Рубежный контроль №2

Тема: Методы построения моделей машинного обучения

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Загрузка необходимых библиотек:

Ввод [1]:

```
as as pd
y as np
orn as sns
n import preprocessing
n import svm
n.model_selection import train_test_split
n.model_selection import cross_val_score
t import XGBClassifier

n.metrics import accuracy_score, balanced_accuracy_score
n.metrics import precision_score, recall_score, f1_score, classification_report
n.metrics import confusion_matrix
n.metrics import mean_absolute_error, mean_squared_error, mean_squared_log_error, med
n.metrics import roc_curve, roc_auc_score

n.ensemble import AdaBoostClassifier
n.impute import SimpleImputer
```

Ввод [2]:

```
data = pd.read_csv('./HRDataset_v14.csv', sep=",")
TARGET_COL_NAME = 'RecruitmentSource'
TARGET_IS_NUMERIC = data[TARGET_COL_NAME].dtype != 'O'
TARGET_IS_NUMERIC
```

Out[2]:

```
False
```

Ввод [3]:

```
data
```

Out[3]:

	Employee_Name	EmpID	MarriedID	MaritalStatusID	GenderID	EmpStatusID	DeptID	PerfS
0	Adinolfi, Wilson K	10026	0	0	1	1	5	
1	Ait Sidi, Karthikeyan	10084	1	1	1	5	3	
2	Akinkuolie, Sarah	10196	1	1	0	5	5	
3	Alagbe,Trina	10088	1	1	0	1	5	
4	Anderson, Carol	10069	0	2	0	5	5	
...	...	...	...	...	...	...	...	
306	Woodson, Jason	10135	0	0	1	1	5	
307	Ybarra, Catherine	10301	0	0	0	5	5	
308	Zamora, Jennifer	10010	0	0	0	1	3	
309	Zhou, Julia	10043	0	0	0	1	3	
310	Zima, Colleen	10271	0	4	0	1	5	

311 rows × 36 columns

Ввод [4]:

```
data.shape
```

Out[4]:

```
(311, 36)
```

Ввод [5]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 311 entries, 0 to 310
Data columns (total 36 columns):
 #   Column                      Non-Null Count  Dtype  
---  ------                      --------------  -----  
 0   Employee_Name               311 non-null    object 
 1   EmpID                       311 non-null    int64  
 2   MarriedID                   311 non-null    int64  
 3   MaritalStatusID             311 non-null    int64  
 4   GenderID                    311 non-null    int64  
 5   EmpStatusID                 311 non-null    int64  
 6   DeptID                      311 non-null    int64  
 7   PerfScoreID                 311 non-null    int64  
 8   FromDiversityJobFairID      311 non-null    int64  
 9   Salary                      311 non-null    int64  
 10  Termd                       311 non-null    int64  
 11  PositionID                  311 non-null    int64  
 12  Position                    311 non-null    object 
 13  State                       311 non-null    object 
 14  Zip                         311 non-null    int64  
 15  DOB                         311 non-null    object 
 16  Sex                         311 non-null    object 
 17  MaritalDesc                 311 non-null    object 
 18  CitizenDesc                 311 non-null    object 
 19  HispanicLatino              311 non-null    object 
 20  RaceDesc                    311 non-null    object 
 21  DateofHire                  311 non-null    object 
 22  DateofTermination           104 non-null    object 
 23  TermReason                  311 non-null    object 
 24  EmploymentStatus            311 non-null    object 
 25  Department                  311 non-null    object 
 26  ManagerName                 311 non-null    object 
 27  ManagerID                   303 non-null    float64
 28  RecruitmentSource           311 non-null    object 
 29  PerformanceScore            311 non-null    object 
 30  EngagementSurvey            311 non-null    float64
 31  EmpSatisfaction             311 non-null    int64  
 32  SpecialProjectsCount        311 non-null    int64  
 33  LastPerformanceReview_Date  311 non-null    object 
 34  DaysLateLast30              311 non-null    int64  
 35  Absences                    311 non-null    int64  
dtypes: float64(2), int64(16), object(18)
memory usage: 87.6+ KB
```

Ввод [6]:

