ativ_4

May 3, 2023

[ ]:
```
# pyright: reportUnusedExpression=false
```

[ ]:
```
# Importando bibliotecas
from tqdm import tqdm
import numpy as np
import pandas as pd
import socceraction.spadl as spd
from socceraction import xthreat as xt
```

[ ]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
import sklearn.metrics as metrics
```

1 [CDAF] Atividade 4

1.1 Nome e matrícula

Nome: Igor Lacerda Faria da Silva Matrícula: 2020041973

1.1.1 LaLiga p/ SPADL com pré-processamentos

[ ]:
```
DATA_FOLDER = "data"
```

[ ]:
```
# Para o depurador...
# DATA_FOLDER = "../data/"
```

[ ]:
```
COUNTRY = "Spain"
```

[ ]:
```
# carregando os eventos
# path = r"C:\Users\Galo\Hugo_Personal\Data\Wyscout_Top_5\events\events_Spain.
  ↪json"
path = f"{DATA_FOLDER}/events/events_{COUNTRY}.json"
events = pd.read_json(path_or_buf=path)
```

[ ]:
```
# pré processamento em colunas da tabela de eventos para facilitar a conversão␣
  ↪p/ SPADL
events = events.rename(
    columns={
        "id": "event_id",
        "eventId": "type_id",
        "subEventId": "subtype_id",
        "teamId": "team_id",
        "playerId": "player_id",
        "matchId": "game_id",
    }
)
events["milliseconds"] = events["eventSec"] * 1000
events["period_id"] = events["matchPeriod"].replace({"1H": 1, "2H": 2})
```

[ ]:

```
# carregando as partidas, pois vamos saber quais times jogam em casa e fora p/␣
 ↪usar como parametro do SPADL
# path = r"C:\Users\Galo\Hugo_Personal\Data\Wyscout_Top_5\matches\matches_Spain.
 ↪json"
path = f"{DATA_FOLDER}/matches/matches_{COUNTRY}.json"
matches = pd.read_json(path_or_buf=path)
```

[ ]:

```
# as informações dos times de cada partida estão em um dicionário dentro da␣
 ↪coluna 'teamsData', então vamos separar essas informações
team_matches = []
for i in tqdm(range(len(matches))):
    teams_data = matches.loc[i, "teamsData"]
    if isinstance(teams_data, dict):  # check if teams_data is a␣
 ↪dictionary-like object
        match = pd.DataFrame(teams_data).T
        match["matchId"] = matches.loc[i, "wyId"]
        team_matches.append(match)
    else:
        # handle the case where teams_data is not a dictionary-like object
        print(f"teamsData for match {matches.loc[i, 'match_id']} is not a␣
 ↪dictionary.")
team_matches = pd.concat(team_matches).reset_index(drop=True)
```

[ ]:

```
# fazendo a conversão p/ SPADL, padronizando a direção de jogo da esquerda p/ a␣
 ↪direita e adicionando os nomes dos tipos de ações
actions = []
game_ids = events.game_id.unique().tolist()
for g in tqdm(game_ids):
    match_events = events.loc[events.game_id == g]
    match_home_id = team_matches.query(f"matchId == {g} and side == 'home'")[
        "teamId"
    ].values[0]
    match_actions = spd.wyscout.convert_to_actions(
        events=match_events, home_team_id=match_home_id
    )
    match_actions = spd.play_left_to_right(
        actions=match_actions, home_team_id=match_home_id
    )
    match_actions = spd.add_names(match_actions)
    actions.append(match_actions)
spadl = pd.concat(actions).reset_index(drop=True)
```

[ ]:

```
# adicionando o nome dos jogadores
# path = r"C:\Users\Galo\Hugo_Personal\Data\Wyscout_Top_5\players.json"
path = f"{DATA_FOLDER}/players/players.json"
players = pd.read_json(path_or_buf=path)
players["player_name"] = players["shortName"].apply(
    lambda x: x.encode("utf-8").decode("unicode-escape")  # conserte as strings
)
players = players[["wyId", "player_name"]].rename(columns={"wyId": "player_id"})
spadl = spadl.merge(players, on="player_id", how="left")
```

1.2 Questão 1

- Crie um dataframe “shots” à partir do dataframe “spadl”, contendo apenas os chutes.
- Crie 4 colunas no dataframe “shots” a serem usadas como features de um modelo de xG.
- Justifique a escolha das features.

[1]:

