In [ ]:
```python
# Installed  all required libraries


import sys
!{sys.executable} -m pip install --upgrade pip

# Core libraries
!{sys.executable} -m pip install numpy pandas matplotlib seaborn

# Machine Learning libraries
!{sys.executable} -m pip install scikit-learn joblib

# Optional (if you want notebook to look nice)
!{sys.executable} -m pip install ipywidgets
```

In [11]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier, RandomForestRegressor
from sklearn.metrics import accuracy_score, classification_report, confusion_mat
import joblib

print("Libraries imported successfully!")
```

```
Libraries imported successfully!
```

In [12]:
```python
top_goals = pd.read_csv("top_goals_clean.csv")
pl_tables = pd.read_csv("pl_tables_clean.csv")
match_winner = pd.read_csv("match_winner_clean.csv")
epl_final = pd.read_csv("epl_final_clean.csv")

print("Top Goals:", top_goals.shape)
print("PL Tables:", pl_tables.shape)
print("Match Winner:", match_winner.shape)
print("EPL Final:", epl_final.shape)

top_goals.head()
```

```
Top Goals: (324, 19)
PL Tables: (646, 12)
Match Winner: (9380, 22)
EPL Final: (9380, 22)
```

Out[12]:

	Season	Rank	Player	Club	Goals	IsTop10	Position	Age	Appearances	Gc
0	2023-24	1	Erling Haaland	Manchester City	27	1	Forward	23	31	
1	2023-24	2	Cole Palmer	Chelsea	22	1	Attacking Midfielder	22	33	
