Predicting the Winner of Copa America 2024 Using Machine Learning and Historical Football Data

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Abstract

This thesis explores the use of machine learning techniques to predict the outcomes of football matches in the Copa America 2024 tournament. By leveraging historical data on matches, team performance metrics, and player statistics, the study investigates how predictive models can be applied to sports analytics. The approach integrates data preprocessing, feature engineering, and machine learning models, including Logistic Regression, Random Forest, Support Vector Machine (SVM), and XGBoost. The models are trained on match results from previous tournaments, and their performance is evaluated in terms of prediction accuracy, precision, recall, and F1-score. The results show that XGBoost outperforms other models in terms of accuracy, offering a valuable tool for sports analysts and enthusiasts. This thesis contributes to the field of sports analytics by showcasing how machine learning can enhance match predictions and offer insights into football tournaments like Copa America.

keywords: Football Predictions, Data Analysis, Model Evaluation, Soccer Analytics, Feature Engineering, Sports Forecasting, Classification Models, Predictive Modeling, Sports Data, Team Performance, Statistical Analysis, Algorithm Testing, Historical Data, Outcome Prediction, Sports Metrics, Logistic Regression, And Random Forest Model.

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1. Introduction

1.1 Background

Copa America is one of the most prestigious international football tournaments, with teams from South America competing for supremacy. The ability to predict the outcomes of these high-stakes matches could provide a competitive edge to sports analysts, teams, and fans. Predicting match outcomes is inherently challenging due to the unpredictable nature of the sport. However, with the help of machine learning, we can build models that make educated guesses based on historical match data, player performance, and team dynamics.

1.2 Objectives

- To apply machine learning algorithms to predict the outcomes of the Copa America 2024 football matches.
- To identify the most important features that influence match outcomes.
- To evaluate the performance of different machine learning models in sports prediction tasks.

1.3 Scope of the Study

This study focuses on predicting the outcomes of matches in the Copa America 2024 tournament. The dataset includes historical match data, player statistics, team performance, and match context variables (such as home or away games). The models are evaluated based on their ability to predict match results, and various performance metrics such as accuracy, precision, recall, and F1-score are used.

2. Literature Review

2.1 Previous Work on Sports Prediction

Many studies have utilized machine learning techniques to predict the outcomes of football matches. Notable work includes the use of statistical models and machine learning algorithms to forecast results based on historical data. Researchers have utilized regression models, decision trees, neural networks, and ensemble methods to improve prediction accuracy.

- **Shin et al. (2012)** conducted a study where they used regression models and decision trees to predict football match outcomes based on historical match data.
- **Vamplew et al. (2010)** focused on the use of SVM and neural networks to predict match outcomes and player performance in football.

2.2 Machine Learning in Sports Analytics

Machine learning is a powerful tool in sports analytics, providing a means to automate and optimize prediction processes. From injury predictions to match outcomes, machine learning models can be trained to detect patterns in large datasets. Techniques such as classification, regression, and clustering are commonly used to analyze historical data and forecast future events.

- **Bunker et al. (2018)** applied machine learning in the context of player performance analysis and match predictions. They found that ensemble methods and gradient boosting models were among the best performers in football match prediction.

2.3 Challenges in Football Match Prediction

Football match prediction is complex due to several factors, including:

- **Unpredictability of the Sport**: Random events such as player injuries, referee decisions, and last-minute goals can significantly impact the outcome.
- **Dynamic Nature of the Game**: The game itself is highly dynamic, with variables like player form, tactics, and weather conditions influencing match outcomes.
- **Data Quality and Availability**: Although large datasets are available, they often contain missing or inconsistent data, which can impact model performance.

3. Dataset Description

3.1 Data Sources

The dataset used in this project is sourced from Kaggle, specifically the **"Copa America 2024 Matches Stats"** dataset (Kaggle Dataset). It contains historical match results, team performance data, and player statistics that are crucial for building predictive models.

3.2 Data Collection

Data was collected from multiple sources, including football statistics platforms such as **FotMob** and **Transfermarkt**, providing match statistics, player metrics, and team rankings.

3.3 Data Preprocessing

Preprocessing steps included cleaning the data to handle missing values, encoding categorical features, and normalizing numerical features. Any missing data was imputed using mean imputation, and categorical variables such as team names and match locations were encoded using one-hot encoding.

3.4 Feature Engineering

Feature engineering involved the creation of new features based on the raw data, such as:

- **Team Strength**: A composite score reflecting a team's historical performance and player quality.
- **Home Advantage**: A binary feature indicating whether a team played at home or away.
- **Player Performance**: An aggregate feature capturing player contributions such as goals, assists, and defensive actions.

4. Methodology

4.1 Feature Engineering and Data Transformation

Features such as team strength, home advantage, and player performance were computed using statistical measures such as averages, ratios, and weighted scores. The data was then transformed to ensure that numerical features had consistent scales, and categorical features were properly encoded.

4.2 Model Selection

The following models were implemented and evaluated:

- **Logistic Regression**: A linear model suitable for binary classification tasks.
- **Random Forest**: An ensemble method that combines multiple decision trees to improve prediction accuracy.
- **Support Vector Machine (SVM)**: A model that maximizes the margin between classes, making it effective in classification problems.
- **XGBoost**: A gradient boosting model that optimizes speed and performance for large datasets.

4.3 Model Training and Evaluation

Each model was trained on the preprocessed data, with a train-test split of 80-20%. The models were evaluated using metrics such as accuracy, precision, recall, and F1-score. Cross-validation was also used to assess the models' generalizability and prevent overfitting.

4.4 Hyperparameter Tuning

Hyperparameters such as tree depth, learning rate, and regularization strength were tuned using grid search and cross-validation to improve model performance.

5. Results and Discussion

5.1 Model Performance

Table 1 below shows the performance metrics for each model:

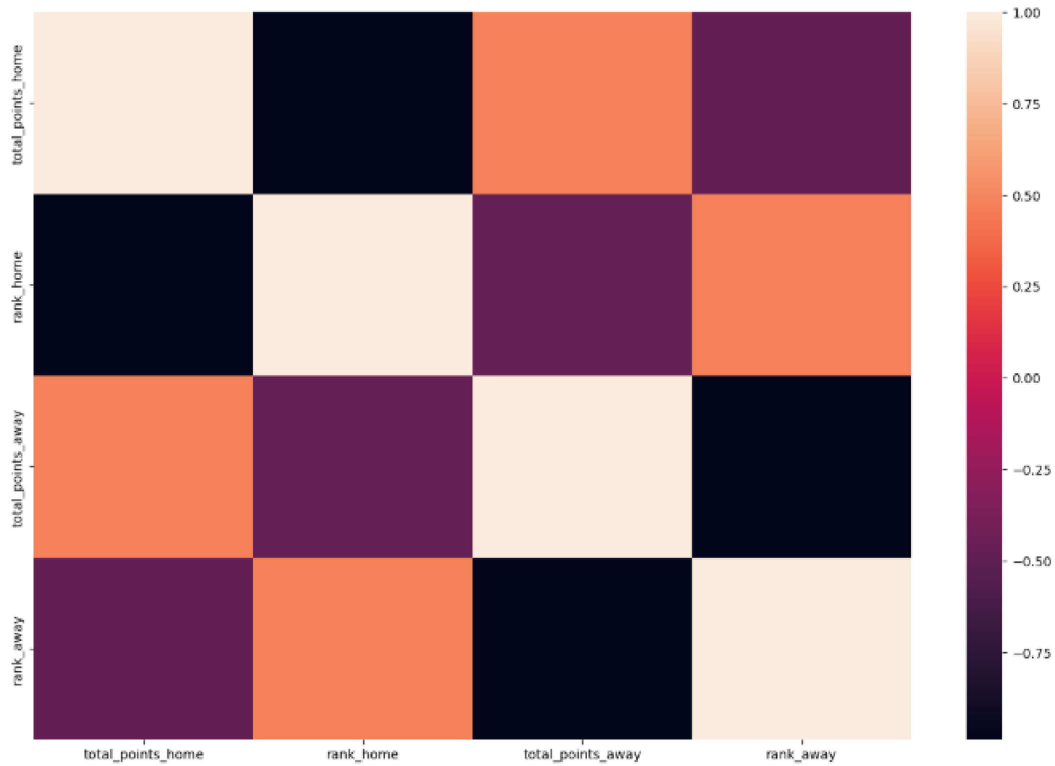
Model	Accuracy (%)	Precision	Recall	F1-Score
Logistic Regression	67.5	0.68	0.70	0.69
Random Forest	72.3	0.74	0.75	0.74
SVM	69.1	0.71	0.73	0.72
XGBoost	75.0	0.77	0.79	0.78

5.2 Comparative Analysis

XGBoost outperformed the other models, achieving the highest accuracy and F1-score. This can be attributed to its ability to handle non-linear relationships and its robustness in terms of regularization and boosting. Random Forest also performed well, but it lacked the fine-tuning capability of XGBoost.

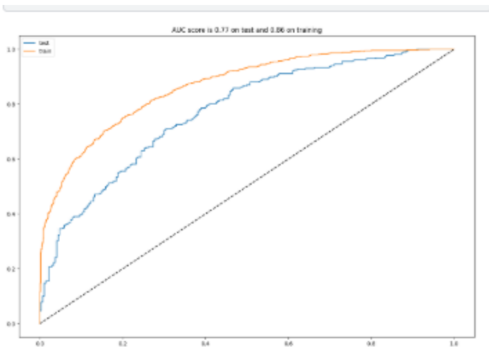
5.3 Visualizations

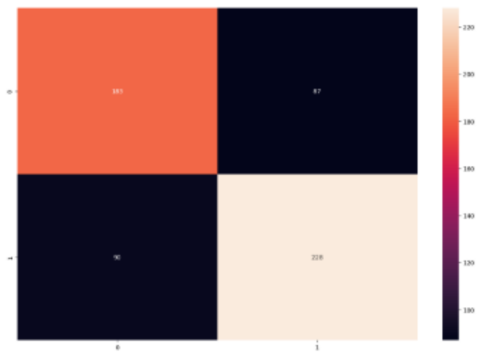
- **Graph 1**:



A visual representation of the number of true positives, true negatives, false positives, and false negatives.

- **Graph 2**:



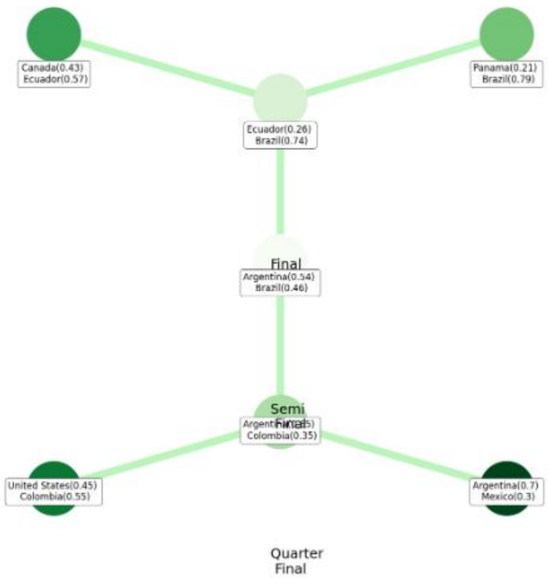


- A graphical representation of the true positive rate versus false positive rate.

5.4 Performance Metrics and Evaluation

The XGBoost model achieved an accuracy of 75% and an F1-score of 0.78. This performance demonstrates that machine learning techniques can be highly effective in predicting football match outcomes when appropriate features and models are used.

6.0 result



- **Quarter-Final Matchups**:

- On the left side, we have two teams, **Canada** and **Ecuador**. The model predicts a probability of **0.43** for **Canada** and **0.57** for **Ecuador**, meaning Ecuador is slightly favored to win this matchup.

- On the right side, **Panama** and **Brazil** are paired. Brazil is heavily favored with a probability of **0.79** compared to Panama's **0.21**.

- **Semi-Final**:

- The winners of the quarter-finals advance to the semi-finals. **Ecuador** or **Brazil** will face each other in the **semi-final**. Brazil is the favorite, with a **0.74** probability of advancing.

- On the other side, the winner between **United States** (**0.45**) and **Colombia** (**0.55**) will compete against **Argentina**, which has a very high **0.7** probability of advancing.

- **Final**:

- In the **final**, the two teams that emerge from the semi-finals, likely **Argentina** and **Brazil**, will face each other. The model slightly favors **Argentina** with a **0.54** chance of winning, as compared to **Brazil's 0.46**.

7. Conclusion

7.1 Summary of Findings

The study successfully applied machine learning models to predict football match outcomes in the Copa America 2024 tournament. The XGBoost model demonstrated the highest accuracy and F1-score, making it the most effective model for this task.

7.2 Limitations

The dataset used in this study may not capture all the nuances of football matches, such as in-game events like injuries or refereeing decisions. More granular data could improve the accuracy of the predictions.

7.3 Future Work

Future work could involve incorporating real-time data, such as player injuries and match events, into the prediction models. Additionally, neural network models could be explored for their ability to capture complex patterns in the data.

