ИУ5-62Б Корчевский Александр

РК2. Вариант 11

Задание. Для заданного набора данных (по Вашему варианту) постройте модели классификации или регрессии (в зависимости от конкретной задачи, рассматриваемой в наборе данных). Для построения моделей используйте методы: Метод опорных векторов, Случайный лес. Оцените качество моделей на основе подходящих метрик качества (не менее двух метрик). 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.

In [1]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split,  GridSearchCV
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier
```

In [2]:
```
data = pd.read_csv('data.csv')
data.head()
```

Out[2]:

	Unnamed: 0	ID	Name	Age	Photo	Nationality	Flag	Overall	Potential
0	0	158023	L. Messi	31	https://cdn.sofifa.org/players/4/19/158023.png	Argentina	https://cdn.sofifa.org/flags/52.png	94	94
1	1	20801	Cristiano Ronaldo	33	https://cdn.sofifa.org/players/4/19/20801.png	Portugal	https://cdn.sofifa.org/flags/38.png	94	94
2	2	190871	Neymar Jr	26	https://cdn.sofifa.org/players/4/19/190871.png	Brazil	https://cdn.sofifa.org/flags/54.png	92	93
3	3	193080	De Gea	27	https://cdn.sofifa.org/players/4/19/193080.png	Spain	https://cdn.sofifa.org/flags/45.png	91	93
4	4	192985	K. De Bruyne	27	https://cdn.sofifa.org/players/4/19/192985.png	Belgium	https://cdn.sofifa.org/flags/7.png	91	92

5 rows × 89 columns

In [3]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 18207 entries, 0 to 18206
Data columns (total 89 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   Unnamed: 0                18207 non-null  int64
 1   ID                        18207 non-null  int64
 2   Name                      18207 non-null  object
 3   Age                       18207 non-null  int64
 4   Photo                     18207 non-null  object
 5   Nationality               18207 non-null  object
 6   Flag                      18207 non-null  object
 7   Overall                   18207 non-null  int64
 8   Potential                 18207 non-null  int64
 9   Club                      17966 non-null  object
 10  Club Logo                 18207 non-null  object
 11  Value                     18207 non-null  object
 12  Wage                      18207 non-null  object
 13  Special                   18207 non-null  int64
 14  Preferred Foot            18159 non-null  object
 15  International Reputation  18159 non-null  float64
 16  Weak Foot                 18159 non-null  float64
 17  Skill Moves               18159 non-null  float64
 18  Work Rate                 18159 non-null  object
 19  Body Type                 18159 non-null  object
 20  Real Face                 18159 non-null  object
 21  Position                  18147 non-null  object
 22  Jersey Number             18147 non-null  float64
 23  Joined                    16654 non-null  object
 24  Loaned From               1264 non-null   object
 25  Contract Valid Until      17918 non-null  object
 26  Height                    18159 non-null  object
 27  Weight                    18159 non-null  object
 28  LS                        16122 non-null  object
 29  ST                        16122 non-null  object
 30  RS                        16122 non-null  object
 31  LW                        16122 non-null  object
 32  LF                        16122 non-null  object
 33  CF                        16122 non-null  object
 34  RF                        16122 non-null  object
 35  RW                        16122 non-null  object
 36  LAM                       16122 non-null  object
 37  CAM                       16122 non-null  object
 38  RAM                       16122 non-null  object
 39  LM                        16122 non-null  object
 40  LCM                       16122 non-null  object
 41  CM                        16122 non-null  object
 42  RCM                       16122 non-null  object
 43  RM                        16122 non-null  object
 44  LWB                       16122 non-null  object
 45  LDM                       16122 non-null  object
 46  CDM                       16122 non-null  object
 47  RDM                       16122 non-null  object
 48  RWB                       16122 non-null  object
 49  LB                        16122 non-null  object
 50  LCB                       16122 non-null  object
 51  CB                        16122 non-null  object
 52  RCB                       16122 non-null  object
 53  RB                        16122 non-null  object
 54  Crossing                  18159 non-null  float64
 55  Finishing                 18159 non-null  float64
 56  HeadingAccuracy           18159 non-null  float64
 57  ShortPassing              18159 non-null  float64
 58  Volleys                   18159 non-null  float64
 59  Dribbling                 18159 non-null  float64
 60  Curve                     18159 non-null  float64
 61  FKAccuracy                18159 non-null  float64
 62  LongPassing               18159 non-null  float64
 63  BallControl               18159 non-null  float64
 64  Acceleration              18159 non-null  float64
 65  SprintSpeed               18159 non-null  float64
 66  Agility                   18159 non-null  float64
 67  Reactions                 18159 non-null  float64
 68  Balance                   18159 non-null  float64
 69  ShotPower                 18159 non-null  float64
 70  Jumping                   18159 non-null  float64
 71  Stamina                   18159 non-null  float64
 72  Strength                  18159 non-null  float64
 73  LongShots                 18159 non-null  float64
 74  Aggression                18159 non-null  float64
 75  Interceptions             18159 non-null  float64
 76  Positioning               18159 non-null  float64
 77  Vision                    18159 non-null  float64
 78  Penalties                 18159 non-null  float64
 79  Composure                 18159 non-null  float64
 80  Marking                   18159 non-null  float64
 81  StandingTackle            18159 non-null  float64
 82  SlidingTackle             18159 non-null  float64
 83  GKDiving                  18159 non-null  float64
 84  GKHandling                18159 non-null  float64
 85  GKKicking                 18159 non-null  float64
 86  GKPositioning             18159 non-null  float64
 87  GKReflexes                18159 non-null  float64
 88  Release Clause            16643 non-null  object
dtypes: float64(38), int64(6), object(45)
memory usage: 12.4+ MB
```

