

## Task 2(a)

```
In [1]: import pandas as pd

# Replace 'file_path.csv' with the actual file path of your CSV file
file_path = "C:/Users/Jaskaran/Downloads/kbopitchingdata.csv"

# Use the pd.read_csv() function to read the CSV file into a DataFrame
df_JS = pd.read_csv(file_path)
```

## Displaying the first few rows of the dataset

```
In [2]: print("Preview of the dataset:")
print(df_JS.head())
```

Preview of the dataset:

	id	year	team	average_age	runs_per_game	wins	losses	\
0	1	2021	LG Twins	26.3	3.90	72	57	
1	2	2021	KT Wiz	28.4	4.06	75	59	
2	3	2021	Doosan Bears	27.5	4.57	70	65	
3	4	2021	Samsung Lions	28.8	4.57	75	59	
4	5	2021	NC Dinos	27.7	4.80	67	67	

	win_loss_percentage	ERA	run_average_9	...	hit_batter	balks	\
0	0.558	3.57	3.96	...	97	5.0	
1	0.560	3.67	4.17	...	42	1.0	
2	0.519	4.28	4.66	...	73	7.0	
3	0.560	4.29	4.70	...	51	3.0	
4	0.500	4.50	4.95	...	77	8.0	

	wild_pitches	batters_faced	WHIP	hits_9	homeruns_9	walks_9	\
0	43.0	5416	1.312	8.0	0.6	3.9	
1	56.0	5359	1.316	8.4	0.6	3.5	
2	51.0	5596	1.487	9.2	0.7	4.2	
3	56.0	5496	1.450	9.3	0.9	3.8	
4	74.0	5575	1.476	9.1	0.9	4.2	

	strikeouts_9	strikeout_walk
0	7.6	1.96
1	7.5	2.16
2	7.4	1.77
3	7.4	1.96
4	7.5	1.79

[5 rows x 34 columns]

## Understanding basic information about the dataset

```
In [3]: print("\nDataset information:")
print(df_JS.info())
```

```

Dataset information:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 323 entries, 0 to 322
Data columns (total 34 columns):
#   Column                Non-Null Count  Dtype
---  -
0   id                    323 non-null   int64
1   year                 323 non-null   int64
2   team                 323 non-null   object
3   average_age          323 non-null   float64
4   runs_per_game        323 non-null   float64
5   wins                 323 non-null   int64
6   losses               323 non-null   int64
7   win_loss_percentage  323 non-null   float64
8   ERA                  323 non-null   float64
9   run_average_9        323 non-null   float64
10  games                323 non-null   int64
11  games_started        184 non-null   float64
12  games_finished       184 non-null   float64
13  complete_game        323 non-null   int64
14  shutouts             323 non-null   int64
15  saves                323 non-null   int64
16  innings_pitched      323 non-null   float64
17  hits                 323 non-null   int64
18  runs                 323 non-null   int64
19  earned_runs          323 non-null   int64
20  home_runs            323 non-null   int64
21  walks                323 non-null   int64
22  intentional_walks    184 non-null   float64
23  strikeouts           323 non-null   int64
24  hit_batter           323 non-null   int64
25  balks                184 non-null   float64
26  wild_pitches         184 non-null   float64
27  batters_faced        323 non-null   int64
28  WHIP                 323 non-null   float64
29  hits_9               323 non-null   float64
30  homeruns_9           323 non-null   float64
31  walks_9              323 non-null   float64
32  strikeouts_9         323 non-null   float64
33  strikeout_walk       323 non-null   float64
dtypes: float64(17), int64(16), object(1)
memory usage: 85.9+ KB
None

```

## Printing summary statistics of the numerical columns

```

In [4]: print("\nSummary Statistics:")
        print(df_JS.describe())

```

#### Summary Statistics:

	id	year	average_age	runs_per_game	wins	\
count	323.000000	323.000000	323.000000	323.000000	323.000000	
mean	162.000000	2002.944272	26.886687	4.621858	62.507740	
std	93.386294	11.501957	1.608472	0.734223	12.508225	
min	1.000000	1982.000000	23.300000	2.980000	15.000000	
25%	81.500000	1993.000000	25.700000	4.040000	54.000000	
50%	162.000000	2003.000000	26.900000	4.620000	63.000000	
75%	242.500000	2013.000000	28.000000	5.060000	71.000000	
max	323.000000	2021.000000	32.400000	7.180000	93.000000	

	losses	win_loss_percentage	ERA	run_average_9	games	\
count	323.000000	323.000000	323.000000	323.000000	323.000000	
mean	62.482972	0.500043	4.207833	4.689783	128.142415	
std	12.446988	0.087081	0.750075	0.768520	12.996350	
min	24.000000	0.188000	2.540000	3.030000	80.000000	
25%	53.000000	0.444500	3.630000	4.090000	126.000000	
50%	62.000000	0.504000	4.220000	4.670000	128.000000	
75%	71.500000	0.561500	4.700000	5.180000	133.000000	
max	97.000000	0.706000	6.350000	7.470000	144.000000	

	hit_batter	balks	wild_pitches	batters_faced	WHIP	\
count	323.000000	184.000000	184.000000	323.000000	323.000000	
mean	66.294118	3.902174	56.983696	4935.439628	1.400588	
std	20.035144	2.244896	15.775223	574.410547	0.115192	
min	29.000000	0.000000	21.000000	2830.000000	1.106000	
25%	51.500000	2.000000	46.000000	4697.500000	1.314000	
50%	66.000000	4.000000	55.000000	4969.000000	1.402000	
75%	79.000000	5.000000	66.250000	5264.000000	1.478000	
max	120.000000	11.000000	103.000000	5937.000000	1.761000	

