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Кафедра «Системы обработки информации и управления»

Отчет

Лабораторная работа №5

По курсу Технологии машинного обучения»

ИСПОЛНИТЕЛЬ:
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Lab5

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[1]:
```
import numpy as np
import pandas as pd
from typing import Dict, Tuple
from scipy import stats
from IPython.display import Image
from io import StringIO
from IPython.display import Image
import graphviz
import pydotplus
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import train_test_split, validation_curve,␣
 ↪learning_curve
from sklearn.model_selection import GridSearchCV, RandomizedSearchCV
from sklearn.metrics import confusion_matrix
from sklearn.tree import DecisionTreeClassifier, DecisionTreeRegressor,␣
 ↪export_graphviz
from sklearn.ensemble import RandomForestClassifier, RandomForestRegressor
from sklearn.metrics import mean_absolute_error, mean_squared_error,␣
 ↪mean_squared_log_error, median_absolute_error, r2_score
from sklearn.metrics import roc_curve, roc_auc_score
import numpy as np
from catboost import Pool, CatBoostRegressor
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
sns.set(style="ticks")

from sklearn.preprocessing import LabelEncoder, StandardScaler


from contextlib import contextmanager
import sys, os

@contextmanager
def suppress_stdout():
    with open(os.devnull, "w") as devnull:
        old_stdout = sys.stdout
```

```
        sys.stdout = devnull
        try:
            yield
        finally:
            sys.stdout = old_stdout
```

[2]:
```
data = pd.read_csv('world-happiness-report-2021.csv', sep=',')
```

[3]:
```
data.head()
```

[3]:
```
  Country name Regional indicator  Ladder score  \
0      Finland     Western Europe         7.842
1      Denmark     Western Europe         7.620
2  Switzerland     Western Europe         7.571
3      Iceland     Western Europe         7.554
4  Netherlands     Western Europe         7.464

   Standard error of ladder score  upperwhisker  lowerwhisker  \
0                           0.032         7.904         7.780
1                           0.035         7.687         7.552
2                           0.036         7.643         7.500
3                           0.059         7.670         7.438
4                           0.027         7.518         7.410

   Logged GDP per capita  Social support  Healthy life expectancy  \
0                 10.775           0.954                     72.0
1                 10.933           0.954                     72.7
2                 11.117           0.942                     74.4
3                 10.878           0.983                     73.0
4                 10.932           0.942                     72.4

   Freedom to make life choices  Generosity  Perceptions of corruption  \
0                         0.949      -0.098                      0.186
1                         0.946       0.030                      0.179
2                         0.919       0.025                      0.292
3                         0.955       0.160                      0.673
4                         0.913       0.175                      0.338

   Ladder score in Dystopia  Explained by: Log GDP per capita  \
0                      2.43                             1.446
1                      2.43                             1.502
2                      2.43                             1.566
3                      2.43                             1.482
4                      2.43                             1.501

   Explained by: Social support  Explained by: Healthy life expectancy  \
0                         1.106                                  0.741
```

```
1                   1.108                          0.763
2                   1.079                          0.816
3                   1.172                          0.772
4                   1.079                          0.753

   Explained by: Freedom to make life choices  Explained by: Generosity  \
0                                       0.691                     0.124
1                                       0.686                     0.208
2                                       0.653                     0.204
3                                       0.698                     0.293
4                                       0.647                     0.302

   Explained by: Perceptions of corruption  Dystopia + residual
0                                    0.481                3.253
1                                    0.485                2.868
2                                    0.413                2.839
3                                    0.170                2.967
4                                    0.384                2.798
```

Удалим 1й признак тк это фактически id, целевой признак - Ladder Score

В описании датасета сказано, что колонуи Explained_by не имеют отношения к результату, на их основе формируется LS in Dystopia. Также необходимо удалить upper и lowerwhisker, тк они отношения не имеют

[4]:
```
data.drop(columns=['Explained by: Log GDP per capita','Explained by: Log GDP per␣
↪capita','Explained by: Healthy life expectancy','Explained by: Freedom to make␣
↪life choices','Explained by: Generosity','Explained by: Perceptions of␣
↪corruption', 'Explained by: Social support'], inplace=True)
```

[5]:
```
data.drop(columns=data.columns[0], inplace=True)
data.drop(columns=['upperwhisker', 'lowerwhisker'], inplace=True)
```