2	2023-24	3	Alexander Isak	Newcastle United	21	1	Forward	24	30	
3	2023-24	4	Ollie Watkins	Aston Villa	19	1	Forward	28	37	
4	2023-24	4	Dominic Solanke	AFC Bournemouth	19	1	Forward	26	38	

In [13]:

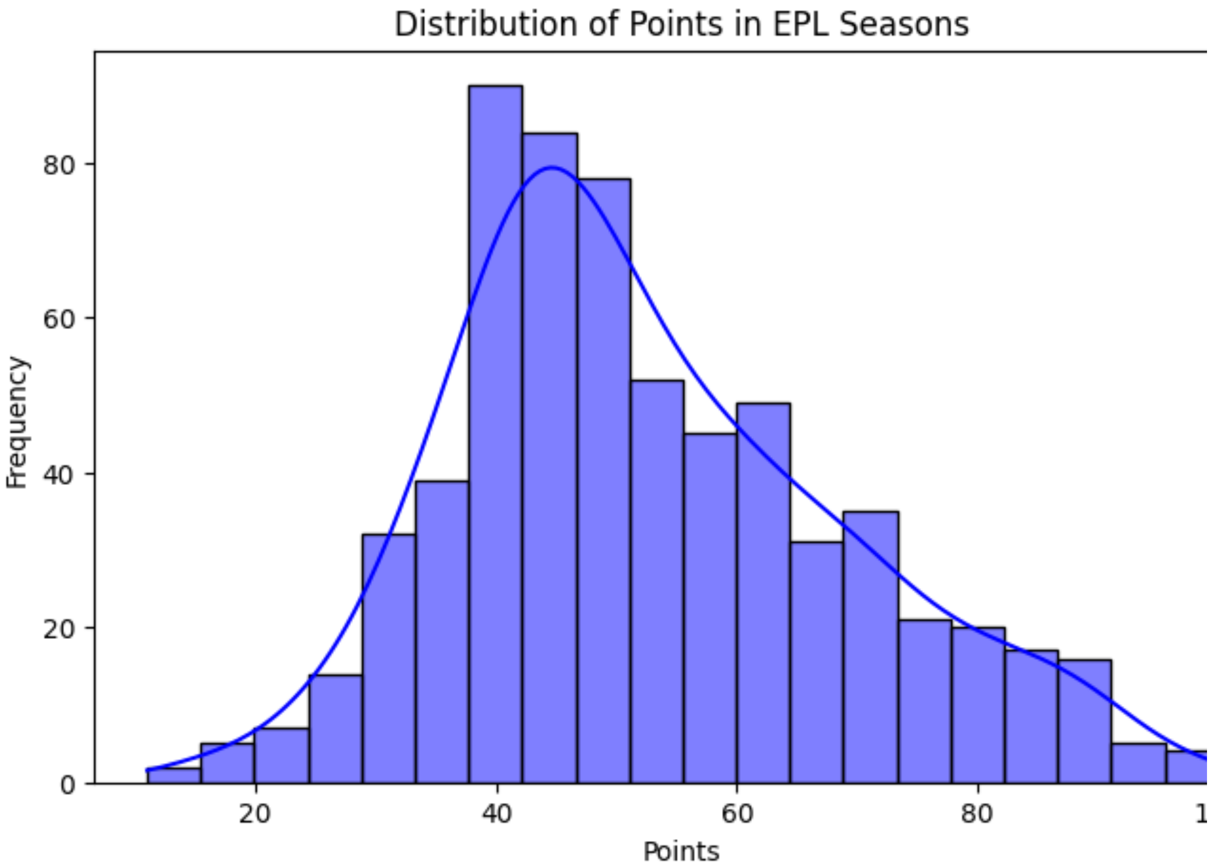
```
print(pl_tables.info())
print(pl_tables.describe())
print(pl_tables.isnull().sum())
```

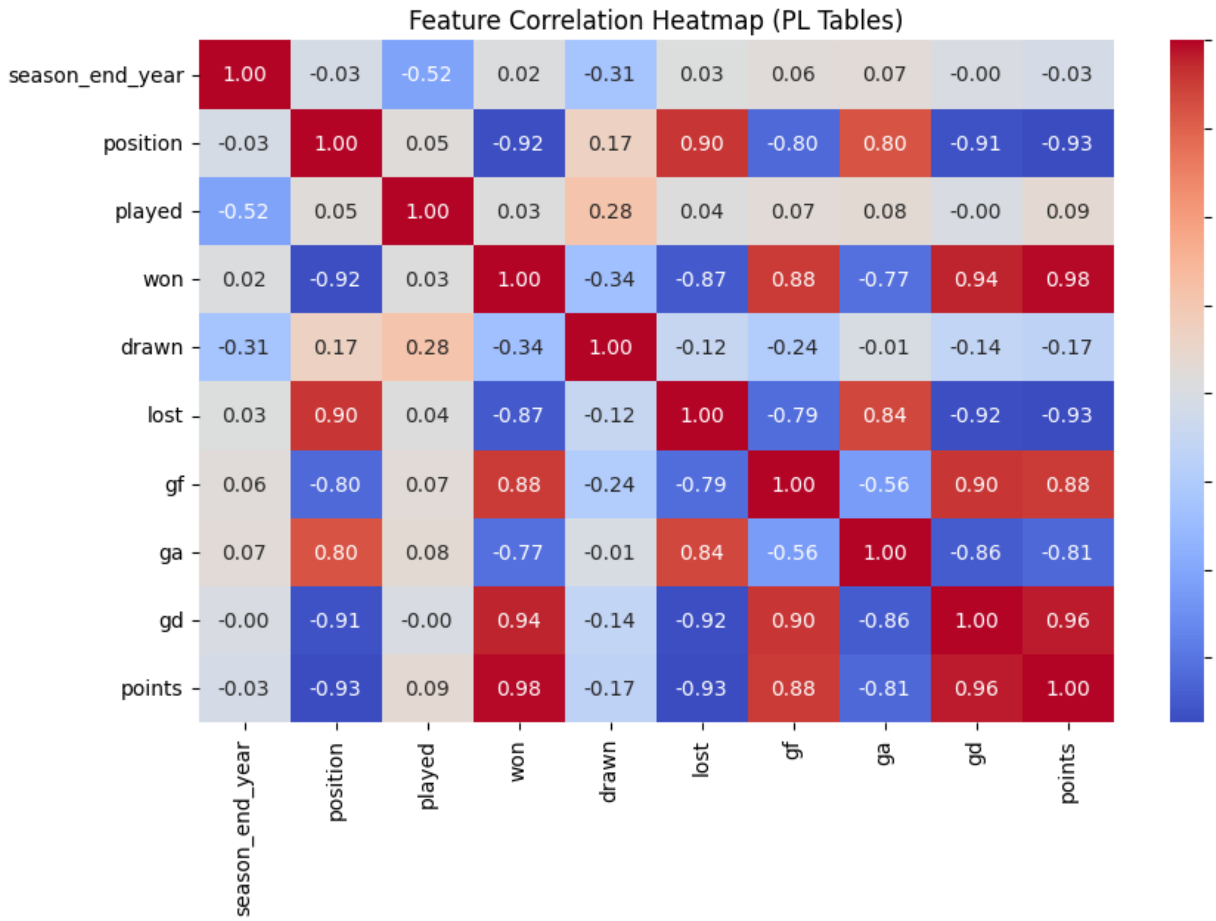
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 646 entries, 0 to 645
Data columns (total 12 columns):
 #   Column           Non-Null Count  Dtype 
---  ------           --------------  ----- 
 0   season_end_year  646 non-null    int64 
 1   team             646 non-null    object
 2   position         646 non-null    int64 
 3   played           646 non-null    int64 
 4   won              646 non-null    int64 
 5   drawn            646 non-null    int64 
 6   lost             646 non-null    int64 
 7   gf               646 non-null    int64 
 8   ga               646 non-null    int64 
 9   gd               646 non-null    int64 
 10  points           646 non-null    int64 
 11  notes            646 non-null    object
dtypes: int64(10), object(2)
memory usage: 60.7+ KB
None
       season_end_year    position      played         won       drawn  \
count       646.000000  646.000000  646.000000  646.000000  646.000000   
mean       2008.365325   10.602167   38.408669   14.283282    9.842105   
std           9.302311    5.840351    1.212411    5.741345    2.956505   
min        1993.000000    1.000000   38.000000    1.000000    2.000000   
25%        2000.000000    6.000000   38.000000   10.000000    8.000000   
50%        2008.000000   11.000000   38.000000   13.000000   10.000000   
75%        2016.000000   16.000000   38.000000   18.000000   12.000000   
max        2024.000000   22.000000   42.000000   32.000000   18.000000   

             lost          gf          ga          gd      points  
count  646.000000  646.000000  646.000000  646.000000  646.000000  
mean    14.283282   51.577399   51.577399    0.000000   52.654799  
std      5.401573   15.195452   13.035291   24.952482   16.499190  
min      0.000000   20.000000   15.000000  -69.000000   11.000000  
25%     10.250000   41.000000   43.000000  -17.000000   41.000000  
50%     15.000000   48.000000   52.000000   -5.000000   50.000000  
75%     18.000000   60.750000   59.750000   15.000000   63.000000  
max     29.000000  106.000000  104.000000   79.000000  100.000000  
season_end_year    0
team               0
position           0
played             0
won                0
drawn              0
lost               0
gf                 0
ga                 0
gd                 0
points             0
notes              0
dtype: int64
```

