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1 Оглавление

2 Задание (к оглавлению)

1. Выберите набор данных (датасет) для решения задачи классификации или регрессии.
2. С использованием метода train_test_split разделите выборку на обучающую и тестовую.
3. Обучите модель ближайших соседей для произвольно заданного гиперпараметра K. Оцените качество модели с помощью подходящих для задачи метрик.
4. Произведите подбор гиперпараметра K с использованием GridSearchCV и/или RandomizedSearchCV и кросс-валидации, оцените качество оптимальной модели. Желательно использование нескольких стратегий кросс-валидации.
5. Сравните метрики качества исходной и оптимальной моделей.

3 Описание датасета (к оглавлению)

Digital payments are evolving, but so are cyber criminals.

According to the Data Breach Index, more than 5 million records are being stolen on a daily basis, a concerning statistic that shows - fraud is still very common both for Card-Present and Card-not Present type of payments.

In today's digital world where trillions of Card transaction happens per day, detection of fraud is challenging.

This Dataset sourced by some unnamed institute.

Feature Explanation:

`distancefromhome` - the distance from home where the transaction happened.

`distancefromlast_transaction` - the distance from last transaction happened.

`ratiotomedianpurchaseprice` - Ratio of purchased price transaction to median purchase price.

`repeat_retailer` - Is the transaction happened from same retailer.

`used_chip` - Is the transaction through chip (credit card).

`usedpinnumber` - Is the transaction happened by using PIN number.

`online_order` - Is the transaction an online order.

`fraud` - Is the transaction fraudulent.

4 Импорт библиотек (к оглавлению)

Ввод [1]:
```
import numpy as np
import pandas as pd
from typing import Dict, Tuple
from scipy import stats

from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier

from sklearn.metrics import accuracy_score, recall_score
from sklearn.metrics import plot_confusion_matrix
from sklearn.metrics import classification_report
from sklearn.metrics import roc_curve, roc_auc_score
from sklearn.metrics import precision_recall_curve, PrecisionRecallDisplay

from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import cross_val_score, cross_validate
from sklearn.model_selection import learning_curve, validation_curve
from sklearn.model_selection import KFold, StratifiedKFold

import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
sns.set(style="ticks")
```

5 Загрузка и первичный анализ данных (к оглавлению)

Ввод [2]:
```
df = pd.read_csv("card_transdata.csv")
df.head()
```

Out[2]:

	distance_from_home	distance_from_last_transaction	ratio_to_median_purchase_price	repeat_retailer	used_chip	used_pin_number	online_order
0	57.877857	0.311140	1.945940	1.0	1.0	0.0	0.0
1	10.829943	0.175592	1.294219	1.0	0.0	0.0	0.0
2	5.091079	0.805153	0.427715	1.0	0.0	0.0	1.0
3	2.247564	5.600044	0.362663	1.0	1.0	0.0	1.0
4	44.190936	0.566486	2.222767	1.0	1.0	0.0	1.0

Ввод [3]:
```
df = df.rename(columns={
    "distance_from_home": "dist_home",
    "distance_from_last_transaction": "dist_last",
    "ratio_to_median_purchase_price": "ratio",
    "repeat_retailer": "repeat",
    "used_chip": "chip",
    "used_pin_number": "pin",
    "online_order": "online"
})
```

Ввод [4]:
```
df.describe()
```

Out[4]:

	dist_home	dist_last	ratio	repeat	chip	pin	online	fraud
count	1000000.000000	1000000.000000	1000000.000000	1000000.000000	1000000.000000	1000000.000000	1000000.000000	1000000.000000
mean	26.628792	5.036519	1.824182	0.881536	0.350399	0.100608	0.650552	0.087403
std	65.390784	25.843093	2.799589	0.323157	0.477095	0.300809	0.476796	0.282425
min	0.004874	0.000118	0.004399	0.000000	0.000000	0.000000	0.000000	0.000000
25%	3.878008	0.296671	0.475673	1.000000	0.000000	0.000000	0.000000	0.000000
50%	9.967760	0.998650	0.997717	1.000000	0.000000	0.000000	1.000000	0.000000
75%	25.743985	3.355748	2.096370	1.000000	1.000000	0.000000	1.000000	0.000000
max	10632.723672	11851.104565	267.802942	1.000000	1.000000	1.000000	1.000000	1.000000