```
spadl.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 473894 entries, 0 to 473893
Data columns (total 18 columns):
 #   Column             Non-Null Count   Dtype
---  ------             --------------   -----
 0   game_id            473894 non-null  int64
 1   period_id          473894 non-null  int64
 2   time_seconds       473894 non-null  float64
 3   team_id            473894 non-null  int64
 4   player_id          473894 non-null  int64
 5   start_x            473894 non-null  float64
 6   start_y            473894 non-null  float64
 7   end_x              473894 non-null  float64
 8   end_y              473894 non-null  float64
 9   original_event_id  441653 non-null  object
 10  bodypart_id        473894 non-null  int64
 11  type_id            473894 non-null  int64
 12  result_id          473894 non-null  int64
 13  action_id          473894 non-null  int64
 14  type_name          473894 non-null  object
 15  result_name        473894 non-null  object
 16  bodypart_name      473894 non-null  object
 17  player_name        470015 non-null  object
dtypes: float64(5), int64(8), object(5)
```

```
memory usage: 68.7+ MB
```

[2]:
```
types_of_shot = ["shot", "shot_freekick", "shot_penalty"]
df_shots: pd.DataFrame = spadl.query("type_name in @types_of_shot")
df_shots
```

[2]:
```
        game_id  period_id  time_seconds  …  result_name  bodypart_name
player_name
20      2565548          1     57.771186  …         fail           foot  José
Luis Morales
22      2565548          1     60.727239  …         fail           foot
J. Lerma
93      2565548          1    446.986112  …         fail           foot
C. Bacca
96      2565548          1    488.929113  …         fail           foot
A. Rukavina
178     2565548          1    948.872079  …         fail           foot  José
Luis Morales
…           …         …            …  …          …            …
…
473673  2565927          2   1944.188119  …         fail           foot
R. Martínez
473806  2565927          2   2385.837008  …      success           foot
Samu Castillejo
473828  2565927          2   2672.823612  …         fail           foot
Samu Castillejo
473851  2565927          2   2722.835144  …         fail           foot
K. Benzema
473878  2565927          2   2857.346465  …         fail           foot
Lucas Vázquez

[8545 rows x 18 columns]
```

[ ]:
```
GOAL_CENTER_X: int = 105
GOAL_CENTER_Y: int = 34

UPPER_CROSSBAR_X: int = 105
UPPER_CROSSBAR_Y: int = 38

LOWER_CROSSBAR_X: int = 105
LOWER_CROSSBAR_Y: int = 30
```

[ ]:
```
df_shots["shot_distance"] = np.sqrt(
    (df_shots["start_x"] - GOAL_CENTER_X) ** 2
    + (df_shots["start_y"] - GOAL_CENTER_Y) ** 2
)
```

[ ]:

```
def get_shot_angle(shot_pos_x, shot_pos_y):
    u = np.array([UPPER_CROSSBAR_X - shot_pos_x, UPPER_CROSSBAR_Y - shot_pos_y])
    v = np.array([LOWER_CROSSBAR_X - shot_pos_x, LOWER_CROSSBAR_Y - shot_pos_y])
    return np.arccos(np.dot(u / np.linalg.norm(u), v / np.linalg.norm(v)))


df_shots["shot_angle"] = df_shots[["start_x", "start_y"]].apply(
    lambda pos: get_shot_angle(pos["start_x"], pos["start_y"]), axis=1
)
```

[ ]:

```
df_shots["distance_x_angle"] = df_shots["shot_angle"] *␣
 ↪df_shots["shot_distance"]
```

[ ]:

```
df_shots["bodypart_weight"] = df_shots["bodypart_name"].apply(
    lambda x: 1 if x == "foot" else 0.3
)
```

[3]:

