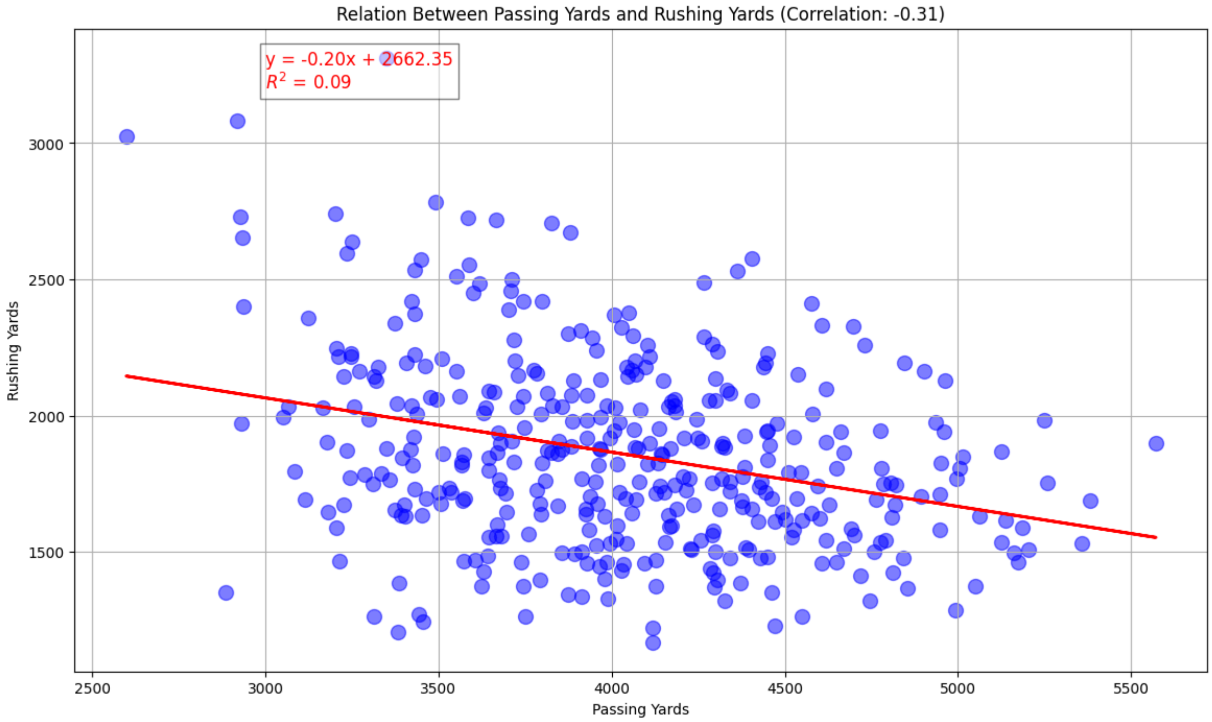
- **Total Touchdowns**: Approximately **46 touchdowns** are needed for a winning season.
- **Touchdowns per Game**: A team needs to score around **2.71 touchdowns per game** on average to achieve at least 9 wins in a 17-game season.
- **Touchdowns points per Game**: A team would need to average approximately **16.26 touchdown points per game** to reach 9 wins.

Next steps

- How many touchdown points are needed to achieve the top seed in each conference

Relation between passing yards and rushing yards

In [ ]:
```
# Calculating the correlation coefficient between passing and rushing yards
corr = df['passing_yards'].corr(df['rushing_yards'])

# Fitting a regression line
m, b = np.polyfit(df['passing_yards'], df['rushing_yards'], 1)

# Calculate R-squared (coefficient of determination)
r_squared = corr**2


# Plotting relation between passing yards and rushing yards with enhanced readabili
plt.figure(figsize=(14,8))
plt.scatter(df['passing_yards'], df['rushing_yards'], c='blue', alpha=0.5, s=100)

# Plotting the regression line
plt.plot(df['passing_yards'], m * df['passing_yards'] + b, color='red', linewidth=2

plt.title('Relation Between Passing Yards and Rushing Yards (Correlation: {:.2f})'.
plt.xlabel('Passing Yards')
plt.ylabel('Rushing Yards')

# Adding grid for better readability
plt.grid(True)

# Adding the equation of the regression line as text on the plot
plt.text(3000, 3200, 'y = {:.2f}x + {:.2f}\n$R^2$ = {:.2f}'.format(m, b, r_squared)
         fontsize=12, color='red', bbox=dict(facecolor='white', alpha=0.5))

plt.show()
```



From the scatter plot, showing the relationship between passing yards and rushing yards, you can infer the following:

1. **No Strong Correlation**: There does not seem to be a strong linear relationship between passing yards and rushing yards. The points are widely dispersed, indicating that teams with high passing yards do not necessarily have high rushing yards, and vice versa.

2. **Balanced Distribution**: Most teams fall within a certain range (3000-4500 passing yards, 1500-2500 rushing yards). This suggests that teams tend to have a somewhat balanced offensive strategy between passing and rushing, but outliers exist where some teams excel more in one area.

3. **Outliers**: There are a few outliers where teams have unusually high rushing yards (above 3000) or passing yards (over 5000). These teams may be more specialized in one form of offense.

4. **Complementary Strategies**: The negative correlation could suggest that teams may focus on one aspect of their offensive game more than the other—either relying more on passing or on rushing. This could indicate that teams often choose to specialize rather than balance both rushing and passing yards equally.

5. **(R^2) Value**:The negative slope and low (R^2) value (0.09) suggest a weak, inverse relationship between passing and rushing yards, with passing yards explaining only 9% of the variability in rushing yards. This indicates that other factors likely play a more significant role in determining rushing yards.

6. **Y-intercept Value**:The y-intercept of 2662.35 indicates that when passing yards are zero, the model predicts 2662.35 rushing yards. However, since this scenario is

unrealistic in actual gameplay, the intercept mainly reflects a baseline value from the linear relationship but doesn't have much practical significance for NFL teams.

Suggestions for Further Analysis

- **Categorize by Winning Teams**: It might be interesting to split the data based on team success (e.g., high-win vs. low-win teams) and see if high-performing teams rely more on passing or rushing.
- **Color by Category (optional)**: To add depth to the visualization, you can color the points by categories such as team rankings, conference, or even wins. This could help reveal if high-performing teams favor passing or rushing offenses.

Fumbles, interceptions, incomplete, and turnover

To evaluate the impact of **fumbles** on a team's ability to win games, we can explore the relationship between fumbles (both total fumbles and fumbles lost) and the number of wins. The fumble-related columns from the dataset that are relevant for this analysis are:

- `fumble`: Total number of fumbles by the team.
- `fumble_lost`: The number of times the team lost possession due to a fumble.

1. Correlation Analysis

We can compute the correlation between these fumble-related metrics and wins to understand the general relationship.

Correlation Results:

- **Fumbles and Wins**: This shows whether more fumbles are associated with winning or losing.
- **Fumbles Lost and Wins**: This shows how losing possession due to fumbles correlates with wins.

2. Regression Analysis

We can perform a linear regression to estimate how much **fumbles** and **fumbles lost** contribute to the number of wins. This would tell us quantitatively how fumbles affect winning outcomes.

Using a simple linear regression model, the relationship might look like this:

$$\text{Wins} = \beta_0 + \beta_1 \times \text{fumble} + \beta_2 \times \text{fumble\textbackslash\_lost}$$

Where:

$$\beta_1 \text{ and } \beta_2$$

are the coefficients that indicate how much wins decrease (or increase) with each additional fumble or fumble lost.

3. Expected Outcome

Typically, fumbles (and especially **fumbles lost**) negatively impact a team's chances of winning games. Losing possession of the ball gives the opposing team more opportunities to score and reduces the offensive momentum. We would expect:

- A **negative correlation** between **fumbles lost** and **wins**, meaning more fumbles lost likely leads to fewer wins.
- A smaller or weaker negative correlation between total **fumbles** and wins, as not all fumbles lead to lost possession.