	hits_9	homeruns_9	walks_9	strikeouts_9	strikeout_walk
count	323.000000	323.000000	323.000000	323.000000	323.000000
mean	9.063777	0.836223	3.543963	5.943653	1.703282
std	0.784845	0.246000	0.495432	1.194754	0.392679
min	7.300000	0.300000	2.400000	2.300000	0.560000
25%	8.500000	0.700000	3.200000	5.100000	1.445000
50%	9.000000	0.800000	3.500000	6.200000	1.700000
75%	9.500000	1.000000	3.900000	6.800000	1.960000
max	11.600000	1.500000	5.100000	8.400000	2.820000

[8 rows x 33 columns]

## Check for missing values in the entire data frame

True indicating missing values and False indicates non missing values

```
In [5]: missing_values = df_JS.isnull()
print(missing_values)
```

	id	year	team	average_age	runs_per_game	wins	losses	\
0	False	False	False	False	False	False	False	
1	False	False	False	False	False	False	False	
2	False	False	False	False	False	False	False	
3	False	False	False	False	False	False	False	
4	False	False	False	False	False	False	False	
..	...	...	...	...	...	...	...	
318	False	False	False	False	False	False	False	
319	False	False	False	False	False	False	False	
320	False	False	False	False	False	False	False	
321	False	False	False	False	False	False	False	
322	False	False	False	False	False	False	False	

	win_loss_percentage	ERA	run_average_9	...	hit_batter	balks	\
0		False	False	False	...	False	False
1		False	False	False	...	False	False
2		False	False	False	...	False	False
3		False	False	False	...	False	False
4		False	False	False	...	False	False
..		...	...	...	...	...	...
318		False	False	False	...	False	True
319		False	False	False	...	False	True
320		False	False	False	...	False	True
321		False	False	False	...	False	True
322		False	False	False	...	False	True

	wild_pitches	batters_faced	WHIP	hits_9	homeruns_9	walks_9	\
0	False	False	False	False	False	False	
1	False	False	False	False	False	False	
2	False	False	False	False	False	False	
3	False	False	False	False	False	False	
4	False	False	False	False	False	False	
..	...	...	...	...	...	...	
318	True	False	False	False	False	False	
319	True	False	False	False	False	False	
320	True	False	False	False	False	False	
321	True	False	False	False	False	False	
322	True	False	False	False	False	False	

	strikeouts_9	strikeout_walk
0	False	False
1	False	False
2	False	False
3	False	False
4	False	False
..	...	...
318	False	False
319	False	False
320	False	False
321	False	False
322	False	False

[323 rows x 34 columns]

## Get the count of non missing values in each column

```
In [6]: missing_count = df_JS.isnull().sum()
        print(missing_count)
```

```

id                0
year              0
team              0
average_age       0
runs_per_game     0
wins              0
losses            0
win_loss_percentage 0
ERA               0
run_average_9     0
games             0
games_started     139
games_finished    139
complete_game     0
shutouts          0
saves             0
innings_pitched   0
hits              0
runs              0
earned_runs       0
home_runs         0
walks             0
intentional_walks 139
strikeouts        0
hit_batter        0
balks             139
wild_pitches      139
batters_faced     0
WHIP              0
hits_9            0
homeruns_9        0
walks_9           0
strikeouts_9      0
strikeout_walk    0
dtype: int64

```

## Printing the data types for all the columns

```

In [7]: data_types = df_JS.dtypes
print(data_types)

```

```

id                int64
year              int64
team              object
average_age       float64
runs_per_game     float64
wins              int64
losses            int64
win_loss_percentage float64
ERA               float64
run_average_9     float64
games             int64
games_started     float64
games_finished    float64
complete_game     int64
shutouts          int64
saves             int64
innings_pitched   float64
hits              int64
runs              int64
earned_runs       int64
home_runs         int64
walks             int64
intentional_walks float64
strikeouts        int64
hit_batter        int64
balks             float64
wild_pitches      float64
batters_faced     int64
WHIP              float64
hits_9            float64
homeruns_9        float64
walks_9           float64
strikeouts_9      float64
strikeout_walk    float64
dtype: object