```
df_shots.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 8545 entries, 20 to 473878
Data columns (total 22 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   game_id            8545 non-null   int64
 1   period_id          8545 non-null   int64
 2   time_seconds       8545 non-null   float64
 3   team_id            8545 non-null   int64
 4   player_id          8545 non-null   int64
 5   start_x            8545 non-null   float64
 6   start_y            8545 non-null   float64
 7   end_x              8545 non-null   float64
 8   end_y              8545 non-null   float64
 9   original_event_id  8545 non-null   object
 10  bodypart_id        8545 non-null   int64
 11  type_id            8545 non-null   int64
 12  result_id          8545 non-null   int64
 13  action_id          8545 non-null   int64
 14  type_name          8545 non-null   object
 15  result_name        8545 non-null   object
 16  bodypart_name      8545 non-null   object
 17  player_name        8544 non-null   object
 18  shot_distance      8545 non-null   float64
 19  shot_angle         8545 non-null   float64
 20  distance_x_angle   8545 non-null   float64
 21  bodypart_weight    8545 non-null   float64
dtypes: float64(9), int64(8), object(5)
memory usage: 1.5+ MB
```

1.2.1 Escolhas

- Distância: um candidato óbvio, pois é muito mais fácil acertar chutes de perto.
- Ângulo: outro parâmetro clássico, sem muito o que falar.
- `distance_x_angle`: aumentando o peso dos parâmetros tradicionais, peguei mais porque o Meira comentou em uma das aulas.
- `bodypart_weight`: pra fechar o time com chave de ouro, é reduzido o peso de partes do corpo que não são os pés, porque, presumivelmente, é mais difífil fazer gol com outras partes.

1.3 Questão 2

- Crie uma coluna numérica binária "goal" no dataframe "shots" indicando se o chute resultou em gol ou não.
- Use regressão logística p/ treinar (.fit(X_train, y_train)) um modelo de xG usando as features criadas na questão 1.
- Use 70% dos dados para treino e 30% para teste.
- Reporte a acurácia do modelo para os conjuntos de treino (.score(X_train, y_train)) e teste (.score(X_test, y_test)).

[ ]:

```
# Não é necessário criar uma coluna nova, basta usar a coluna de result_id
```

[ ]:

```
x_train, x_test, y_train, y_test = train_test_split(
    df_shots[["shot_distance", "shot_angle", "distance_x_angle",␣
 ↪"bodypart_weight"]],
    df_shots["result_id"],
    test_size=0.3,
)
```

[4]:

```
model = LogisticRegression()
model.fit(x_train, y_train)
```

[4]:

```
LogisticRegression()
```

[5]:

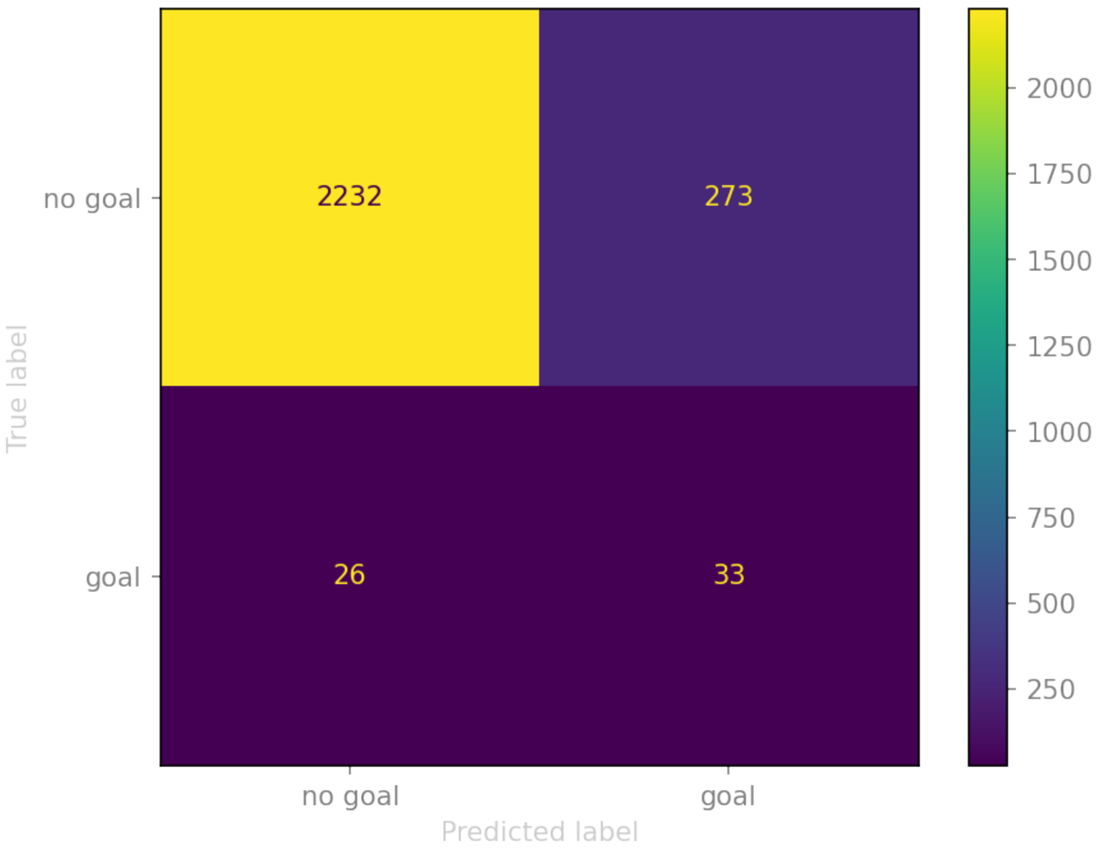
```
y_train_acc = model.score(x_train, y_train)
y_test_acc = model.score(x_test, y_test)