[6]:
```
data.duplicated().sum()
```

[6]: 0

[7]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 149 entries, 0 to 148
Data columns (total 11 columns):
 #   Column                         Non-Null Count  Dtype
---  ------                         --------------  -----
 0   Regional indicator             149 non-null    object
 1   Ladder score                   149 non-null    float64
 2   Standard error of ladder score 149 non-null    float64
 3   Logged GDP per capita          149 non-null    float64
 4   Social support                 149 non-null    float64
```

```
 5   Healthy life expectancy         149 non-null    float64
 6   Freedom to make life choices    149 non-null    float64
 7   Generosity                      149 non-null    float64
 8   Perceptions of corruption       149 non-null    float64
 9   Ladder score in Dystopia        149 non-null    float64
 10  Dystopia + residual             149 non-null    float64
dtypes: float64(10), object(1)
memory usage: 12.9+ KB
```

labels

[8]:
```
le = LabelEncoder()
le.fit_transform(data['Regional indicator'])
data['Regional indicator'] = le.fit_transform(data['Regional indicator'])
for i in range(10):
    print(f'{i}: {le.inverse_transform([i]).tolist()[0]}')
```

```
0: Central and Eastern Europe
1: Commonwealth of Independent States
2: East Asia
3: Latin America and Caribbean
4: Middle East and North Africa
5: North America and ANZ
6: South Asia
7: Southeast Asia
8: Sub-Saharan Africa
9: Western Europe
```

[9]:
```
col_num = data.dtypes[data.dtypes!=object].index.values.tolist()
col_num.remove("Ladder score")
se = StandardScaler()
data[col_num] = se.fit_transform(data[col_num])
```

[10]:
```
data.head()
```

[10]:
```
   Regional indicator  Ladder score  Standard error of ladder score  \
0            1.254062         7.842                       -1.220020
1            1.254062         7.620                       -1.083204
2            1.254062         7.571                       -1.037599
3            1.254062         7.554                        0.011325
4            1.254062         7.464                       -1.448047

   Logged GDP per capita  Social support  Healthy life expectancy  \
0               1.162885        1.216171                 1.039750
1               1.299717        1.216171                 1.143618
2               1.459064        1.111370                 1.395869
3               1.252086        1.469440                 1.188133
4               1.298851        1.111370                 1.099103
```

```
   Freedom to make life choices  Generosity  Perceptions of corruption  \
0                      1.393550   -0.551886                  -3.031228
1                      1.366990    0.300594                  -3.070416
2                      1.127948    0.267294                  -2.437802
3                      1.446671    1.166393                  -0.304829
4                      1.074828    1.266293                  -2.180278