In [4]:
```
print('Количество пропущенных значений')
data.isnull().sum()
```

Out[4]:
```
Количество пропущенных значений
Unnamed: 0           0
ID                   0
Name                 0
Age                  0
Photo                0
                  ...
GKHandling          48
GKKicking           48
GKPositioning       48
GKReflexes          48
Release Clause    1564
Length: 89, dtype: int64
```

Удалим строки с пропущенными значениями и столбцы, не влияющие на целевой признак

In [5]:
```
del data['Unnamed: 0']
del data['Name']
del data['Photo']
del data['Flag']
del data['Club Logo']
del data['Loaned From']
del data['Joined']
del data['Contract Valid Until']
```

In [6]:
```
data = data.dropna()
data.isnull().sum()
```

Out[6]:
```
ID                0
Age               0
Nationality       0
Overall           0
Potential         0
                 ..
GKHandling        0
GKKicking         0
GKPositioning     0
GKReflexes        0
Release Clause    0
Length: 81, dtype: int64
```

In [7]:
```
data = data[:500]
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 500 entries, 0 to 588
Data columns (total 81 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   ID                        500 non-null    int64
 1   Age                       500 non-null    int64
 2   Nationality               500 non-null    object
 3   Overall                   500 non-null    int64
 4   Potential                 500 non-null    int64
 5   Club                      500 non-null    object
 6   Value                     500 non-null    object
 7   Wage                      500 non-null    object
 8   Special                   500 non-null    int64
 9   Preferred Foot            500 non-null    object
 10  International Reputation  500 non-null    float64
 11  Weak Foot                 500 non-null    float64
 12  Skill Moves               500 non-null    float64
 13  Work Rate                 500 non-null    object
 14  Body Type                 500 non-null    object
 15  Real Face                 500 non-null    object
 16  Position                  500 non-null    object
 17  Jersey Number             500 non-null    float64
 18  Height                    500 non-null    object
 19  Weight                    500 non-null    object
 20  LS                        500 non-null    object
 21  ST                        500 non-null    object
 22  RS                        500 non-null    object
 23  LW                        500 non-null    object
 24  LF                        500 non-null    object
 25  CF                        500 non-null    object
 26  RF                        500 non-null    object
 27  RW                        500 non-null    object
 28  LAM                       500 non-null    object
 29  CAM                       500 non-null    object
 30  RAM                       500 non-null    object
 31  LM                        500 non-null    object
 32  LCM                       500 non-null    object
 33  CM                        500 non-null    object
 34  RCM                       500 non-null    object
 35  RM                        500 non-null    object
 36  LWB                       500 non-null    object
 37  LDM                       500 non-null    object
 38  CDM                       500 non-null    object
 39  RDM                       500 non-null    object
 40  RWB                       500 non-null    object
 41  LB                        500 non-null    object
 42  LCB                       500 non-null    object
 43  CB                        500 non-null    object
 44  RCB                       500 non-null    object