print(f"Acurácia nos dados de treino: {y_train_acc}")
print(f"Acurácia nos dados de teste: {y_test_acc}")
```

```
Acurácia nos dados de treino: 0.8891489717438555
Acurácia nos dados de teste: 0.8833853354134166
```

[6]:

```
y_pred = model.predict(x_test)
cm = metrics.confusion_matrix(y_pred, y_test)
cm_display = metrics.ConfusionMatrixDisplay(
    confusion_matrix=cm, display_labels=["no goal", "goal"]
)
cm_display.plot()
```



```
[6]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at
0x7f3e1de1beb0>
```

1.4 Questão 3

- Use o modelo treinado na questão 2 p/ prever a probabilidade de gol de todos os chutes do dataframe "shots". Reporte essas probabilidades no dataframe "shots" em uma coluna "xG".
- Agrupe o dataframe "shots" por "player_name" e reporte a soma dos "goal" e "xG".
- Reporte os 10 jogadores com maior xG.
- Reporte os 10 jogadores com maior diferença de Gols e xG.

```
[7]: probabilities = model.predict_proba(
         df_shots[["shot_distance", "shot_angle", "distance_x_angle",␣
      ↪"bodypart_weight"]]
)
df_shots["xG"] = probabilities[:, 1]
df_shots["xG"]
```

```
[7]: 20        0.112814
     22        0.062298
     93        0.180006
     96        0.086693
     178       0.033179
                 …
     473673    0.086017
     473806    0.044325
     473828    0.021580
     473851    0.043409
     473878    0.180006
     Name: xG, Length: 8545, dtype: float64
```

```
[8]: columns = ["result_id", "xG"]
     shots_by_player = df_shots.groupby(["player_name"])[columns].sum()
     shots_by_player
```

```
[8]:                 result_id        xG
     player_name
     A. Aquilani             0  0.769327
     A. Arribas              0  0.077680
     A. Fernández            0  0.026776
     A. Griezmann           19  9.123515
     A. Guardado             2  2.043292
     …                     …         …
     Íñigo Martínez          1  2.153181
     Ó. Duarte               0  1.470785
     Óscar Melendo           0  0.758344
     Óscar Romero            0  0.163217
     Š. Vrsaljko             0  0.422765

     [452 rows x 2 columns]
```

```
[9]: shots_by_player.sort_values("xG", ascending=False).head(10)
```

```
[9]:                    result_id         xG
     player_name
     Cristiano Ronaldo          26  26.071219
     L. Messi                   34  22.064910
```

```
L. Suárez                25  21.950556
Gerard Moreno            16  15.967054
Iago Aspas               22  14.729205
Maxi Gómez               18  14.320457
C. Stuani                21  13.285273
C. Bacca                 15  11.026409
J. Calleri                9  10.849497
Jorge Molina              7  10.689162
```

[ ]:

```
shots_by_player["diff"] = shots_by_player["result_id"] - shots_by_player["xG"]
```

[10]:

```
shots_by_player.sort_values("diff", ascending=False)[columns].head(10)
```

[10]:

```
                 result_id         xG
player_name
L. Messi                34  22.064910
A. Griezmann            19   9.123515
C. Stuani               21  13.285273
Iago Aspas              22  14.729205
E. Bardhi                9   2.232741
G. Bale                 16   9.794341
Rodrigo                 16  10.674823
Mikel Oyarzabal         12   6.823400
A. Sanabria              8   3.333896
Ángel                   13   8.423913
```

1.5 Questão 4

- Instancie um objeto ExpectedThreat com parâmetros l=25 e w=16.
- Faça o fit do modelo ExpectedThreat com o dataframe "spadl".

[11]:

```
xT = xt.ExpectedThreat(l=25, w=16)
step = 5000
acc_xT = np.zeros((16, 25))
for i in range(0, len(spadl), step):
    xT.fit(spadl[i : i + step])
    acc_xT += xT.xT
```

```
# iterations:  1
# iterations:  1
# iterations:  1
# iterations:  1
# iterations:  17
# iterations:  19
# iterations:  1
# iterations:  1
# iterations:  20
# iterations:  23
# iterations:  1
# iterations:  1
# iterations:  19
# iterations:  19
# iterations:  19
# iterations:  2
# iterations:  1
# iterations:  1
# iterations:  1
# iterations:  19
# iterations:  1
# iterations:  31
# iterations:  1
# iterations:  1
# iterations:  2
# iterations:  1
# iterations:  1
# iterations:  23
# iterations:  2
# iterations:  1
# iterations:  2
# iterations:  20
# iterations:  2
# iterations:  1
# iterations:  1
# iterations:  1
# iterations:  2
# iterations:  22
# iterations:  1
# iterations:  22
# iterations:  1
# iterations:  1
# iterations:  3
# iterations:  1
# iterations:  1
# iterations:  3
# iterations:  1
# iterations:  2
# iterations:  1
# iterations:  20
# iterations:  22
# iterations:  2
# iterations:  1
# iterations:  1
# iterations:  18
# iterations:  2
# iterations:  1
# iterations:  1
# iterations:  1
# iterations:  1
# iterations:  19
# iterations:  22
# iterations:  2
# iterations:  1
# iterations:  1
# iterations:  1
# iterations:  1
# iterations:  1
# iterations:  1
# iterations:  2
# iterations:  1
# iterations:  1
# iterations:  24
# iterations:  2
# iterations:  1
# iterations:  1
# iterations:  17
# iterations:  1
# iterations:  2
# iterations:  22
# iterations:  19
# iterations:  1
# iterations:  19
# iterations:  13
# iterations:  1
# iterations:  2
# iterations:  1
# iterations:  1
# iterations:  1
# iterations:  1
# iterations:  1
# iterations:  19
# iterations:  1
# iterations:  2
# iterations:  2
```

1.6 Questão 5

- Crie um dataframe "prog_actions" à partir do dataframe "spadl", contendo apenas as ações de progressão e que são bem-sucedidas.
- Use o método rate do objeto ExpectedThreat p/ calcular o valor de cada ação de progressão do dataframe "prog_actions", em uma coluna chamada "action_value".
- Agrupe o dataframe "prog_actions" por "player_name" e reporte a soma dos "action_value".
- Reporte os 10 jogadores com maior "action_value".

[ ]:

```
prog_actions = xt.get_successful_move_actions(spadl)
xT.xT = acc_xT
prog_actions["action_value"] = xT.rate(prog_actions)
```

[ ]:

```
action_value = prog_actions.groupby("player_name")["action_value"].sum()
```

[12]:

```
action_value.nlargest(n=10)
```

[12]:

```
player_name
José Luis Morales    97.141770
Portu                90.276712
L. Messi             90.226312
Lucas Vázquez        81.393274
Isco                 71.801897
Marcelo              68.236663
P. Sisto             65.979041
Gonçalo Guedes       64.054006
A. Guardado          61.597146
José Gayá            61.447502
Name: action_value, dtype: float64
```