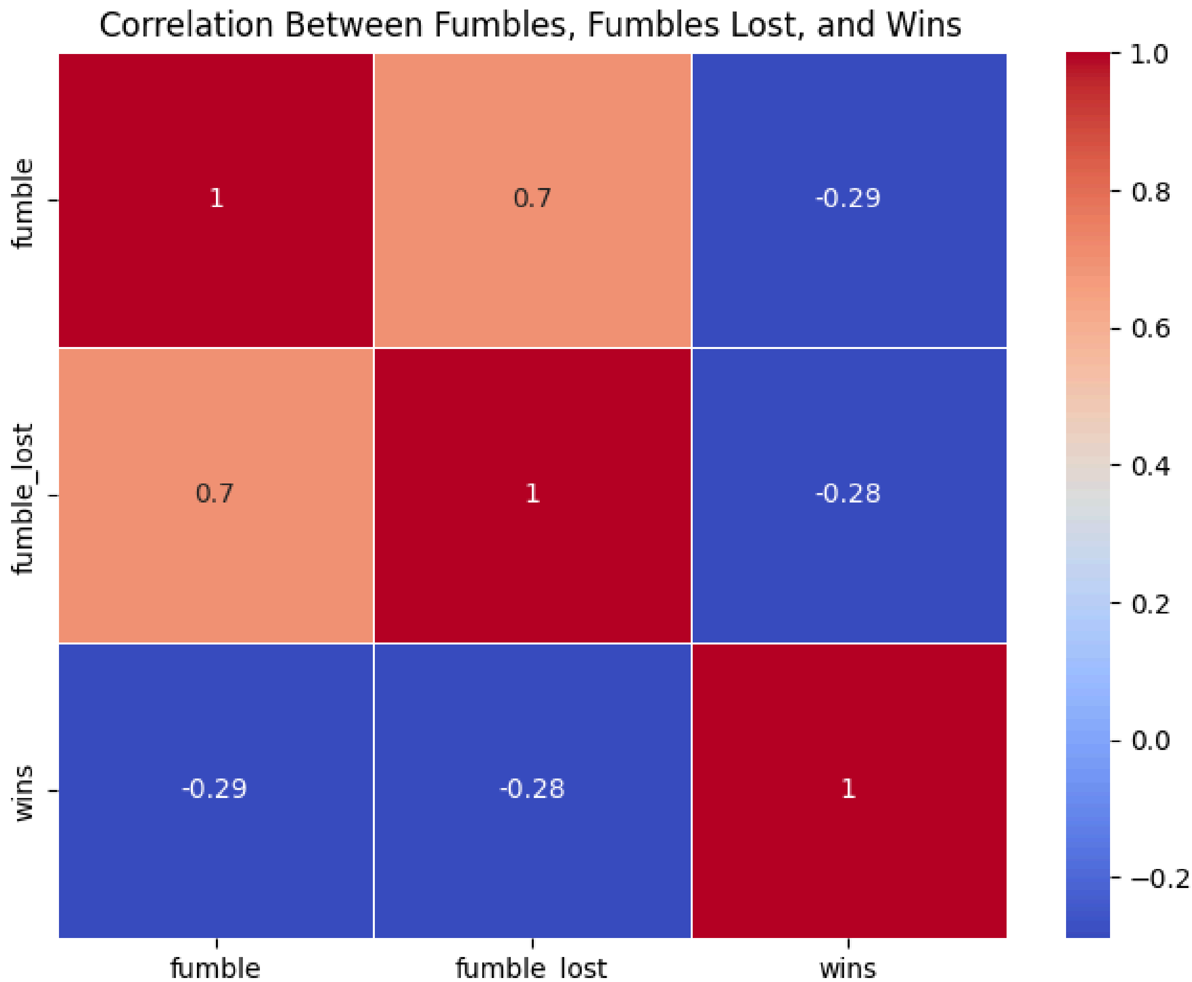
In [ ]:

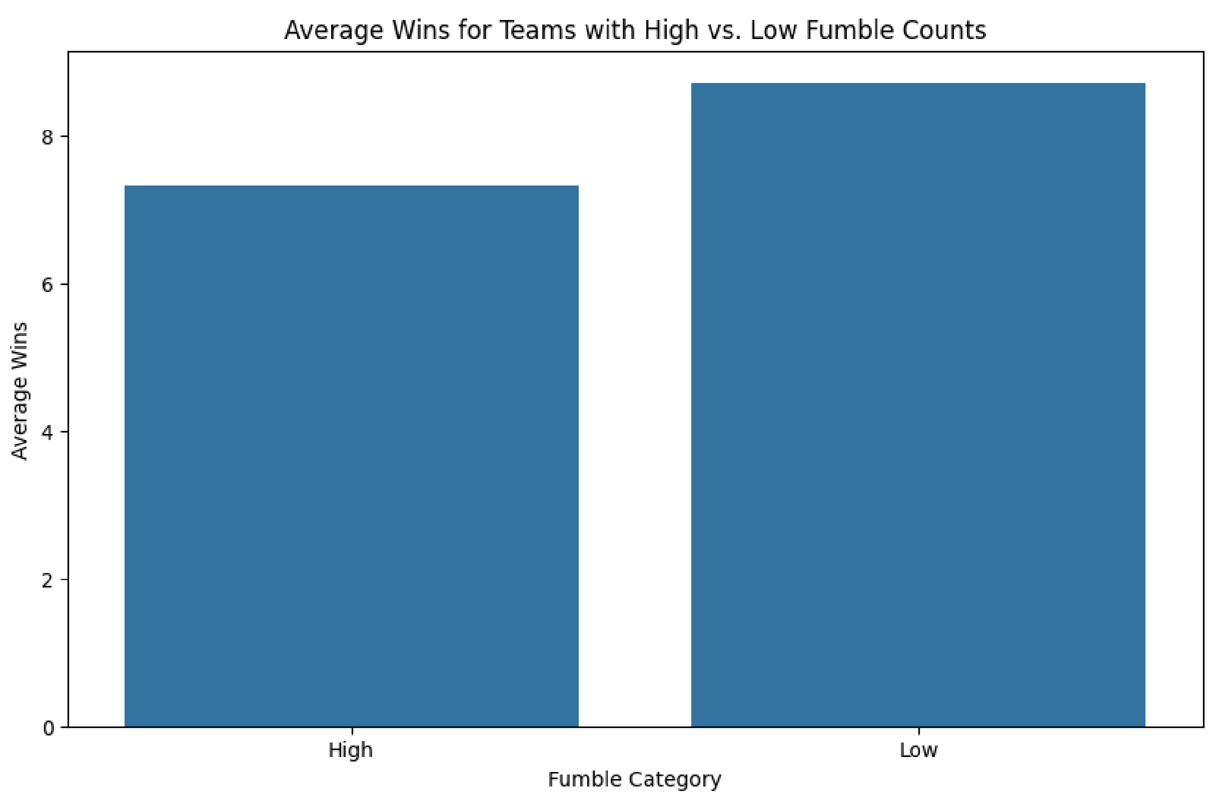
```
# Select relevant columns for analysis
fumble_data = df[['fumble', 'fumble_lost', 'wins']]

# Calculate correlation between fumbles, fumbles lost, and wins
fumble_correlation = fumble_data.corr()

# Perform regression analysis to assess the impact of fumbles and fumbles lost on w
import statsmodels.api as sm

# Define independent variables (fumbles and fumbles lost) and dependent variable (w
X = fumble_data[['fumble', 'fumble_lost']]
y = fumble_data['wins']

# Add a constant to the independent variables matrix
X = sm.add_constant(X)

# Fit the regression model
fumble_model = sm.OLS(y, X).fit()

# Get regression summary
fumble_summary = fumble_model.summary()

# Output correlation and regression results
fumble_correlation, fumble_summary
```