 45  RB                        500 non-null    object
 46  Crossing                  500 non-null    float64
 47  Finishing                 500 non-null    float64
 48  HeadingAccuracy           500 non-null    float64
 49  ShortPassing              500 non-null    float64
 50  Volleys                   500 non-null    float64
 51  Dribbling                 500 non-null    float64
 52  Curve                     500 non-null    float64
 53  FKAccuracy                500 non-null    float64
 54  LongPassing               500 non-null    float64
 55  BallControl               500 non-null    float64
 56  Acceleration              500 non-null    float64
 57  SprintSpeed               500 non-null    float64
 58  Agility                   500 non-null    float64
 59  Reactions                 500 non-null    float64
 60  Balance                   500 non-null    float64
 61  ShotPower                 500 non-null    float64
 62  Jumping                   500 non-null    float64
 63  Stamina                   500 non-null    float64
 64  Strength                  500 non-null    float64
 65  LongShots                 500 non-null    float64
 66  Aggression                500 non-null    float64
 67  Interceptions             500 non-null    float64
 68  Positioning               500 non-null    float64
 69  Vision                    500 non-null    float64
 70  Penalties                 500 non-null    float64
 71  Composure                 500 non-null    float64
 72  Marking                   500 non-null    float64
 73  StandingTackle            500 non-null    float64
 74  SlidingTackle             500 non-null    float64
 75  GKDiving                  500 non-null    float64
 76  GKHandling                500 non-null    float64
 77  GKKicking                 500 non-null    float64
 78  GKPositioning             500 non-null    float64
 79  GKReflexes                500 non-null    float64
 80  Release Clause            500 non-null    object
dtypes: float64(38), int64(5), object(38)
memory usage: 320.3+ KB
```

Для решения задачи классификации выполним кодирование категориальных признаков

In [8]:
```
for col in data.columns:
    print('{} - {}'.format(col, len(data[col].unique())))
```

```
ID - 500
Age - 20
Nationality - 60
Overall - 15
Potential - 17
Club - 102
Value - 116
Wage - 130
Special - 315
Preferred Foot - 2
International Reputation - 5
Weak Foot - 4
Skill Moves - 4
Work Rate - 9
Body Type - 8
Real Face - 2
Position - 26
Jersey Number - 40
Height - 15
Weight - 40
LS - 71
ST - 71
RS - 71
LW - 81
LF - 77
CF - 77
RF - 77
RW - 81
LAM - 75
CAM - 75
RAM - 75
LM - 74
LCM - 65
CM - 65
RCM - 65
RM - 74
LWB - 67
LDM - 76
CDM - 76
RDM - 76
RWB - 67
LB - 72
LCB - 93
CB - 93
RCB - 93
RB - 72
Crossing - 65
Finishing - 74
HeadingAccuracy - 61
ShortPassing - 34
Volleys - 71
Dribbling - 52
Curve - 70
FKAccuracy - 74
LongPassing - 51
BallControl - 42
Acceleration - 59
SprintSpeed - 55
Agility - 61
Reactions - 29
Balance - 68
ShotPower - 52
Jumping - 64
Stamina - 43
Strength - 59
LongShots - 73
Aggression - 63
Interceptions - 72
Positioning - 72
Vision - 61
Penalties - 64
Composure - 35
Marking - 77
StandingTackle - 78
SlidingTackle - 80
GKDiving - 18
GKHandling - 17
GKKicking - 18
GKPositioning - 18
GKReflexes - 19
Release Clause - 320
```

In [9]:
```
data.dtypes
```

Out[9]:
```
ID                 int64
Age                int64
Nationality       object
Overall            int64
Potential          int64
                  ...
GKHandling       float64
GKKicking        float64
GKPositioning    float64
GKReflexes       float64
Release Clause    object
Length: 81, dtype: object
```