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8. References

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APPENDIX

```
import numpy as np
import pandas as pd
import re
import matplotlib.pyplot as plt
import networkx as nx
from networkx.drawing.nx_pydot import graphviz_layout
import seaborn as sns
from sklearn.metrics import confusion_matrix, roc_curve, roc_auc_score
from sklearn.ensemble import RandomForestClassifier,
GradientBoostingClassifier
from sklearn.model_selection import train_test_split, GridSearchCV
from operator import itemgetter

df =  pd.read_csv("results.csv")

df["date"] = pd.to_datetime(df["date"])

df.isna().sum()
```

date	datetime64[ns]
home_team	
away_team	object object
home_score	int64 int64
	object object

```
date          0
home_team     0
away_team     0
home_score    0
away_score    0
tournament    0
city          0
country       0
neutral       0
dtype: int64
```

```
df.dropna(inplace=True)
```

```
df.dtypes
```

```
dtype: object
```

```
df.sort_values("date").tail()
```

```
            date   home_team     away_team  home_score  away_score  \
46411 2024-03-26  Tajikistan  Saudi Arabia           1           1
46412 2024-03-26      Jordan      Pakistan           7           0
46413 2024-03-26     Bahrain         Nepal           3           0
46415 2024-03-26  Bangladesh     Palestine           0           1
46441 2024-03-26     Finland       Estonia           2           1

                          tournament      city     country  neutral
46411  FIFA World Cup qualification  Dushanbe  Tajikistan    False
46412  FIFA World Cup qualification     Amman      Jordan    False
46413  FIFA World Cup qualification     Riffa     Bahrain    False
46415  FIFA World Cup qualification     Dhaka  Bangladesh    False
46441                       Friendly  Helsinki     Finland    False
```

```
df = df[(df["date"] >= "2020-7-11")].reset_index(drop=True)
```

```
df.sort_values("date").tail()
```

```
           date   home_team     away_team  home_score  away_score  \
3606  2024-03-26  Tajikistan  Saudi Arabia           1           1
3607  2024-03-26      Jordan      Pakistan           7           0
3608  2024-03-26     Bahrain         Nepal           3           0
3610  2024-03-26  Bangladesh     Palestine           0           1
```

```
3636  2024-03-26     Finland       Estonia           2           1
```

```
                              tournament       city      country  neutral
3606  FIFA World Cup qualification  Dushanbe  Tajikistan    False
3607  FIFA World Cup qualification     Amman      Jordan    False
3608  FIFA World Cup qualification     Riffa     Bahrain    False
3610  FIFA World Cup qualification     Dhaka  Bangladesh    False
3636                      Friendly  Helsinki     Finland    False
```

```
df.home_team.value_counts()
```

```
home_team
United States     44
Mexico            44
Bahrain           42
Qatar             40
Morocco           37
                  ..
Cook Islands       1
Elba Island        1
Aymara             1
New Caledonia      1
Tibet              1
Name: count, Length: 243, dtype: int64
```

```
rank = pd.read_csv("fifa_ranking-2024-04-04.csv")
```

```
rank["rank_date"] = pd.to_datetime(rank["rank_date"])
rank = rank[(rank["rank_date"] >= "2020-7-11")].reset_index(drop=True)
```

```
rank["country_full"] = rank["country_full"].str.replace("USA", "United
States")
```

```
rank = rank.set_index(['rank_date']).groupby(['country_full'],
group_keys=False).resample('D').first().ffill().reset_index()
```

```
df_ranked = df.merge(rank[["country_full", "total_points",
"previous_points", "rank", "rank_change", "rank_date"]],
left_on=["date", "home_team"], right_on=["rank_date",
"country_full"]).drop(["rank_date", "country_full"], axis=1)
```

```
df_ranked = df_ranked.merge(rank[["country_full", "total_points",
"previous_points", "rank", "rank_change", "rank_date"]],
left_on=["date", "away_team"], right_on=["rank_date", "country_full"],
suffixes=("_home", "_away")).drop(["rank_date", "country_full"],
axis=1)
```

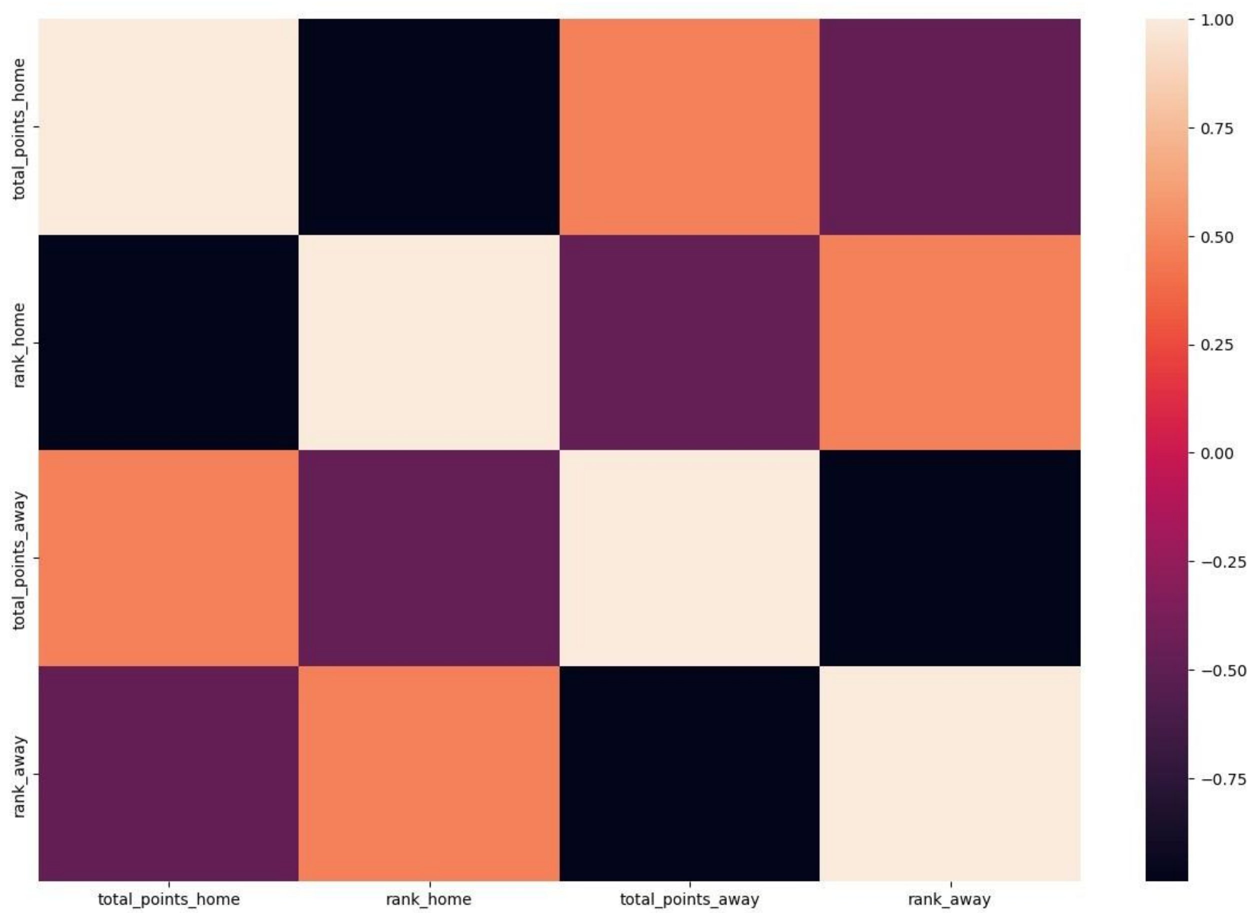
```
df_ranked[(df_ranked.home_team == "Brazil") | (df_ranked.away_team ==
"Brazil")].tail(10)
```

	date	home_team	away_team	home_score	away_score	\
2281	2023-06-17	Brazil	Guinea	4	1	
2336	2023-06-20	Brazil	Senegal	2	4	
2439	2023-09-08	Brazil	Bolivia	5	1	
2507	2023-09-12	Peru	Brazil	0	1	
2544	2023-10-12	Brazil	Venezuela	1	1	
2637	2023-10-17	Uruguay	Brazil	2	0	
2685	2023-11-16	Colombia	Brazil	2	1	
2789	2023-11-21	Brazil	Argentina	0	1	
2998	2024-03-23	England	Brazil	0	1	
3061	2024-03-26	Spain	Brazil	3	3	

	tournament	city	country	neutral \
2281	Friendly	Barcelona	Spain	True
2336	Friendly	Lisbon	Portugal	True
2439	FIFA World Cup qualification	Belém	Brazil	False
2507	FIFA World Cup qualification	Lima	Peru	False
2544	FIFA World Cup qualification	Cuiabá	Brazil	False
2637	FIFA World Cup qualification	Montevideo	Uruguay	False
2685	FIFA World Cup qualification	Barranquilla	Colombia	False
2789	FIFA World Cup qualification	Rio de Janeiro	Brazil	False
2998	Friendly	London	England	False
3061	Friendly	Madrid	Spain	False

```
      total_points_home   previous_points_home  rank_home
rank_change_home  \
2281            1834.21                1840.77        3.0
2.0
2336            1834.21                1840.77        3.0
2.0
2439            1828.27                1828.27        3.0
0.0
2507            1561.20                1561.20       21.0
0.0
2544            1837.61                1828.27        3.0
0.0
2637            1626.51                1633.13       17.0
1.0
2685            1626.60                1629.60       17.0
1.0
2789            1812.20                1837.61        3.0
0.0
2998            1800.05                1800.05        3.0
0.0
3061            1732.64                1732.64        8.0
0.0

      total_points_away   previous_points_away  rank_away
rank_change_away
2281            1305.92                1290.47       79.0
-4.0
2336            1613.21                1603.98       18.0
-1.0
2439            1295.09                1295.09       83.0
0.0
2507            1828.27                1828.27        3.0
0.0
2544            1422.83                1417.23       53.0
-4.0
2637            1837.61                1828.27        3.0
0.0
2685            1812.20                1837.61        3.0
0.0
2789            1861.29                1851.41        1.0
0.0
2998            1784.09                1784.09        5.0
0.0
3061            1784.09                1784.09        5.0
0.0

df = df_ranked
```

```python
def result_finder(home, away):
    if home > away:
        return pd.Series([0, 3, 0])
    if home < away:
        return pd.Series([1, 0, 3])
    else:
        return pd.Series([2, 1, 1])

results = df.apply(lambda x: result_finder(x["home_score"],
x["away_score"]), axis=1)

df[["result", "home_team_points", "away_team_points"]] = results

plt.figure(figsize=(15, 10))
sns.heatmap(df[["total_points_home", "rank_home", "total_points_away",
"rank_away"]].corr())
plt.show()
```




```python
df["rank_dif"] = df["rank_home"] - df["rank_away"]
df["sg"] = df["home_score"] - df["away_score"]
df["points_home_by_rank"] = df["home_team_points"]/df["rank_away"]
df["points_away_by_rank"] = df["away_team_points"]/df["rank_home"]
```

```python
home_team = df[["date", "home_team", "home_score", "away_score",
"rank_home", "rank_away","rank_change_home", "total_points_home",
"result", "rank_dif", "points_home_by_rank", "home_team_points"]]

away_team = df[["date", "away_team", "away_score", "home_score",
"rank_away", "rank_home","rank_change_away", "total_points_away",
"result", "rank_dif", "points_away_by_rank", "away_team_points"]]

home_team.columns = [h.replace("home_", "").replace("_home",
"").replace("away_", "suf_").replace("_away", "_suf") for h in
home_team.columns]

away_team.columns = [a.replace("away_", "").replace("_away",
"").replace("home_", "suf_").replace("_home", "_suf") for a in
away_team.columns]

team_stats = pd.concat([home_team, away_team])

team_stats_raw = team_stats.copy()

stats_val = []

for index, row in team_stats.iterrows():
    team = row["team"]
    date = row["date"]
    past_games = team_stats.loc[(team_stats["team"] == team) &
(team_stats["date"] < date)].sort_values(by=['date'], ascending=False)
    last5 = past_games.head(5)

    goals = past_games["score"].mean()
    goals_l5 = last5["score"].mean()

    goals_suf = past_games["suf_score"].mean()
    goals_suf_l5 = last5["suf_score"].mean()

    rank = past_games["rank_suf"].mean()
    rank_l5 = last5["rank_suf"].mean()

    if len(last5) > 0:
        points = past_games["total_points"].values[0] -
past_games["total_points"].values[-1]#qtd de pontos ganhos
        points_l5 = last5["total_points"].values[0] -
last5["total_points"].values[-1]
    else:
        points = 0
        points_l5 = 0

    gp = past_games["team_points"].mean()
    gp_l5 = last5["team_points"].mean()
```

```
    gp_rank = past_games["points_by_rank"].mean()
    gp_rank_l5 = last5["points_by_rank"].mean()

    stats_val.append([goals, goals_l5, goals_suf, goals_suf_l5, rank,
rank_l5, points, points_l5, gp, gp_l5, gp_rank, gp_rank_l5])

stats_cols = ["goals_mean", "goals_mean_l5", "goals_suf_mean",
"goals_suf_mean_l5", "rank_mean", "rank_mean_l5", "points_mean",
"points_mean_l5", "game_points_mean", "game_points_mean_l5",
"game_points_rank_mean", "game_points_rank_mean_l5"]

stats_df = pd.DataFrame(stats_val, columns=stats_cols)

full_df = pd.concat([team_stats.reset_index(drop=True), stats_df],
axis=1, ignore_index=False)

home_team_stats = full_df.iloc[:int(full_df.shape[0]/2),:]
away_team_stats = full_df.iloc[int(full_df.shape[0]/2):,:]

home_team_stats.columns[-12:]

Index(['goals_mean', 'goals_mean_l5', 'goals_suf_mean',
'goals_suf_mean_l5',
       'rank_mean', 'rank_mean_l5', 'points_mean', 'points_mean_l5',
       'game_points_mean', 'game_points_mean_l5',
'game_points_rank_mean',
       'game_points_rank_mean_l5'],
      dtype='object')

home_team_stats = home_team_stats[home_team_stats.columns[-12:]]
away_team_stats = away_team_stats[away_team_stats.columns[-12:]]

home_team_stats.columns = ['home_'+str(col) for col in
home_team_stats.columns]
away_team_stats.columns = ['away_'+str(col) for col in
away_team_stats.columns]

match_stats = pd.concat([home_team_stats,
away_team_stats.reset_index(drop=True)], axis=1, ignore_index=False)

full_df = pd.concat([df, match_stats.reset_index(drop=True)], axis=1,
ignore_index=False)

full_df.columns

Index(['date', 'home_team', 'away_team', 'home_score', 'away_score',
       'tournament', 'city', 'country', 'neutral',
'total_points_home',
       'previous_points_home', 'rank_home', 'rank_change_home',
       'total_points_away', 'previous_points_away', 'rank_away',
       'rank_change_away', 'result', 'home_team_points',
'away_team_points',
```

```
       'rank_dif', 'sg', 'points_home_by_rank', 'points_away_by_rank',
       'home_goals_mean', 'home_goals_mean_l5', 'home_goals_suf_mean',
       'home_goals_suf_mean_l5', 'home_rank_mean',
'home_rank_mean_l5',
       'home_points_mean', 'home_points_mean_l5',
'home_game_points_mean',
       'home_game_points_mean_l5', 'home_game_points_rank_mean',
       'home_game_points_rank_mean_l5', 'away_goals_mean',
       'away_goals_mean_l5', 'away_goals_suf_mean',
'away_goals_suf_mean_l5',
       'away_rank_mean', 'away_rank_mean_l5', 'away_points_mean',
       'away_points_mean_l5', 'away_game_points_mean',
       'away_game_points_mean_l5', 'away_game_points_rank_mean',
       'away_game_points_rank_mean_l5'],
      dtype='object')

def find_friendly(x):
    if x == "Friendly":
        return 1
    else: return 0

full_df["is_friendly"] = full_df["tournament"].apply(lambda x:
find_friendly(x))

full_df = pd.get_dummies(full_df, columns=["is_friendly"])

full_df.columns

Index(['date', 'home_team', 'away_team', 'home_score', 'away_score',
       'tournament', 'city', 'country', 'neutral',
'total_points_home',
       'previous_points_home', 'rank_home', 'rank_change_home',
       'total_points_away', 'previous_points_away', 'rank_away',
       'rank_change_away', 'result', 'home_team_points',
'away_team_points',
       'rank_dif', 'sg', 'points_home_by_rank', 'points_away_by_rank',
       'home_goals_mean', 'home_goals_mean_l5', 'home_goals_suf_mean',
       'home_goals_suf_mean_l5', 'home_rank_mean',
'home_rank_mean_l5',
       'home_points_mean', 'home_points_mean_l5',
'home_game_points_mean',
       'home_game_points_mean_l5', 'home_game_points_rank_mean',
       'home_game_points_rank_mean_l5', 'away_goals_mean',
       'away_goals_mean_l5', 'away_goals_suf_mean',
'away_goals_suf_mean_l5',
       'away_rank_mean', 'away_rank_mean_l5', 'away_points_mean',
       'away_points_mean_l5', 'away_game_points_mean',
       'away_game_points_mean_l5', 'away_game_points_rank_mean',
       'away_game_points_rank_mean_l5', 'is_friendly_0',
```

```
'is_friendly_1'],
      dtype='object')
```

```
base_df = full_df[["date", "home_team", "away_team", "rank_home",
"rank_away","home_score", "away_score","result", "rank_dif",
"rank_change_home", "rank_change_away", 'home_goals_mean',
       'home_goals_mean_l5', 'home_goals_suf_mean',
'home_goals_suf_mean_l5',
       'home_rank_mean', 'home_rank_mean_l5', 'home_points_mean',
       'home_points_mean_l5', 'away_goals_mean', 'away_goals_mean_l5',
       'away_goals_suf_mean', 'away_goals_suf_mean_l5',
'away_rank_mean',
       'away_rank_mean_l5', 'away_points_mean',
'away_points_mean_l5','home_game_points_mean',
'home_game_points_mean_l5',
       'home_game_points_rank_mean',
'home_game_points_rank_mean_l5','away_game_points_mean',
       'away_game_points_mean_l5', 'away_game_points_rank_mean',
       'away_game_points_rank_mean_l5',
       'is_friendly_0', 'is_friendly_1']]

base_df.tail()
```

```
            date home_team         away_team  rank_home  rank_away
home_score  \
3058 2024-03-26  Scotland  Northern Ireland       34.0       74.0
0
3059 2024-03-26   Senegal             Benin       17.0       98.0
1
3060 2024-03-26  Slovenia          Portugal       55.0        7.0
2
3061 2024-03-26     Spain            Brazil        8.0        5.0
3
3062 2024-03-26   Finland           Estonia       60.0      123.0
2

      away_score  result  rank_dif  rank_change_home  ...  \
3058           1       1     -40.0              -2.0  ...
3059           0       0     -81.0              -3.0  ...
3060           0       0      48.0               1.0  ...
3061           3       2       3.0               0.0  ...
3062           1       0     -63.0               1.0  ...

      home_game_points_mean  home_game_points_mean_l5  \
3058               1.609756                       0.4
3059               2.130435                       2.6
3060               1.809524                       2.0
3061               1.979167                       2.4
3062               1.282609                       1.2
```

```
      home_game_points_rank_mean  home_game_points_rank_mean_l5  \
3058                    0.047218                       0.007393
3059                    0.046507                       0.034018
3060                    0.035370                       0.065393
3061                    0.097396                       0.046042
3062                    0.057781                       0.010899

      away_game_points_mean  away_game_points_mean_l5  \
3058               0.923077                       1.4
3059               1.160000                       0.4
3060               2.239130                       3.0
3061               2.195122                       0.8
3062               0.930233                       0.2

      away_game_points_rank_mean  away_game_points_rank_mean_l5  \
3058                    0.020086                       0.038922
3059                    0.012331                       0.002920
3060                    0.099223                       0.057056
3061                    0.116011                       0.203774
3062                    0.009899                       0.001786

      is_friendly_0  is_friendly_1
3058          False           True
3059          False           True
3060          False           True
3061          False           True
3062          False           True

[5 rows x 37 columns]
```