   Ladder score in Dystopia  Dystopia + residual
0                       0.0             1.535298
1                       0.0             0.816798
2                       0.0             0.762677
3                       0.0             1.001555
4                       0.0             0.686161
```

[11]:
```
cols = data.columns.tolist()
cols = cols[2:] + cols[:2]
```

[12]:
```
data = data[cols]
```

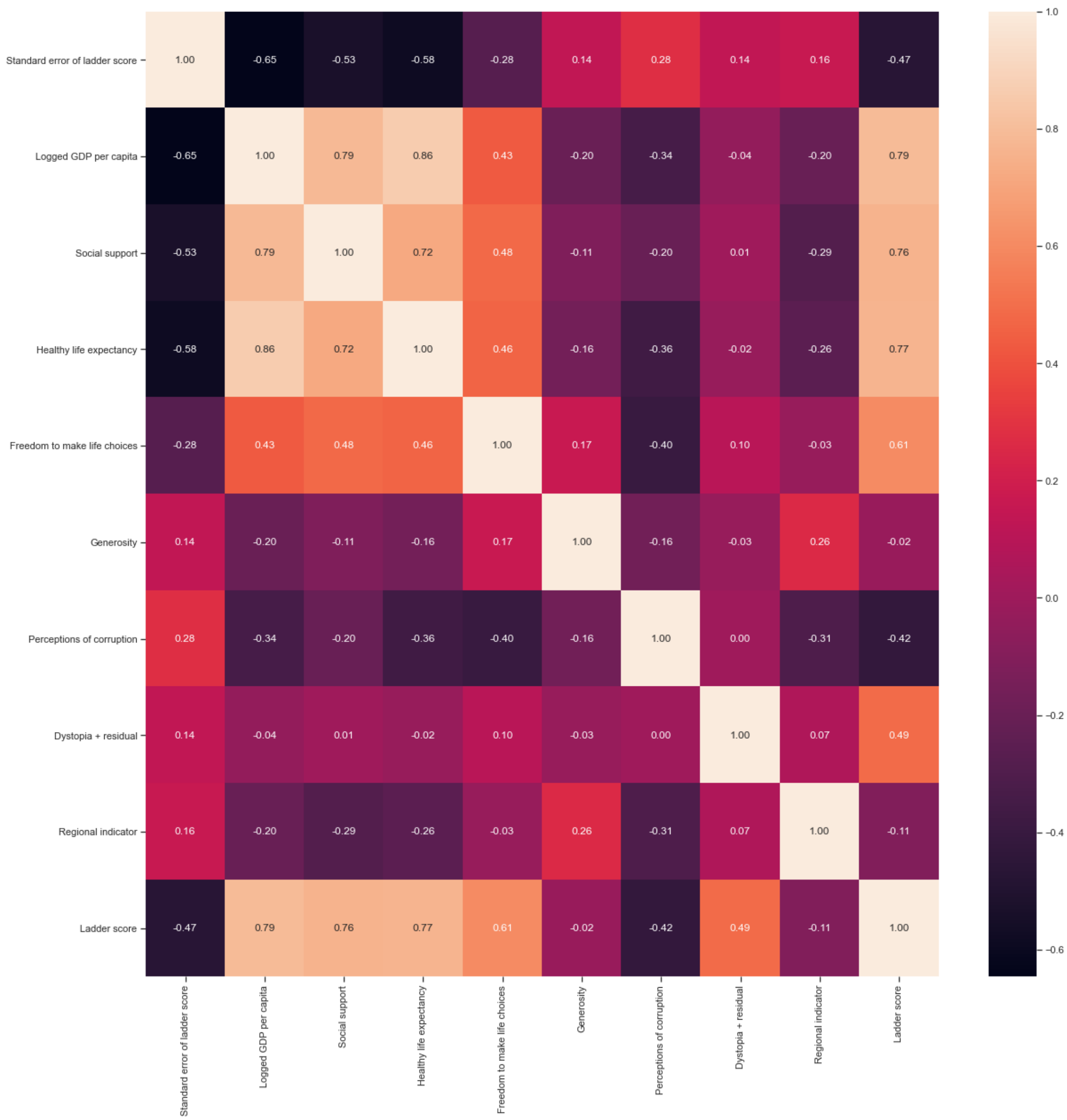
[13]:
```
data.head()
```

[13]:
```
   Standard error of ladder score  Logged GDP per capita  Social support  \
0                       -1.220020               1.162885        1.216171
1                       -1.083204               1.299717        1.216171
2                       -1.037599               1.459064        1.111370
3                        0.011325               1.252086        1.469440
4                       -1.448047               1.298851        1.111370

   Healthy life expectancy  Freedom to make life choices  Generosity  \
0                 1.039750                      1.393550   -0.551886
1                 1.143618                      1.366990    0.300594
2                 1.395869                      1.127948    0.267294
3                 1.188133                      1.446671    1.166393
4                 1.099103                      1.074828    1.266293

   Perceptions of corruption  Ladder score in Dystopia  Dystopia + residual  \
0                  -3.031228                       0.0             1.535298
1                  -3.070416                       0.0             0.816798
2                  -2.437802                       0.0             0.762677
3                  -0.304829                       0.0             1.001555
4                  -2.180278                       0.0             0.686161

   Regional indicator  Ladder score
0            1.254062         7.842
1            1.254062         7.620
2            1.254062         7.571
3            1.254062         7.554
```

```
4            1.254062          7.464
```

[14]:
```python
data.drop(columns=['Ladder score in Dystopia'], inplace=True)
```

[15]:
```python
plt.figure(figsize=(20,20))
g = sns.heatmap(data.corr(), annot=True, fmt='.2f')
```



[16]:
```python
TEST_SIZE = 0.3
RANDOM_STATE = 1
data_X = data.drop(columns='Ladder score')
data_Y = data['Ladder score']
```