In [10]:
```
def money_to_float(v):
    return float(v[1:-1])
money_cols = ['Value', 'Wage', 'Release Clause']
for mc in money_cols:
    data[mc] = data[mc].map(money_to_float)

def height_to_float(h):
    foot_and_inch = h.split('\'')
    return float(float(foot_and_inch[0]) + float(foot_and_inch[1]) / 12.)
data['Height'] = data['Height'].map(height_to_float)

def weight_to_float(w):
    return float(w[:-3])
data['Weight'] = data['Weight'].map(weight_to_float)

def position_to_float(p):
    nums = p.split('+')
    return float(float(nums[0]) + 0.1 * float(nums[1]))

pos_cols = ['LS', 'ST', 'RS', 'LW', 'LF', 'CF', 'RF', 'RW', 'LAM', 'CAM', 'RAM', 'LM', 'LCM', 'CM', 'RCM', 'RM'
for p in pos_cols:
    data[p] = data[p].map(position_to_float)

data.head()
```

Out[10]:

	ID	Age	Nationality	Overall	Potential	Club	Value	Wage	Special	Preferred Foot	...	Composure	Marking	StandingTackle
0	158023	31	Argentina	94	94	FC Barcelona	110.5	565.0	2202	Left	...	96.0	33.0	28.0
1	20801	33	Portugal	94	94	Juventus	77.0	405.0	2228	Right	...	95.0	28.0	31.0
2	190871	26	Brazil	92	93	Paris Saint-Germain	118.5	290.0	2143	Right	...	94.0	27.0	24.0
4	192985	27	Belgium	91	92	Manchester City	102.0	355.0	2281	Right	...	88.0	68.0	58.0
5	183277	27	Belgium	91	91	Chelsea	93.0	340.0	2142	Right	...	91.0	34.0	27.0

5 rows × 81 columns

In [11]:
```
from sklearn.preprocessing import LabelEncoder

cols_to_encode = ['Nationality', 'Club', 'Preferred Foot', 'Work Rate', 'Body Type', 'Real Face', 'Position']
le = LabelEncoder()
for c in cols_to_encode:
    data[c] = le.fit_transform(data[c])
data.head()
```

Out[11]:

	ID	Age	Nationality	Overall	Potential	Club	Value	Wage	Special	Preferred Foot	...	Composure	Marking	StandingTackle
0	158023	31	2	94	94	31	110.5	565.0	2202	0	...	96.0	33.0	28.0
1	20801	33	42	94	94	77	77.0	405.0	2228	1	...	95.0	28.0	31.0
2	190871	26	7	92	93	67	118.5	290.0	2143	1	...	94.0	27.0	24.0
4	192985	27	5	91	92	55	102.0	355.0	2281	1	...	88.0	68.0	58.0
5	183277	27	5	91	91	21	93.0	340.0	2142	1	...	91.0	34.0	27.0

5 rows × 81 columns

In [12]:
```
data.dtypes
```

Out[12]:
```
ID                 int64
Age                int64
Nationality        int64
Overall            int64
Potential          int64
                  ...
GKHandling       float64
GKKicking        float64
GKPositioning    float64
GKReflexes       float64
Release Clause   float64
Length: 81, dtype: object
```

Так как выполняется задача небинарной классификации и в тестовой выборке возможен дисбаланс классов, были выбраны следующие метрики:

- precision
- recall
- f1-score

Всем метрикам был задан уровень детализации average='weighted'.

In [13]:
```
def print_metrics(y_test, y_pred):
    rep = classification_report(y_test, y_pred, output_dict=True)
    print("weighted precision:", rep['weighted avg']['precision'])
    print("weighted recall:", rep['weighted avg']['recall'])
    print("weighted f1-score:", rep['weighted avg']['f1-score'])
    plt.figure(figsize=(4, 3))
    plt.title('Матрица ошибок')
    sns.heatmap(confusion_matrix(y_test, y_pred), annot=True, cmap="Blues")
```

In [14]:
```
x_train, x_test, y_train, y_test = train_test_split(data.drop(['International Reputation'], axis=1), data['Inte
```

SVC. Базовая модель.