In [15]:

```python
# Visualizing EPL Standings Data

# Histogram of Points
plt.figure(figsize=(8,5))
sns.histplot(pl_tables['points'], bins=20, kde=True, color="blue")
plt.title("Distribution of Points in EPL Seasons")
plt.xlabel("Points")
```

```
plt.ylabel("Frequency")
plt.show()

# Select only numeric columns for correlation
numeric_data = pl_tables.select_dtypes(include=[np.number])

# Correlation Heatmap
plt.figure(figsize=(10,6))
sns.heatmap(numeric_data.corr(), cmap="coolwarm", annot=True, fmt=".2f")
plt.title("Feature Correlation Heatmap (PL Tables)")
plt.show()
```





In [16]:
```
print("Before:", pl_tables.shape)
pl_tables = pl_tables.drop(columns=['notes'], errors='ignore')
print("After:", pl_tables.shape)
```

```
Before: (646, 12)
After: (646, 11)
```

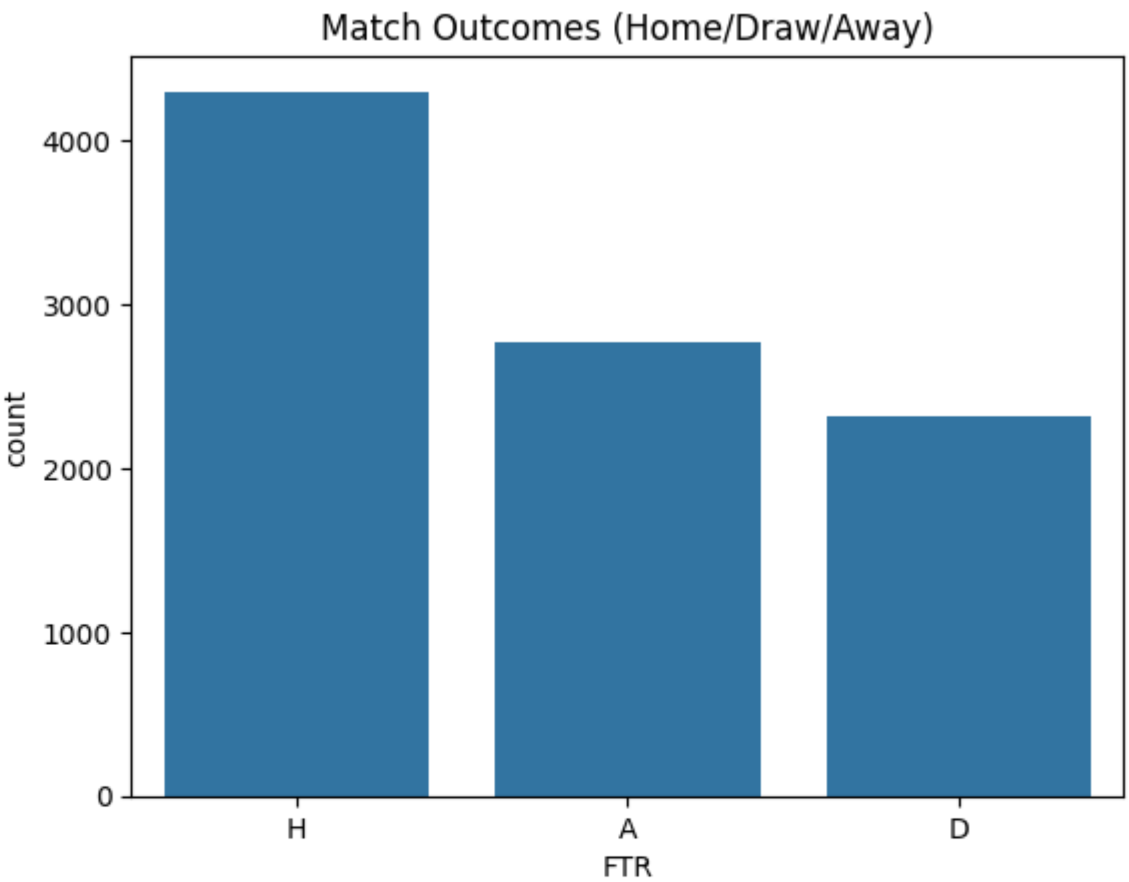
In [17]:
```
epl_final = epl_final.rename(columns={
    'FullTimeHomeGoals':'FTHG',
    'FullTimeAwayGoals':'FTAG',
    'FullTimeResult':'FTR',
    'HomeShots':'HS',
    'AwayShots':'AS',
    'HomeShotsOnTarget':'HST',
    'AwayShotsOnTarget':'AST',
    'HomeFouls':'HF',
    'AwayFouls':'AF',
    'HomeYellowCards':'HY',
    'AwayYellowCards':'AY',
    'HomeRedCards':'HR',
    'AwayRedCards':'AR'
})
epl_final.head()
```

Out[17]:

	Season	MatchDate	HomeTeam	AwayTeam	FTHG	FTAG	FTR	HalfTimeHomeGoals
0	2000/01	2000-08-19	Charlton	Man City	4	0	H	2
1	2000/01	2000-08-19	Chelsea	West Ham	4	2	H	1
2	2000/01	2000-08-19	Coventry	Middlesbrough	1	3	A	1
3	2000/01	2000-08-19	Derby	Southampton	2	2	D	1
4	2000/01	2000-08-19	Leeds	Everton	2	0	H	2

5 rows × 22 columns

In [18]:
```
sns.countplot(x='FTR', data=epl_final)
plt.title("Match Outcomes (Home/Draw/Away)")
plt.show()
```