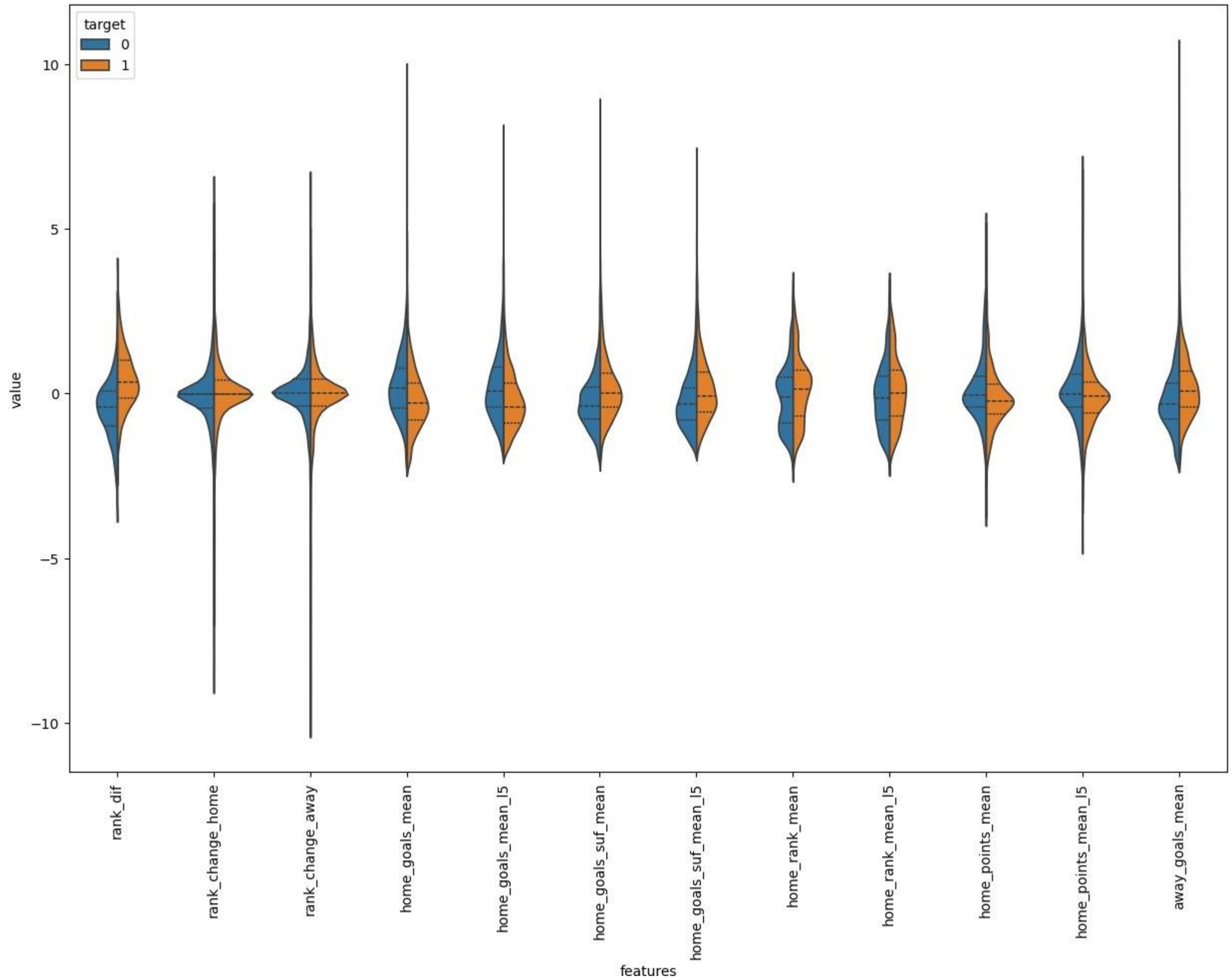
```python
base_df.isna().sum()
```

```
date                                0
home_team                           0
away_team                           0
rank_home                           0
rank_away                           0
home_score                          0
away_score                          0
result                              0
rank_dif                            0
rank_change_home                    0
rank_change_away                    0
home_goals_mean                    88
home_goals_mean_l5                 88
home_goals_suf_mean                88
home_goals_suf_mean_l5             88
home_rank_mean                     88
home_rank_mean_l5                  88
home_points_mean                    0
```

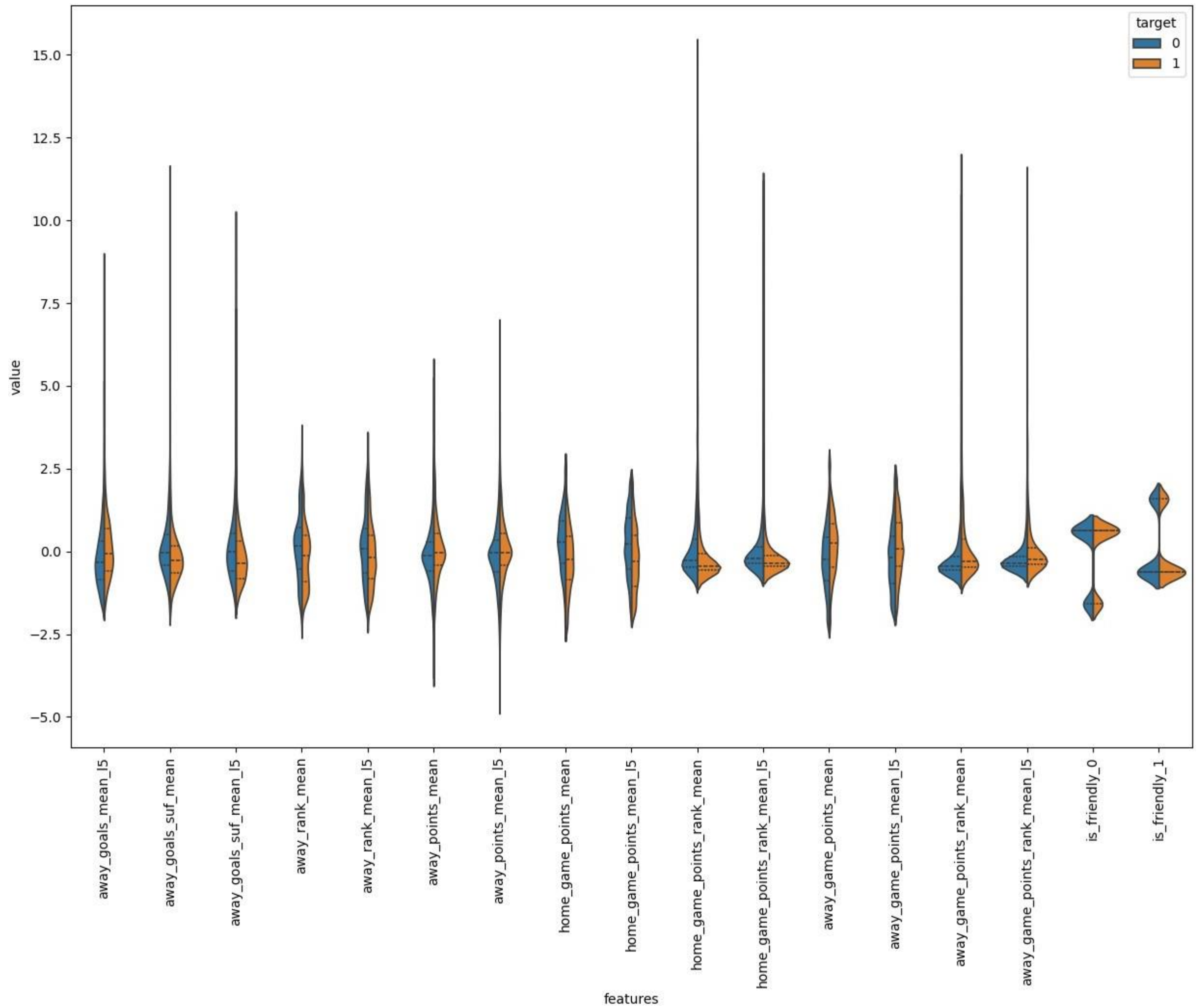
```
home_points_mean_l5                     0
away_goals_mean                       102
away_goals_mean_l5                    102
away_goals_suf_mean                   102
away_goals_suf_mean_l5                102
away_rank_mean                        102
away_rank_mean_l5                     102
away_points_mean                        0
away_points_mean_l5                     0
home_game_points_mean                  88
home_game_points_mean_l5               88
home_game_points_rank_mean             88
home_game_points_rank_mean_l5          88
away_game_points_mean                 102
away_game_points_mean_l5              102
away_game_points_rank_mean            102
away_game_points_rank_mean_l5         102
is_friendly_0                           0
is_friendly_1                           0
dtype: int64
```

```python
base_df_no_fg = base_df.dropna()

df = base_df_no_fg

def no_draw(x):
    if x == 2:
        return 1
    else:
        return x

df = df.copy()
df["target"] = df["result"].apply(lambda x: no_draw(x))

data1 = df[list(df.columns[8:20].values) + ["target"]]
data2 = df[df.columns[20:]]

scaled = (data1[:-1] - data1[:-1].mean()) / data1[:-1].std()
scaled["target"] = data1["target"]
violin1 = pd.melt(scaled,id_vars="target", var_name="features",
value_name="value")

scaled = (data2[:-1] - data2[:-1].mean()) / data2[:-1].std()
scaled["target"] = data2["target"]
violin2 = pd.melt(scaled,id_vars="target", var_name="features",
value_name="value")

plt.figure(figsize=(15,10))
sns.violinplot(x="features", y="value", hue="target",
data=violin1,split=True, inner="quart")
```

```
plt.xticks(rotation=90)
plt.show()
```