```
data_X_train, data_X_test, data_Y_train, data_Y_test = train_test_split \
(data_X, data_Y, test_size = TEST_SIZE, random_state = RANDOM_STATE)
```

[17]:
```
def print_metrics(X_train, Y_train, X_test, Y_test, clf):
    with suppress_stdout():
        clf.fit(X_train, Y_train)
    target = clf.predict(X_test)
    ret = (mean_squared_error(Y_test, target), mean_absolute_error(Y_test,␣
 ↪target), r2_score(Y_test, target))
    print(f'MSE: {ret[0]}, MeanAE: {ret[1]}, R2: {ret[2]}' )
    return ret
```

1 Бустинг с помощью CatRegressor

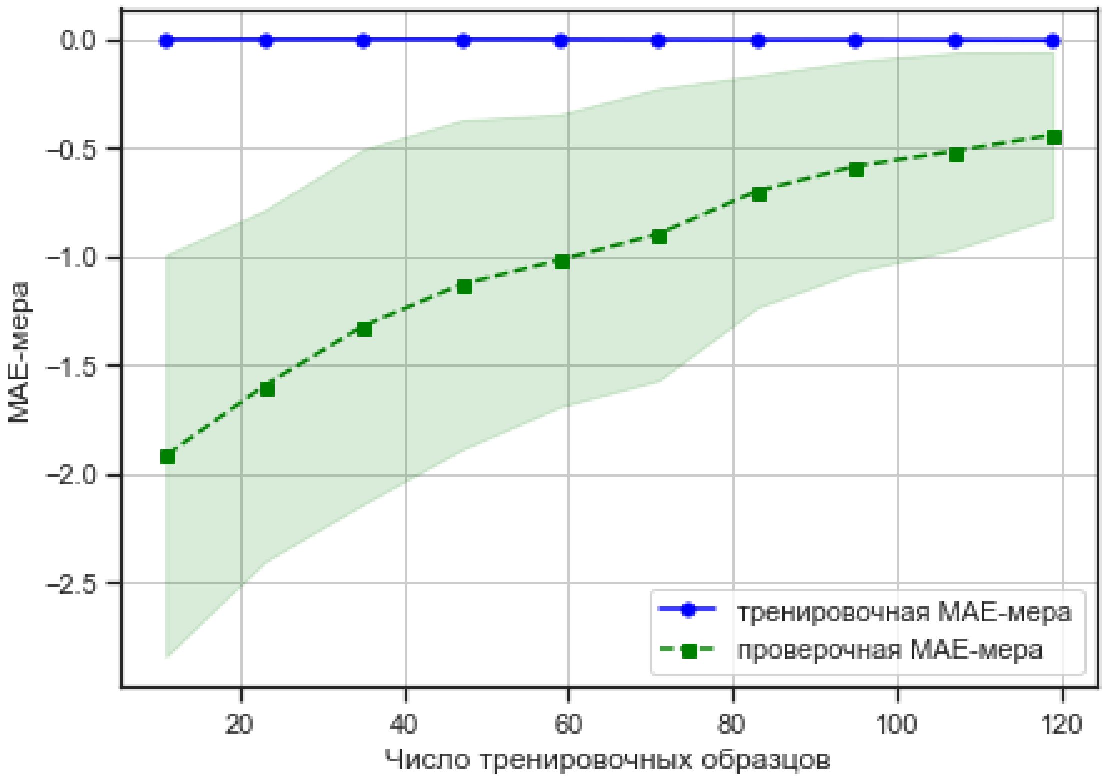
[18]:
```
gb = CatBoostRegressor(random_state=RANDOM_STATE, eval_metric = 'MAE')
```

[19]:
```
boost_metric = print_metrics(data_X_train, data_Y_train, data_X_test,␣
 ↪data_Y_test, CatBoostRegressor(random_state=RANDOM_STATE, eval_metric = 'MAE'))
```

```
MSE: 0.043627848151670374, MeanAE: 0.13530275955642032, R2: 0.956606146208312
```

[20]:
```
def plot_learning_curve(data_X, data_y, clf, score, name):
    with suppress_stdout():
        train_sizes, train_scores, test_scores = learning_curve(estimator=clf,␣
 ↪scoring=score, X=data_X, y=data_y,
                                                            train_sizes=np.
 ↪linspace(0.1, 1.0, 10), cv=5)
    train_mean = np.mean(train_scores, axis=1)
    train_std = np.std(train_scores, axis=1)
    test_mean = np.mean(test_scores, axis=1)
    test_std = np.std(test_scores, axis=1)
    plt.figure(figsize=(7,5))
    plt.plot(train_sizes, train_mean, color='blue', marker='o', markersize=5,␣
 ↪label=f'тренировочная {name}-мера')
    plt.fill_between(train_sizes, train_mean+train_std, train_mean-train_std,␣
 ↪alpha=0.15, color='blue')
    plt.plot(train_sizes, test_mean, color='green', linestyle='--', marker='s',␣
 ↪markersize=5,
             label=f'проверочная {name}-мера')
    plt.fill_between(train_sizes, test_mean+test_std, test_mean-test_std,␣
 ↪alpha=0.15, color='green')
    plt.grid()
    plt.legend(loc='lower right')
    plt.xlabel('Число тренировочных образцов')
    plt.ylabel(f'{name}-мера')
    plt.show()
```