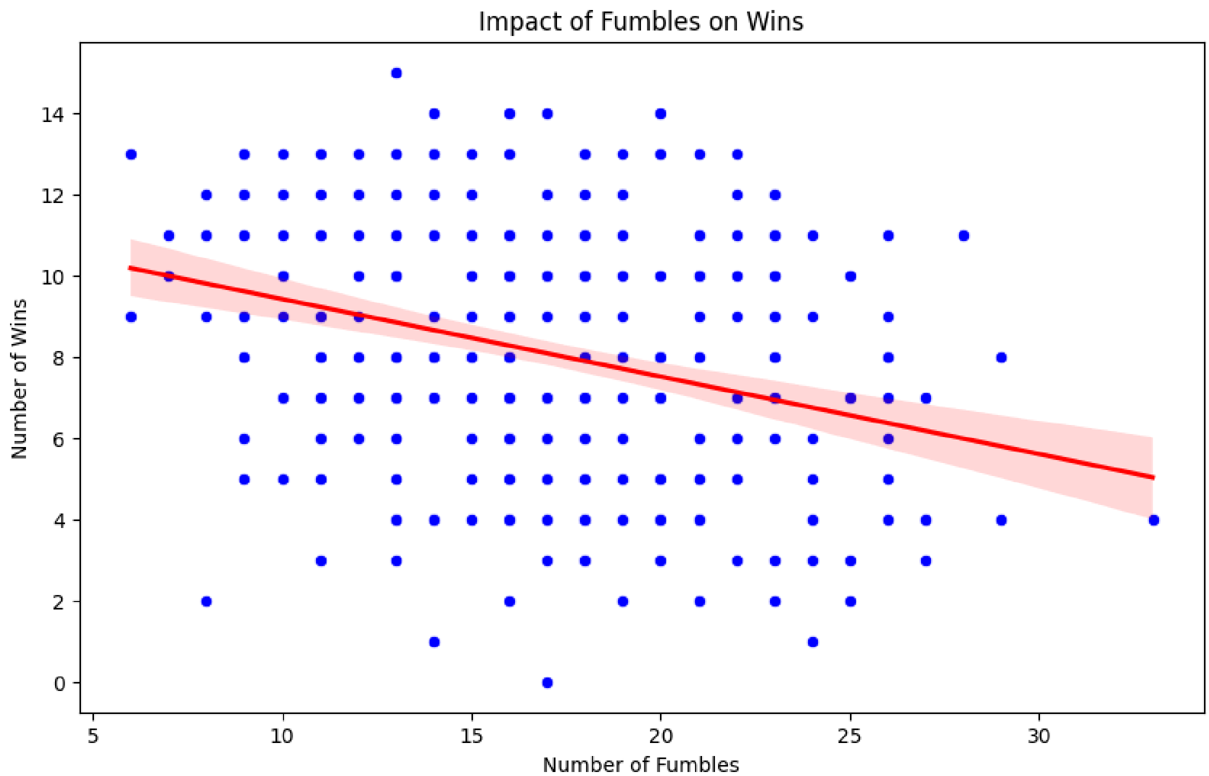
Out[ ]:
```
(              fumble  fumble_lost      wins
 fumble       1.000000     0.695449 -0.288251
 fumble_lost  0.695449     1.000000 -0.284644
 wins        -0.288251    -0.284644  1.000000,
 <class 'statsmodels.iolib.summary.Summary'>
 """
                             OLS Regression Results
 ==============================================================================
 Dep. Variable:                   wins   R-squared:                       0.097
 Model:                            OLS   Adj. R-squared:                  0.092
 Method:                 Least Squares   F-statistic:                     20.42
 Date:                Fri, 01 Nov 2024   Prob (F-statistic):           3.76e-09
 Time:                        14:24:10   Log-Likelihood:                -955.02
 No. Observations:                 384   AIC:                             1916.
 Df Residuals:                     381   BIC:                             1928.
 Df Model:                           2
 Covariance Type:            nonrobust
 ===============================================================================
                   coef    std err          t      P>|t|      [0.025      0.975]
 -------------------------------------------------------------------------------
 const          11.4357      0.567     20.152      0.000      10.320      12.552
 fumble         -0.1157      0.045     -2.581      0.010      -0.204      -0.028
 fumble_lost    -0.1726      0.072     -2.406      0.017      -0.314      -0.032
 ==============================================================================
 Omnibus:                       11.209   Durbin-Watson:                   1.327
 Prob(Omnibus):                  0.004   Jarque-Bera (JB):                5.950
 Skew:                          -0.061   Prob(JB):                       0.0511
 Kurtosis:                       2.403   Cond. No.                         74.2
 ==============================================================================

 Notes:
 [1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
 """)
```

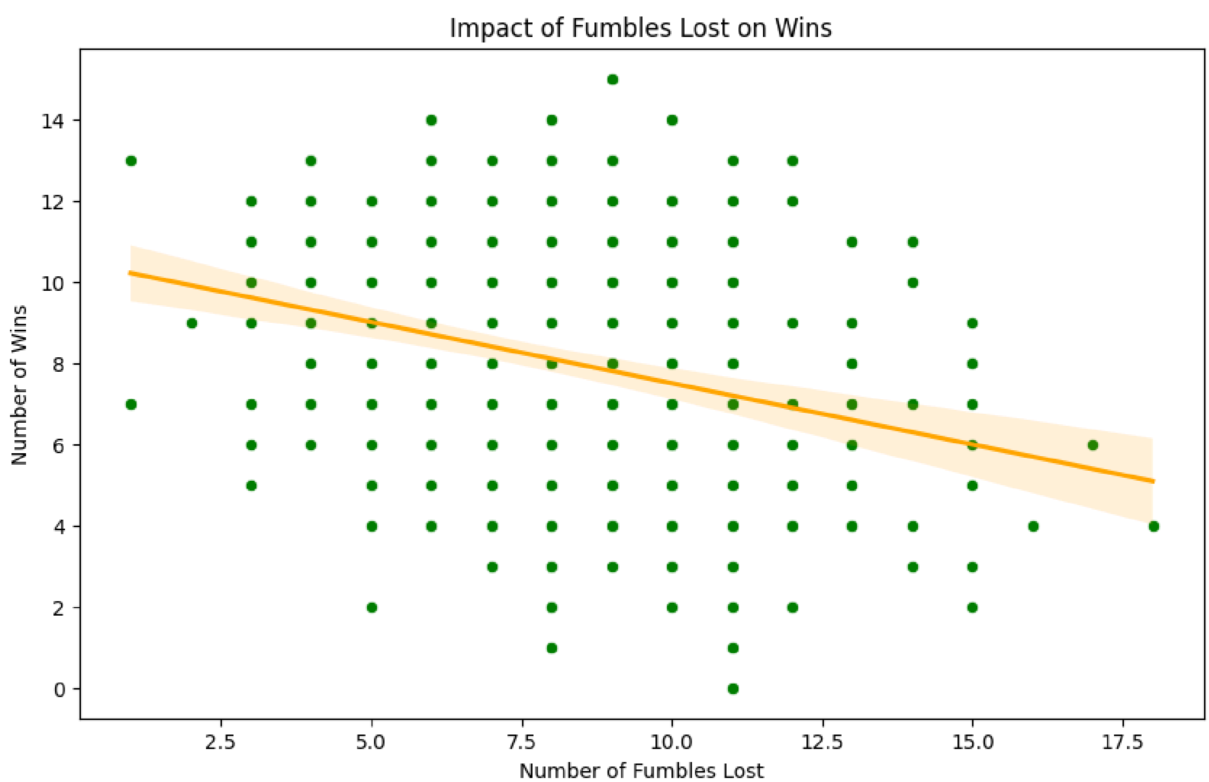
In [ ]:
```
# Select relevant columns for visualization
columns_of_interest = ['fumble', 'fumble_lost', 'wins']
df_selected = df[columns_of_interest]

# Create correlation heatmap
plt.figure(figsize=(8,6))
correlation_matrix = df_selected.corr()
sns.heatmap(correlation_matrix, annot=True, cmap="coolwarm", linewidths=0.5)

plt.title("Correlation Between Fumbles, Fumbles Lost, and Wins")
plt.show()


df_selected = df[columns_of_interest].copy()  # Create a true copy of the DataFrame

# Create thresholds for fumble and fumble_lost
threshold_fumble = df['fumble'].median()
threshold_fumble_lost = df['fumble_lost'].median()

# Use .loc to avoid SettingWithCopyWarning
df_selected.loc[:, 'fumble_category'] = df_selected['fumble'].apply(lambda x: 'High
```

```
df_selected.loc[:, 'fumble_lost_category'] = df_selected['fumble_lost'].apply(lambd

# Bar Plot for average wins based on fumble category
plt.figure(figsize=(10, 6))
avg_wins_by_fumble = df_selected.groupby('fumble_category')['wins'].mean().reset_in
sns.barplot(x='fumble_category', y='wins', data=avg_wins_by_fumble)  # Removed pale
plt.title('Average Wins for Teams with High vs. Low Fumble Counts')
plt.ylabel('Average Wins')
plt.xlabel('Fumble Category')
plt.show()

# Scatter Plot with trend line
plt.figure(figsize=(10, 6))
sns.scatterplot(x='fumble', y='wins', data=df_selected, color='blue')
sns.regplot(x='fumble', y='wins', data=df_selected, scatter=False, color='red')
plt.title('Impact of Fumbles on Wins')
plt.xlabel('Number of Fumbles')
plt.ylabel('Number of Wins')
plt.show()

# Optional: Scatter Plot for Fumbles Lost
plt.figure(figsize=(10, 6))
sns.scatterplot(x='fumble_lost', y='wins', data=df_selected, color='green')
sns.regplot(x='fumble_lost', y='wins', data=df_selected, scatter=False, color='oran
plt.title('Impact of Fumbles Lost on Wins')
plt.xlabel('Number of Fumbles Lost')
plt.ylabel('Number of Wins')
plt.show()
```