In [15]:
```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler().fit(x_train)
x_train_scaled = pd.DataFrame(scaler.transform(x_train), columns=x_train.columns)
x_test_scaled = pd.DataFrame(scaler.transform(x_test), columns=x_train.columns)
x_train_scaled.describe()
```

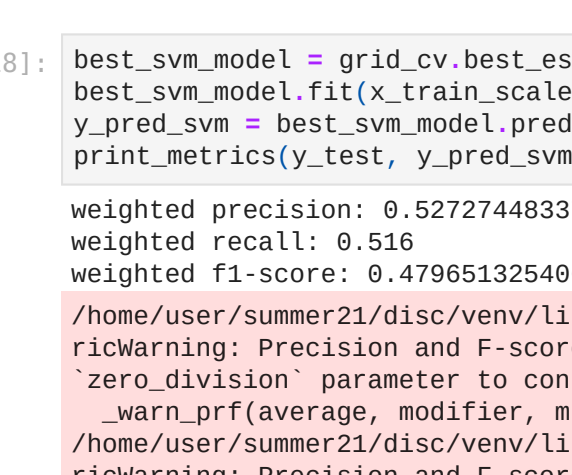
Out[15]:

	ID	Age	Nationality	Overall	Potential	Club	Value	Wage	Speci
count	2.500000e+02	2.500000e+02	2.500000e+02	2.500000e+02	2.500000e+02	2.500000e+02	2.500000e+02	2.500000e+02	2.500000e+0
mean	-2.842171e-16	-2.273737e-16	1.243450e-17	-5.329071e-18	-1.840306e-15	7.105427e-18	2.131628e-17	2.486900e-17	3.694822e-
std	1.002006e+00	1.002006e+00	1.002006e+00	1.002006e+00	1.002006e+00	1.002006e+00	1.002006e+00	1.002006e+00	1.002006e+0
min	-6.012872e-01	-2.081673e+00	-1.442809e+00	-1.235431e+00	-1.566337e+00	-1.744186e+00	-1.444239e+00	-1.163443e+00	-2.946546e+0
25%	-3.981337e-01	-6.743764e-01	-1.109597e+00	-8.824507e-01	-9.587585e-01	-9.381051e-01	-6.154865e-01	-6.908134e-01	-6.096423e-
50%	1.264703e-01	-1.114579e-01	-2.765661e-01	-1.764901e-01	-4.739110e-02	1.280022e-01	-3.152140e-01	-2.499038e-01	1.667694e-
75%	5.636768e-01	7.329199e-01	1.084050e+00	5.294704e-01	5.601872e-01	7.520650e-01	2.853309e-01	3.464344e-01	7.112161e-
max	1.634767e+00	2.421675e+00	1.778242e+00	4.059273e+00	2.990500e+00	1.688159e+00	5.570127e+00	5.992615e+00	2.014821e+0

8 rows × 80 columns

In [16]:
```
svm_model = SVC()
svm_model.fit(x_train_scaled, y_train)
y_pred_svm = svm_model.predict(x_test_scaled)
print_metrics(y_test, y_pred_svm)
```

```
/home/user/summer21/disc/venv/lib/python3.8/site-packages/sklearn/metrics/_classification.py:1318: UndefinedMet
ricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/home/user/summer21/disc/venv/lib/python3.8/site-packages/sklearn/metrics/_classification.py:1318: UndefinedMet
ricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/home/user/summer21/disc/venv/lib/python3.8/site-packages/sklearn/metrics/_classification.py:1318: UndefinedMet
ricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
weighted precision: 0.40951981351981354
weighted recall: 0.472
weighted f1-score: 0.4051585430132882
```