```

## Visualize data distribution using Box plot, Histogram and scatter plot

```

In [8]: import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

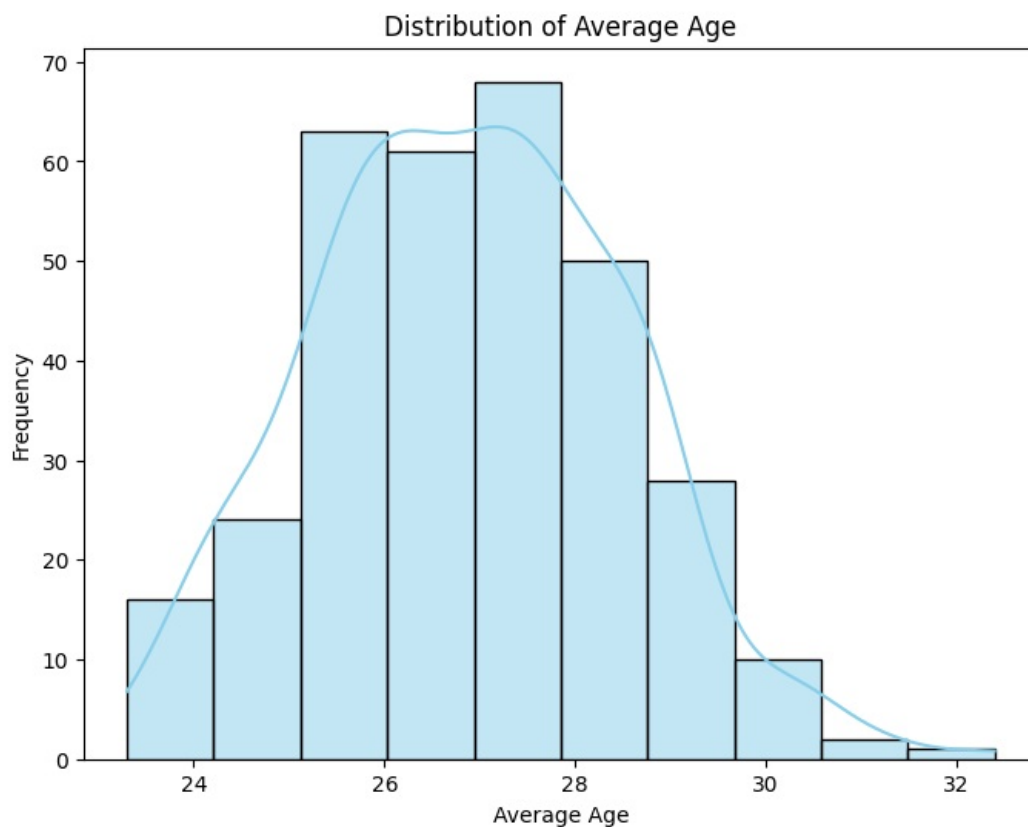
# Load the dataset
data = pd.read_csv("C:/Users/Jaskaran/Downloads/kbopitchingdata.csv")

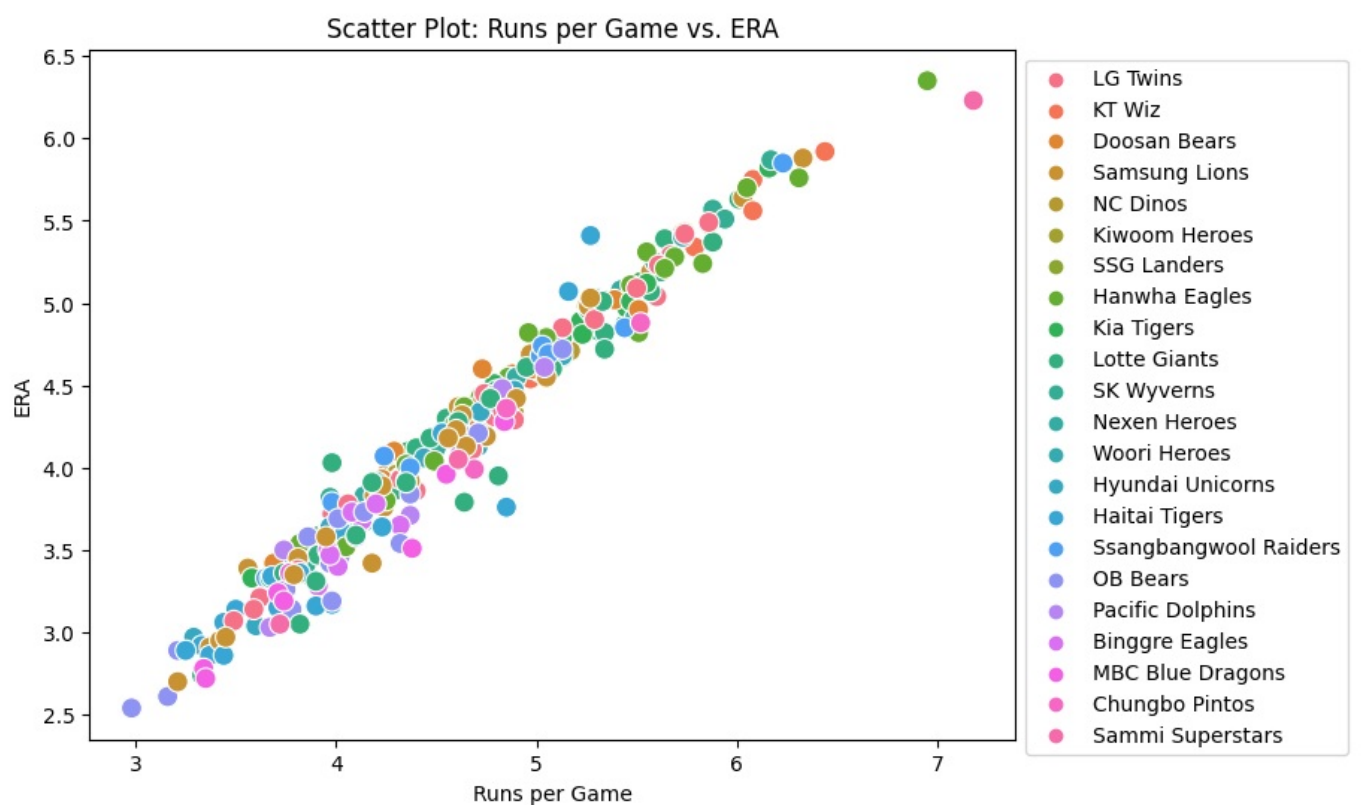
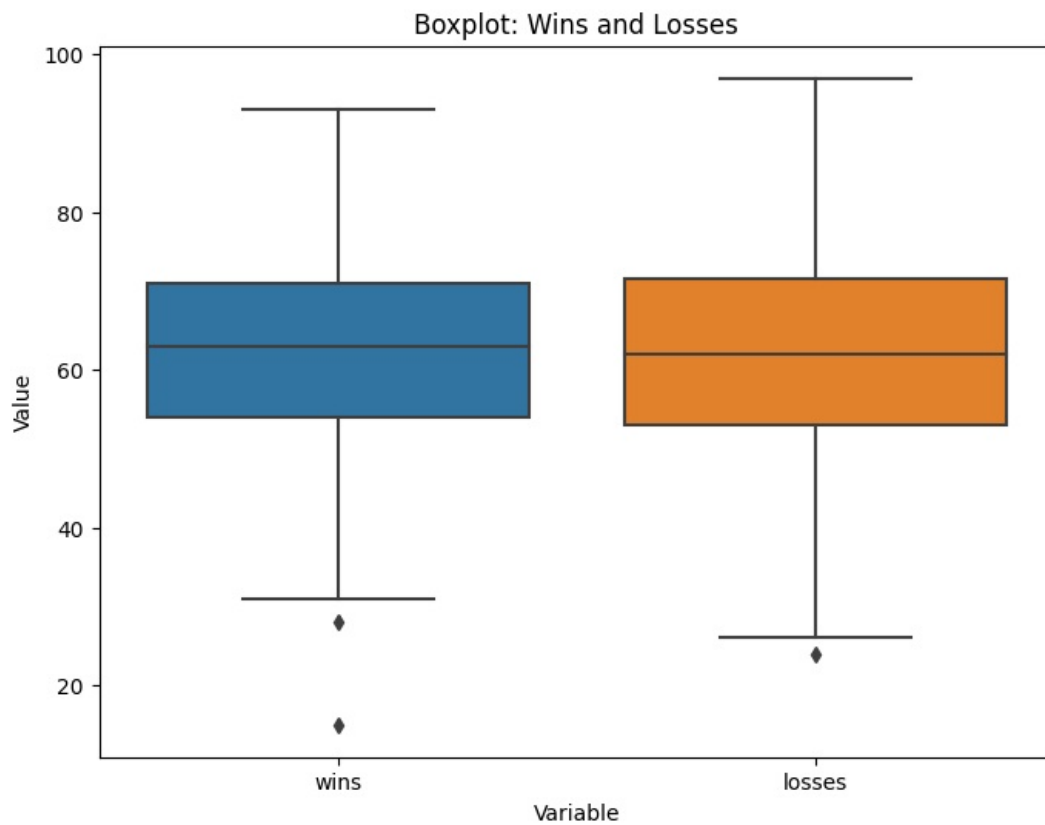
# Histogram: Distribution of 'average_age'
plt.figure(figsize=(8, 6))
sns.histplot(data['average_age'], bins=10, kde=True, color='skyblue')
plt.title('Distribution of Average Age')
plt.xlabel('Average Age')
plt.ylabel('Frequency')
plt.show()

# Boxplot: Comparing 'wins' and 'losses'
plt.figure(figsize=(8, 6))
sns.boxplot(data=data[['wins', 'losses']])
plt.title('Boxplot: Wins and Losses')
plt.xlabel('Variable')
plt.ylabel('Value')
plt.show()

# Scatter plot: 'runs_per_game' vs 'ERA'
plt.figure(figsize=(8, 6))
sns.scatterplot(data=data, x='runs_per_game', y='ERA', hue='team', s=100)
plt.title('Scatter Plot: Runs per Game vs. ERA')
plt.xlabel('Runs per Game')
plt.ylabel('ERA')
plt.legend(loc='upper left', bbox_to_anchor=(1, 1))
plt.show()
()

