efd_starting_kit

January 17, 2021

1 The European Football Database

1.1 1. Introduction

The data give information on the matches played in 11 different European leagues over 8 years (from the 2008/2009 season to the 2015/2016 season). Most of the leagues consist of 20 teams (for example the German league consists of 18 teams) which play 2 matches against each other (one home and one away). In other words, each team plays a total of 38 matches in one season.

A team wins 3 points with each win, 1 point after a draw and wins nothing after a defeat. The team with the most points at the end of the season wins the league. In case of a tie in points between two (or more) teams, the champion is chosen according to the specific rules of each league. For example in Spain, the champion is the winner of the direct matches between the teams concerned.

At the end of a season, the 2 worst performing teams are replaced by the 2 best teams of the second division league. The team ranked 18th plays against the 3rd of second division. The winner plays in first division and the loser plays in second division.

[27]:
```
import problem
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import problem

X_train, y_train = problem.get_train_data()
X_test, y_test = problem.get_test_data()
X_train.columns
```

[27]:
```
Index(['stage', 'date', 'home_team_api_id', 'away_team_api_id',
       'home_player_X1', 'home_player_X2', 'home_player_X3', 'home_player_X4',
       'home_player_X5', 'home_player_X6', 'home_player_X7', 'home_player_X8',
       'home_player_X9', 'home_player_X10', 'home_player_X11',
       'away_player_X1', 'away_player_X2', 'away_player_X3', 'away_player_X4',
       'away_player_X5', 'away_player_X6', 'away_player_X7', 'away_player_X8',
       'away_player_X9', 'away_player_X10', 'away_player_X11',
       'home_player_Y1', 'home_player_Y2', 'home_player_Y3', 'home_player_Y4',
       'home_player_Y5', 'home_player_Y6', 'home_player_Y7', 'home_player_Y8',
       'home_player_Y9', 'home_player_Y10', 'home_player_Y11',
       'away_player_Y1', 'away_player_Y2', 'away_player_Y3', 'away_player_Y4',
```

```
'away_player_Y5', 'away_player_Y6', 'away_player_Y7', 'away_player_Y8',
 'away_player_Y9', 'away_player_Y10', 'away_player_Y11', 'B365H',
 'B365D', 'B365A', 'BWH', 'BWD', 'BWA', 'IWH', 'IWD', 'IWA', 'LBH',
 'LBD', 'LBA', 'PSH', 'PSD', 'PSA', 'WHH', 'WHD', 'WHA', 'SJH', 'SJD',
 'SJA', 'VCH', 'VCD', 'VCA', 'GBH', 'GBD', 'GBA', 'BSH', 'BSD', 'BSA'],
dtype='object')
```

[22]:
```
y_test.value_counts()
```

[22]:
```
0    2953
1    1993
2    1705
dtype: int64
```

1.2 2. Description of the columns

Now, time to present the features we have, in the `X` dataframe.

1.2.1 2.1. Non-discriminative variables:

- `date`: date of the match
- `stage` : means the order of the match within the season. Goes from 1 to 38
- `home_team_api_id`: id of the home team
- `away_team_api_id`: id of the visitor team

1.2.2 2.2. Discriminative variables:

- `home_player_Xi`, `home_player_Yi`, `away_player_Xi`, `away_player_Yi`: X/Y coordinate for the i-th player of the home/away team in the field, at the beginning of the match
- `B365H`: Bet factor favouring home team win according to B365 betting website
- `B365A`: Bet factor favouring away team win according to B365 betting website
- `B365D`: Bet factor favouring a draw according to B365 betting website
- Same goes when we replace `B365` with: `BW`, `IW`, `LB`, `PS`, `WH`, `SJ`, `VC`, `GB` and `SH`.

1.2.3 2.3. Target categories

There are 3 possible classes, corresponding to the 3 possible outcomes of a match.

- 0; home team wins
- 1: away team wins
- 2: draw match, none of the teams wins

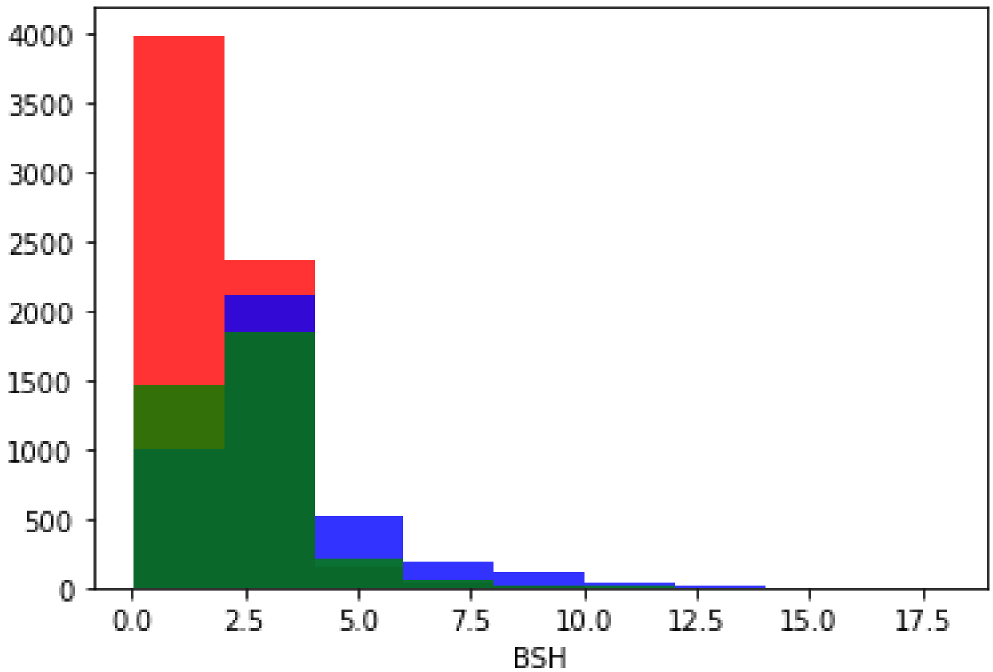
1.3 3. Exploratory Data Analysis

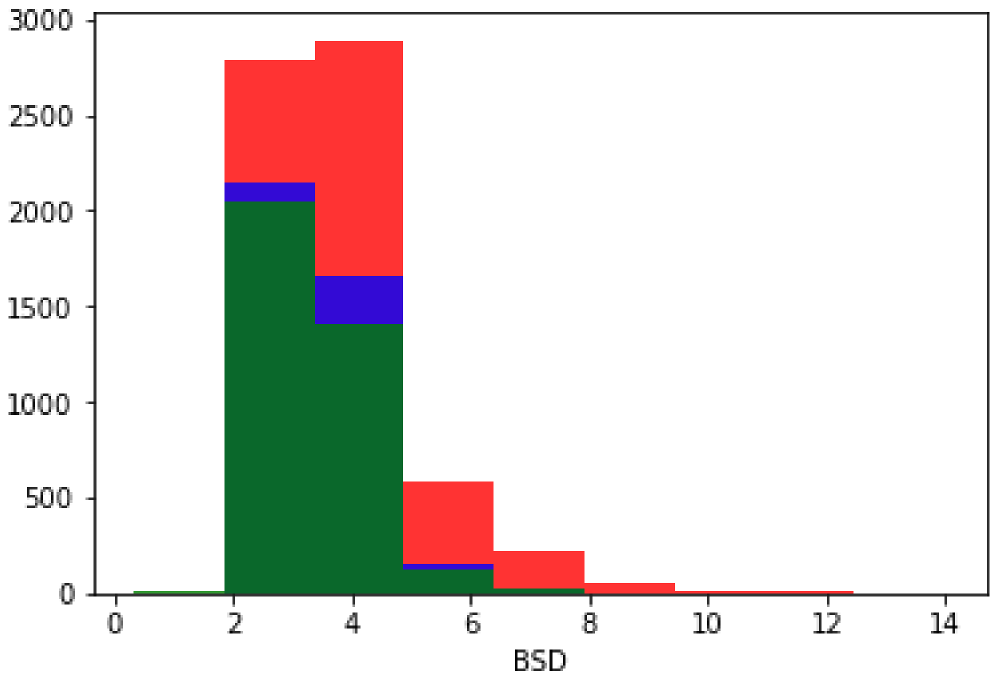
We'll do here some plots, as seen in the Stars challenge

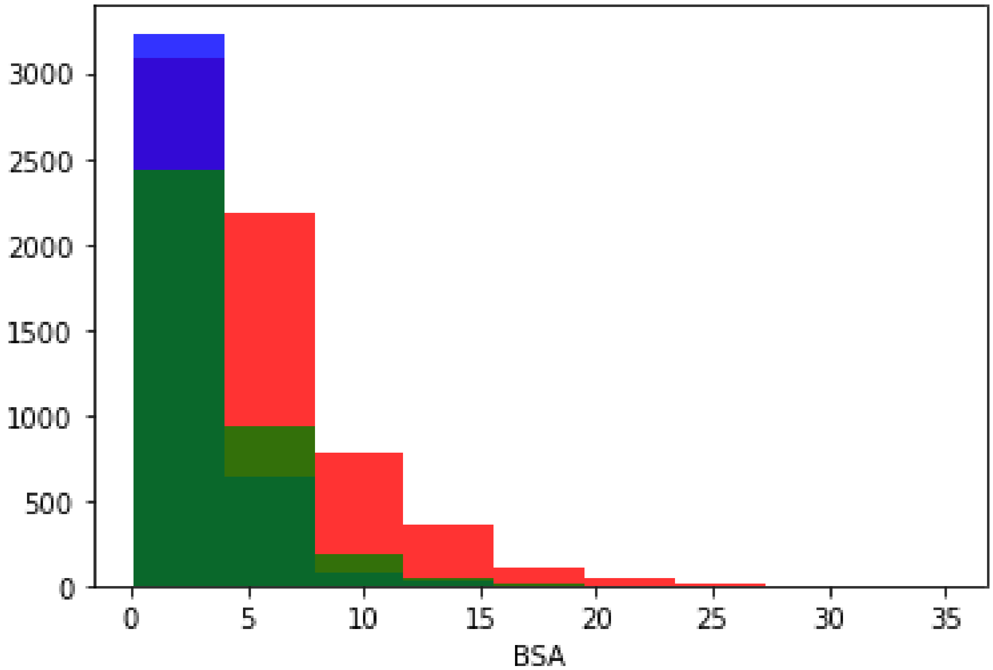
[30]:
```
# Visualisation selon les variables :

colors = ['r', 'b', 'g']
labels = [0,1,2]

def plot_classwise_normalized(feature, bins=None):
    if bins is None:
        bins = np.linspace(X_train[feature].min()-1, X_train[feature].max()+1,␣
 ↪10)
    for label, color in zip(labels, colors):
        plt.hist(X_train[y_train == label][feature].values, density=False,␣
 ↪bins=bins,
                 alpha=0.8, color=color)
        plt.xlabel(feature)

def plot_classwise_scatter(feature1, feature2, range1=None, range2=None):
    if range1 is None:
        range1 = [X_train[feature1].min(), X_train[feature1].max()]
    if range2 is None:
        range2 = [X_train[feature2].min(), X_train[feature2].max()]
    for label, color in zip(labels, colors):
        plt.xlim(range1[0], range1[1])
        plt.ylim(range2[0], range2[1])
        plt.scatter(X_train[y_train == label][feature1],
                    X_train[y_train == label][feature2],
            alpha=0.3, s=80, c=color, marker='.')
```

In the plots below, the ordinate corresponds to the number of matches while the abscissa corresponds to the bet factor of the corresponding feature. The color refers to the outcome of the game. We can see for exemple in the first plot where the bet factor of home team winning was giving the lowest values, since the home team winning was considered more likely, the majority of those matches ended up with the home team winning while some ended up with a draw and very few of none with the away team winning.

[31]:
```
features = ["BSH","BSD","BSA"]
for feature in features :
    plt.figure()
    plot_classwise_normalized(feature)
```

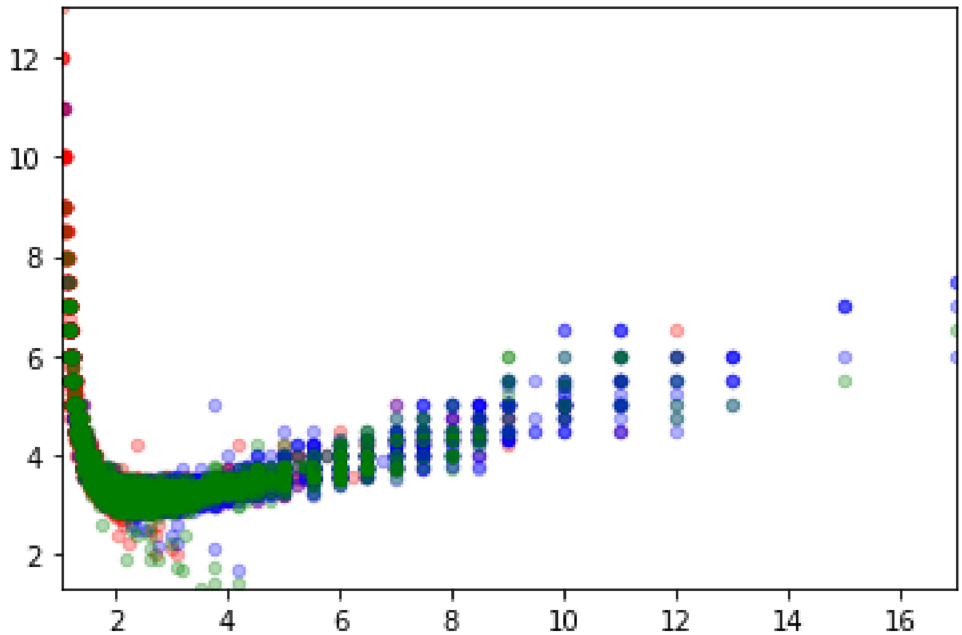

4000
3500
3000
2500
2000
1500
1000
500
0
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
BSH

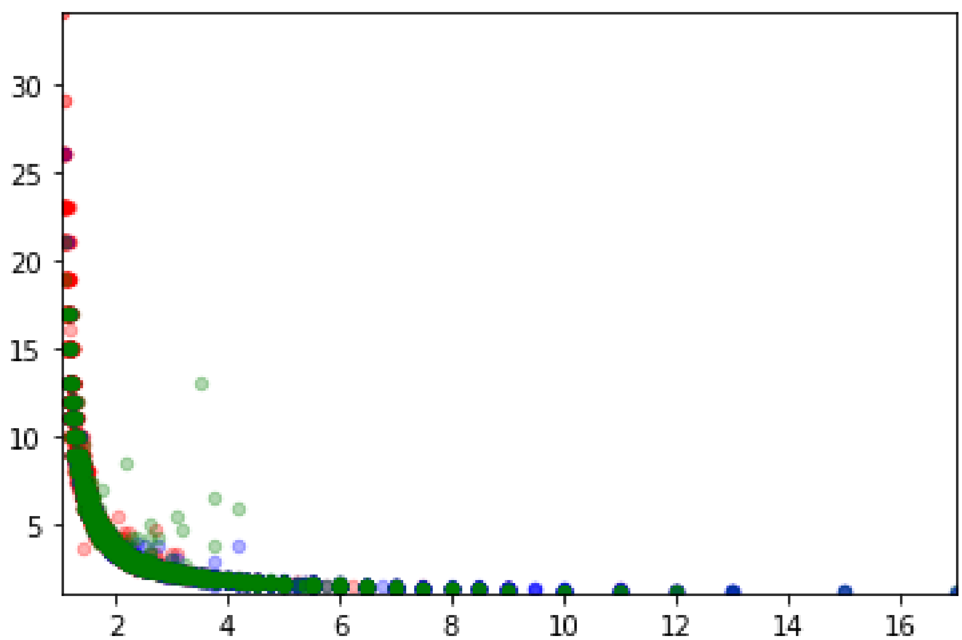

3000
2500
2000
1500
1000
500
0
0
2
4
6
8
10
12
14
BSD

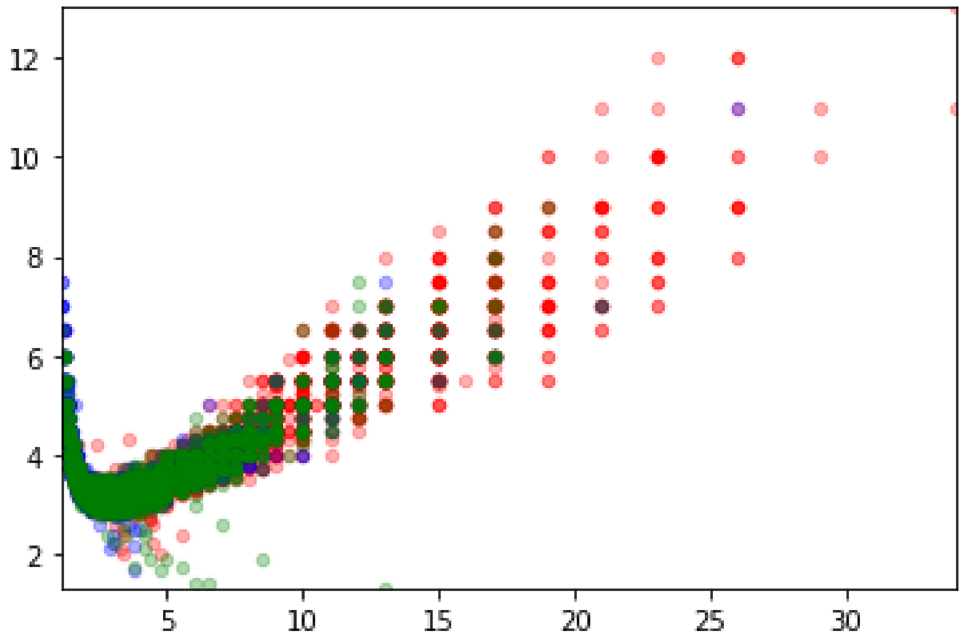


In the plots below, we are plotting for each game the value of the bet factor of 2 features and the color corresponds to the outcome of that game.

[25]:
```
plt.figure()
plot_classwise_scatter("BSH","BSD")
plt.figure()
plot_classwise_scatter("BSH","BSA")
plt.figure()
plot_classwise_scatter("BSA","BSD")
```

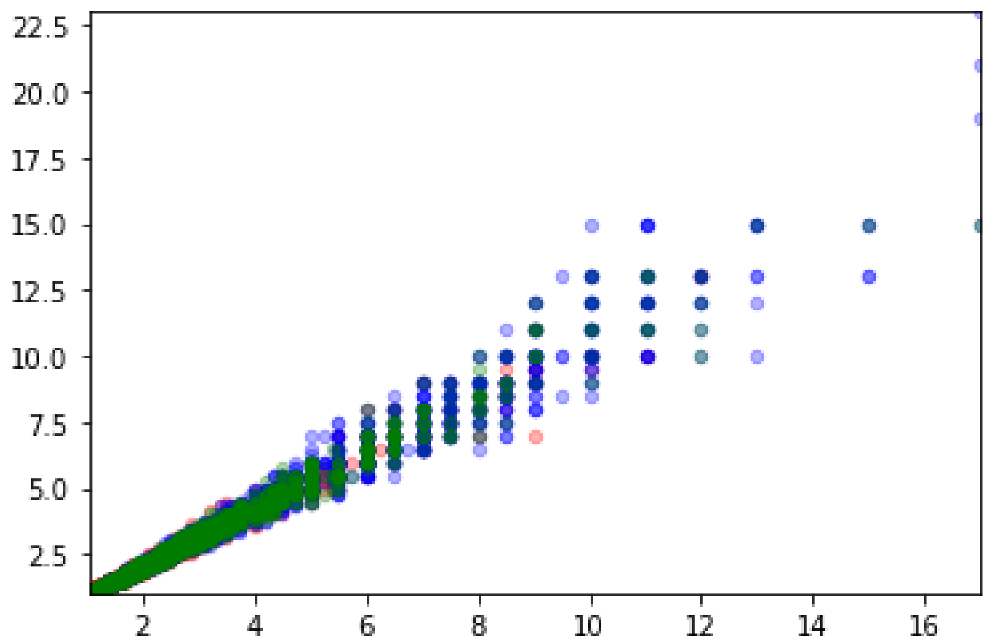

12
10
8
6
4
2
2
4
6
8
10
12
14
16

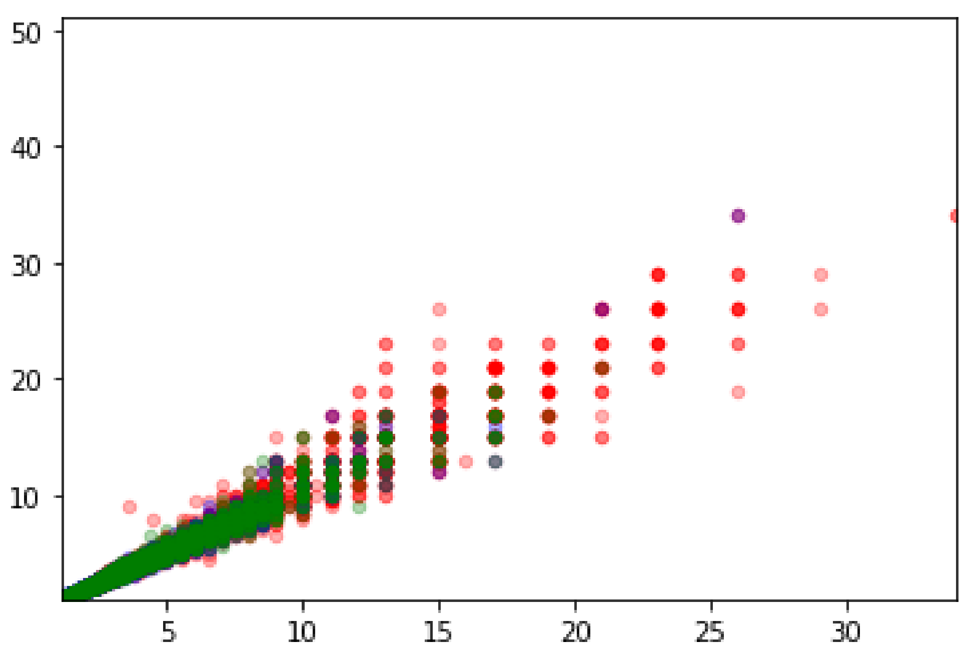

30
25
20
15
10
5
2
4
6
8
10
12
14
16

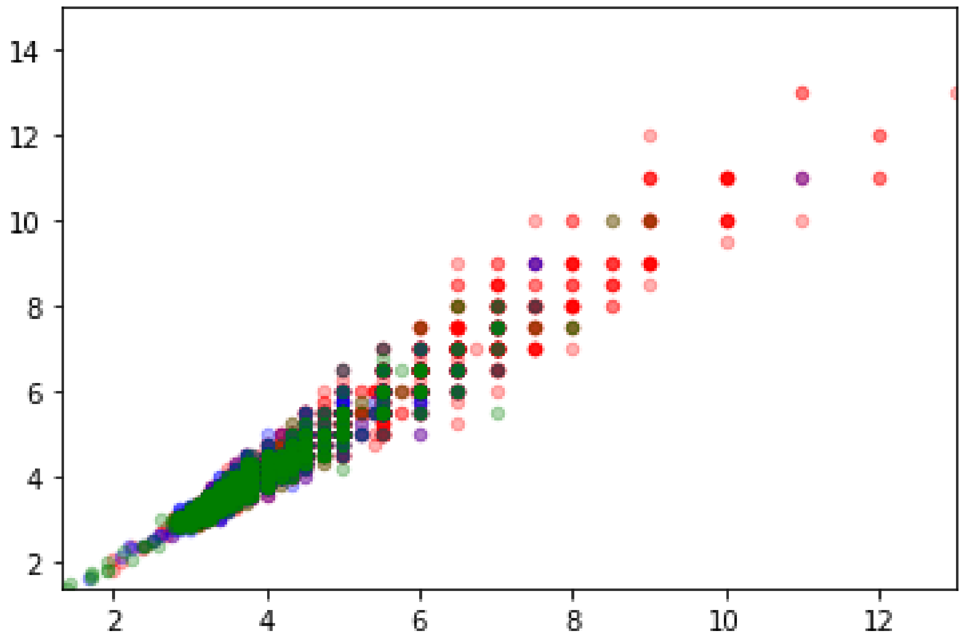


In these plots we compare for each game the bet factor of the same results giving by 2 different websites and the color corresponds to the outcome of that game. In the first plot we compare the bet factor favoring home team win and in the second one the bet factor favoring away team and in the third plot we compare the bet value favoring a draw.

[26]:
```
plt.figure()
plot_classwise_scatter("BSH", "B365H")
plt.figure()
plot_classwise_scatter("BSA", "B365A")
plt.figure()
plot_classwise_scatter("BSD", "B365D")
```


22.5
20.0
17.5
15.0
12.5
10.0
7.5
5.0
2.5
2
4
6
8
10
12
14
16


50
40
30
20
10
5
10
15
20
25
30



1.4 4. Explanation of the challenge

The goal is to predict the outcome of a match, given the data we have. We make the (strong) hypothesis the outcome of the match depends only on the columns given. But one can compute aggregated features using the previous columns, as they are ordered chronologically, using the wonderful `sklearn`'s `FunctionTransformers`.

1.4.1 Example of pipeline with a Random Forests classifier

[19]:
```
from sklearn.pipeline import make_pipeline
from sklearn.ensemble import RandomForestClassifier
from sklearn.impute import SimpleImputer
from sklearn.metrics import accuracy_score

cols = X_train.columns.drop('date')

transformer = make_column_transformer(
    ('passthrough', cols)
)

pipe = make_pipeline(
    transformer,
    SimpleImputer(strategy='most_frequent'),
    RandomForestClassifier(max_depth=3, n_estimators=20)
)
```

```
pipe.fit(X_train, y_train)

y_pred = pipe.predict(X_test)

print(accuracy_score(y_test, y_pred))
```

```
0.5104495564576755
```

1.5 5. Submission

To submit your code, you can refer to the online documentation.