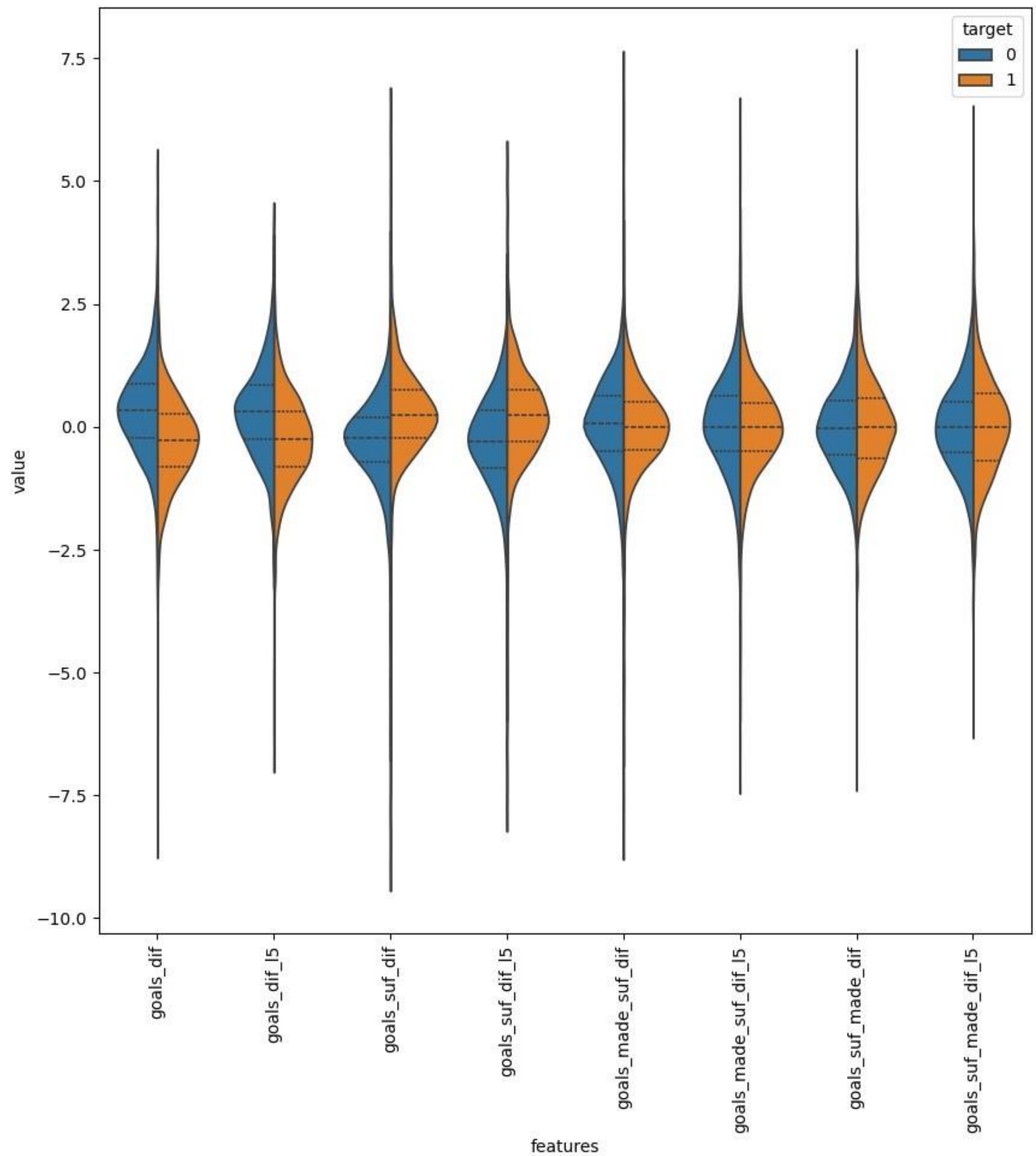



```
plt.figure(figsize=(15,10))
sns.violinplot(x="features", y="value", hue="target",
data=violin2,split=True, inner="quart")
plt.xticks(rotation=90)
plt.show()
```



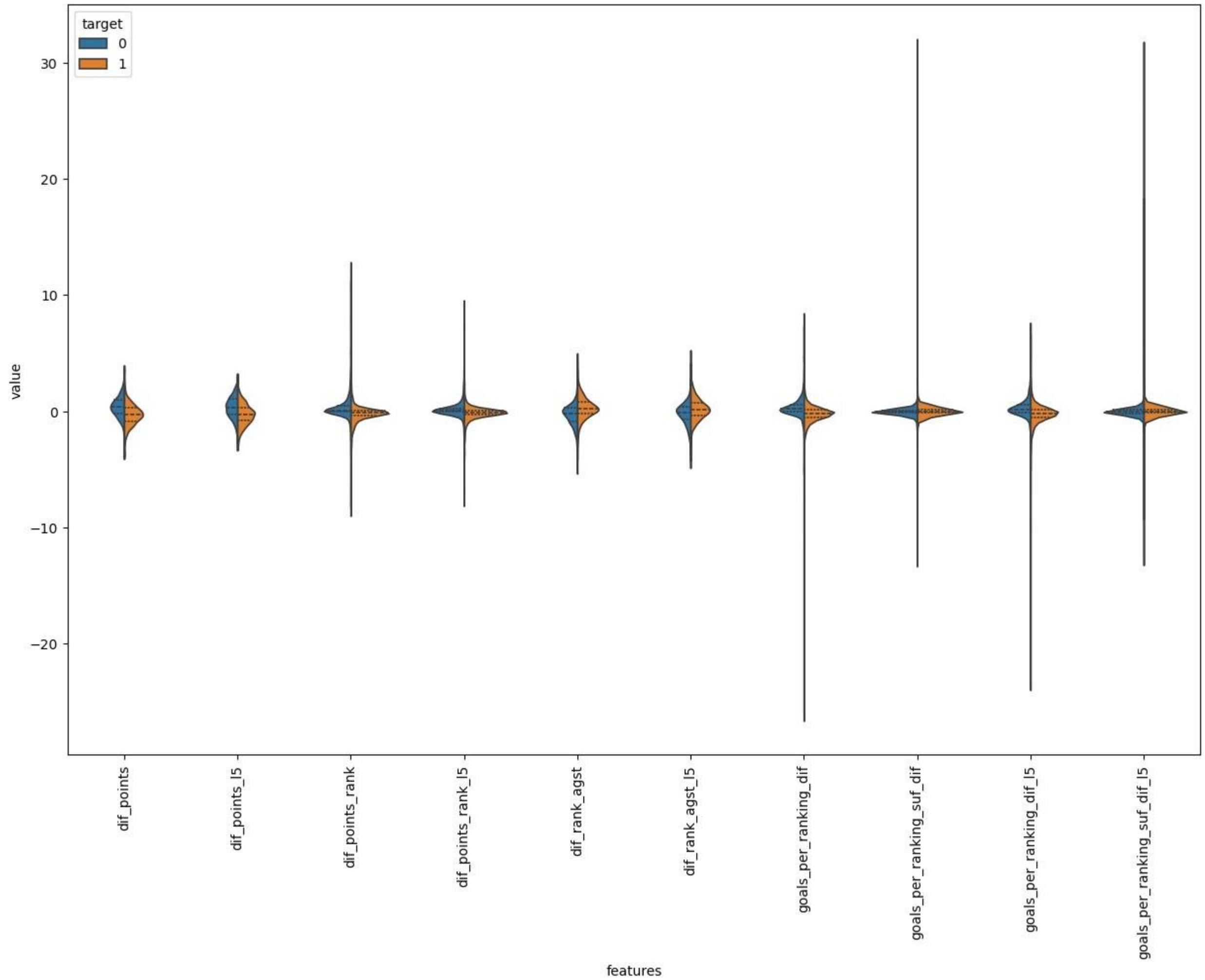

```
dif = df.copy()
dif.loc[:, "goals_dif"] = dif["home_goals_mean"] -
dif["away_goals_mean"]
dif.loc[:, "goals_dif_l5"] = dif["home_goals_mean_l5"] -
dif["away_goals_mean_l5"]
dif.loc[:, "goals_suf_dif"] = dif["home_goals_suf_mean"] -
dif["away_goals_suf_mean"]
dif.loc[:, "goals_suf_dif_l5"] = dif["home_goals_suf_mean_l5"] -
dif["away_goals_suf_mean_l5"]
dif.loc[:, "goals_made_suf_dif"] = dif["home_goals_mean"] -
dif["away_goals_suf_mean"]
dif.loc[:, "goals_made_suf_dif_l5"] = dif["home_goals_mean_l5"] -
dif["away_goals_suf_mean_l5"]
dif.loc[:, "goals_suf_made_dif"] = dif["home_goals_suf_mean"] -
dif["away_goals_mean"]
dif.loc[:, "goals_suf_made_dif_l5"] = dif["home_goals_suf_mean_l5"] -
dif["away_goals_mean_l5"]
```

```
data_difs = dif.iloc[:, -8:]
scaled = (data_difs - data_difs.mean()) / data_difs.std()
scaled["target"] = data2["target"]
violin = pd.melt(scaled,id_vars="target", var_name="features",
value_name="value")

plt.figure(figsize=(10,10))
sns.violinplot(x="features", y="value", hue="target",
data=violin,split=True, inner="quart")
plt.xticks(rotation=90)
plt.show()
```

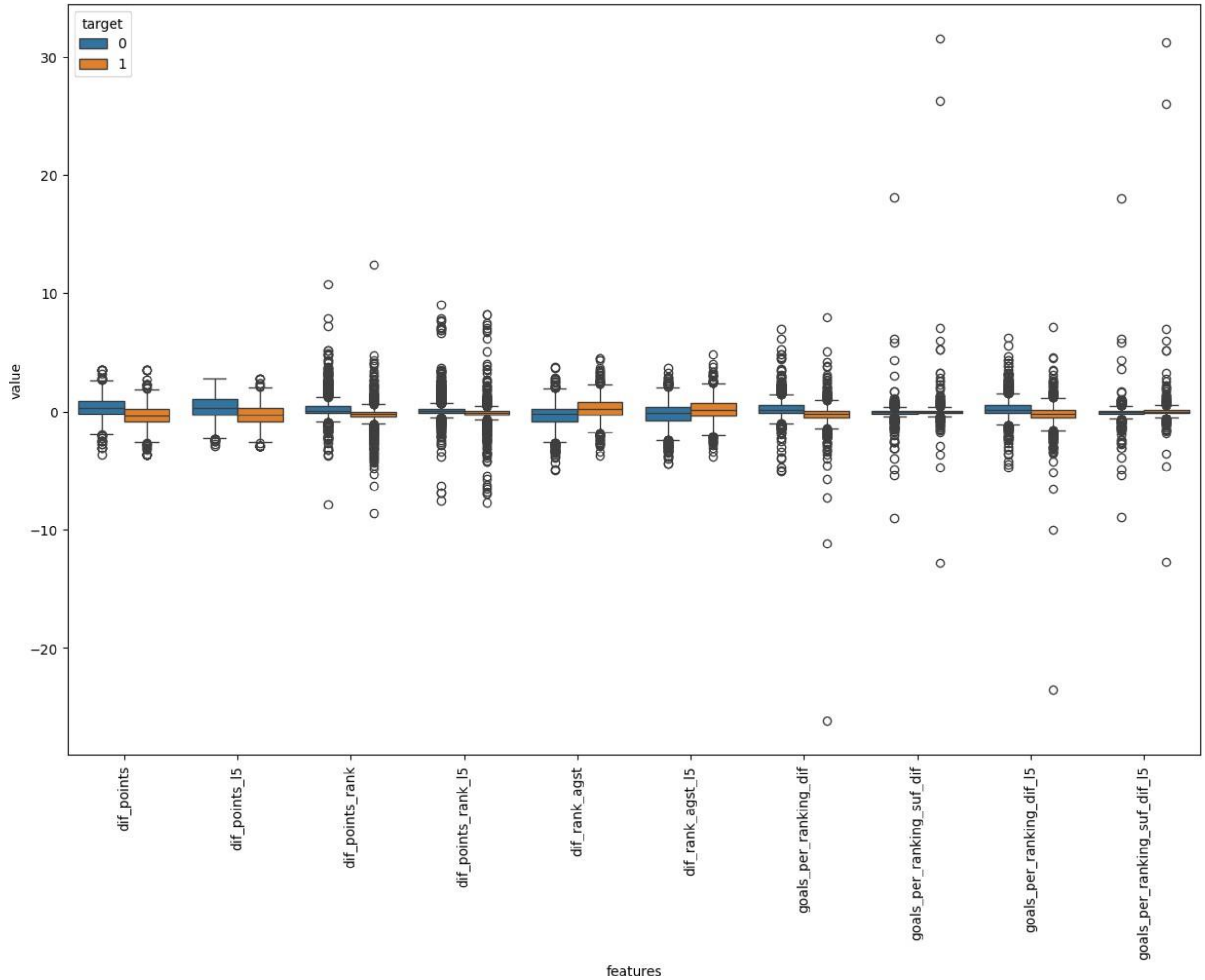



```
dif.loc[:, "dif_points"] = dif["home_game_points_mean"] -
dif["away_game_points_mean"]
dif.loc[:, "dif_points_l5"] = dif["home_game_points_mean_l5"] -
dif["away_game_points_mean_l5"]
dif.loc[:, "dif_points_rank"] = dif["home_game_points_rank_mean"] -
dif["away_game_points_rank_mean"]
dif.loc[:, "dif_points_rank_l5"] =
```