Correlation Between Fumbles, Fumbles Lost, and Wins
fumble
fumble_lost
wins
1
0.7
-0.29
0.7
1
-0.28
-0.29
-0.28
1
1.0
0.8
0.6
0.4
0.2
0.0
−0.2


Average Wins for Teams with High vs. Low Fumble Counts
Average Wins
0
2
4
6
8
High
Low
Fumble Category





Based on the correlation matrix and regression analysis results, here are the key findings regarding how fumbles affect a team's winning performance:

1. **Correlation Matrix**:

- There is a negative correlation between both **fumbles** and **wins** (-0.288) as well as **fumbles lost** and **wins** (-0.285). This suggests that as the number of fumbles or

fumbles lost increases, the number of wins decreases.
- Fumbles and fumbles lost have a strong positive correlation (0.695), indicating that teams that fumble more often tend to lose possession of the ball frequently.

2. **OLS Regression Results**:

   - The model shows an **R-squared value of 0.097**, meaning that approximately 9.7% of the variability in wins can be explained by the number of fumbles and fumbles lost.
   - Both **fumble** and **fumble_lost** have statistically significant negative coefficients:
     - For every additional fumble, the team is expected to win **0.1157 fewer games**.
     - For every additional fumble lost, the team is expected to win **0.1726 fewer games**.
   - Both fumble-related variables have p-values less than 0.05 (fumble: 0.010, fumble_lost: 0.017), indicating that they have a statistically significant impact on the number of wins.

Conclusion:

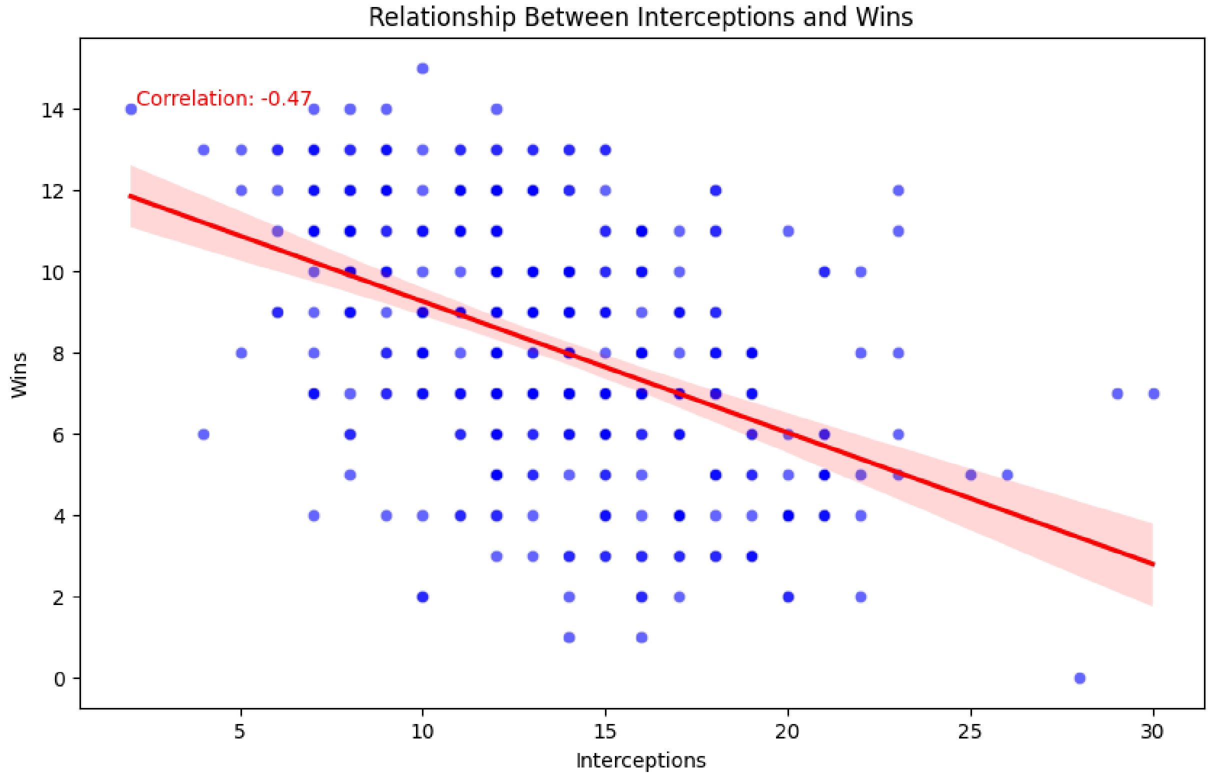
The analysis suggests that fumbles (especially lost fumbles) negatively impact a team's chance of winning. As fumbles and fumbles lost increase, the likelihood of a winning season decreases. This highlights the importance of minimizing turnovers to improve team performance and win more games.

Additional:

- Average fumbles for a losing season

Correlation of interceptions on a team's ability to win games

In [ ]:
```
# Calculate correlation
correlation = df['interception'].corr(df['wins'])

plt.figure(figsize=(10, 6))
sns.scatterplot(x='interception', y='wins', data=df, color='b', alpha=0.6)
sns.regplot(x='interception', y='wins', data=df, scatter=False, color='r')
plt.xlabel("Interceptions")
plt.ylabel("Wins")
plt.title("Relationship Between Interceptions and Wins")

# Add correlation annotation
plt.text(0.05, 0.9, f"Correlation: {correlation:.2f}", transform=plt.gca().transAxe

plt.show()
```



This plot shows a scatter plot analyzing the relationship between interceptions and wins for NFL teams, with a negative correlation coefficient of -0.47. This suggests a moderate inverse relationship, indicating that as the number of interceptions increases, the number of wins tends to decrease. The red regression line shows a downward trend, reinforcing this inverse relationship, and the shaded area represents the confidence interval for the regression line.

To determine the minimum number of interceptions a team can allow per game or per season to have a winning season (typically defined as more than 8 wins in a 16-game season or 9 wins in a 17-game season), we can use the regression line from the graph and the correlation data provided.

Assuming we approximate the relationship between interceptions and wins with a linear regression equation derived from the plot:

$$\text{Wins} = m \times \text{Interceptions} + b$$

Given that the plot shows a negative slope and a correlation of -0.47, we can approximate a relationship, but we'd need the exact equation to make precise predictions. However, let's assume you have a basic form of this line, and let's take the winning season threshold as follows:

1. **For a 16-game season**, a team needs at least 9 wins to have a winning season.
2. **For a 17-game season**, a team needs at least 9 wins as well.

Using these thresholds, we can solve for the maximum number of interceptions that would still yield a winning season, assuming the approximate line from the graph.