```





Out[8]: ()

## Task 3(a)

```
In [10]: #3.1
import pandas as pd

# Load the data from the CSV file
data = pd.read_csv("C:/Users/Jaskaran/Downloads/kbopitchingdata.csv")

# Remove unnecessary columns
columns_to_drop = ['hits_9', 'homeruns_9', 'walks_9', 'strikeouts_9']
data = data.drop(columns=columns_to_drop)

# Clean team names by removing special characters
data['team'] = data['team'].str.replace('[^a-zA-Z\s]', '')

# Handle missing values by filling with appropriate values
data['games_started'].fillna(0, inplace=True)
data['games_finished'].fillna(0, inplace=True)
data['intentional_walks'].fillna(0, inplace=True)
data['balks'].fillna(0, inplace=True)
data['wild_pitches'].fillna(0, inplace=True)

# Define the path to save the preprocessed data
preprocessed_file_path = "C:/Users/Jaskaran/Desktop/Preprocessed_kbopitchingdata.csv"

# Save the preprocessed data to a CSV file
data.to_csv(preprocessed_file_path, index=False)
data=pd.read_csv(r"C:/Users/Jaskaran/Desktop/Preprocessed_kbopitchingdata.csv")

print("Data preprocessing completed and saved to:", preprocessed_file_path)
print(data.head())
```