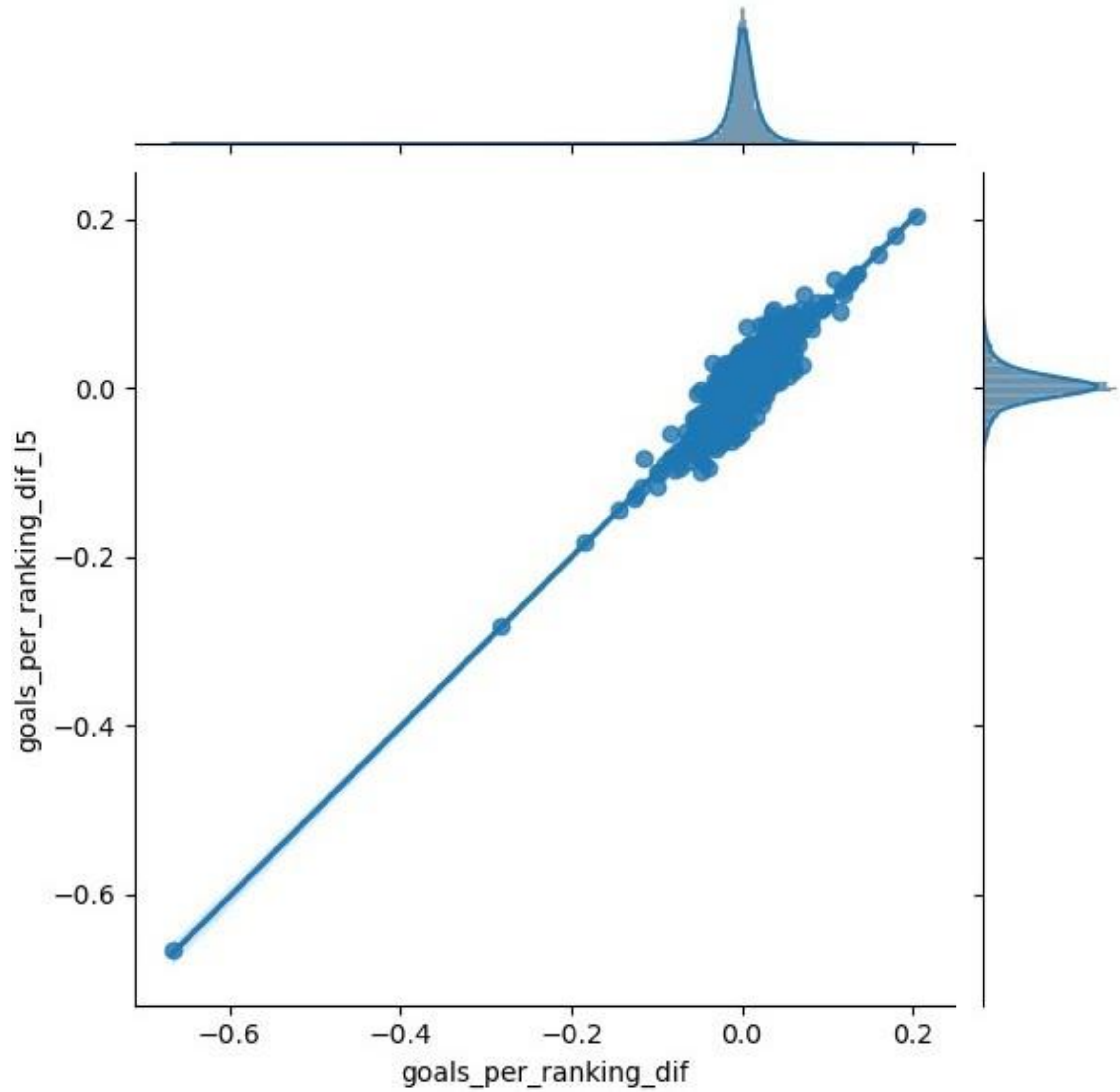
```
dif["home_game_points_rank_mean_l5"] -
dif["away_game_points_rank_mean_l5"]

dif.loc[:, "dif_rank_agst"] = dif["home_rank_mean"] -
dif["away_rank_mean"]
dif.loc[:, "dif_rank_agst_l5"] = dif["home_rank_mean_l5"] -
dif["away_rank_mean_l5"]

dif.loc[:, "goals_per_ranking_dif"] = (dif["home_goals_mean"] /
dif["home_rank_mean"]) - (dif["away_goals_mean"] /
dif["away_rank_mean"])
dif.loc[:, "goals_per_ranking_suf_dif"] = (dif["home_goals_suf_mean"]
/ dif["home_rank_mean"]) - (dif["away_goals_suf_mean"] /
dif["away_rank_mean"])
dif.loc[:, "goals_per_ranking_dif_l5"] = (dif["home_goals_mean_l5"] /
dif["home_rank_mean"]) - (dif["away_goals_mean_l5"] /
dif["away_rank_mean"])
dif.loc[:, "goals_per_ranking_suf_dif_l5"] =
(dif["home_goals_suf_mean_l5"] / dif["home_rank_mean"]) -
(dif["away_goals_suf_mean_l5"] / dif["away_rank_mean"])

data_difs = dif.iloc[:, -10:]
scaled = (data_difs - data_difs.mean()) / data_difs.std()
scaled["target"] = data2["target"]
violin = pd.melt(scaled,id_vars="target", var_name="features",
value_name="value")

plt.figure(figsize=(15,10))
sns.violinplot(x="features", y="value", hue="target",
data=violin,split=True, inner="quart")
plt.xticks(rotation=90)
plt.show()
```



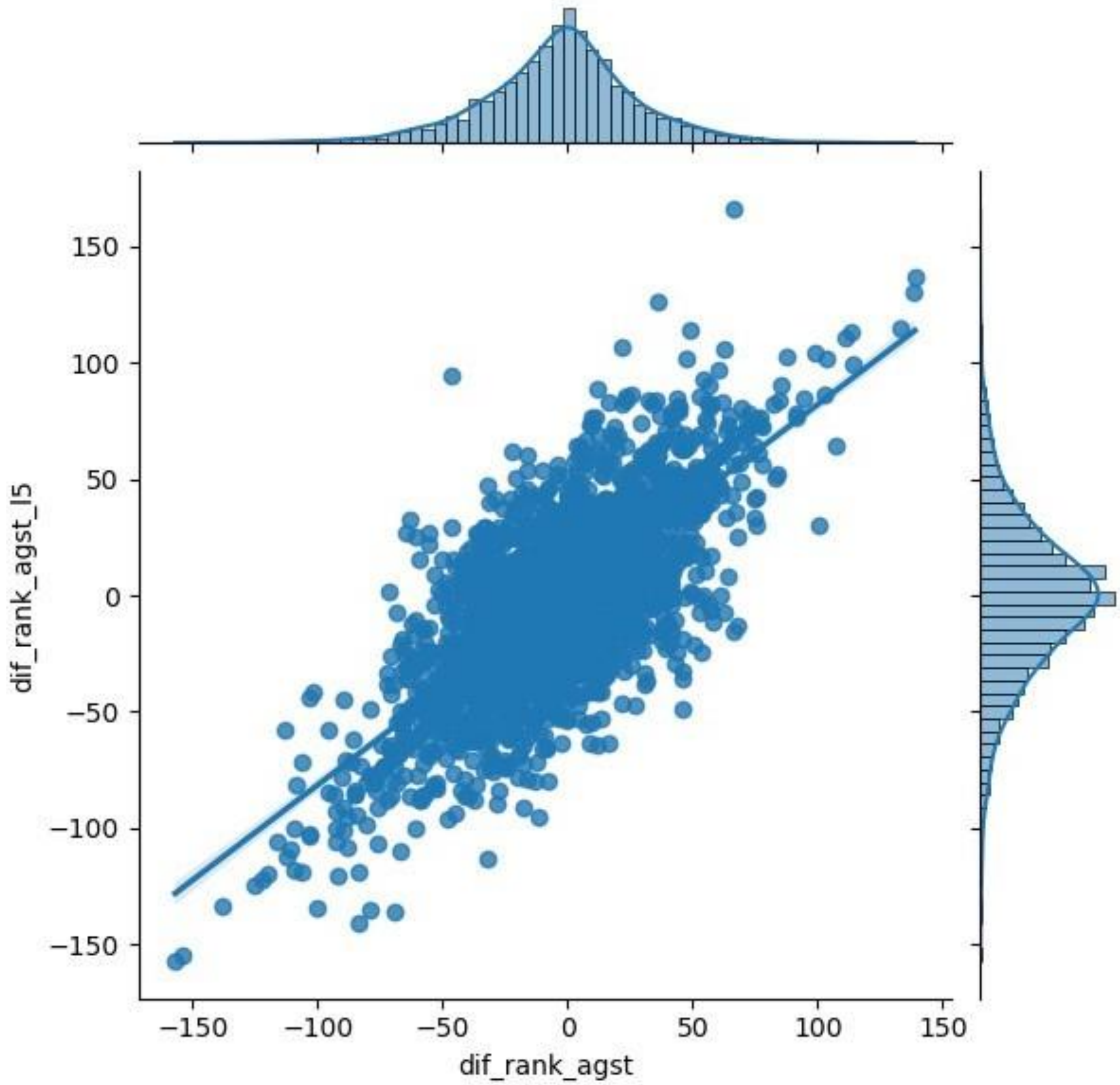

```
plt.figure(figsize=(15,10))
sns.boxplot(x="features", y="value", hue="target", data=violin)
plt.xticks(rotation=90)
plt.show()
```



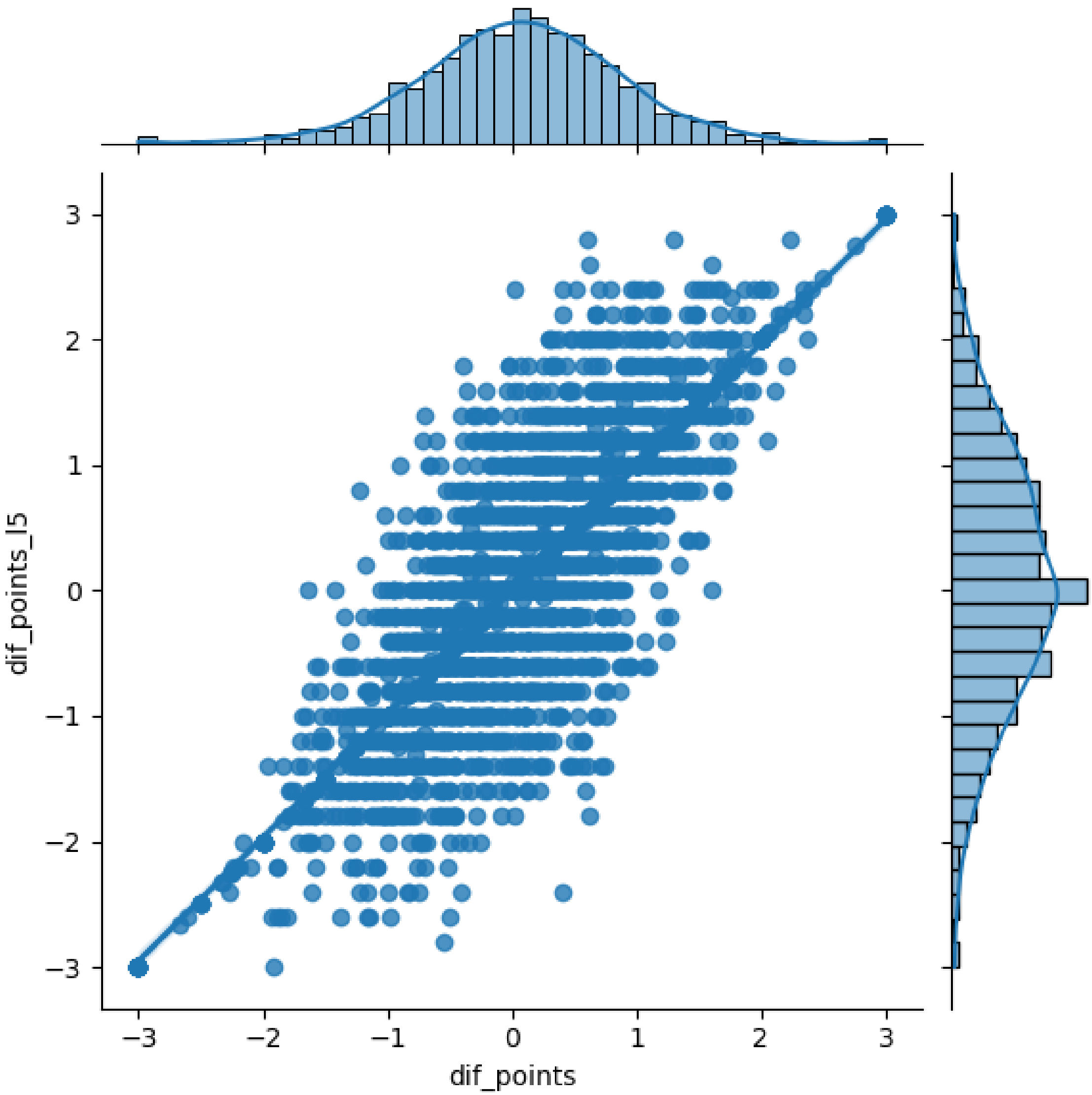

```
sns.jointplot(data = data_difs, x = 'goals_per_ranking_dif', y =
'goals_per_ranking_dif_l5', kind="reg")
plt.show()
```