In [ ]:
```
# Filter relevant columns (wins and interceptions)
data = df[['wins', 'interception']].dropna()

# Define the target and feature
X = data['interception']
y = data['wins']

# Add a constant to the predictor variable for statsmodels
X = sm.add_constant(X)

# Fit the linear regression model
model = sm.OLS(y, X).fit()

# Print the model summary
print(model.summary())

# Calculate the threshold for a winning season
intercept = model.params['const']
slope = model.params['interception']
target_wins = 9
max_interceptions = (target_wins - intercept) / slope
print(f"Maximum interceptions for a winning season (9 wins): {max_interceptions:.2f
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                   wins   R-squared:                       0.224
Model:                            OLS   Adj. R-squared:                  0.222
Method:                 Least Squares   F-statistic:                     110.3
Date:                Fri, 01 Nov 2024   Prob (F-statistic):           7.66e-23
Time:                        14:24:11   Log-Likelihood:                -925.85
No. Observations:                 384   AIC:                             1856.
Df Residuals:                     382   BIC:                             1864.
Df Model:                           1
Covariance Type:            nonrobust
================================================================================
                   coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
const           12.4751      0.440     28.379      0.000      11.611      13.339
interception    -0.3229      0.031    -10.504      0.000      -0.383      -0.262
==============================================================================
Omnibus:                        3.793   Durbin-Watson:                   1.414
Prob(Omnibus):                  0.150   Jarque-Bera (JB):                3.212
Skew:                          -0.131   Prob(JB):                        0.201
Kurtosis:                       2.636   Cond. No.                         45.7
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly spe
cified.
Maximum interceptions for a winning season (9 wins): 10.76
```

To convert the season threshold of approximately 10.76 interceptions into a per-game average, we can divide it by the number of games in a season:

For a 17-game season: $\frac{10.76}{17} \approx 0.63 \text{ interceptions per game}$

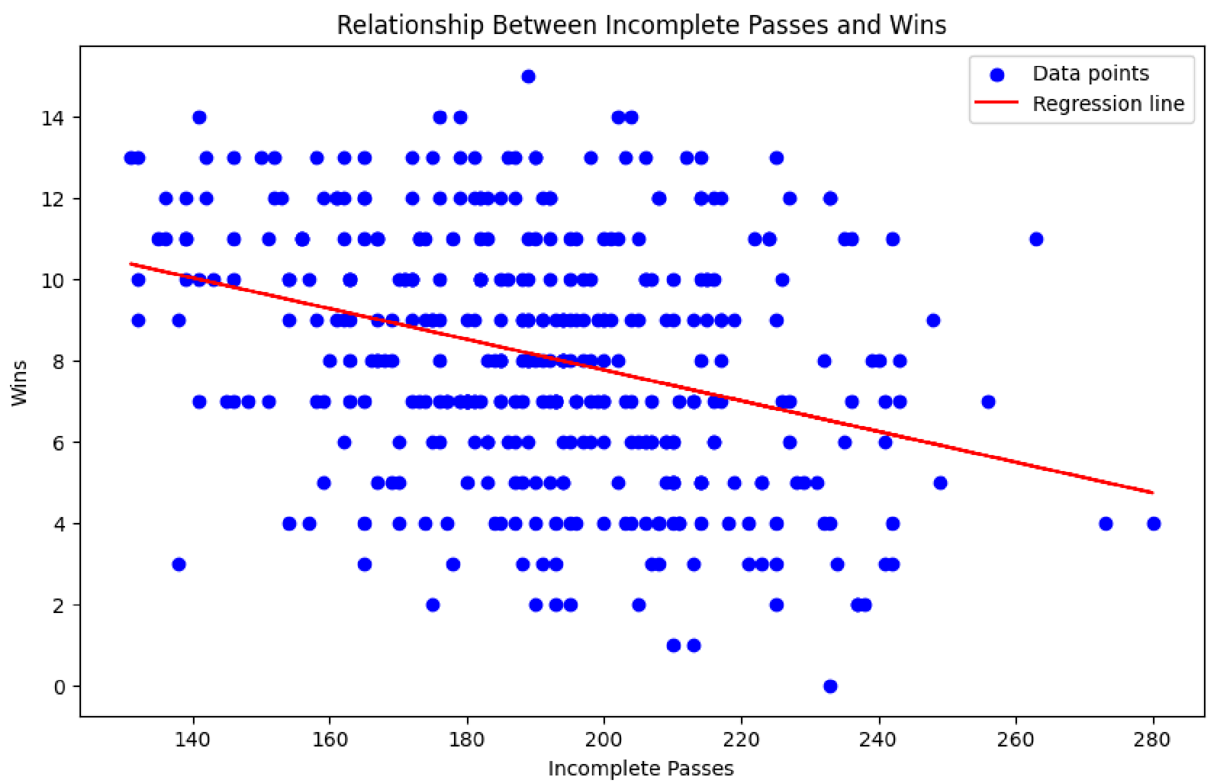
For a 16-game season: $\frac{10.76}{16} \approx 0.67 \text{ interceptions per game}$

So, to maintain a winning season, a team should aim to limit interceptions to about **0.63 per game in a 17-game season** or **0.67 per game in a 16-game season**. This translates to roughly 1 interception every 1.5 to 2 games, supporting a better chance of achieving a winning record.

Effect of incompletes on wins

In [ ]:
```
# Filter relevant columns (wins and incompletes)
data = df[['wins', 'incomplete_pass']].dropna()

# Define the target and feature
X = data['incomplete_pass']
y = data['wins']

# Add a constant to the predictor variable for statsmodels
X = sm.add_constant(X)

# Fit the linear regression model
model = sm.OLS(y, X).fit()

# Print the model summary
print(model.summary())

# Calculate the threshold for a winning season
intercept = model.params['const']
slope = model.params['incomplete_pass']
target_wins = 9
max_incompletes = (target_wins - intercept) / slope
print(f"Maximum incomplete passes for a winning season (9 wins): {max_incompletes:.

# Plot the regression line and data
plt.figure(figsize=(10, 6))
plt.scatter(data['incomplete_pass'], data['wins'], color='blue', label="Data points
plt.plot(data['incomplete_pass'], model.predict(X), color='red', label="Regression
plt.xlabel("Incomplete Passes")
plt.ylabel("Wins")
plt.title("Relationship Between Incomplete Passes and Wins")
plt.legend()
plt.show()
```

```
                            OLS Regression Results                            
==============================================================================
Dep. Variable:                   wins   R-squared:                       0.108
Model:                            OLS   Adj. R-squared:                  0.105
Method:                 Least Squares   F-statistic:                     46.02
Date:                Fri, 01 Nov 2024   Prob (F-statistic):           4.48e-11
Time:                        14:24:11   Log-Likelihood:                -952.73
No. Observations:                 384   AIC:                             1909.
Df Residuals:                     382   BIC:                             1917.
Df Model:                           1                                         
Covariance Type:            nonrobust                                         
===================================================================================
                      coef    std err          t      P>|t|      [0.025      0.975]
-----------------------------------------------------------------------------------
const              15.3098      1.074     14.250      0.000      13.197      17.422
incomplete_pass    -0.0378      0.006     -6.784      0.000      -0.049      -0.027
==============================================================================
Omnibus:                        8.987   Durbin-Watson:                   1.295
Prob(Omnibus):                  0.011   Jarque-Bera (JB):                5.018
Skew:                          -0.016   Prob(JB):                       0.0814
Kurtosis:                       2.441   Cond. No.                     1.40e+03
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly spe
cified.
[2] The condition number is large, 1.4e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
Maximum incomplete passes for a winning season (9 wins): 167.02
```



The result from the linear regression analysis shows that the maximum number of incomplete passes a team should aim for over a season to have a winning record (at least 9 wins) is approximately **167.02**.

Per-Game Conversion

To convert this to a per-game average for different season lengths:

- **For a 17-game season**: $\frac{167.02}{17} \approx 9.83 \text{ incomplete passes per game}$
- **For a 16-game season**: $\frac{167.02}{16} \approx 10.44 \text{ incomplete passes per game}$

So, to maintain a winning season, a team should aim to limit incomplete passes to about **9.83 per game in a 17-game season** or **10.44 per game in a 16-game season**.

Interpretation

The negative slope of -0.0378 indicates that fewer incomplete passes are generally associated with more wins. While the (R^2) value (0.108) suggests that incomplete passes alone don't strongly predict wins (only about 10.8% of the variance in wins is explained by incomplete passes), the relationship is still statistically significant, as indicated by the low p-value. This means that minimizing incomplete passes does contribute to improving a team's win chances, though it's likely one of several important factors.