```
[21]: plot_learning_curve(data_X, data_Y, gb, score = 'neg_mean_absolute_error',
      name='MAE')
```



В итоге получаем очень хорошую модель

2 Случайный лес

```
[22]: rf = RandomForestRegressor()
```

```
[23]: params = {
          'max_depth': [3, 4, 5, 6, 7, 8],
          'min_samples_leaf': [0.02, 0.04, 0.05, 0.06],
          'max_features': [0.7, 0.8, 0.9, 0.99]
      }
```

```
[24]: grid = GridSearchCV(estimator = RandomForestRegressor(random_state=1),
      param_grid=params, cv=10, scoring='neg_mean_squared_error')
```

[25]:
```
grid.fit(data_X_train, data_Y_train)
print(f'Best Param = {grid.best_params_}, score = {grid.best_score_}')
```

```
Best Param = {'max_depth': 8, 'max_features': 0.9, 'min_samples_leaf': 0.02},
score = -0.1286631281344961
```

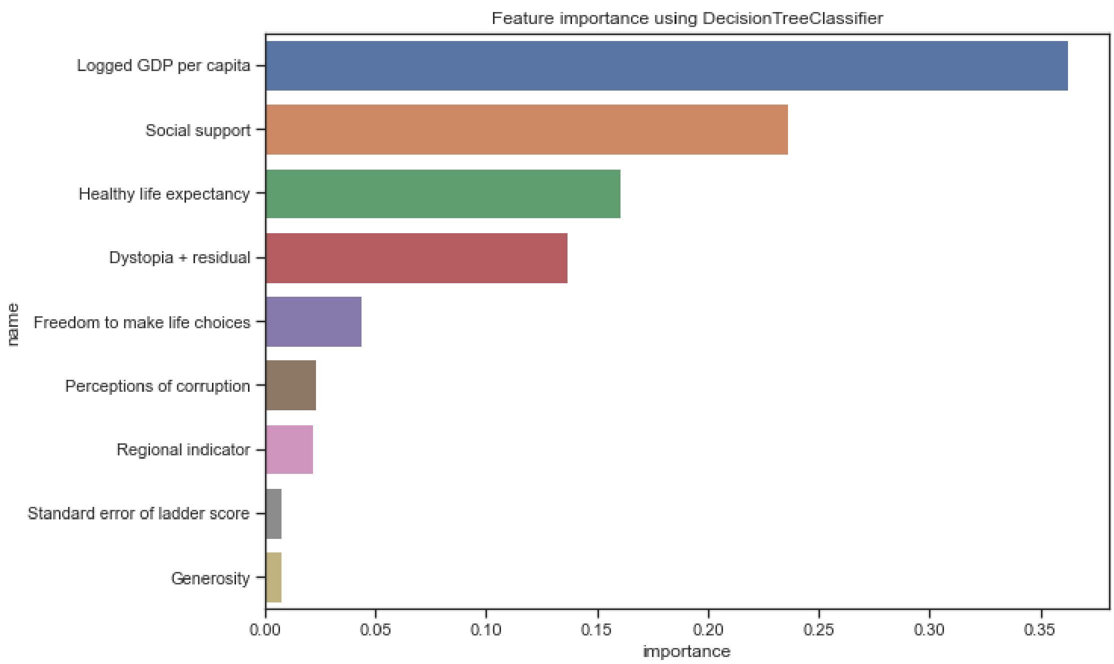
[26]:
```
rf = RandomForestRegressor(random_state=1, max_depth=grid.best_params_.
 ↪get('max_depth'),\
                           max_features=grid.best_params_.get('max_features'),\
                           min_samples_leaf=grid.best_params_.
 ↪get('min_samples_leaf'))
```

[27]:
```
def show_feature_importance(importance, col_names):
    data = pd.DataFrame({'feature_names':np.
 ↪array(col_names),'feature_importance':np.array(importance)})
    data.sort_values(by=['feature_importance'], ascending=False,inplace=True)