Data preprocessing completed and saved to: C:/Users/Jaskaran/Desktop/Preprocessed\_kbopitchingdata.csv

	id	year	team	average_age	runs_per_game	wins	losses	\
0	1	2021	LG Twins	26.3	3.90	72	57	
1	2	2021	KT Wiz	28.4	4.06	75	59	
2	3	2021	Doosan Bears	27.5	4.57	70	65	
3	4	2021	Samsung Lions	28.8	4.57	75	59	
4	5	2021	NC Dinos	27.7	4.80	67	67	

	win_loss_percentage	ERA	run_average	9	...	home_runs	walks	\
0	0.558	3.57	3.96	...	79	542		
1	0.560	3.67	4.17	...	85	486		
2	0.519	4.28	4.66	...	104	586		
3	0.560	4.29	4.70	...	129	526		
4	0.500	4.50	4.95	...	122	585		

	intentional_walks	strikeouts	hit_batter	balks	wild_pitches	\
0	17.0	1062	97	5.0	43.0	
1	18.0	1051	42	1.0	56.0	
2	16.0	1037	73	7.0	51.0	
3	13.0	1031	51	3.0	56.0	
4	14.0	1046	77	8.0	74.0	

	batters_faced	WHIP	strikeout_walk
0	5416	1.312	1.96
1	5359	1.316	2.16
2	5596	1.487	1.77
3	5496	1.450	1.96
4	5575	1.476	1.79

[5 rows x 30 columns]

## Task3(b)

```
In [14]: import pandas as pd
import numpy as np
from sklearn.preprocessing import StandardScaler

# Load the preprocessed data from the CSV file
preprocessed_file_path = "C:/Users/Jaskaran/Desktop/Preprocessed_kbopitchingdata.csv"
data = pd.read_csv(preprocessed_file_path)

# Missing values were handled already in the preprocessing step.

# 1. Drop unnecessary columns
```



```

data.drop(['id', 'year', 'team'], axis=1, inplace=True)

# Identifying Outliers
# Let's identify outliers using the Interquartile Range (IQR) method.

def identify_outliers(column):
    Q1 = np.percentile(column, 25)
    Q3 = np.percentile(column, 75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    return (column < lower_bound) | (column > upper_bound)

outliers = identify_outliers(data['ERA'])
data = data[~outliers]

# Feature Engineering

# Let's create a new feature 'win percentage' which is wins / games.
data['Wins_Percentage'] = data['wins'] / data['games']
print(data.head())

# Standardize Numeric Features
numeric_columns = ['average_age', 'runs_per_game', 'wins', 'losses', 'win_loss_percentage', 'ERA', 'run_average',
                    'games_finished', 'complete_game', 'shutouts', 'saves', 'innings_pitched', 'hits', 'runs', 'e',
                    'intentional_walks', 'strikeouts', 'hit_batter', 'balks', 'wild_pitches', 'batters_faced', 'l']

scaler = StandardScaler()
data[numeric_columns] = scaler.fit_transform(data[numeric_columns])

# Save the preprocessed and engineered data to a new CSV file
final_data_file_path = "C:/Users/Jaskaran/Desktop/Final_kbopitchingdata.csv"
data.to_csv(final_data_file_path, index=False)

print("Data preprocessing, outlier removal, feature engineering, and scaling completed.")
print("Final data saved to:", final_data_file_path)

```

	average_age	runs_per_game	wins	losses	win_loss_percentage	ERA	\
0	26.3	3.90	72	57	0.558	3.57	
1	28.4	4.06	75	59	0.560	3.67	
2	27.5	4.57	70	65	0.519	4.28	
3	28.8	4.57	75	59	0.560	4.29	
4	27.7	4.80	67	67	0.500	4.50	

	run_average_9	games	games_started	games_finished	...	walks	\
0	3.96	143	143.0	143.0	...	542	
1	4.17	143	143.0	141.0	...	486	
2	4.66	143	143.0	141.0	...	586	
3	4.70	143	143.0	141.0	...	526	
4	4.95	143	143.0	140.0	...	585	

	intentional_walks	strikeouts	hit_batter	balks	wild_pitches	\
0	17.0	1062	97	5.0	43.0	
1	18.0	1051	42	1.0	56.0	
2	16.0	1037	73	7.0	51.0	
3	13.0	1031	51	3.0	56.0	
4	14.0	1046	77	8.0	74.0	

	batters_faced	WHIP	strikeout_walk	Wins_Percentage
0	5416	1.312	1.96	0.503497
1	5359	1.316	2.16	0.524476
2	5596	1.487	1.77	0.489510
3	5496	1.450	1.96	0.524476
4	5575	1.476	1.79	0.468531

[5 rows x 28 columns]

Data preprocessing, outlier removal, feature engineering, and scaling completed.

Final data saved to: C:/Users/Jaskaran/Desktop/Final\_kbopitchingdata.csv

## Task 4(a)

## Implementing Random Forest Classifier Model Below.

```

In [18]: import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier

```

```

from sklearn.metrics import accuracy_score, classification_report, confusion_matrix

# Load the dataset
data = pd.read_csv('C:/Users/Jaskaran/Desktop/Final_kbopitchingdata.csv')

# Convert Wins_Percentage into classes
bins = [-float('inf'), 0.4, 0.6, float('inf')]
labels = ['low', 'medium', 'high']
data['Wins_Class'] = pd.cut(data['Wins_Percentage'], bins=bins, labels=labels)

# Split the dataset into features (X) and target (y)
X = data.drop(columns=['Wins_Percentage', 'Wins_Class'])
y = data['Wins_Class']

# Split the dataset into training and testing sets (80% train, 20% test)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Train Random Forest Classifier model
rf_model = RandomForestClassifier(n_estimators=100, random_state=42)
rf_model.fit(X_train, y_train)

# Evaluate Random Forest Classifier model
rf_pred = rf_model.predict(X_test)
rf_accuracy = accuracy_score(y_test, rf_pred)
rf_report = classification_report(y_test, rf_pred)
rf_conf_matrix = confusion_matrix(y_test, rf_pred)

# Print evaluation results
print("Random Forest Classifier Accuracy:", rf_accuracy)
print("Random Forest Classifier Classification Report:")
print(rf_report)
print("Random Forest Classifier Confusion Matrix:")
print(rf_conf_matrix)

```

Random Forest Classifier Accuracy: 0.9692307692307692

Random Forest Classifier Classification Report:

	precision	recall	f1-score	support
high	1.00	1.00	1.00	4
low	1.00	0.80	0.89	10
medium	0.96	1.00	0.98	51
accuracy			0.97	65
macro avg	0.99	0.93	0.96	65
weighted avg	0.97	0.97	0.97	65

Random Forest Classifier Confusion Matrix:

```

[[ 4  0  0]
 [ 0  8  2]
 [ 0  0 51]]

```

```

In [19]: import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix

# Load the dataset
data = pd.read_csv('C:/Users/Jaskaran/Desktop/Final_kbopitchingdata.csv')

# Convert Wins_Percentage into classes
bins = [-float('inf'), 0.4, 0.6, float('inf')]
labels = ['low', 'medium', 'high']
data['Wins_Class'] = pd.cut(data['Wins_Percentage'], bins=bins, labels=labels)

# Split the dataset into features (X) and target (y)
X = data.drop(columns=['Wins_Percentage', 'Wins_Class'])
y = data['Wins_Class']

# Split the dataset into training and testing sets (80% train, 20% test)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Train SVM model
svm_model = SVC(kernel='linear', random_state=42)
svm_model.fit(X_train, y_train)

# Evaluate SVM model
svm_pred = svm_model.predict(X_test)
svm_accuracy = accuracy_score(y_test, svm_pred)
svm_report = classification_report(y_test, svm_pred)
svm_conf_matrix = confusion_matrix(y_test, svm_pred)

# Print evaluation results
print("SVM Classifier Accuracy:", svm_accuracy)
print("SVM Classifier Classification Report:")

```

```
print(svm_report)
print("SVM Classifier Confusion Matrix:")
print(svm_conf_matrix)
```

SVM Classifier Accuracy: 0.9538461538461539

SVM Classifier Classification Report:

	precision	recall	f1-score	support
high	1.00	0.75	0.86	4
low	1.00	0.80	0.89	10
medium	0.94	1.00	0.97	51
accuracy			0.95	65
macro avg	0.98	0.85	0.91	65
weighted avg	0.96	0.95	0.95	65

SVM Classifier Confusion Matrix:

```
[[ 3  0  1]
 [ 0  8  2]
 [ 0  0 51]]
```

In [21]: *# Print evaluation results for Random Forest Classifier model*

```
print("Random Forest Classifier Accuracy:", rf_accuracy)
print("Random Forest Classifier Classification Report:")
print(rf_report)
print("Random Forest Classifier Confusion Matrix:")
print(rf_conf_matrix)
```

*# Train SVM model*

```
svm_model = SVC(kernel='linear', random_state=42)
svm_model.fit(X_train, y_train)
```

*# Evaluate SVM model*

```
svm_pred = svm_model.predict(X_test)
svm_accuracy = accuracy_score(y_test, svm_pred)
svm_report = classification_report(y_test, svm_pred)
svm_conf_matrix = confusion_matrix(y_test, svm_pred)
```

*# Print evaluation results for SVM Classifier model*

```
print("\nSVM Classifier Accuracy:", svm_accuracy)
print("SVM Classifier Classification Report:")
print(svm_report)
print("SVM Classifier Confusion Matrix:")
print(svm_conf_matrix)
```

Random Forest Classifier Accuracy: 0.9692307692307692

Random Forest Classifier Classification Report:

	precision	recall	f1-score	support
high	1.00	1.00	1.00	4
low	1.00	0.80	0.89	10
medium	0.96	1.00	0.98	51
accuracy			0.97	65
macro avg	0.99	0.93	0.96	65
weighted avg	0.97	0.97	0.97	65

Random Forest Classifier Confusion Matrix:

```
[[ 4  0  0]
 [ 0  8  2]
 [ 0  0 51]]
```

SVM Classifier Accuracy: 0.9538461538461539

SVM Classifier Classification Report:

	precision	recall	f1-score	support
high	1.00	0.75	0.86	4
low	1.00	0.80	0.89	10
medium	0.94	1.00	0.97	51
accuracy			0.95	65
macro avg	0.98	0.85	0.91	65
weighted avg	0.96	0.95	0.95	65

SVM Classifier Confusion Matrix:

```
[[ 3  0  1]
 [ 0  8  2]
 [ 0  0 51]]
```

## Task5 Visualization with Python (Scatterplot, Heatmap & Barchart)

In [24]: `import pandas as pd`

```

import matplotlib.pyplot as plt
import seaborn as sns

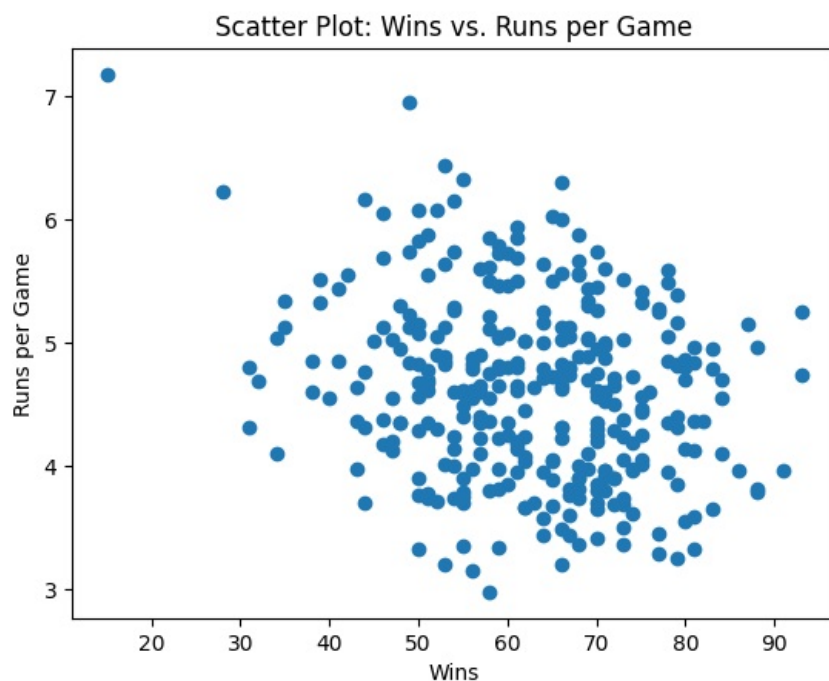
# Load the dataset
data = pd.read_csv('C:/Users/Jaskaran/Downloads/kbopitchingdata.csv')

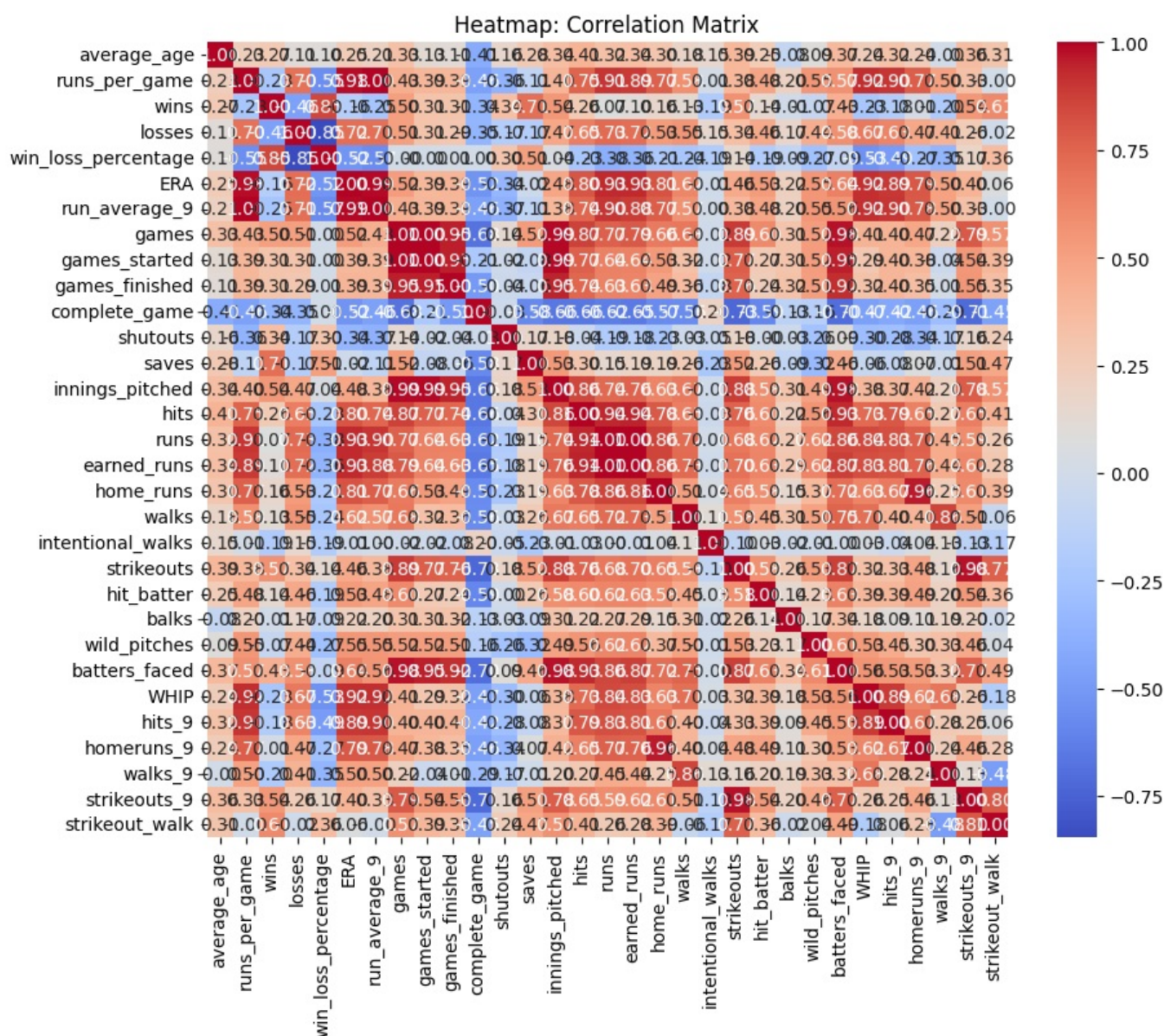
# Scatter Plot: Wins vs. Runs Per Game
plt.scatter(data['wins'], data['runs_per_game'])
plt.xlabel('Wins')
plt.ylabel('Runs per Game')
plt.title('Scatter Plot: Wins vs. Runs per Game')
plt.show()

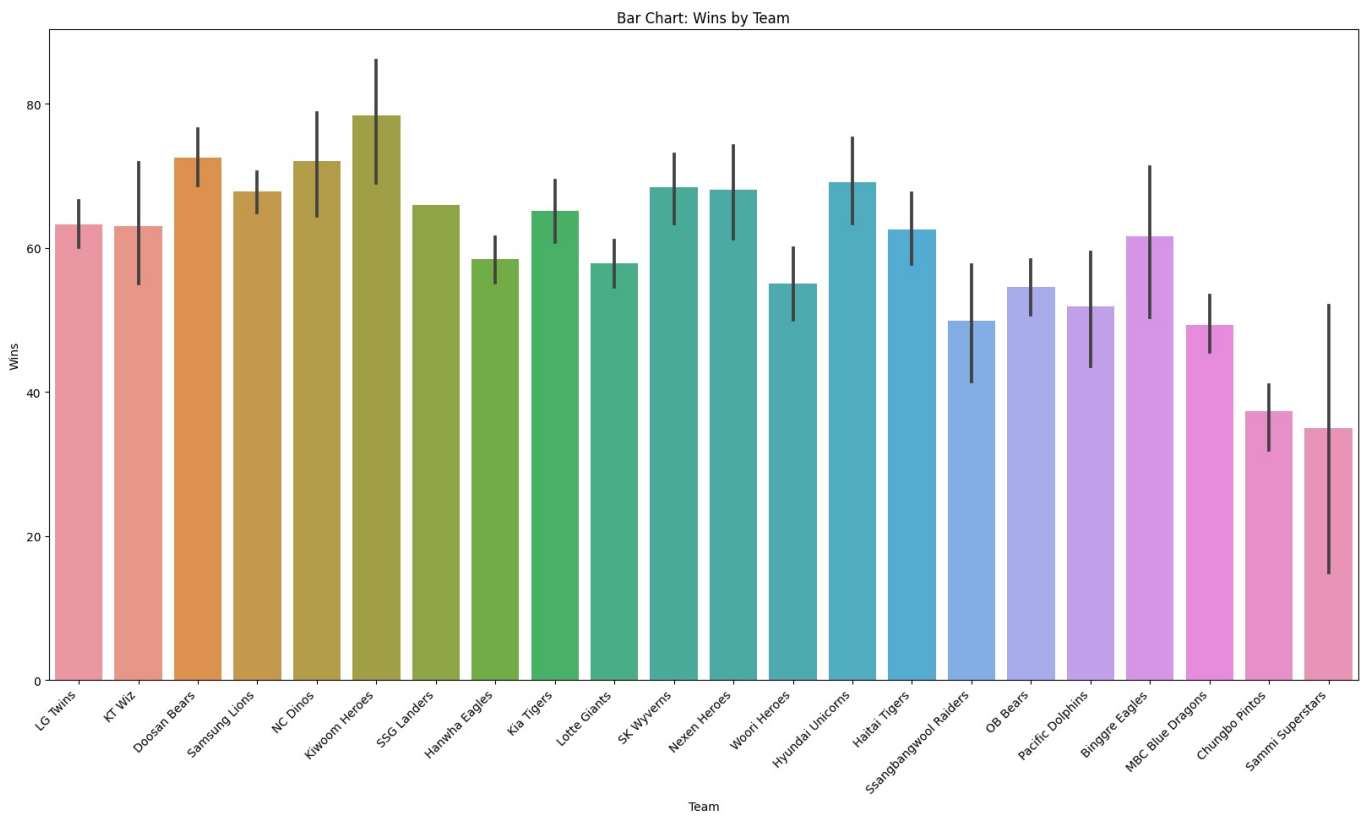
# Heatmap: Correlation Matrix (excluding non-numeric columns)
numeric_data = data.drop(columns=['id', 'year', 'team'])
corr_matrix = numeric_data.corr()
plt.figure(figsize=(10, 8))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt='.2f')
plt.title('Heatmap: Correlation Matrix')
plt.show()

# Bar Chart: Team vs. Wins
plt.figure(figsize=(20, 10))
sns.barplot(x='team', y='wins', data=data)
plt.xticks(rotation=45, ha='right')
plt.xlabel('Team')
plt.ylabel('Wins')
plt.title('Bar Chart: Wins by Team')
plt.show()

```







In [ ]:

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