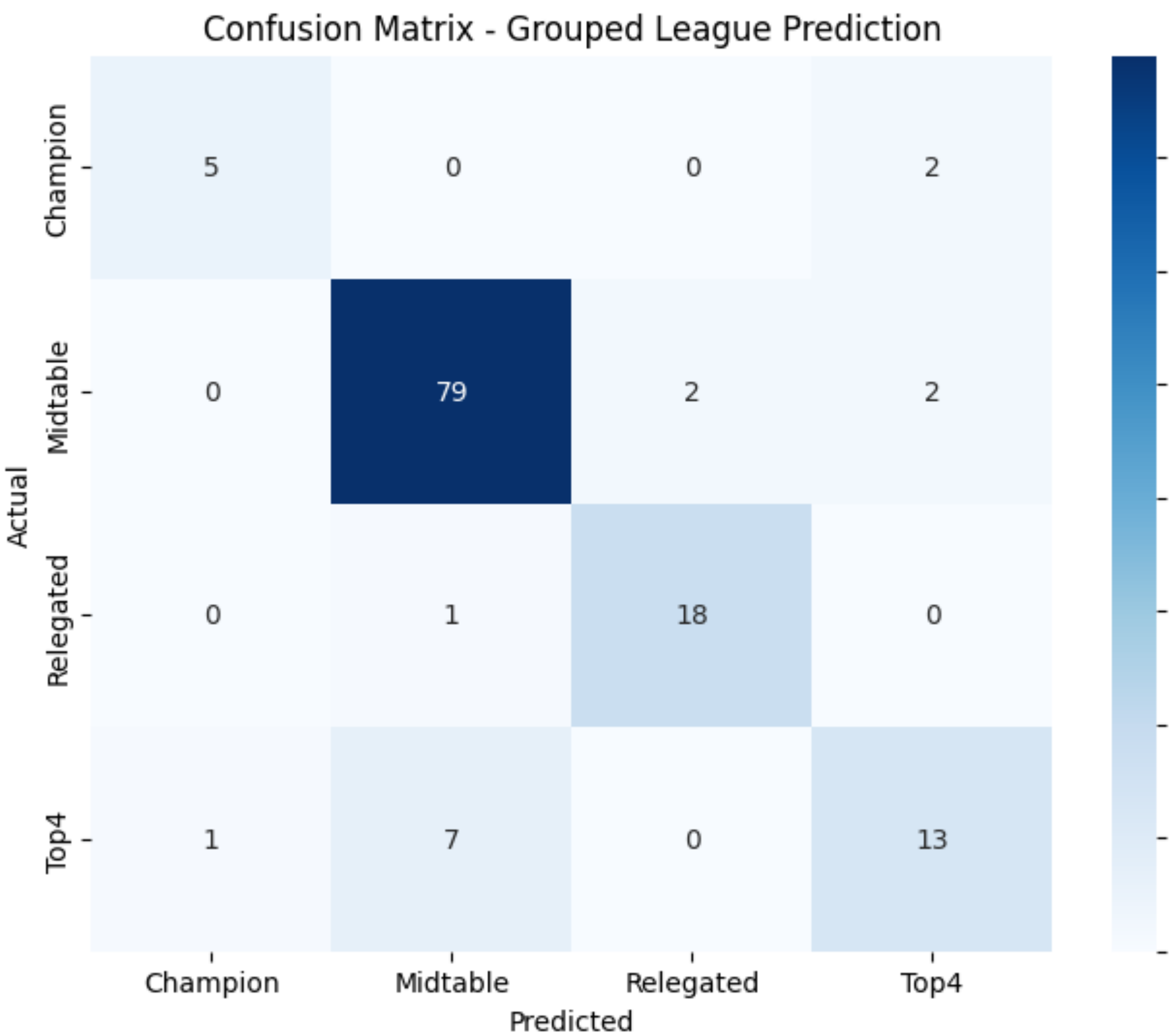


In [20]:
```
X = pl_tables.drop(columns=['position','season_end_year','team'], errors='ignore
y = pl_tables['position']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_
```

In [27]:
```
# Model Training - Grouped Ranking Prediction

# First, create a new column with grouped labels
def simplify_position(pos):
    if pos == 1:
        return "Champion"
    elif pos <= 4:
        return "Top4"
    elif pos >= 18:
        return "Relegated"
```