The plot shows the relationship between incomplete passes and wins for NFL teams. There is a slight negative trend, as indicated by the red regression line, suggesting that as incomplete passes increase, the number of wins tends to decrease. The regression line, however, has a relatively shallow slope, which aligns with the low R 2 R 2 value (0.108) from the OLS results. This means that incomplete passes do have some association with fewer wins, but they don't strongly predict the overall number of wins by themselves.

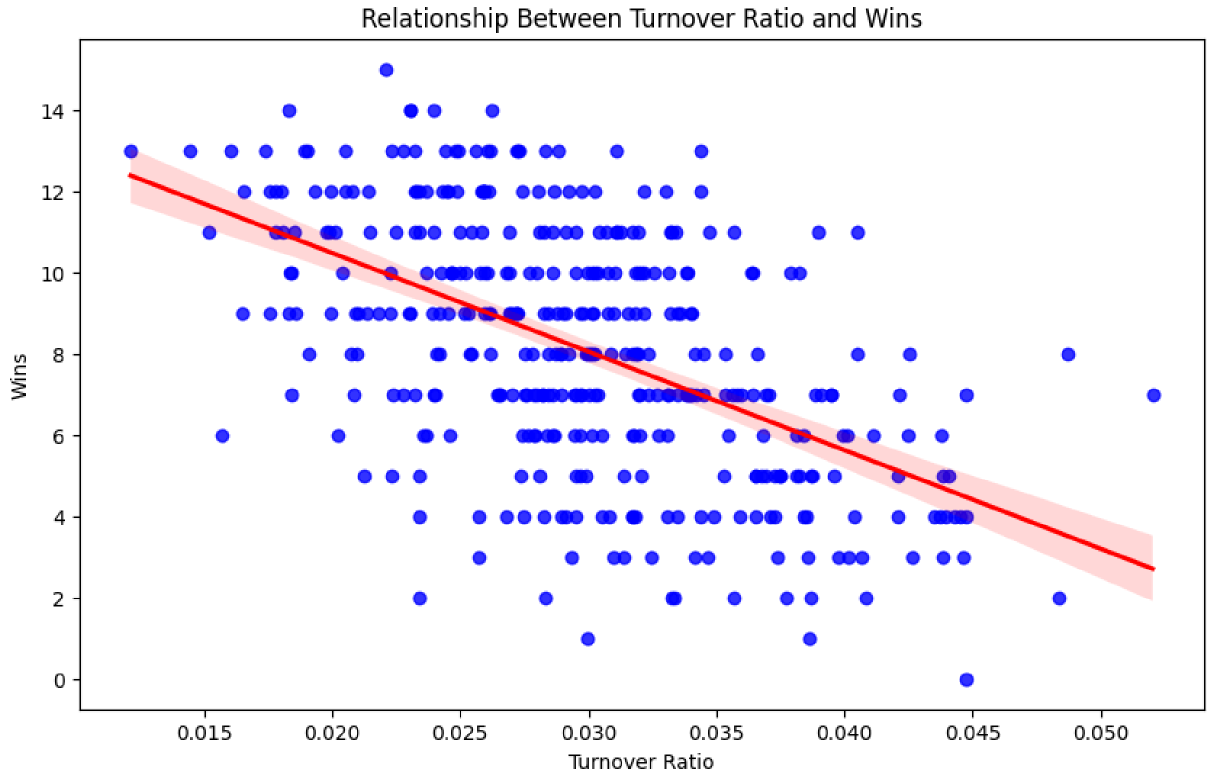
The threshold of approximately 167 incomplete passes for a winning season corresponds to about 9.83 incomplete passes per game in a 17-game season. Therefore, teams aiming to maximize their win potential should ideally keep their incomplete passes around this level or lower. However, given the low correlation, incomplete passes are only one factor among many that contribute to a team's success.

Impact of turnover on wins

In [ ]:
```
X = df[['turnover_ratio', 'fumble_lost', 'pass_fumble_lost']]
y = df['wins']

# Add a constant to the predictors for the intercept in the regression model
X = sm.add_constant(X)

# Fit the OLS regression model
model = sm.OLS(y, X).fit()
```

```
# Print the summary of the regression model
print(model.summary())

# Calculate and display correlation between turnover-related metrics and wins
correlation = df[['turnover_ratio', 'fumble_lost', 'pass_fumble_lost', 'wins']].cor
print("Correlation between Turnovers and Wins:\n", correlation['wins'])

# Plot turnover ratio vs. wins to visualize the relationship
plt.figure(figsize=(10, 6))
sns.regplot(x='turnover_ratio', y='wins', data=df, scatter_kws={'color': 'blue'}, l
plt.title('Relationship Between Turnover Ratio and Wins')
plt.xlabel('Turnover Ratio')
plt.ylabel('Wins')
plt.show()
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                   wins   R-squared:                       0.308
Model:                            OLS   Adj. R-squared:                  0.303
Method:                 Least Squares   F-statistic:                     56.43
Date:                Fri, 01 Nov 2024   Prob (F-statistic):           3.43e-30
Time:                        14:24:11   Log-Likelihood:                -903.82
No. Observations:                 384   AIC:                             1816.
Df Residuals:                     380   BIC:                             1831.
Df Model:                           3
Covariance Type:            nonrobust
====================================================================================
                       coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------------
const               15.3659      0.591     26.017      0.000      14.205      16.527
turnover_ratio    -250.2490     23.193    -10.790      0.000    -295.851    -204.647
fumble_lost          0.2104      0.080      2.627      0.009       0.053       0.368
pass_fumble_lost    -0.2991      0.095     -3.158      0.002      -0.485      -0.113
==============================================================================
Omnibus:                        6.010   Durbin-Watson:                   1.523
Prob(Omnibus):                  0.050   Jarque-Bera (JB):                5.362
Skew:                          -0.223   Prob(JB):                       0.0685
Kurtosis:                       2.630   Cond. No.                     1.80e+03
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly spe
cified.
[2] The condition number is large, 1.8e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
Correlation between Turnovers and Wins:
 turnover_ratio     -0.538209
fumble_lost        -0.284644
pass_fumble_lost   -0.300378
wins                1.000000
Name: wins, dtype: float64
```



The regression results and correlation analysis provide insights into how turnovers affect team wins. Here's a breakdown of what each finding indicates:

1. **R-squared (0.308)**: This value suggests that around 30.8% of the variance in wins can be explained by the turnover variables (`turnover_ratio` , `fumble_lost` , and `pass_fumble_lost`). While not very high, this indicates that turnovers are a significant factor in wins, though other variables (like offense, defense, and special teams) also play a role.

2. **Coefficients**:

   - **Turnover Ratio (-250.25)**: This coefficient is quite large and negative, meaning that as the turnover ratio increases, wins significantly decrease. For every 1 unit increase in the turnover ratio, wins decrease by about 250 on average, according to this model. This large effect suggests that limiting turnovers is highly important for achieving a winning season.
   - **Fumble Lost (0.21)**: This small positive coefficient is somewhat surprising. It indicates a slight increase in wins as fumbles lost increase, but this effect is small and could be due to interaction effects or anomalies in the data. Generally, we expect fumbles lost to negatively impact wins.
   - **Pass Fumble Lost (-0.299)**: A negative coefficient here implies that each additional lost pass fumble correlates with a small decrease in wins. This aligns with expectations, as losing fumbles on passing plays can disrupt offensive momentum.
3. **P-values**:

- All variables have p-values less than 0.05, indicating that they are statistically significant. This implies a reliable association between these turnover metrics and wins, particularly the turnover ratio.

4. **Correlations**:

   - **Turnover Ratio (-0.538)**: There's a moderately strong negative correlation between turnover ratio and wins. This implies that higher turnover ratios are associated with fewer wins.
   - **Fumble Lost (-0.285)** and **Pass Fumble Lost (-0.300)**: These also show negative correlations with wins, but they are weaker. The impacts of fumbles are present but not as strong as the turnover ratio.

5. **Turnovers ratio**:

To calculate the minimum number of turnovers required for a winning season (defined as at least 9 wins), we can use the regression model. Based on the OLS regression results:

$$\text{wins} = 15.3659 - 250.249 \times \text{turnover\\_ratio} + 0.2104 \times \text{fumble\\_lost} - 0.2991 \times \text{pass\\}$$

The minimum turnover ratio required to achieve a winning season (9 wins) is approximately 0.026, or 2.6%. This suggests that to maintain a winning season, a team should aim to keep their turnover ratio around or below this level.