Ввод [5]:
```
df.shape
```

Out[5]: (1000000, 8)

Ввод [6]:
```
#возьмем только 50000 первых строк
df = df.head(50000)
```

Ввод [7]:
```
discrete_features = [
    "repeat",
    "chip",
    "pin",
    "online",
    "fraud"
]

for feat in discrete_features:
    df[feat] = df[feat].astype(int)
    print(f'Колонка {feat}: {df[feat].unique()}')
```

```
Колонка repeat: [1 0]
Колонка chip: [1 0]
Колонка pin: [0 1]
Колонка online: [0 1]
Колонка fraud: [0 1]
```

Ввод [8]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50000 entries, 0 to 49999
Data columns (total 8 columns):
 #   Column     Non-Null Count  Dtype  
---  ------     --------------  -----  
 0   dist_home  50000 non-null  float64
 1   dist_last  50000 non-null  float64
 2   ratio      50000 non-null  float64
 3   repeat     50000 non-null  int64  
 4   chip       50000 non-null  int64  
 5   pin        50000 non-null  int64  
 6   online     50000 non-null  int64  
 7   fraud      50000 non-null  int64  
dtypes: float64(3), int64(5)
memory usage: 3.1 MB
```

Ввод [9]:
```
df.corr()
```

Out[9]:

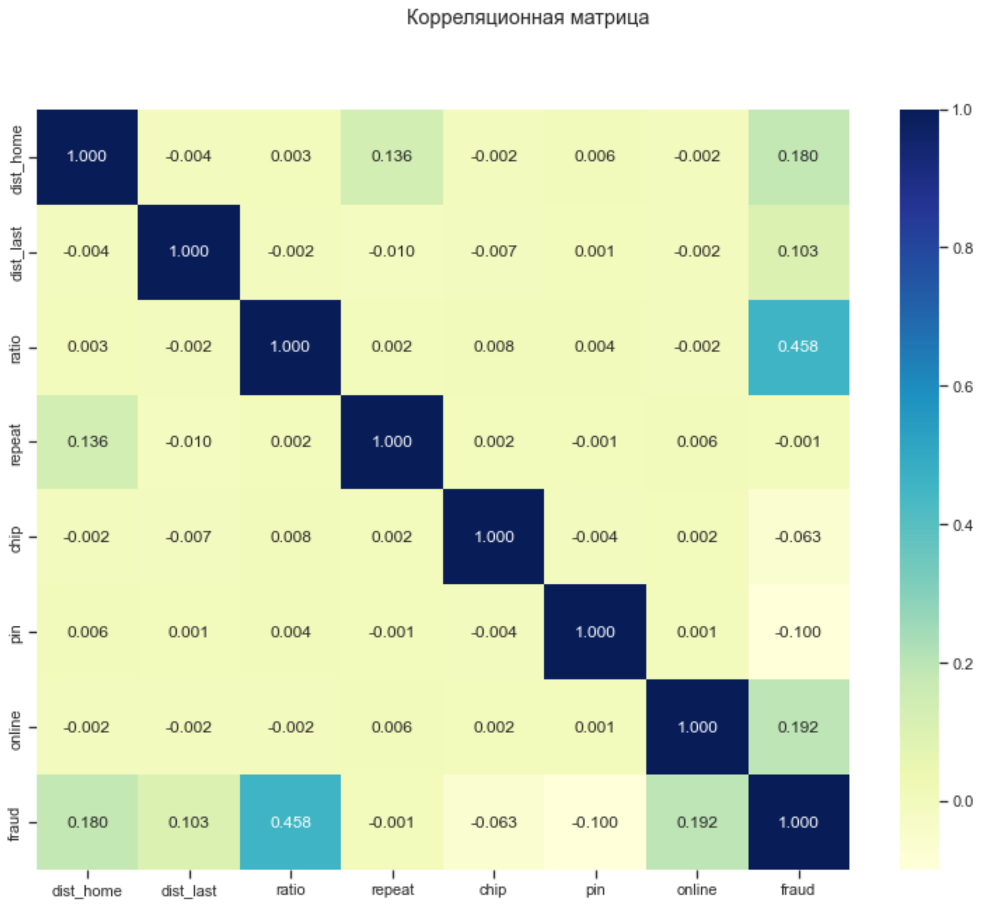
	dist_home	dist_last	ratio	repeat	chip	pin	online	fraud
dist_home	1.000000	-0.004150	0.002670	0.136132	-0.001765	0.005620	-0.001649	0.180288
dist_last	-0.004150	1.000000	-0.001902	-0.010311	-0.006626	0.001329	-0.001758	0.103179
ratio	0.002670	-0.001902	1.000000	0.001572	0.008193	0.004216	-0.002310	0.458288
repeat	0.136132	-0.010311	0.001572	1.000000	0.002110	-0.000668	0.006170	-0.001257
chip	-0.001765	-0.006626	0.008193	0.002110	1.000000	-0.004120	0.001536	-0.062658
pin	0.005620	0.001329	0.004216	-0.000668	-0.004120	1.000000	0.000945	-0.100114
online	-0.001649	-0.001758	-0.002310	0.006170	0.001536	0.000945	1.000000	0.192275
fraud	0.180288	0.103179	0.458288	-0.001257	-0.062658	-0.100114	0.192275	1.000000

Ввод [10]:
```
df.corr()['fraud']