    plt.figure(figsize=(10,7))
    sns.barplot(x=data['feature_importance'], y=data['feature_names'])
    plt.title('Feature importance using DecisionTreeClassifier')
    plt.xlabel('importance')
    plt.ylabel('name')
```

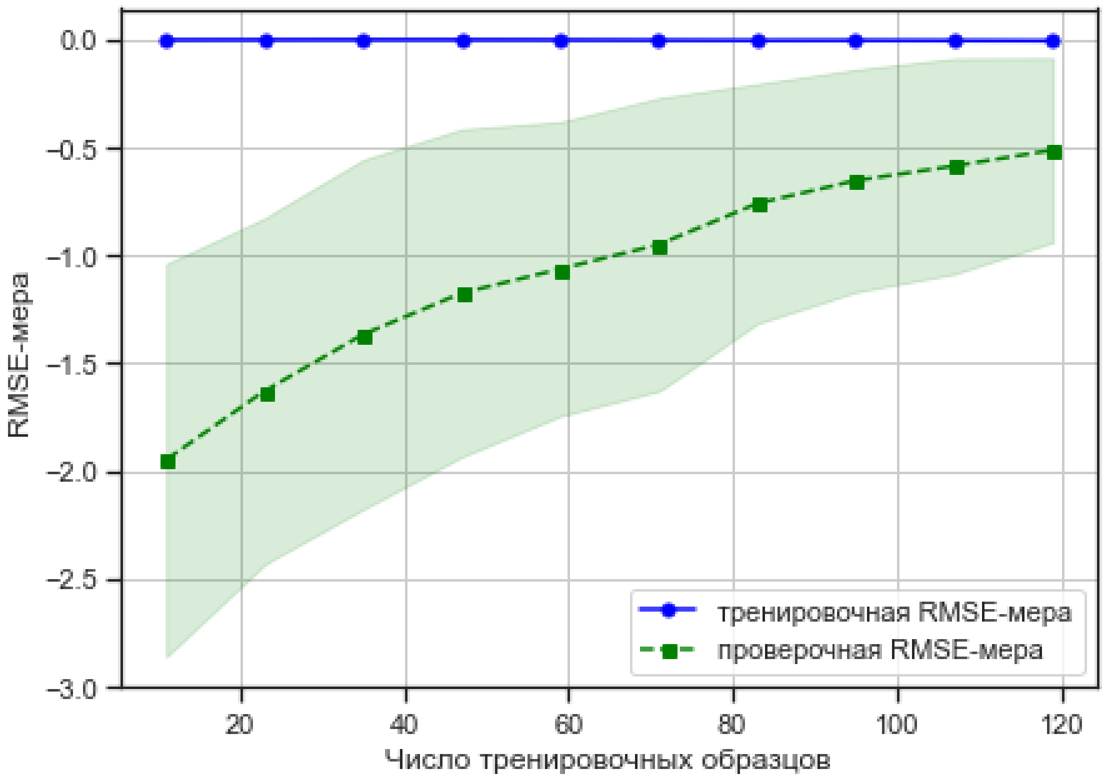
[28]:
```
tree_metric = print_metrics(data_X_train, data_Y_train, data_X_test,␣
 ↪data_Y_test, rf)
```

```
MSE: 0.08224406852351604, MeanAE: 0.2039995074111799, R2: 0.9181970407448028
```

[29]:
```
show_feature_importance(rf.feature_importances_, data_X_test.columns.tolist())
```



[30]:
```
plot_learning_curve(data_X, data_Y, gb, score = 'neg_root_mean_squared_error',␣
    ↪name='RMSE')
```



3 Итог

[31]:
```
labels=['GradBoost', 'RandomForest']
scores={'MSE': [boost_metric[0],tree_metric[0]], 'MAE':␣
    ↪[boost_metric[1],tree_metric[1]], 'R2': [boost_metric[2],tree_metric[2]]}
pd.DataFrame(scores, index=labels)
```

[31]:

	MSE	MAE	R2
GradBoost	0.043628	0.135303	0.956606
RandomForest	0.082244	0.204000	0.918197

CatBoostRegressor справился лучше чем RF по всем метрикам

[ ]:
```
```