Conclusion

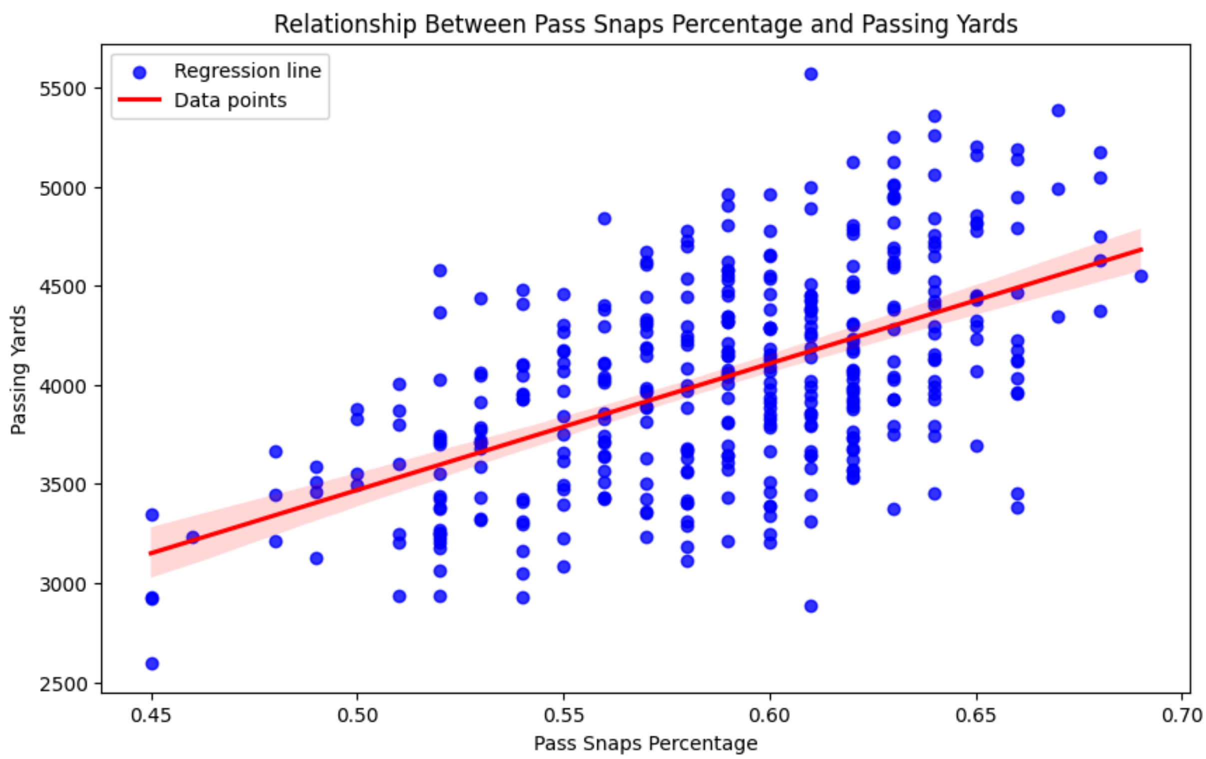
The analysis suggests that turnover ratio is a critical factor in determining team success, with higher ratios strongly correlating with fewer wins. Reducing turnovers, especially through strategies that control or minimize risky plays, appears essential for improving win outcomes. The model also indicates that pass fumbles are detrimental to success, while lost fumbles have a smaller, more nuanced impact, potentially due to data variability or other confounding factors.

This finding reinforces the importance of maintaining possession and minimizing mistakes, particularly in high-stakes passing plays, to increase a team's chances of winning.

Relationship betweeen Pass snaps percent and passing yards

In [ ]:
```
data = df[["pass_snaps_pct", "passing_yards"]]

# Scatter plot with regression line
plt.figure(figsize=(10, 6))
sns.regplot(x='pass_snaps_pct', y='passing_yards', data=data, color='blue', line_kw
plt.xlabel("Pass Snaps Percentage")
plt.ylabel("Passing Yards")
```

```
plt.title("Relationship Between Pass Snaps Percentage and Passing Yards")
plt.legend(["Regression line", "Data points"])
plt.show()

# Simple linear regression analysis
X = data[['pass_snaps_pct']]
y = data['passing_yards']

# Adding constant to the independent variable
X = sm.add_constant(X)

# Fitting the model
model = sm.OLS(y, X).fit()

# Displaying the summary
print(model.summary())
```



```
                            OLS Regression Results
==============================================================================
Dep. Variable:          passing_yards   R-squared:                       0.309
Model:                            OLS   Adj. R-squared:                  0.307
Method:                 Least Squares   F-statistic:                     170.5
Date:                Fri, 01 Nov 2024   Prob (F-statistic):           1.76e-32
Time:                        14:24:11   Log-Likelihood:                -2886.5
No. Observations:                 384   AIC:                             5777.
Df Residuals:                     382   BIC:                             5785.
Df Model:                           1
Covariance Type:            nonrobust
==================================================================================
                     coef    std err          t      P>|t|      [0.025      0.975]
----------------------------------------------------------------------------------
const            279.6519    288.239      0.970      0.333    -287.082     846.386
pass_snaps_pct  6378.2509    488.416     13.059      0.000    5417.930    7338.571
==============================================================================
Omnibus:                        3.568   Durbin-Watson:                   1.154
Prob(Omnibus):                  0.168   Jarque-Bera (JB):                2.791
Skew:                           0.078   Prob(JB):                        0.248
Kurtosis:                       2.613   Cond. No.                         28.9
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly spe
cified.
```

The regression results provide insights into the relationship between `pass_snaps_pct` (percentage of passing snaps) and `passing_yards`. Here's what we can interpret from the results:

1. **R-squared**: The R-squared value is 0.309, meaning that approximately 30.9% of the variance in `passing_yards` is explained by `pass_snaps_pct`. While this suggests a moderate relationship, other factors likely contribute to variations in passing yards.

2. **Coefficients**:

   - The **intercept** (constant) is estimated at 279.65, which is the baseline passing yards when `pass_snaps_pct` is zero. However, this value isn't highly meaningful by itself, as a `pass_snaps_pct` of zero is unrealistic in this context.
   - The coefficient for `pass_snaps_pct` is 6378.25, meaning that for each 1% increase in the pass snaps percentage, passing yards increase by an average of 63.78 yards. This positive and significant coefficient suggests that higher passing snaps percentage tends to be associated with greater passing yards.
3. **P-value**: The p-value for `pass_snaps_pct` is extremely low (near zero), indicating that the relationship between `pass_snaps_pct` and `passing_yards` is statistically significant.