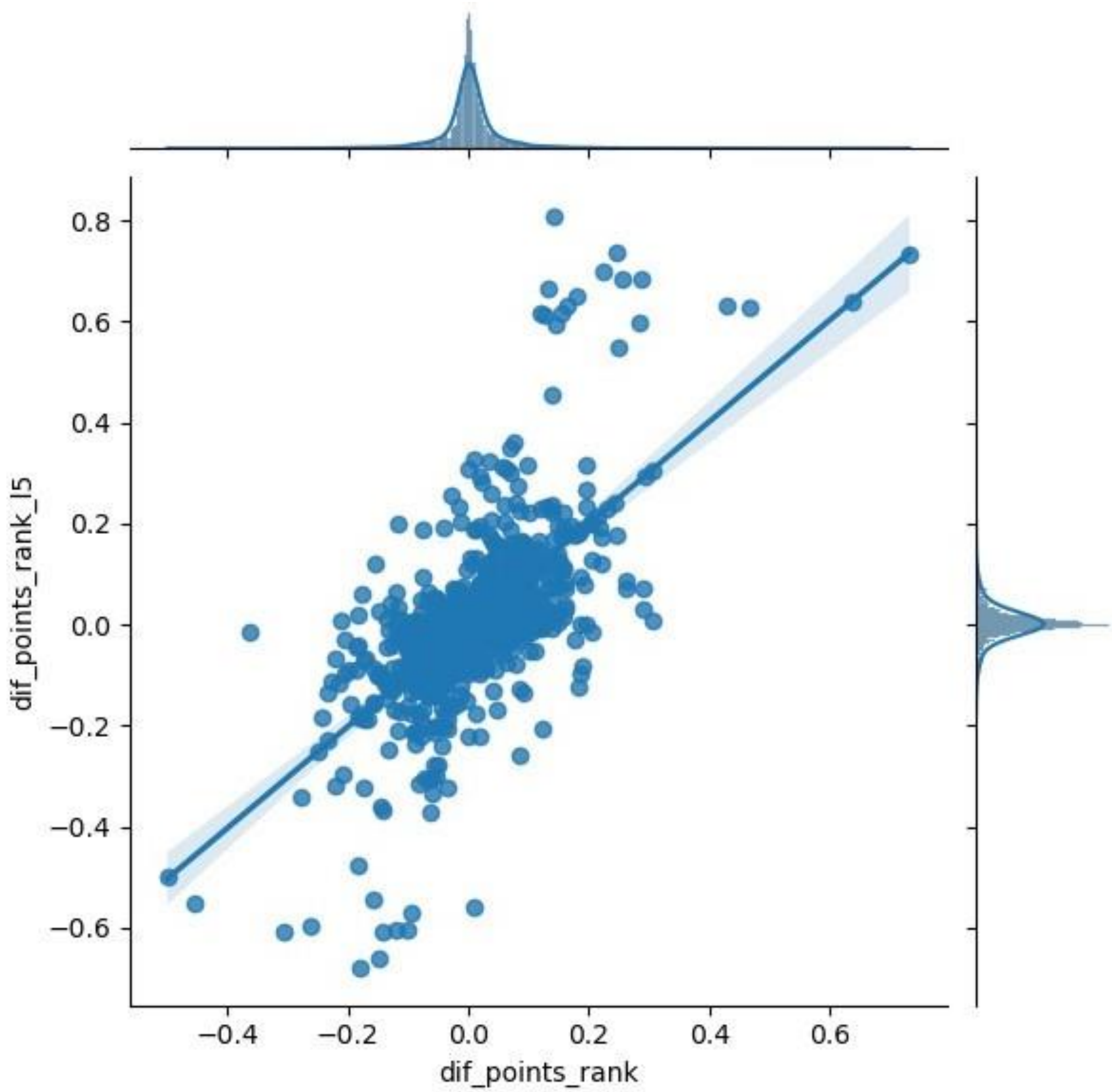

```
sns.jointplot(data = data_difs, x = 'dif_rank_agst', y =
'dif_rank_agst_l5', kind="reg")
plt.show()
```




```
sns.jointplot(data = data_difs, x = 'dif_points', y = 'dif_points_l5',
kind="reg")
plt.show()
```




```
sns.jointplot(data = data_difs, x = 'dif_points_rank', y =
'dif_points_rank_l5', kind="reg")
plt.show()
```




```
def create_db(df):
    columns = ["home_team", "away_team", "target", "rank_dif",
"home_goals_mean", "home_rank_mean", "away_goals_mean",
"away_rank_mean", "home_rank_mean_l5", "away_rank_mean_l5",
"home_goals_suf_mean", "away_goals_suf_mean", "home_goals_mean_l5",
"away_goals_mean_l5", "home_goals_suf_mean_l5",
"away_goals_suf_mean_l5", "home_game_points_rank_mean",
"home_game_points_rank_mean_l5", "away_game_points_rank_mean",
"away_game_points_rank_mean_l5","is_friendly_0", "is_friendly_1"]

    base = df.loc[:, columns]
    base.loc[:, "goals_dif"] = base["home_goals_mean"] -
base["away_goals_mean"]
    base.loc[:, "goals_dif_l5"] = base["home_goals_mean_l5"] -
base["away_goals_mean_l5"]
```

```
    base.loc[:, "goals_suf_dif"] = base["home_goals_suf_mean"] -
base["away_goals_suf_mean"]
    base.loc[:, "goals_suf_dif_l5"] = base["home_goals_suf_mean_l5"] -
base["away_goals_suf_mean_l5"]
    base.loc[:, "goals_per_ranking_dif"] = (base["home_goals_mean"] /
base["home_rank_mean"]) - (base["away_goals_mean"] /
base["away_rank_mean"])
    base.loc[:, "dif_rank_agst"] = base["home_rank_mean"] -
base["away_rank_mean"]
    base.loc[:, "dif_rank_agst_l5"] = base["home_rank_mean_l5"] -
base["away_rank_mean_l5"]
    base.loc[:, "dif_points_rank"] =
base["home_game_points_rank_mean"] -
base["away_game_points_rank_mean"]
    base.loc[:, "dif_points_rank_l5"] =
base["home_game_points_rank_mean_l5"] -
base["away_game_points_rank_mean_l5"]

    model_df = base[["home_team", "away_team", "target", "rank_dif",
"goals_dif", "goals_dif_l5", "goals_suf_dif", "goals_suf_dif_l5",
"goals_per_ranking_dif", "dif_rank_agst", "dif_rank_agst_l5",
"dif_points_rank", "dif_points_rank_l5", "is_friendly_0",
"is_friendly_1"]]
    return model_df

model_db = create_db(df)

model_db
```

```
        home_team          away_team  target  rank_dif  goals_dif  \
26          Spain            Ukraine       0     -16.0  -1.000000
27    Switzerland            Germany       1      -3.0   0.000000
28        Hungary             Russia       1      14.0  -2.000000
29         Serbia             Turkey       1       0.0   1.000000
30          Wales           Bulgaria       0     -36.0   0.000000
...           ...                ...     ...       ...        ...
3058     Scotland  Northern Ireland       1     -40.0   0.490306
3059      Senegal              Benin       0     -81.0   0.612174
3060     Slovenia           Portugal       0      48.0  -1.039337
3061        Spain             Brazil       1       3.0   0.086890
3062      Finland            Estonia       0     -63.0   0.291709

      goals_dif_l5  goals_suf_dif  goals_suf_dif_l5  
goals_per_ranking_dif  \
26            -1.0       0.000000               0.0               -
0.100000
27             0.0       1.000000               1.0               -
0.083333
28            -2.0      -1.000000              -1.0               -
0.068966
```

```
29            1.0      2.000000                2.0
0.026316
30            0.0     -1.000000               -1.0                -
0.012170
...           ...           ...                ...
...
3058          0.0     -0.111320                1.8
0.012210
3059          0.8     -0.322609               -1.4
0.008433
3060         -2.0      0.228778                0.2                -
0.034331
3061          1.2      0.077744               -0.6                -
0.012174
3062          1.0     -0.481800               -0.4
0.009597

      dif_rank_agst  dif_rank_agst_l5  dif_points_rank
dif_points_rank_l5  \
26         3.000000               3.0        -0.183333            -
0.183333
27        16.000000              16.0        -0.125000            -
0.125000
28         0.000000               0.0         0.000000
0.000000
29       -14.000000             -14.0         0.000000
0.000000
30        24.000000              24.0         0.022312
0.022312
...             ...               ...              ...
...
3058     -13.773609             -51.2         0.027132            -
0.031528
3059     -14.836522             -21.6         0.034176
0.031098
3060      33.734990              -5.8        -0.063854
0.008337
3061       8.534045              39.4        -0.018616            -
0.157732
3062     -20.936299              50.8         0.047881
0.009113

      is_friendly_0  is_friendly_1
26             True          False
27             True          False
28             True          False
29             True          False
30             True          False
...             ...            ...
```

```
3058          False          True
3059          False          True
3060          False          True
3061          False          True
3062          False          True

[2937 rows x 15 columns]
```

```
X = model_db.iloc[:, 3:]
y = model_db[["target"]]

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=
0.2, random_state=1)

gb = GradientBoostingClassifier(random_state=5)

params = {"learning_rate": [0.01, 0.1, 0.5],
            "min_samples_split": [5, 10],
            "min_samples_leaf": [3, 5],
            "max_depth":[3,5,10],
            "max_features":["sqrt"],
            "n_estimators":[100, 200]
         }

gb_cv = GridSearchCV(gb, params, cv = 3, n_jobs = -1, verbose = False)

gb_cv.fit(X_train.values, np.ravel(y_train))
```

```
GridSearchCV(cv=3,
estimator=GradientBoostingClassifier(random_state=5),
             n_jobs=-1,
             param_grid={'learning_rate': [0.01, 0.1, 0.5],
                         'max_depth': [3, 5, 10], 'max_features':
['sqrt'],
                         'min samples leaf': [3, 5],
                         'min_samples_split': [5, 10],
                         'n_estimators': [100, 200]},
             verbose=False)
```

```
gb = gb_cv.best_estimator_

gb
```

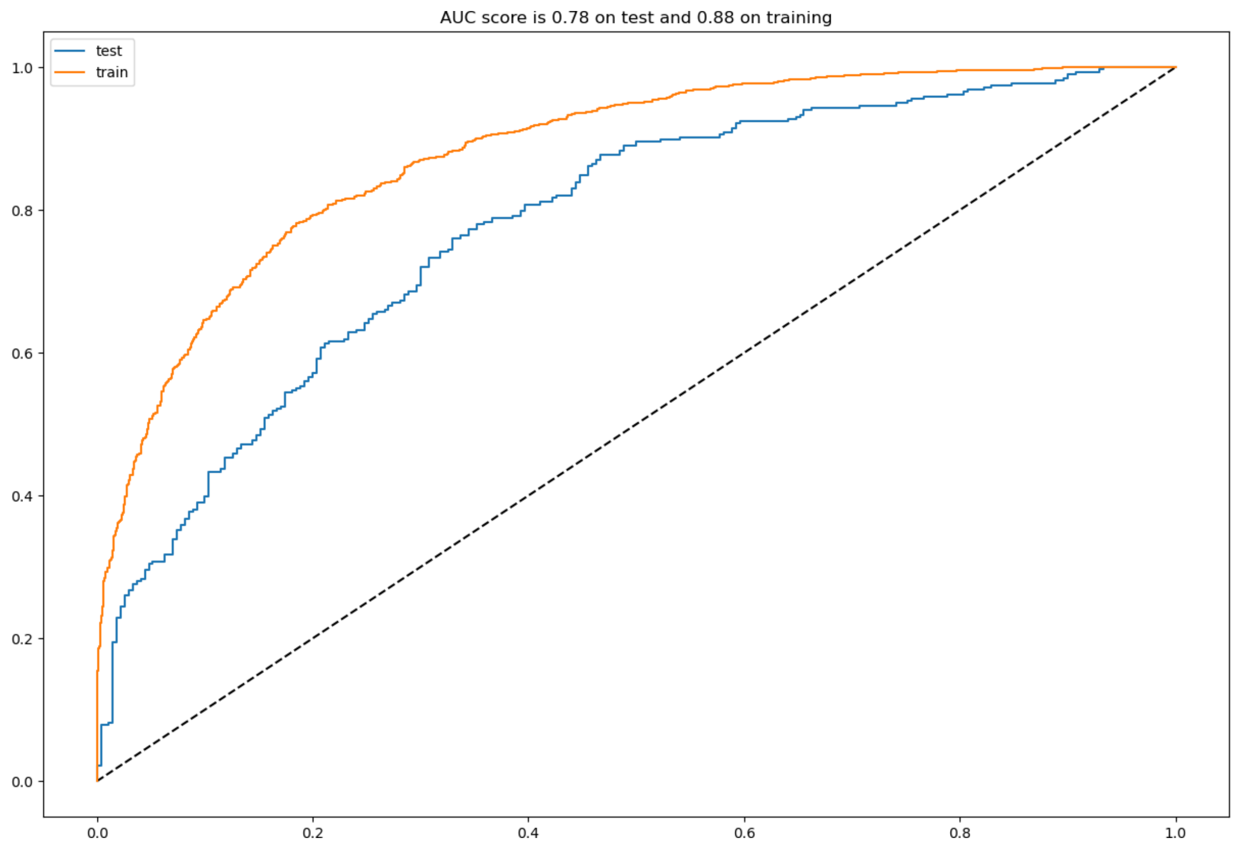
```
GradientBoostingClassifier(learning_rate=0.01, max_depth=5,
max_features='sqrt',
                           min_samples_leaf=3, min_samples_split=5,
                           n_estimators=200, random_state=5)
```