Подбор гиперпараметров

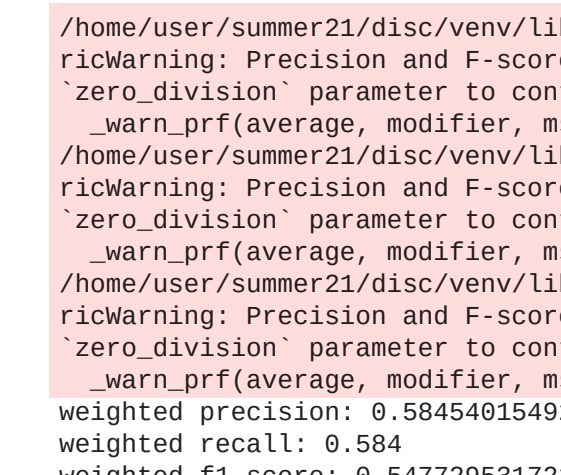
In [17]:
```
params = {'C': np.concatenate([np.arange(0.1, 2, 0.03), np.arange(2, 20, 1)])}
grid_cv = GridSearchCV(estimator=svm_model, param_grid=params, cv=10, n_jobs=-1, scoring='f1_macro')
grid_cv.fit(x_train_scaled, y_train)
print(grid_cv.best_params_)
```

```
/home/user/summer21/disc/venv/lib/python3.8/site-packages/sklearn/model_selection/_split.py:676: UserWarning: T
he least populated class in y has only 3 members, which is less than n_splits=10.
  warnings.warn(
{'C': 3.0}
```

Лучшая модель

In [18]:
```
best_svm_model = grid_cv.best_estimator_
best_svm_model.fit(x_train_scaled, y_train)
y_pred_svm = best_svm_model.predict(x_test_scaled)
print_metrics(y_test, y_pred_svm)
```

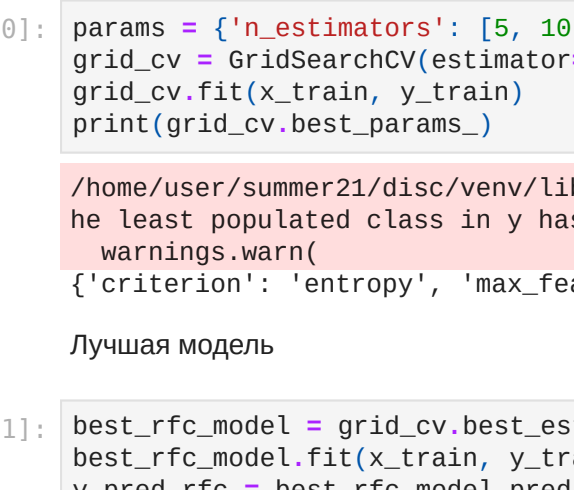
```
weighted precision: 0.527274483378257
weighted recall: 0.516
weighted f1-score: 0.479651325406396
/home/user/summer21/disc/venv/lib/python3.8/site-packages/sklearn/metrics/_classification.py:1318: UndefinedMet
ricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/home/user/summer21/disc/venv/lib/python3.8/site-packages/sklearn/metrics/_classification.py:1318: UndefinedMet
ricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/home/user/summer21/disc/venv/lib/python3.8/site-packages/sklearn/metrics/_classification.py:1318: UndefinedMet
ricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```



RandomForestClassifier. Базовая модель

In [19]:
```
rfc_model = RandomForestClassifier()
rfc_model.fit(x_train, y_train)
y_pred_rfc = rfc_model.predict(x_test)
print_metrics(y_test, y_pred_rfc)
```

```
/home/user/summer21/disc/venv/lib/python3.8/site-packages/sklearn/metrics/_classification.py:1318: UndefinedMet
ricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/home/user/summer21/disc/venv/lib/python3.8/site-packages/sklearn/metrics/_classification.py:1318: UndefinedMet
ricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/home/user/summer21/disc/venv/lib/python3.8/site-packages/sklearn/metrics/_classification.py:1318: UndefinedMet
ricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
weighted precision: 0.5845401549225389
weighted recall: 0.584
weighted f1-score: 0.5477295317221876
```



Подбор гиперпараметров

In [20]:
```
params = {'n_estimators': [5, 10, 50, 100], 'max_features': [2, 3, 4], 'criterion': ['gini', 'entropy'], 'min_sa
grid_cv = GridSearchCV(estimator=rfc_model, param_grid=params, cv=10, n_jobs=-1, scoring='f1_weighted')
grid_cv.fit(x_train, y_train)
print(grid_cv.best_params_)
```