```
# проверим есть ли пропущенные значения
data.isnull().sum()
```

Out[6]:

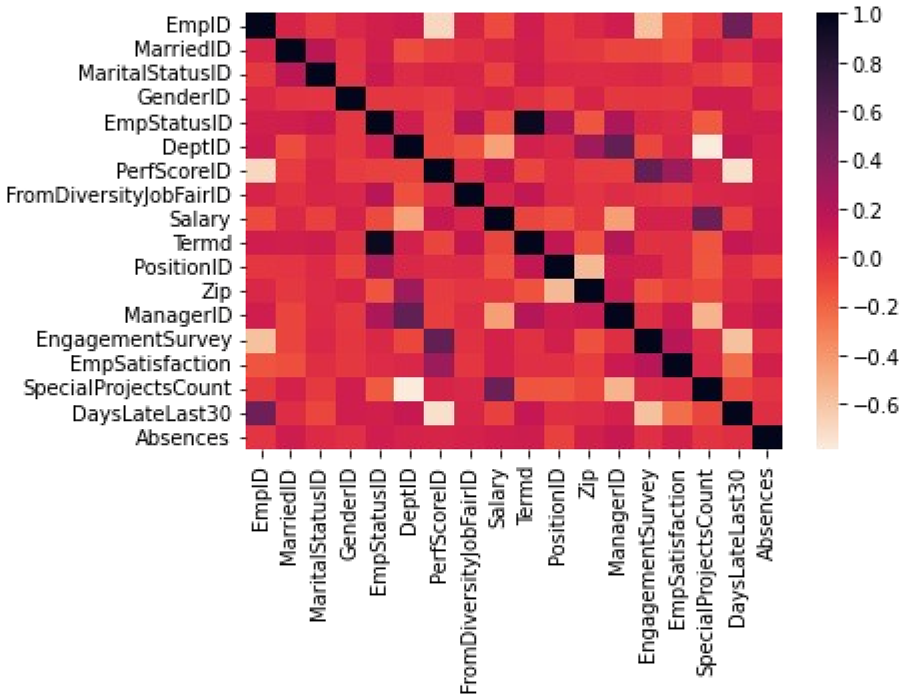
```
Employee_Name                   0
EmpID                           0
MarriedID                       0
MaritalStatusID                 0
GenderID                        0
EmpStatusID                     0
DeptID                          0
PerfScoreID                     0
FromDiversityJobFairID          0
Salary                          0
Termd                           0
PositionID                      0
Position                        0
State                           0
Zip                             0
DOB                             0
Sex                             0
MaritalDesc                     0
CitizenDesc                     0
HispanicLatino                  0
RaceDesc                        0
DateofHire                      0
DateofTermination             207
TermReason                      0
EmploymentStatus                0
Department                      0
ManagerName                     0
ManagerID                       8
RecruitmentSource               0
PerformanceScore                0
EngagementSurvey                0
EmpSatisfaction                 0
SpecialProjectsCount            0
LastPerformanceReview_Date      0
DaysLateLast30                  0
Absences                        0
dtype: int64
```

Удалим колонки, которые не влияют на целевой признак

Построим heatmap для лучшего визуального представления всез корреляций

Ввод [7]:

```
cmap = sns.cm.rocket_r
ax = sns.heatmap(data.corr(), cmap=cmap)
```



Ввод [8]:

```
data = data.drop(columns=['Employee_Name', 'EmpID', 'DateofTermination', 'ManagerID'
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 311 entries, 0 to 310
Data columns (total 32 columns):
 #   Column                      Non-Null Count  Dtype  
---  ------                      --------------  -----  
 0   MarriedID                   311 non-null    int64  
 1   MaritalStatusID             311 non-null    int64  
 2   GenderID                    311 non-null    int64  
 3   EmpStatusID                 311 non-null    int64  
 4   DeptID                      311 non-null    int64  
 5   PerfScoreID                 311 non-null    int64  
 6   FromDiversityJobFairID      311 non-null    int64  
 7   Salary                      311 non-null    int64  
 8   Termd                       311 non-null    int64  
 9   PositionID                  311 non-null    int64  
 10  Position                    311 non-null    object 
 11  State                       311 non-null    object 
 12  Zip                         311 non-null    int64  
 13  DOB                         311 non-null    object 
 14  Sex                         311 non-null    object 
 15  MaritalDesc                 311 non-null    object 
 16  CitizenDesc                 311 non-null    object 
 17  HispanicLatino              311 non-null    object 
 18  RaceDesc                    311 non-null    object 
 19  DateofHire                  311 non-null    object 
 20  TermReason                  311 non-null    object 
 21  EmploymentStatus            311 non-null    object 
 22  Department                  311 non-null    object 
 23  ManagerName                 311 non-null    object 
 24  RecruitmentSource           311 non-null    object 
 25  PerformanceScore            311 non-null    object 
 26  EngagementSurvey            311 non-null    float64
 27  EmpSatisfaction             311 non-null    int64  
 28  SpecialProjectsCount        311 non-null    int64  
 29  LastPerformanceReview_Date  311 non-null    object 
 30  DaysLateLast30              311 non-null    int64  
 31  Absences                    311 non-null    int64  
dtypes: float64(1), int64(15), object(16)
memory usage: 77.9+ KB
```

Обработка пропусков

Ввод [9]:

```
# Импьютация наиболее частыми значениями
imp = SimpleImputer(missing_values=np.nan, strategy='most_frequent')

imputed = {}

for col in data:
    contains_nan = data[col].isnull().sum() != 0
    if contains_nan:
        data_imp = data[[col]]
        data_imp = imp.fit_transform(data_imp)
        imputed[col] = data_imp

for col_name in imputed:
    df = pd.DataFrame({col_name:imputed[col_name].T[0]})
    data[col_name] = df.copy()

data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 311 entries, 0 to 310
Data columns (total 32 columns):
 #   Column                      Non-Null Count  Dtype  
---  ------                      --------------  -----  
 0   MarriedID                   311 non-null    int64  
 1   MaritalStatusID             311 non-null    int64  
 2   GenderID                    311 non-null    int64  
 3   EmpStatusID                 311 non-null    int64  
 4   DeptID                      311 non-null    int64  
 5   PerfScoreID                 311 non-null    int64  
 6   FromDiversityJobFairID      311 non-null    int64  
 7   Salary                      311 non-null    int64  
 8   Termd                       311 non-null    int64  
 9   PositionID                  311 non-null    int64  
 10  Position                    311 non-null    object 
 11  State                       311 non-null    object 
 12  Zip                         311 non-null    int64  
 13  DOB                         311 non-null    object 
 14  Sex                         311 non-null    object 
 15  MaritalDesc                 311 non-null    object 
 16  CitizenDesc                 311 non-null    object 
 17  HispanicLatino              311 non-null    object 
 18  RaceDesc                    311 non-null    object 
 19  DateofHire                  311 non-null    object 
 20  TermReason                  311 non-null    object 
 21  EmploymentStatus            311 non-null    object 
 22  Department                  311 non-null    object 
 23  ManagerName                 311 non-null    object 
 24  RecruitmentSource           311 non-null    object 
 25  PerformanceScore            311 non-null    object 
 26  EngagementSurvey            311 non-null    float64
 27  EmpSatisfaction             311 non-null    int64  
 28  SpecialProjectsCount        311 non-null    int64  
 29  LastPerformanceReview_Date  311 non-null    object 
 30  DaysLateLast30              311 non-null    int64  
 31  Absences                    311 non-null    int64  
dtypes: float64(1), int64(15), object(16)
memory usage: 77.9+ KB
```

Кодирование строковых признаков (LabelEncoding)

Ввод [10]:

```
not_number_cols = data.select_dtypes(include=['object'])
number_cols = data.select_dtypes(exclude=['object'])
```

Ввод [11]:

```
le = preprocessing.LabelEncoder()

for col_name in not_number_cols:
    data[col_name] = le.fit_transform(data[col_name])

data
```

Out[11]:

	MarriedID	MaritalStatusID	GenderID	EmpStatusID	DeptID	PerfScoreID	FromDiversityJobF
0	0	0	1	1	5	4	
1	1	1	1	5	3	3	
2	1	1	0	5	5	3	
3	1	1	0	1	5	3	
4	0	2	0	5	5	3	
...	...	...	...	...	...	...	
306	0	0	1	1	5	3	
307	0	0	0	5	5	1	
308	0	0	0	1	3	4	
309	0	0	0	1	3	3	
310	0	4	0	1	5	3	

311 rows × 32 columns

Масштабируем числовые данные

Ввод [12]:

```
scaler = preprocessing.MinMaxScaler()

number_fields_source = number_cols.loc[:, number_cols.columns!=TARGET_COL_NAME] if T

for col_name in number_fields_source:
    data[col_name] = scaler.fit_transform(data[[col_name]])

data
```

Out[12]:

	MarriedID	MaritalStatusID	GenderID	EmpStatusID	DeptID	PerfScoreID	FromDiversityJobF
0	0.0	0.00	1.0	0.0	0.8	1.000000	
1	1.0	0.25	1.0	1.0	0.4	0.666667	
2	1.0	0.25	0.0	1.0	0.8	0.666667	
3	1.0	0.25	0.0	0.0	0.8	0.666667	
4	0.0	0.50	0.0	1.0	0.8	0.666667	
...	...	...	...	...	...	...	
306	0.0	0.00	1.0	0.0	0.8	0.666667	
307	0.0	0.00	0.0	1.0	0.8	0.000000	
308	0.0	0.00	0.0	0.0	0.4	1.000000	
309	0.0	0.00	0.0	0.0	0.4	0.666667	
310	0.0	1.00	0.0	0.0	0.8	0.666667	

311 rows × 32 columns

Делим выборку на обучающую и тестовую

Ввод [13]:

```
target = data[TARGET_COL_NAME]
data_X_train, data_X_test, data_y_train, data_y_test = train_test_split(
    data, target, test_size=0.2, random_state=1)
```

Ввод [14]:

```
data_X_train.shape, data_y_train.shape
```

Out[14]:

```
((248, 32), (248,))
```

Ввод [15]:

```
data_X_test.shape, data_y_test.shape
```

Out[15]:

```
((63, 32), (63,))
```

Ввод [16]:

```
np.unique(target)
```

Out[16]:

```
array([0, 1, 2, 3, 4, 5, 6, 7, 8])
```

Метод опорных векторов

Ввод [17]:

```
svr_1 = svm.LinearSVC()
svr_1.fit(data_X_train, data_y_train)
```

```
/Users/vadim/opt/anaconda3/lib/python3.9/site-packages/sklearn/svm/_ba
se.py:985: ConvergenceWarning: Liblinear failed to converge, increase
the number of iterations.
  warnings.warn("Liblinear failed to converge, increase "
```

Out[17]:

```
LinearSVC()
```

Ввод [18]:

```
data_y_pred_1 = svr_1.predict(data_X_test)
accuracy_score(data_y_test, data_y_pred_1)
```

Out[18]:

```
0.2698412698412698
```

Ввод [19]:

```
f1_score(data_y_test, data_y_pred_1, average='micro')
```

Out[19]:

```
0.2698412698412698
```

Ввод [20]:

```
f1_score(data_y_test, data_y_pred_1, average='macro')
```

Out[20]:

```
0.19544586132821426
```

Ввод [21]:

```
f1_score(data_y_test, data_y_pred_1, average='weighted')
```

Out[21]:

```
0.25382983030041856
```

Ввод [22]:

```
svr_2 = svm.LinearSVC(C=1.0, max_iter=10000)
svr_2.fit(data_X_train, data_y_train)
```

```
/Users/vadim/opt/anaconda3/lib/python3.9/site-packages/sklearn/svm/_ba
se.py:985: ConvergenceWarning: Liblinear failed to converge, increase
the number of iterations.
  warnings.warn("Liblinear failed to converge, increase "
```

Out[22]:

```
LinearSVC(max_iter=10000)
```

Ввод [23]:

```
data_y_pred_2 = svr_2.predict(data_X_test)
accuracy_score(data_y_test, data_y_pred_2)
```

Out[23]:

```
0.4603174603174603
```

Ввод [24]:

```
f1_score(data_y_test, data_y_pred_2, average='micro')
```

Out[24]:

```
0.4603174603174603
```

Ввод [25]:

```
f1_score(data_y_test, data_y_pred_2, average='macro')
```

Out[25]:

```
0.35007859826700405
```

Ввод [26]:

```
f1_score(data_y_test, data_y_pred_2, average='weighted')
```

Out[26]:

```
0.48227841861382226
```

Ввод [27]:

```
svr_3 = svm.LinearSVC(C=1.0, penalty='l1', dual=False, max_iter=10000)
svr_3.fit(data_X_train, data_y_train)
```

Out[27]:

```
LinearSVC(dual=False, max_iter=10000, penalty='l1')
```

Ввод [28]:

```
data_y_pred_3_0 = svr_3.predict(data_X_train)
accuracy_score(data_y_train, data_y_pred_3_0)
```

Out[28]:

0.7943548387096774

Ввод [29]:

```
data_y_pred_3 = svr_3.predict(data_X_test)
accuracy_score(data_y_test, data_y_pred_3)
```

Out[29]:

0.5714285714285714

Ввод [30]:

```
f1_score(data_y_test, data_y_pred_3, average='micro')
```

Out[30]:

0.5714285714285714

Ввод [31]:

```
f1_score(data_y_test, data_y_pred_3, average='macro')
```

Out[31]:

0.5131972789115646

Ввод [32]:

```
f1_score(data_y_test, data_y_pred_3, average='weighted')
```

Out[32]:

0.5757105064247922

Градиентный бустинг

Ввод [33]:

```
ab1 = AdaBoostClassifier()
ab1.fit(data_X_train, data_y_train)
data_y_pred_1 = ab1.predict(data_X_test)
data_y_pred_1_0 = ab1.predict(data_X_train)
accuracy_score(data_y_train, data_y_pred_1_0)
```

Out[33]:

0.7661290322580645

Ввод [34]:

```
accuracy_score(data_y_test, data_y_pred_1)
```

Out[34]:

0.6031746031746031

Ввод [35]:

```
f1_score(data_y_test, data_y_pred_1, average='micro')
```

Out[35]:

0.6031746031746031

Ввод [36]:

```
f1_score(data_y_test, data_y_pred_1, average='macro')
```

Out[36]:

0.634920634920635

Ввод [37]:

```
f1_score(data_y_test, data_y_pred_1, average='weighted')
```

Out[37]:

0.5149911816578483

Выводы

При использовании метода опорных векторов наилучшую точность (0.794) показала модель с параметрами`C=1.0, penalty='l1', dual=False, max_iter=10000` . При дальнейшей манипуляции с параметрами можно было бы добиться неплохих результатов.

При использовании градиентного бустинга в целом показатели гораздо выше, предпочтительнее использовать его.