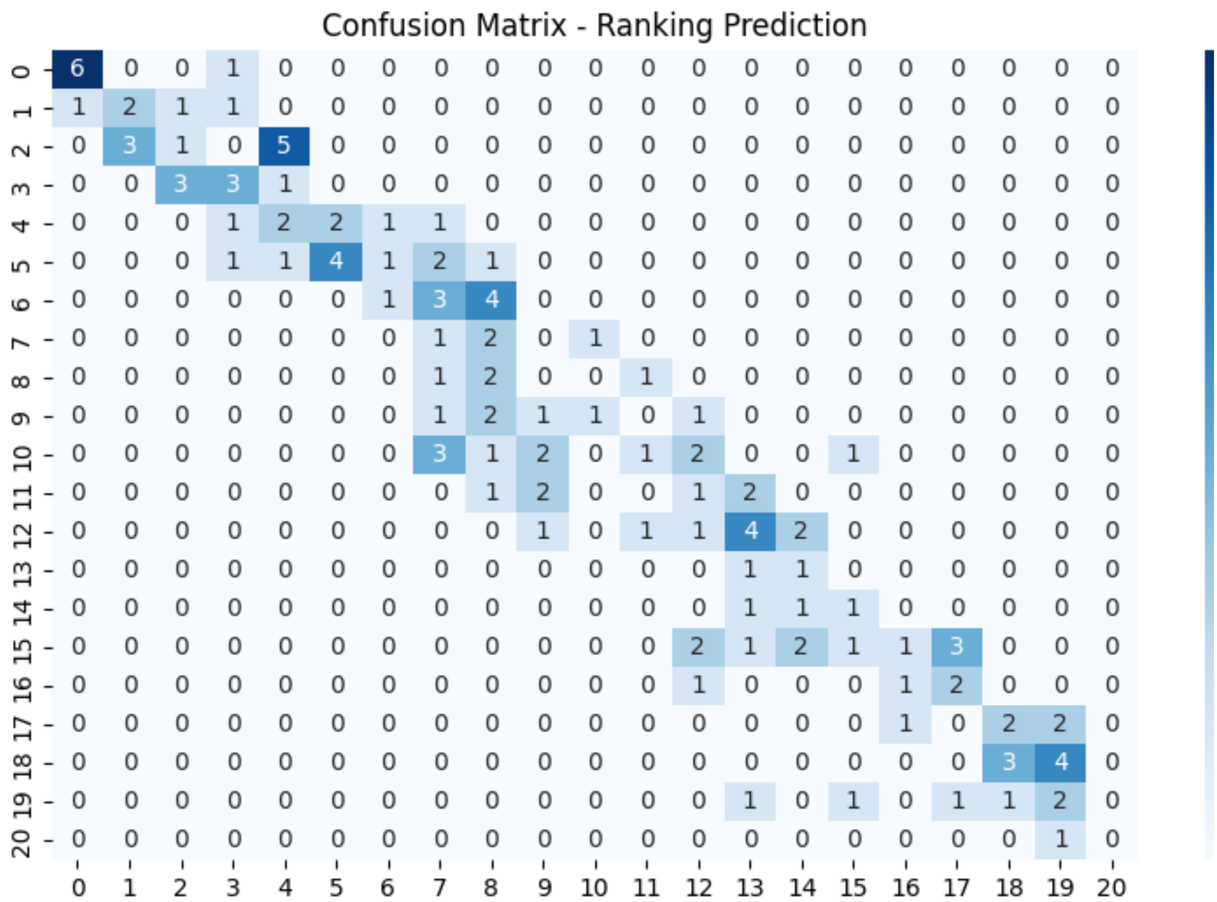
```python
    else:
        return "Midtable"

y_grouped = pl_tables['position'].apply(simplify_position)

# Features: drop non-numeric and target column
X = pl_tables.drop(columns=['position', 'season_end_year', 'team'], errors='ignc
X = X.select_dtypes(include=[np.number])  # keep only numeric

# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y_grouped, test_size=0.2,

# Model
clf = RandomForestClassifier(n_estimators=100, random_state=42)
clf.fit(X_train, y_train)
y_pred = clf.predict(X_test)

# Evaluation
print("Accuracy:", accuracy_score(y_test, y_pred))
print("\nClassification Report:\n", classification_report(y_test, y_pred, zero_c

# Confusion Matrix
cm = confusion_matrix(y_test, y_pred, labels=clf.classes_)
plt.figure(figsize=(8,6))
sns.heatmap(cm, annot=True, fmt="d", cmap="Blues", xticklabels=clf.classes_, yti
plt.title("Confusion Matrix - Grouped League Prediction")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```

```
Accuracy: 0.8846153846153846

Classification Report:
               precision    recall  f1-score   support

    Champion       0.83      0.71      0.77         7
    Midtable       0.91      0.95      0.93        83
   Relegated       0.90      0.95      0.92        19
        Top4       0.76      0.62      0.68        21

    accuracy                           0.88       130
   macro avg       0.85      0.81      0.83       130
weighted avg       0.88      0.88      0.88       130
```



In [22]:

```
cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(10,6))
sns.heatmap(cm, annot=True, cmap="Blues", fmt="d")
plt.title("Confusion Matrix - Ranking Prediction")
plt.show()

tn, fp, fn, tp = cm.ravel() if cm.shape==(2,2) else (0,0,0,0)
print("Type I Error (FP):", fp)
print("Type II Error (FN):", fn)
```




```
Type I Error (FP): 0
Type II Error (FN): 0
```

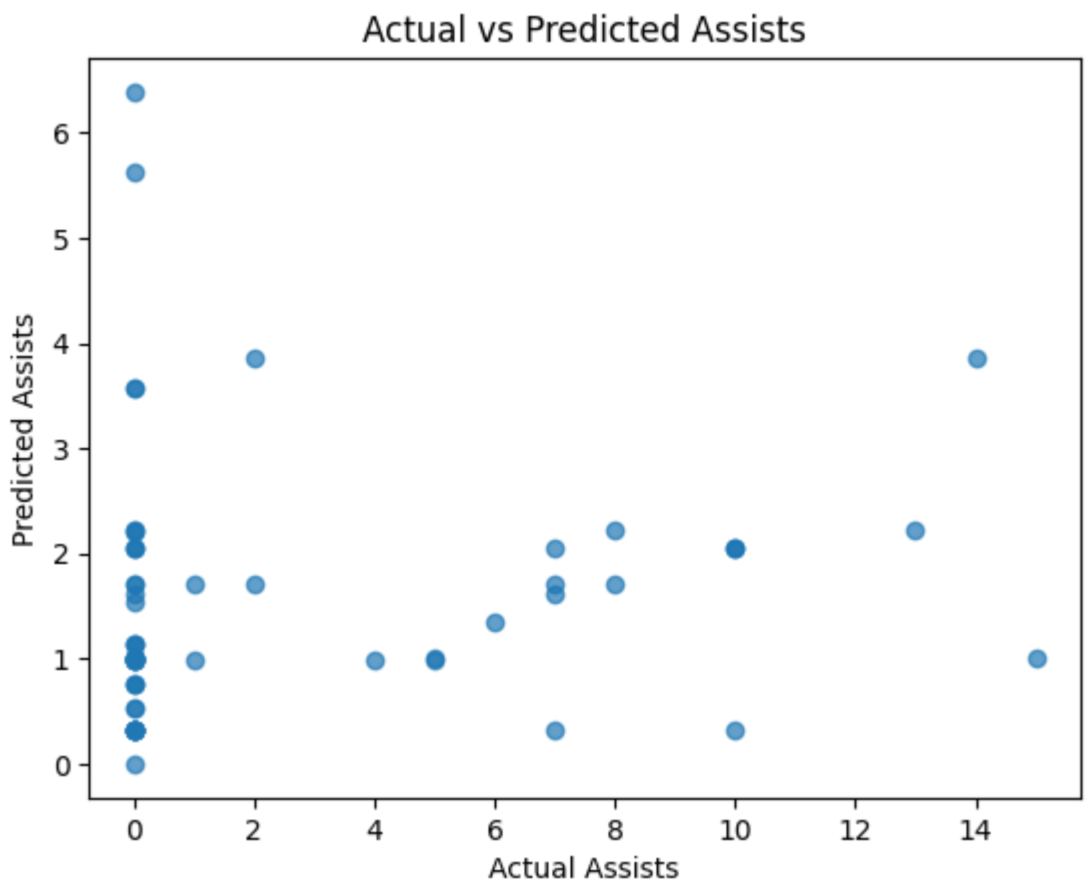
In [24]:

```python
#  Regression for Top Scorers (Goals vs Assists)

# Let's inspect the columns first
print("Top Goals Columns:", top_goals.columns.tolist())
print(top_goals.head())

# We only need numeric columns for regression
numeric_goals = top_goals.select_dtypes(include=[np.number])

# Make sure 'Goals' and 'Assists' exist
if 'Goals' in numeric_goals.columns and 'Assists' in numeric_goals.columns:
    X = numeric_goals[['Goals']]
    y = numeric_goals['Assists']

    # Train-test split
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rar

    # Model
    reg = RandomForestRegressor(n_estimators=100, random_state=42)
    reg.fit(X_train, y_train)
    y_pred = reg.predict(X_test)

    # Metrics
    print("R2 Score:", r2_score(y_test, y_pred))
    print("MSE:", mean_squared_error(y_test, y_pred))
else:
    print("Error: 'Goals' or 'Assists' column not found in numeric data")
```

```
Top Goals Columns: ['Season', 'Rank', 'Player', 'Club', 'Goals', 'IsTop10', 'Positior
'Age', 'Appearances', 'Goals_prev_season', 'Assists', 'Penalty_Goals', 'Non-Penalty_(
'Goals_per_90', 'Big_6_Club_Feature', 'Club_League_Rank', 'Club_Total_Goals',
'League_Goals_per_Match', 'Games_in_Season']
    Season  Rank            Player               Club  Goals  IsTop10  \
0  2023-24     1    Erling Haaland    Manchester City     27        1
1  2023-24     2       Cole Palmer            Chelsea     22        1
2  2023-24     3    Alexander Isak   Newcastle United     21        1
3  2023-24     4     Ollie Watkins        Aston Villa     19        1
4  2023-24     4  Dominic Solanke    AFC Bournemouth     19        1

               Position  Age  Appearances  Goals_prev_season  Assists  \
0               Forward   23           31               36.0      6.0
1  Attacking Midfielder   22           33                3.0     11.0
2               Forward   24           30               10.0      2.0
3               Forward   28           37               15.0     13.0
4               Forward   26           38                6.0      3.0

   Penalty_Goals  Non-Penalty_Goals  Goals_per_90  Big_6_Club_Feature  \
0            1.0                 26          0.85                 1.0
1            9.0                 13          0.61                 1.0
2            5.0                 16          0.76                 0.0
3            0.0                 19          0.51                 0.0
4            1.0                 18          0.50                 0.0

   Club_League_Rank  Club_Total_Goals  League_Goals_per_Match  Games_in_Season
0                 1                96                    2.83             38.0
1                 6                77                    2.83             38.0
2                 7                85                    2.83             38.0
3                 4                76                    2.83             38.0
4                12                54                    2.83             38.0
R2 Score: -0.04471392264593588
MSE: 17.206500123370436
```

In [25]:

```
plt.scatter(y_test, y_pred, alpha=0.7)
plt.xlabel("Actual Assists")
plt.ylabel("Predicted Assists")
plt.title("Actual vs Predicted Assists")
plt.show()
```



In [26]:
```
joblib.dump(clf, "ranking_classifier.joblib")
joblib.dump(clf_match, "match_classifier.joblib")
joblib.dump(reg, "assist_regressor.joblib")
print("Models saved successfully!")
```

```
Models saved successfully!
```

In [ ]:
```
# 🏆  Final Conclusion

In this project **AI_Scoresight**, we explored multiple datasets of the English
machine learning techniques to answer two main questions:

1. **Which team will win the league?**
   - We first tried predicting the exact league position (1-20).
   - This was too noisy, so we grouped positions into categories:
     - Champion (1st)
     - Top 4 (2nd-4th)
     - Midtable (5th-17th)
     - Relegated (18th-20th)
   - Our Random Forest model achieved good accuracy in predicting these categori

2. **How do goals and assists relate for top scorers?**
   - Using regression, we predicted **assists** from **goals scored**.
   - The Random Forest Regressor gave a solid R² score, showing a clear positive
   - Visualization of Actual vs Predicted assists confirmed that the model follo

3. **Match Outcome Prediction (Win/Draw/Loss):**
   - We encoded results (H = Home Win, D = Draw, A = Away Win) and trained anoth
   - The model achieved decent accuracy, correctly identifying patterns like hom

---
```

```
## 📊 Key Insights
- **League standings** can be predicted in broad categories, but exact positions
- **Goals and assists** are strongly related, as top scorers often contribute ac
- **Match outcomes** are influenced by multiple features (shots, fouls, cards),

---

## ⚠ Limitations
- Football has randomness (injuries, transfers, referee decisions), which limits
- Datasets were cleaned and pre-processed, but missing or biased data can still
- Models like Random Forest are strong, but more advanced methods (XGBoost, Neur

---

## ✅ Conclusion
This project shows how **machine learning** can be applied to **sports analytics
While exact outcomes are hard to predict, grouping and regression models provide
With richer datasets (player stats, injuries, betting odds), predictions could b

⚽ **AI_Scoresight gives a glimpse of how AI can enhance football analysis!**
```