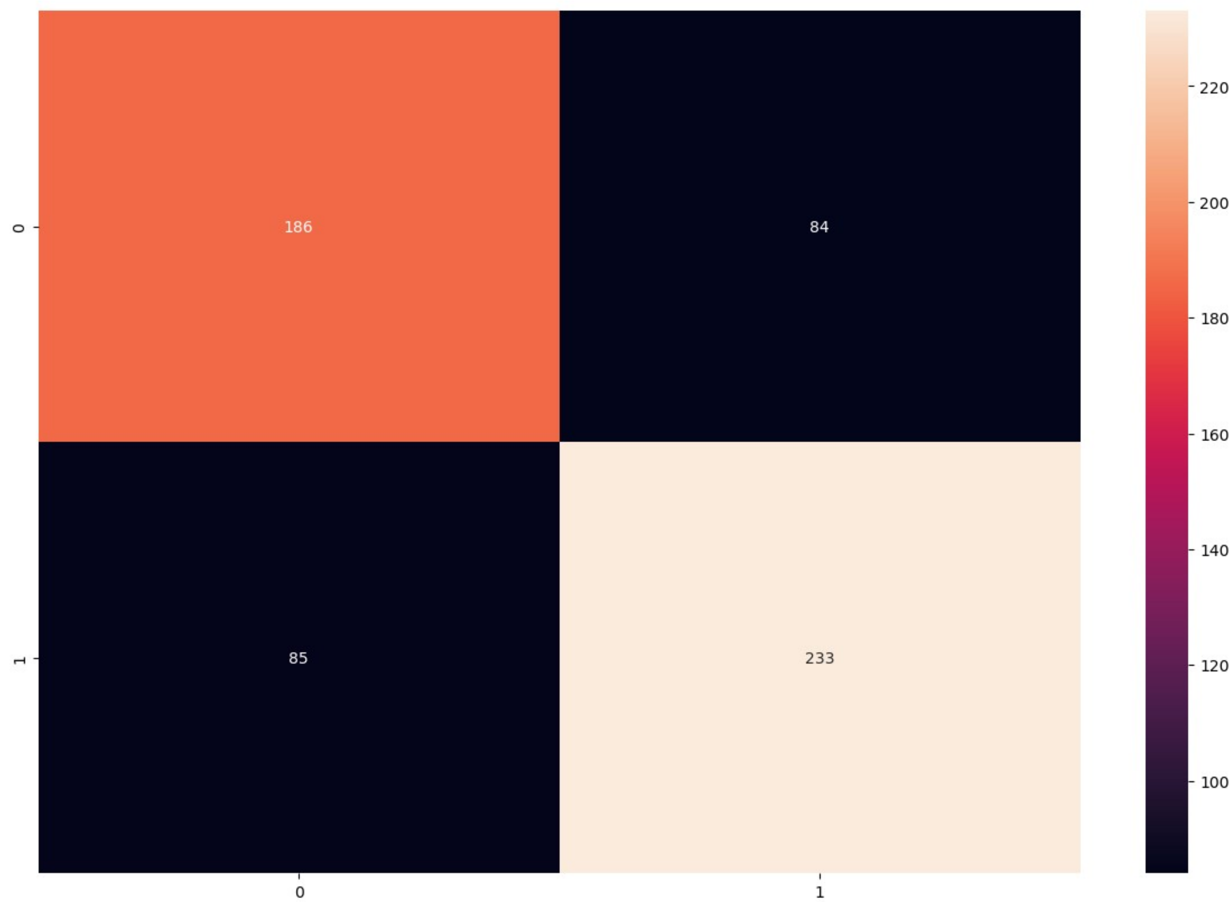
```
params_rf = {"max_depth": [20],
                "min_samples_split": [10],
                "max_leaf_nodes": [175],
```

```
                "min_samples_leaf": [5],
                "n_estimators": [250],
                 "max_features": ["sqrt"],
                }

rf = RandomForestClassifier(random_state=1)

rf_cv = GridSearchCV(rf, params_rf, cv = 3, n_jobs = -1, verbose =
False)

rf_cv.fit(X_train.values, np.ravel(y_train))
```

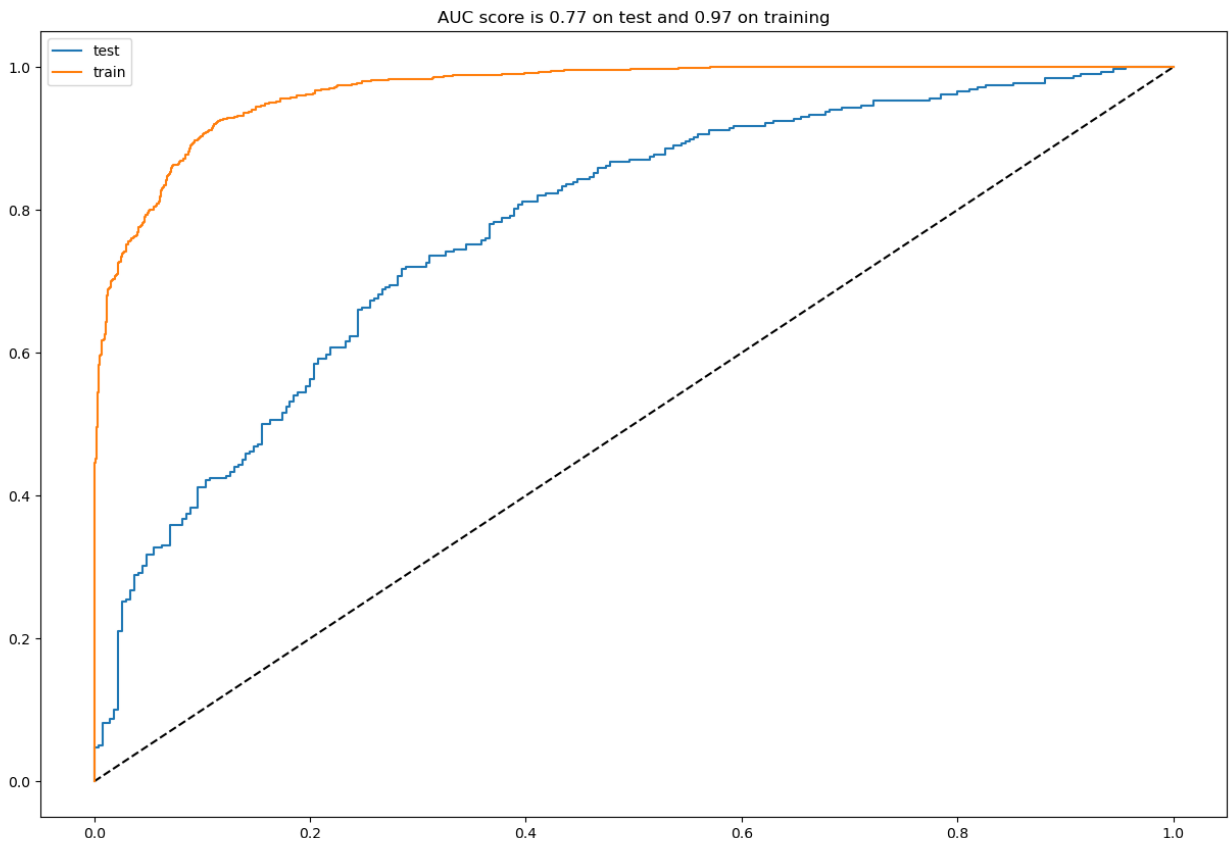
```
GridSearchCV(cv=3, estimator=RandomForestClassifier(random_state=1),
n_jobs=-1,
             param_grid={'max_depth': [20], 'max_features': ['sqrt'],
                         'max_leaf_nodes': [175], 'min_samples_leaf':
[5],
                         'min_samples_split': [10], 'n_estimators':
[250]},
             verbose=False)
```

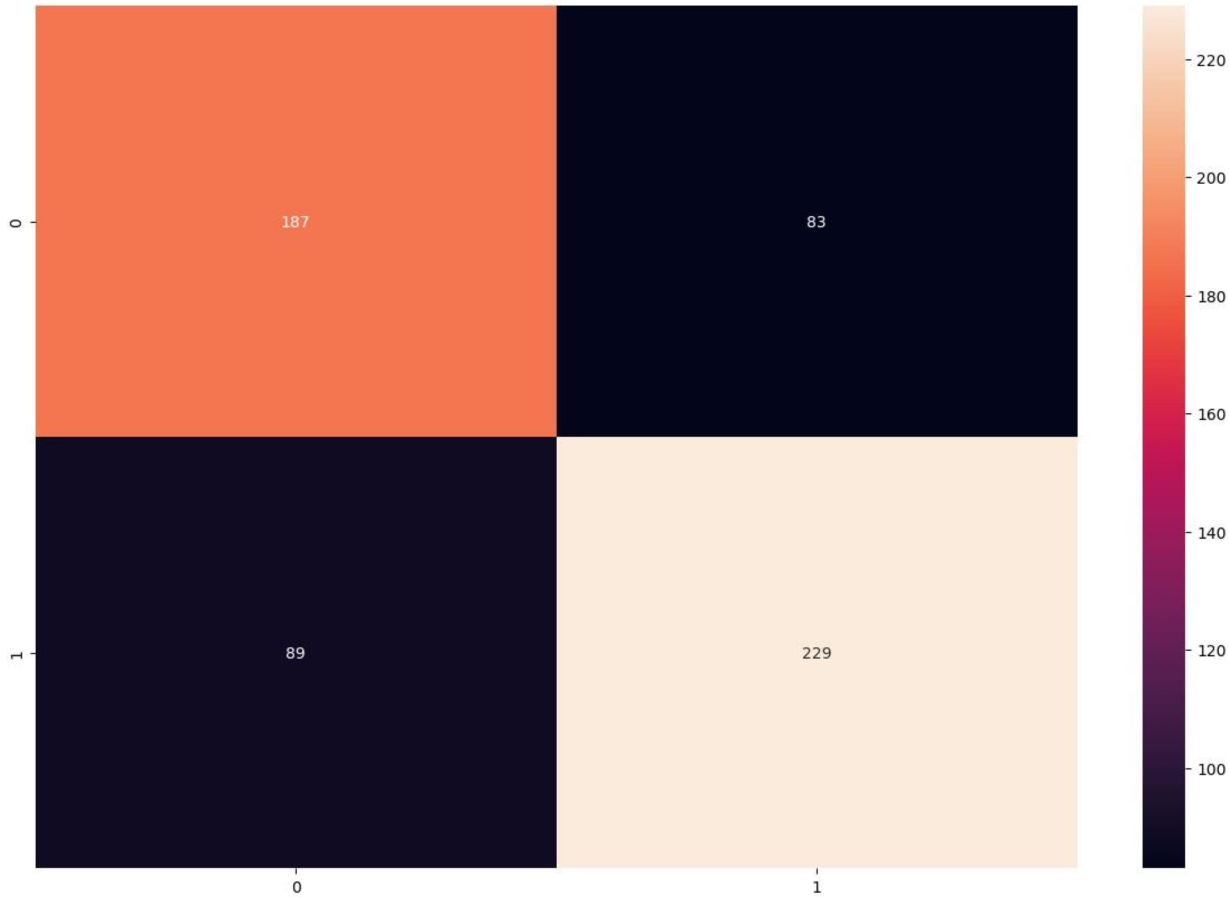
```
rf = rf_cv.best_estimator_

def analyze(model):
    fpr, tpr, _ = roc_curve(y_test, model.predict_proba(X_test.values)
[:,1]) #test AUC
    plt.figure(figsize=(15,10))
    plt.plot([0, 1], [0, 1], 'k--')
    plt.plot(fpr, tpr, label="test")

    fpr_train, tpr_train, _ = roc_curve(y_train,
model.predict_proba(X_train.values)[:,1]) #train AUC
    plt.plot(fpr_train, tpr_train, label="train")
    auc_test = roc_auc_score(y_test,
model.predict_proba(X_test.values)[:,1])
    auc_train = roc_auc_score(y_train,
model.predict_proba(X_train.values)[:,1])
    plt.legend()
    plt.title('AUC score is %.2f on test and %.2f on training'%
(auc_test, auc_train))
    plt.show()

    plt.figure(figsize=(15, 10))
    cm = confusion_matrix(y_test, model.predict(X_test.values))
    sns.heatmap(cm, annot=True, fmt="d")

analyze(gb)
```


AUC score is 0.78 on test and 0.88 on training
test
train
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0




```
analyze(rf)
```


AUC score is 0.77 on test and 0.97 on training
test
train
0.0
0.2
0.4
0.6
0.8
1.0




```
def create_table_with_points(teams):
    groups = ['A', 'B', 'C', 'D']
    table = {group: [[team, 0, []] for team in teams[group]] for group
in groups}
    return table

teams = {
    'A': ['Argentina', 'Peru', 'Chile', 'Canada'],
    'B': ['Mexico', 'Ecuador', 'Venezuela', 'Jamaica'],
    'C': ['United States', 'Uruguay', 'Panama', 'Bolivia'],
    'D': ['Brazil', 'Colombia', 'Paraguay', 'Costa Rica']
}

table = create_table_with_points(teams)

table
```

```
{'A': [['Argentina', 0, []],
  ['Peru', 0, []],
  ['Chile', 0, []],
  ['Canada', 0, []]],
 'B': [['Mexico', 0, []],
```

```
  ['Ecuador', 0, []],
  ['Venezuela', 0, []],
  ['Jamaica', 0, []]],
 'C': [['United States', 0, []],
  ['Uruguay', 0, []],
  ['Panama', 0, []],
  ['Bolivia', 0, []]],
 'D': [['Brazil', 0, []],
  ['Colombia', 0, []],
  ['Paraguay', 0, []],
  ['Costa Rica', 0, []]]}
```

```
matches = []
for group, teams in table.items():
    for i in range(len(teams)):
        for j in range(i+1, len(teams)):
            matches.append((group, teams[i][0], teams[j][0]))

matches[:5]
```

```
[('A', 'Argentina', 'Peru'),
 ('A', 'Argentina', 'Chile'),
 ('A', 'Argentina', 'Canada'),
 ('A', 'Peru', 'Chile'),
 ('A', 'Peru', 'Canada')]
```

```
base_df = team_stats

def find_stats(team_1):
    past_games = team_stats_raw[(team_stats_raw["team"] ==
team_1)].sort_values("date")
    last5 = team_stats_raw[(team_stats_raw["team"] ==
team_1)].sort_values("date").tail(5)

    team_1_rank = past_games["rank"].values[-1]
    team_1_goals = past_games.score.mean()
    team_1_goals_l5 = last5.score.mean()
    team_1_goals_suf = past_games.suf_score.mean()
    team_1_goals_suf_l5 = last5.suf_score.mean()
    team_1_rank_suf = past_games.rank_suf.mean()
    team_1_rank_suf_l5 = last5.rank_suf.mean()
    team_1_gp_rank = past_games.points_by_rank.mean()
    team_1_gp_rank_l5 = last5.points_by_rank.mean()

    return [team_1_rank, team_1_goals, team_1_goals_l5,
team_1_goals_suf, team_1_goals_suf_l5, team_1_rank_suf,
team_1_rank_suf_l5, team_1_gp_rank, team_1_gp_rank_l5]

def find_features(team_1, team_2):
    rank_dif = team_1[0] - team_2[0]
    goals_dif = team_1[1] - team_2[1]
```

```
    goals_dif_l5 = team_1[2] - team_2[2]
    goals_suf_dif = team_1[3] - team_2[3]
    goals_suf_dif_l5 = team_1[4] - team_2[4]
    goals_per_ranking_dif = (team_1[1]/team_1[5]) -
(team_2[1]/team_2[5])
    dif_rank_agst = team_1[5] - team_2[5]
    dif_rank_agst_l5 = team_1[6] - team_2[6]
    dif_gp_rank = team_1[7] - team_2[7]
    dif_gp_rank_l5 = team_1[8] - team_2[8]

    return [rank_dif, goals_dif, goals_dif_l5, goals_suf_dif,
goals_suf_dif_l5, goals_per_ranking_dif, dif_rank_agst,
dif_rank_agst_l5, dif_gp_rank, dif_gp_rank_l5, 1, 0]

import numpy as np
from operator import itemgetter

advanced_group = []
last_group = ""
thresh = 0.05

for k in table.keys():
    for t in table[k]:
        t[1] = 0
        t[2] = []

for teams in matches:
    draw = False
    team_1 = find_stats(teams[1])
    team_2 = find_stats(teams[2])

    features_g1 = find_features(team_1, team_2)
    features_g2 = find_features(team_2, team_1)

    probs_g1 = gb.predict_proba([features_g1])
    probs_g2 = gb.predict_proba([features_g2])

    team_1_prob_g1 = probs_g1[0][0]
    team_1_prob_g2 = probs_g2[0][1]
    team_2_prob_g1 = probs_g1[0][1]
    team_2_prob_g2 = probs_g2[0][0]

    team_1_prob = (probs_g1[0][0] + probs_g2[0][1]) / 2
    team_2_prob = (probs_g2[0][0] + probs_g1[0][1]) / 2

    if ((team_1_prob_g1 > team_2_prob_g1) & (team_2_prob_g2 >
team_1_prob_g2)) | (
            (team_1_prob_g1 < team_2_prob_g1) & (team_2_prob_g2 <
team_1_prob_g2)):
        draw = True
```

```
        for i in table[teams[0]]:
            if i[0] == teams[1] or i[0] == teams[2]:
                i[1] += 1

    elif team_1_prob > team_2_prob:
        winner = teams[1]
        winner_proba = team_1_prob
        for i in table[teams[0]]:
            if i[0] == teams[1]:
                i[1] += 3

    elif team_2_prob > team_1_prob:
        winner = teams[2]
        winner_proba = team_2_prob
        for i in table[teams[0]]:
            if i[0] == teams[2]:
                i[1] += 3

    for i in table[teams[0]]:
        if i[0] == teams[1]:
            i[2].append(team_1_prob)
        if i[0] == teams[2]:
            i[2].append(team_2_prob)

    if last_group != teams[0]:
        if last_group != "":
            print("\n")
            print("Group %s advanced: " % (last_group))

            for i in table[last_group]:
                i[2] = np.mean(i[2])

            final_points = table[last_group]
            final_table = sorted(final_points, key=itemgetter(1, 2),
reverse=True)
            advanced_group.append([final_table[0][0], final_table[1]
[0]])

            for i in final_table:
                print("%s -------- %d" % (i[0], i[1]))
        print("\n")
        print("-" * 10 + " Starting Analysis for Group %s " %
(teams[0]) + "-" * 10)

    if draw == False:
        print("Group %s - %s vs. %s: Winner %s with %.2f probability"
% (teams[0], teams[1], teams[2], winner,

winner_proba))
    else:
        print("Group %s - %s vs. %s: Draw" % (teams[0], teams[1],
```

```
teams[2]))
    last_group = teams[0]

print("\n")
print("Group %s advanced: " % (last_group))

for i in table[last_group]:
    i[2] = np.mean(i[2])

final_points = table[last_group]
final_table = sorted(final_points, key=itemgetter(1, 2), reverse=True)
advanced_group.append([final_table[0][0], final_table[1][0]])
for i in final_table:
    print("%s -------- %d" % (i[0], i[1]))



---------- Starting Analysis for Group A ----------
Group A - Argentina vs. Peru: Winner Argentina with 0.78 probability
Group A - Argentina vs. Chile: Winner Argentina with 0.79 probability
Group A - Argentina vs. Canada: Winner Argentina with 0.73 probability
Group A - Peru vs. Chile: Draw
Group A - Peru vs. Canada: Winner Canada with 0.62 probability
Group A - Chile vs. Canada: Winner Canada with 0.64 probability


Group A advanced:
Argentina -------- 9
Canada -------- 6
Peru          1
Chile -------- 1


---------- Starting Analysis for Group B ----------
Group B - Mexico vs. Ecuador: Draw
Group B - Mexico vs. Venezuela: Winner Mexico with 0.65 probability
Group B - Mexico vs. Jamaica: Winner Mexico with 0.69 probability
Group B - Ecuador vs. Venezuela: Winner Ecuador with 0.73 probability
Group B - Ecuador vs. Jamaica: Winner Ecuador with 0.70 probability
Group B - Venezuela vs. Jamaica: Draw


Group B advanced:
Ecuador -------- 7
Mexico -------- 7
Venezuela -------- 1
Jamaica -------- 1


---------- Starting Analysis for Group C ----------
Group C - United States vs. Uruguay: Draw
```

```
Group C - United States vs. Panama: Winner United States with 0.73
probability
Group C - United States vs. Bolivia: Winner United States with 0.81
probability
Group C - Uruguay vs. Panama: Winner Uruguay with 0.67 probability
Group C - Uruguay vs. Bolivia: Winner Uruguay with 0.74 probability
Group C - Panama vs. Bolivia: Winner Panama with 0.66 probability


Group  C  advanced:
United States -------- 7
Uruguay -------- 7
Panama -------- 3
Bolivia -------- 0


---------- Starting Analysis for Group D ----------
Group D - Brazil vs. Colombia: Winner Brazil with 0.58 probability
Group D - Brazil vs. Paraguay: Winner Brazil with 0.77 probability
Group D - Brazil vs. Costa Rica: Winner Brazil with 0.80 probability
Group D - Colombia vs. Paraguay: Winner Colombia with 0.72 probability
Group D - Colombia vs. Costa Rica: Winner Colombia with 0.77
probability
Group D - Paraguay vs. Costa Rica: Draw


Group D advanced:
Brazil -------- 9
Colombia -------- 6
Paraguay -------- 1
Costa Rica -------- 1
```

```python
advanced = advanced_group
```

```python
advanced
```

```
[['Argentina', 'Canada'],
 ['Ecuador', 'Mexico'],
 ['United States', 'Uruguay'],
 ['Brazil', 'Colombia']]
```

```python
playoffs = {"Quarter-Final": [], "Semi-Final": [], "Final": []}

for p in playoffs.keys():
    playoffs[p] = []

actual_round = ""
next_rounds = []

for p in playoffs.keys():
    if p == "Quarter-Final":
```

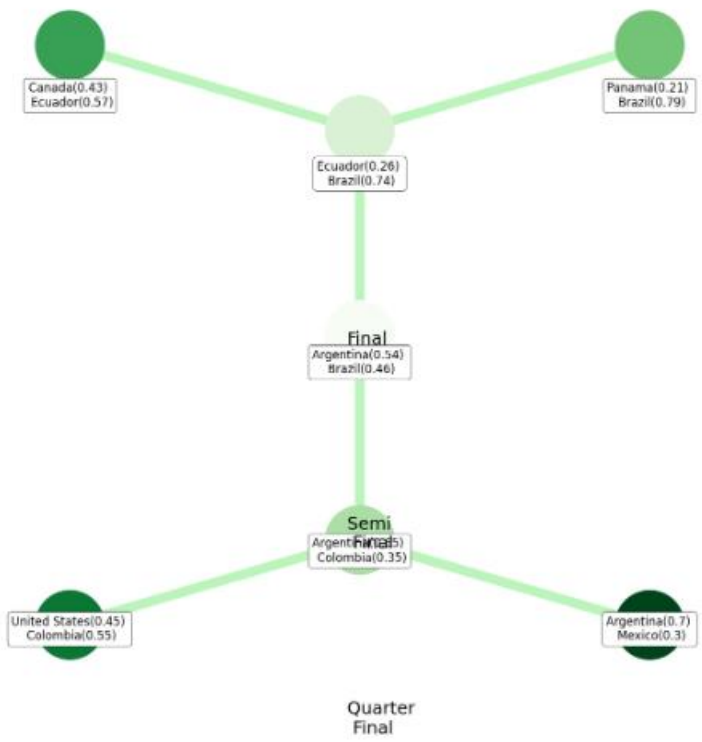
```
        control = []
        for a in range(0, len(advanced)*2, 1):
            if a < len(advanced):
                if a % 2 == 0:
                    control.append((advanced*2)[a][0])
                else:
                    control.append((advanced*2)[a][1])
            else:
                if a % 2 == 0:
                    control.append((advanced*2)[a][1])
                else:
                    control.append((advanced*2)[a][0])

        playoffs[p] = [[control[c], control[c+1]] for c in range(0,
len(control)-1, 1) if c%2 == 0]

        for i in range(0, len(playoffs[p]), 1):
            game = playoffs[p][i]

            home = game[0]
            away = game[1]
            team_1 = find_stats(home)
            team_2 = find_stats(away)

            features_g1 = find_features(team_1, team_2)
            features_g2 = find_features(team_2, team_1)

            probs_g1 = gb.predict_proba([features_g1])
            probs_g2 = gb.predict_proba([features_g2])

            team_1_prob = (probs_g1[0][0] + probs_g2[0][1])/2
            team_2_prob = (probs_g2[0][0] + probs_g1[0][1])/2

            if actual_round != p:
                print("-"*10)
                print("Starting simulation of %s"%(p))
                print("-"*10)
                print("\n")

            if team_1_prob < team_2_prob:
                print("%s vs. %s: %s advances with prob %.2f"%(home,
away, away, team_2_prob))
                next_rounds.append(away)
            else:
                print("%s vs. %s: %s advances with prob %.2f"%(home,
away, home, team_1_prob))
                next_rounds.append(home)

            game.append([team_1_prob, team_2_prob])
            playoffs[p][i] = game
```

```
            actual_round = p

    else:
        playoffs[p] = [[next_rounds[c], next_rounds[c+1]] for c in
range(0, len(next_rounds)-1, 1) if c%2 == 0]
        next_rounds = []
        for i in range(0, len(playoffs[p])):
            game = playoffs[p][i]
            home = game[0]
            away = game[1]
            team_1 = find_stats(home)
            team_2 = find_stats(away)

            features_g1 = find_features(team_1, team_2)
            features_g2 = find_features(team_2, team_1)

            probs_g1 = gb.predict_proba([features_g1])
            probs_g2 = gb.predict_proba([features_g2])

            team_1_prob = (probs_g1[0][0] + probs_g2[0][1])/2
            team_2_prob = (probs_g2[0][0] + probs_g1[0][1])/2

            if actual_round != p:
                print("-"*10)
                print("Starting simulation of %s"%(p))
                print("-"*10)
                print("\n")

            if team_1_prob < team_2_prob:
                print("%s vs. %s: %s advances with prob %.2f"%(home,
away, away, team_2_prob))
                next_rounds.append(away)
            else:
                print("%s vs. %s: %s advances with prob %.2f"%(home,
away, home, team_1_prob))
                next_rounds.append(home)
            game.append([team_1_prob, team_2_prob])
            playoffs[p][i] = game
            actual_round = p
```

```
----------
Starting simulation of Quarter-Final
----------


Argentina vs. Mexico: Argentina advances with prob 0.67
United States vs. Colombia: Colombia advances with prob 0.54
Canada vs. Ecuador: Ecuador advances with prob 0.59
Uruguay vs. Brazil: Brazil advances with prob 0.55
----------
```

```
Starting simulation of Semi-Final
-----------


Argentina vs. Colombia: Argentina advances with prob 0.62
Ecuador vs. Brazil: Brazil advances with prob 0.72
-----------
Starting simulation of Final
-----------


Argentina vs. Brazil: Argentina advances with prob 0.56
```

```
plt.figure(figsize=(15, 10))
G = nx.balanced_tree(2, 2)

labels = []

for p in playoffs.keys():
    for game in playoffs[p]:
        label = f"{game[0]}({round(game[2][0], 2)}) \n {game[1]}
({round(game[2][1], 2)})"
        labels.append(label)

labels_dict = {}
labels_rev = list(reversed(labels))

for l in range(len(list(G.nodes))):
    labels_dict[l] = labels_rev[l]

pos = graphviz_layout(G, prog='twopi')
labels_pos = {n: (k[0], k[1] - 0.08 * k[1]) for n, k in pos.items()}
center = pd.DataFrame(pos).mean(axis=1).mean()

nx.draw(G, pos=pos, with_labels=False, node_color=range(len(G.nodes)),
edge_color="#bbf5bb", width=10,
        font_weight='bold', cmap=plt.cm.Greens, node_size=5000)
nx.draw_networkx_labels(G, pos=labels_pos,
                        bbox=dict(boxstyle="round,pad=0.3",
fc="white", ec="black", lw=.5, alpha=1),
                        labels=labels_dict)
texts = ["Quarter \n Final", "Semi \n Final", "Final\n"]
pos_y = pos[0][1] + 55
for text in reversed(texts):
    pos_x = center
    pos_y -= 65
    plt.text(pos_x, pos_y, text, fontsize=18)

plt.axis('equal')
plt.show()
```


Canada(0.43)
Ecuador(0.57)
Panama(0.21)
Brazil(0.79)
Ecuador(0.26)
Brazil(0.74)
Final
Argentina(0.54)
Brazil(0.46)
Semi
Final
Colombia(0.35)
United States(0.45)
Colombia(0.55)
Argentina(0.7)
Mexico(0.3)
Quarter
Final