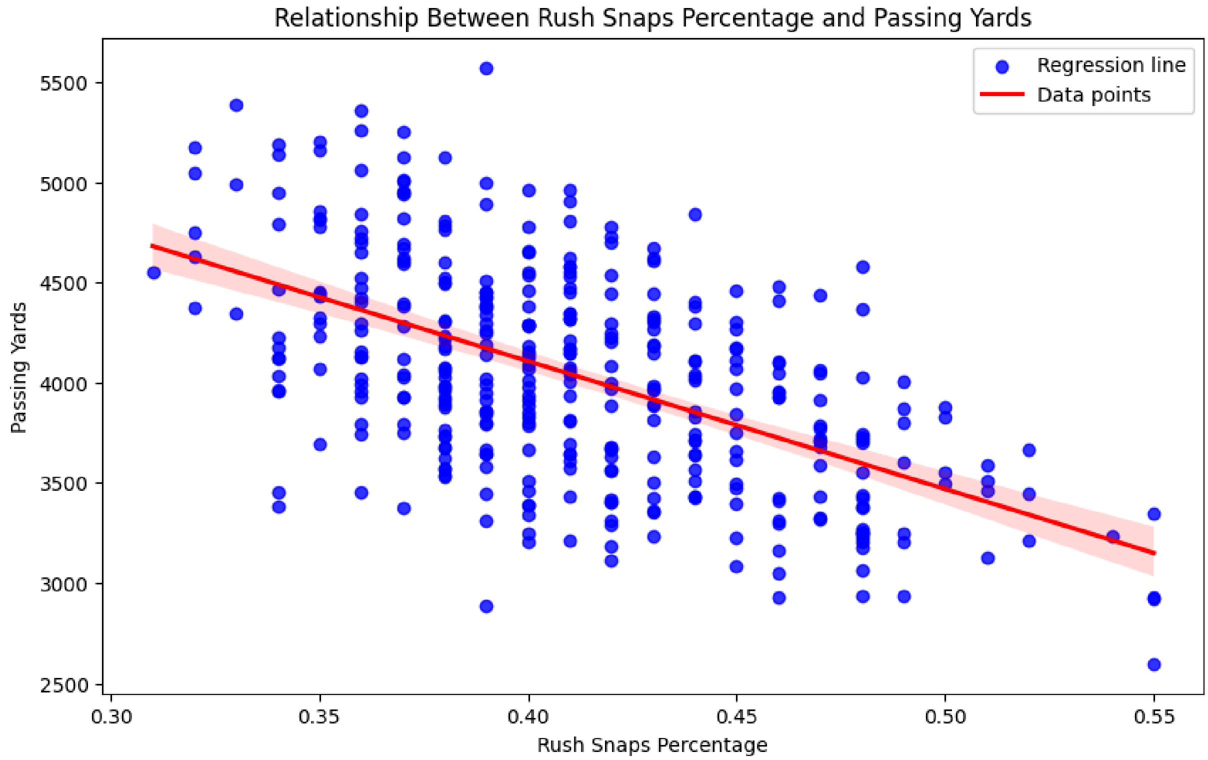
4. **F-statistic**: The F-statistic (170.5) and its corresponding p-value (<0.0001) confirm that the model as a whole is statistically significant.

5. **Durbin-Watson**: The Durbin-Watson statistic is 1.154, which is a bit low and might indicate some positive autocorrelation in the residuals. This can be a sign that there are patterns in the residuals over time that the model isn't fully capturing.

Overall, this regression analysis suggests that a higher pass snaps percentage is associated with an increase in passing yards, supporting the idea that teams that pass more frequently tend to accumulate more passing yards. However, with an R-squared of 0.309, the model indicates that other factors beyond pass snaps percentage are also significant in determining passing yards.

Relationship between rush snaps percent and passing yards

In [ ]:
```
# Scatter plot with regression line
plt.figure(figsize=(10, 6))
sns.regplot(x='rush_snaps_pct', y='passing_yards', data=df, color='blue', line_kws=
plt.xlabel("Rush Snaps Percentage")
plt.ylabel("Passing Yards")
plt.title("Relationship Between Rush Snaps Percentage and Passing Yards")
plt.legend(["Regression line", "Data points"])
plt.show()

# Simple linear regression analysis
X = df[['rush_snaps_pct']]
y = df['passing_yards']

# Adding constant to the independent variable
X = sm.add_constant(X)

# Fitting the model
model = sm.OLS(y, X).fit()

# Displaying the summary
print(model.summary())
```




```
                            OLS Regression Results
==============================================================================
Dep. Variable:          passing_yards   R-squared:                       0.309
Model:                            OLS   Adj. R-squared:                  0.307
Method:                 Least Squares   F-statistic:                     170.5
Date:                Fri, 01 Nov 2024   Prob (F-statistic):           1.76e-32
Time:                        14:24:12   Log-Likelihood:                -2886.5
No. Observations:                 384   AIC:                             5777.
Df Residuals:                     382   BIC:                             5785.
Df Model:                           1
Covariance Type:            nonrobust
==================================================================================
                     coef    std err          t      P>|t|      [0.025      0.975]
----------------------------------------------------------------------------------
const           6657.9028    202.362     32.901      0.000    6260.020    7055.785
rush_snaps_pct -6378.2509    488.416    -13.059      0.000   -7338.571   -5417.930
==============================================================================
Omnibus:                        3.568   Durbin-Watson:                   1.154
Prob(Omnibus):                  0.168   Jarque-Bera (JB):                2.791
Skew:                           0.078   Prob(JB):                        0.248
Kurtosis:                       2.613   Cond. No.                         25.1
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly spe
cified.
```

From the regression results and plot, we can observe the following about the relationship between **rush snaps percentage** and **passing yards**:

1. **Negative Relationship**: The coefficient for `rush_snaps_pct` is -6378.25, indicating a significant negative relationship between rush snaps percentage and passing yards. This

suggests that as the proportion of rushing plays increases, passing yards tend to decrease. This could imply that teams that run more often accumulate fewer passing yards, as they may prioritize the running game over passing.

2. **R-squared Value**: The R-squared value is 0.309, meaning approximately 30.9% of the variance in passing yards can be explained by rush snaps percentage. While this is not extremely high, it suggests that rush snaps percentage has a moderate explanatory power regarding passing yards.

3. **Significance of the Relationship**: The p-value associated with the `rush_snaps_pct` coefficient is very low ($p < 0.001$), which confirms that the relationship is statistically significant. This indicates strong evidence that the negative relationship between rushing frequency and passing yards is not due to random chance.

4. **Intercept**: The intercept (constant) is 6657.90, representing the estimated passing yards when the rush snaps percentage is zero. While this is a hypothetical scenario, it serves as a baseline for the model.

5. **Interpretation of Slope**: The slope of -6378.25 implies that for each 1% increase in rush snaps percentage, passing yards decrease by an average of 63.78 yards. This steep negative slope aligns with the idea that teams with higher rush percentages may rely less on the passing game.

6. **Model Fit and Diagnostics**:

   - The Durbin-Watson statistic is around 1.15, which suggests mild positive autocorrelation in residuals, though further checks would be needed for a thorough assessment.
   - The residuals show a slight skew but generally seem close to normal, as indicated by the Jarque-Bera test, which does not suggest a significant deviation from normality.

Summary

The analysis shows a clear inverse relationship between rushing frequency and passing yardage. This is likely due to the fact that teams focusing more on rushing will naturally have fewer opportunities or need to pass, leading to lower passing yard totals. This relationship helps confirm strategic trends in offensive play-calling, where a higher focus on rushing generally limits passing opportunities and passing output.

Further Studies

Building on this analysis, you could explore:

- **Team-specific Analysis**: Some teams might deviate from this trend based on their unique offensive strategies. A breakdown by team or offensive scheme could reveal

interesting insights.
- **Game Situational Analysis**: Examine how rush snaps percentage changes in specific situations, such as close games vs. large leads, to see if this affects passing yards in a different way.
- **Multivariate Model**: Add other predictors, like total snaps or passing attempts, to see if the explanatory power of the model improves when considering other factors.

Futher Analysis

- Number of wins/points/yards needed to be top of coference
- Points difference of each team (Bar plot)
- Comparison of points and opponent points (Bar Plot)
- Frequency of penalties per team
- comparison of scoring percentage and turnover percentage

Conclusion

Based on my comprehensive analysis of NFL statistics from 2012-2023, I've uncovered several key insights:

1. Scoring and Wins:

- There is a strong positive correlation (0.697) between total points scored and wins
- Teams that score more touchdowns and successfully convert extra points tend to win more games
- Field goals have a relatively weaker correlation with wins (0.281), suggesting they're less impactful

2. Offensive Efficiency:

- Passing efficiency (0.487) has a stronger correlation with wins than rushing efficiency (0.229)
- Teams with higher yards per snap tend to be more successful
- There's an inverse relationship between rushing and passing yards, showing distinct offensive strategies

3. Turnovers and Game Control:

- Turnovers have a significant negative impact on wins (-0.538 correlation)
- Both fumbles (-0.288) and interceptions (-0.473) hurt win probability
- Teams that protect the ball better tend to win more games

4. Strategic Insights:

- The analysis reveals that while both offense and defense matter, scoring efficiency and turnover control are crucial
- Teams don't necessarily need to lead in total yards to be successful, but they need to convert opportunities into points
- A balanced approach between rushing and passing appears optimal, though passing shows slightly more correlation with success

These findings provide valuable insights for understanding team performance and could help inform strategic decisions in game planning and team development. The data suggests that focusing on scoring efficiency, minimizing turnovers, and developing an effective passing game are key factors for NFL success.