```
/home/user/summer21/disc/venv/lib/python3.8/site-packages/sklearn/model_selection/_split.py:676: UserWarning: T
he least populated class in y has only 3 members, which is less than n_splits=10.
  warnings.warn(
{'criterion': 'entropy', 'max_features': 3, 'min_samples_leaf': 2, 'n_estimators': 100}
```

Лучшая модель

In [21]:
```
best_rfc_model = grid_cv.best_estimator_
best_rfc_model.fit(x_train, y_train)
y_pred_rfc = best_rfc_model.predict(x_test)
print_metrics(y_test, y_pred_rfc)
```

```
/home/user/summer21/disc/venv/lib/python3.8/site-packages/sklearn/metrics/_classification.py:1318: UndefinedMet
ricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/home/user/summer21/disc/venv/lib/python3.8/site-packages/sklearn/metrics/_classification.py:1318: UndefinedMet
ricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/home/user/summer21/disc/venv/lib/python3.8/site-packages/sklearn/metrics/_classification.py:1318: UndefinedMet
ricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
weighted precision: 0.5586348600508906
weighted recall: 0.568
weighted f1-score: 0.5125000953652489
```

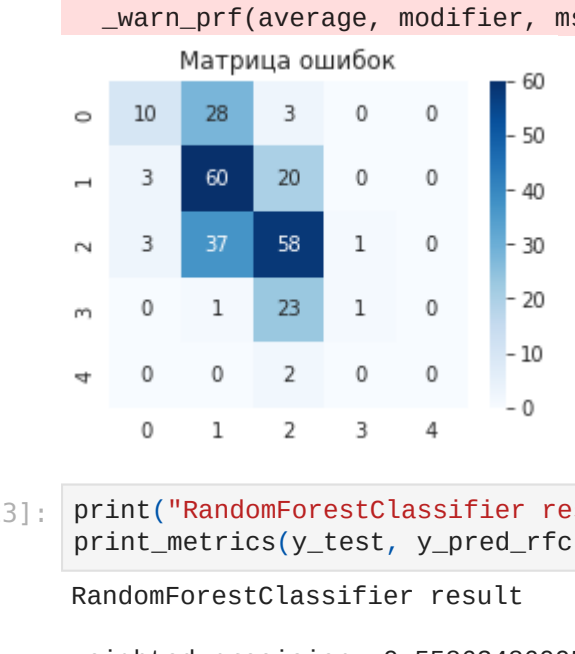
Сравнение результатов

Выведем лучшие результаты моделей

In [22]:
```
print("SVC result\n")
print_metrics(y_test, y_pred_svm)
```

```
SVC result

weighted precision: 0.527274483378257
weighted recall: 0.516
weighted f1-score: 0.479651325406396
/home/user/summer21/disc/venv/lib/python3.8/site-packages/sklearn/metrics/_classification.py:1318: UndefinedMet
ricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/home/user/summer21/disc/venv/lib/python3.8/site-packages/sklearn/metrics/_classification.py:1318: UndefinedMet
ricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/home/user/summer21/disc/venv/lib/python3.8/site-packages/sklearn/metrics/_classification.py:1318: UndefinedMet
ricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```



In [23]:
```
print("RandomForestClassifier result\n")
print_metrics(y_test, y_pred_rfc)
```

```
RandomForestClassifier result

weighted precision: 0.5586348600508906
weighted recall: 0.568
weighted f1-score: 0.5125000953652489
/home/user/summer21/disc/venv/lib/python3.8/site-packages/sklearn/metrics/_classification.py:1318: UndefinedMet
ricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/home/user/summer21/disc/venv/lib/python3.8/site-packages/sklearn/metrics/_classification.py:1318: UndefinedMet
ricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/home/user/summer21/disc/venv/lib/python3.8/site-packages/sklearn/metrics/_classification.py:1318: UndefinedMet
ricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

Вывод: для метода случайного леса модель по умолчанию оказалась лучше модели с подобранными параметрами. Эта же модель показала лучшие результаты по сравнению с моделями SVM. Вывод: небинарную классификацию в условии дисбаланса класса лучше всего реализовал метод Случайного леса.

In [23]: