Рубежный контроль №2

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Применяемые методы:

```
Метод опорных векторов
Градиентный бустинг
```

Задание

Для заданного набора данных постройте модели классификации или регрессии (в зависимости от конкретной задачи, рассматриваемой в наборе данных).

Для построения моделей используйте методы: Метод опорных векторов, Градиентный бустинг.

Оцените качество моделей на основе подходящих метрик качества (двух).

```
Какие метрики качества Вы использовали и почему?

Какие выводы Вы можете сделать о качестве построенных моделей?
```

Для построения моделей необходимо выполнить требуемую предобработку данных: заполнение пропусков, кодирование категориальных признаков, и т.д.

Реализация

Импорт библиотек

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn import preprocessing
from io import StringIO
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import MinMaxScaler, StandardScaler,
Normalizer
from sklearn.svm import SVC

from sklearn.neighbors import KNeighborsClassifier,
KNeighborsRegressor
from sklearn.metrics import accuracy_score, confusion_matrix,
roc_auc_score, ConfusionMatrixDisplay, precision_score, recall_score,
f1_score, classification_report, roc_curve, plot_roc_curve, auc,
precision_recall_curve, plot_precision_recall_curve,
```

```
average_precision_score
from sklearn.ensemble import GradientBoostingClassifier,
RandomForestClassifier

from sklearn.model_selection import train_test_split, cross_val_score,
GridSearchCV



%matplotlib inline
sns.set(style="ticks")

# скроем предупреждения о возможных ошибках для лучшей читаемости
import warnings
warnings.filterwarnings('ignore')
```

Смотрим на датасет

```
df = pd.read_csv('./FIFA 2018 Statistics.csv')

df.shape

(128, 27)

df.head()

         Date           Team      Opponent  Goal Scored  Ball
Possession %  \
0  14-06-2018         Russia  Saudi Arabia            5
40
1  14-06-2018  Saudi Arabia        Russia            0
60
2  15-06-2018         Egypt       Uruguay            0
43
3  15-06-2018       Uruguay         Egypt            1
57
4  15-06-2018       Morocco          Iran            0
64

   Attempts  On-Target  Off-Target  Blocked  Corners  ...  Yellow Card
\
0        13          7           3        3        6  ...            0

1         6          0           3        3        2  ...            0

2         8          3           3        2        0  ...            2

3        14          4           6        4        5  ...            0

4        13          3           6        4        5  ...            1
```

```
   Yellow & Red  Red  Man of the Match  1st Goal        Round  PSO  \
0             0    0               Yes      12.0  Group Stage   No
1             0    0                No       NaN  Group Stage   No
2             0    0                No       NaN  Group Stage   No
3             0    0               Yes      89.0  Group Stage   No
4             0    0                No       NaN  Group Stage   No

   Goals in PSO  Own goals  Own goal Time
0             0        NaN            NaN
1             0        NaN            NaN
2             0        NaN            NaN
3             0        NaN            NaN
4             0        1.0           90.0

[5 rows x 27 columns]
```

```
df.describe()
```

```
       Goal Scored  Ball Possession %    Attempts   On-Target  Off-
Target  \
count   128.000000         128.000000  128.000000  128.000000
128.000000
mean      1.320312          49.992188   12.593750    3.914062
5.273438
std       1.156519          10.444074    5.245827    2.234403
2.409675
min       0.000000          25.000000    3.000000    0.000000
1.000000
25%       0.000000          42.000000    9.000000    2.000000
4.000000
50%       1.000000          50.000000   12.000000    3.500000
5.000000
75%       2.000000          58.000000   15.000000    5.000000
7.000000
max       6.000000          75.000000   26.000000   12.000000
11.000000

          Blocked     Corners    Offsides  Free Kicks       Saves  ...
\
count  128.000000  128.000000  128.000000  128.000000  128.000000  ...

mean     3.359375    4.718750    1.343750   14.890625    2.726562  ...

std      2.403195    2.446072    1.193404    4.724262    2.049447  ...

min      0.000000    0.000000    0.000000    5.000000    0.000000  ...

25%      1.750000    3.000000    0.000000   11.000000    1.000000  ...

50%      3.000000    5.000000    1.000000   15.000000    2.000000  ...
```

```
75%      4.000000    6.000000    2.000000   18.000000    4.000000  ...
max     10.000000   11.000000    5.000000   26.000000    9.000000  ...


             Passes  Distance Covered (Kms)  Fouls Committed  Yellow
Card  \
count   128.000000              128.000000       128.000000
128.000000
mean    462.648438              106.664062        13.546875
1.695312
std     151.186311               11.749537         4.619131
1.325454
min     189.000000               80.000000         5.000000
0.000000
25%     351.000000              101.000000        10.000000
1.000000
50%     462.000000              104.500000        13.000000
2.000000
75%     555.250000              109.000000        16.000000
2.000000
max    1137.000000              148.000000        25.000000
6.000000

       Yellow & Red         Red   1st Goal  Goals in PSO  Own goals  \
count    128.000000  128.000000  94.000000    128.000000       12.0
mean       0.015625    0.015625  39.457447      0.203125        1.0
std        0.124507    0.124507  24.496506      0.807049        0.0
min        0.000000    0.000000   1.000000      0.000000        1.0
25%        0.000000    0.000000  18.250000      0.000000        1.0
50%        0.000000    0.000000  39.000000      0.000000        1.0
75%        0.000000    0.000000  54.750000      0.000000        1.0
max        1.000000    1.000000  90.000000      4.000000        1.0

       Own goal Time
count      12.000000
mean       45.833333
std        29.978275
min        12.000000
25%        21.750000
50%        35.000000
75%        75.750000
max        90.000000

[8 rows x 21 columns]
```

```
print("Размер набора:")
print(f'В датасете {df.shape[0]} строк и {df.shape[1]} колонок.')
```

```
Размер набора:
В датасете 128 строк и 27 колонок.
```

```
df.dtypes
```

```
Date                          object
Team                          object
Opponent                      object
Goal Scored                    int64
Ball Possession %              int64
Attempts                       int64
On-Target                      int64
Off-Target                     int64
Blocked                        int64
Corners                        int64
Offsides                       int64
Free Kicks                     int64
Saves                          int64
Pass Accuracy %                int64
Passes                         int64
Distance Covered (Kms)         int64
Fouls Committed                int64
Yellow Card                    int64
Yellow & Red                   int64
Red                            int64
Man of the Match              object
1st Goal                     float64
Round                         object
PSO                           object
Goals in PSO                   int64
Own goals                    float64
Own goal Time                float64
dtype: object
```

```
df.isnull().sum()
```

```
Date                          0
Team                          0
Opponent                      0
Goal Scored                   0
Ball Possession %             0
Attempts                      0
On-Target                     0
Off-Target                    0
Blocked                       0
Corners                       0
Offsides                      0
Free Kicks                    0
Saves                         0
Pass Accuracy %               0
```

```
Passes                        0
Distance Covered (Kms)        0
Fouls Committed               0
Yellow Card                   0
Yellow & Red                  0
Red                           0
Man of the Match              0
1st Goal                     34
Round                         0
PSO                           0
Goals in PSO                  0
Own goals                   116
Own goal Time               116
dtype: int64
```

```
df = df.drop(['Own goals', 'Own goal Time', '1st Goal'], axis=1)
```

```
df.isnull().sum()
```

```
Date                        0
Team                        0
Opponent                    0
Goal Scored                 0
Ball Possession %           0
Attempts                    0
On-Target                   0
Off-Target                  0
Blocked                     0
Corners                     0
Offsides                    0
Free Kicks                  0
Saves                       0
Pass Accuracy %             0
Passes                      0
Distance Covered (Kms)      0
Fouls Committed             0
Yellow Card                 0
Yellow & Red                0
Red                         0
Man of the Match            0
Round                       0
PSO                         0
Goals in PSO                0
dtype: int64
```

Приступаем к выбору задачи и ее решению

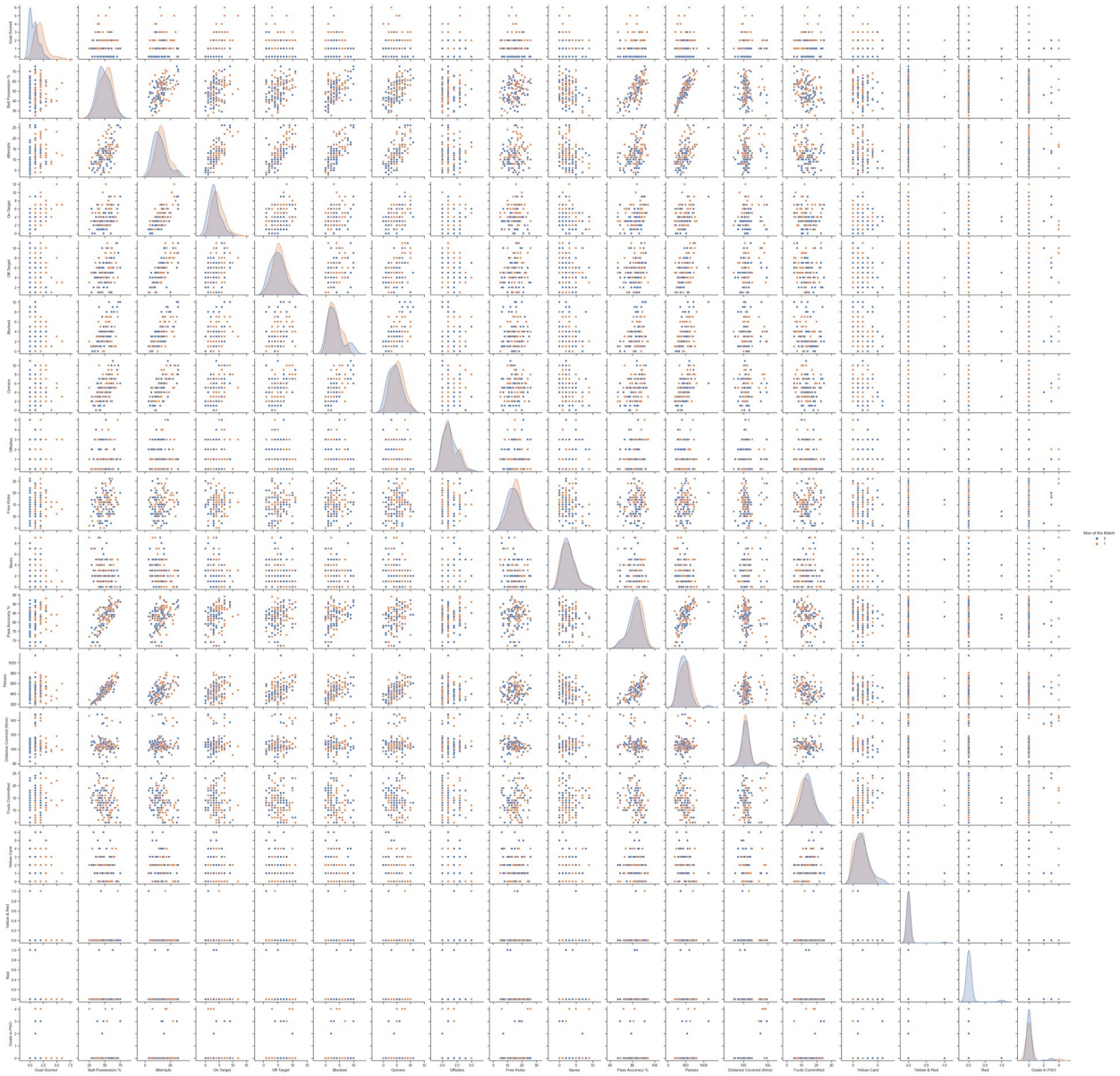
Столбец "Man of the Match" выберем как классификатор. Для этого заменим переменные

```
cleanup_nums = {"Man of the Match":     {"Yes": 1, "No": 0}}

df = df.replace(cleanup_nums)

df["Man of the Match"].value_counts()
```

```
1    64
0    64
Name: Man of the Match, dtype: int64
```

```
int_df = df.select_dtypes(include=['int64', 'float64']).copy()

sns.pairplot(df, hue="Man of the Match")
```

```
<seaborn.axisgrid.PairGrid at 0x1762e6bf370>
```



С использованием метода train_test_split разделите выборку на обучающую и тестовую.

```
X = int_df.drop('Man of the Match', axis=1)
Y = int_df['Man of the Match']

X_train, X_test, Y_train, Y_test = train_test_split(X, Y,
test_size=0.25, random_state=2)
print('{}, {}'.format(X_train.shape, X_test.shape))
print('{}, {}'.format(Y_train.shape, Y_test.shape))
```

```
(96, 18), (32, 18)
(96,), (32,)
```

```
SVC1 = SVC()
SVC1.fit(X_train, Y_train)
```

```
SVC()
```

```
My_KNN_target_1_0 = SVC1.predict(X_train)
My_KNN_Y_Pred = SVC1.predict(X_test)
print(f'Accuracy:',     accuracy_score(Y_train,My_KNN_target_1_0),
accuracy_score(Y_test,My_KNN_Y_Pred))
print(f'Precision:',    precision_score(Y_train,My_KNN_target_1_0),
precision_score(Y_test,My_KNN_Y_Pred))
print(f'F1:',           f1_score(Y_train,My_KNN_target_1_0),
f1_score(Y_test,My_KNN_Y_Pred))
print(f'Recall:',       recall_score(Y_train,My_KNN_target_1_0),
recall_score(Y_test,My_KNN_Y_Pred))
```

```
Accuracy: 0.5520833333333334 0.5625
Precision: 0.5517241379310345 0.7
F1: 0.42666666666666664 0.5
Recall: 0.34782608695652173 0.3888888888888889
```

```
GBC = GradientBoostingClassifier()
GBC.fit(X_train, Y_train)
```

```
GradientBoostingClassifier()
```

```
My_KNN_target_1_0 = GBC.predict(X_train)
My_KNN_Y_Pred = GBC.predict(X_test)
print(f'Accuracy:',     accuracy_score(Y_train,My_KNN_target_1_0),
accuracy_score(Y_test,My_KNN_Y_Pred))
print(f'Precision:',    precision_score(Y_train,My_KNN_target_1_0),
precision_score(Y_test,My_KNN_Y_Pred))
print(f'F1:',           f1_score(Y_train,My_KNN_target_1_0),
f1_score(Y_test,My_KNN_Y_Pred))
print(f'Recall:',       recall_score(Y_train,My_KNN_target_1_0),
recall_score(Y_test,My_KNN_Y_Pred))
```

```
Accuracy: 1.0 0.625
Precision: 1.0 0.6666666666666666
F1: 1.0 0.6666666666666666
Recall: 1.0 0.6666666666666666
```