```

Out[10]:
```
dist_home    0.180288
dist_last    0.103179
ratio        0.458288
repeat      -0.001257
chip        -0.062658
pin         -0.100114
online       0.192275
fraud        1.000000
Name: fraud, dtype: float64
```

Ввод [11]:
```
fig, ax = plt.subplots(1, 1, sharex='col', sharey='row', figsize=(13,10))
fig.suptitle('Корреляционная матрица')
sns.heatmap(df.corr(), ax=ax, annot=True, fmt='.3f', cmap='YlGnBu')
```

Out[11]: <AxesSubplot:>



6 Построение модели ([к оглавлению]())

Ввод [12]:
```
X_train, X_test, y_train, y_test = \
train_test_split(df.loc[:, df.columns != 'fraud'], df["fraud"], test_size=0.2, random_state=1)
```

Ввод [13]:
```
def class_proportions(array: np.ndarray) -> Dict[int, Tuple[int, float]]:
    labels, counts = np.unique(array, return_counts=True)
    counts_perc = counts/array.size
    res = dict()
    for label, count2 in zip(labels, zip(counts, counts_perc)):
        res[label] = count2
    return res

def print_class_proportions(array: np.ndarray):
    proportions = class_proportions(array)
    if len(proportions)>0:
        print('Метка \t Количество \t Процент встречаемости')
    for i in proportions:
        val, val_perc = proportions[i]
        val_perc_100 = round(val_perc * 100, 2)
        print('{} \t {:<10} \t {}%'.format(i, val, val_perc_100))
```

Ввод [14]:
```
print_class_proportions(y_train)
```

```
Метка    Количество      Процент встречаемости
0        36538           91.34%
1        3462            8.65%
```

Ввод [15]:
```
print_class_proportions(y_test)
```

```
Метка    Количество      Процент встречаемости
0        9145            91.45%
1        855             8.55%
```

Ввод [16]:
```
knn10 = KNeighborsClassifier(n_neighbors=10)
knn10.fit(X_train, y_train)
target10 = knn10.predict(X_test)
len(target10), target10
```

Out[16]:
```
(10000, array([0, 0, 0, ..., 0, 0, 0]))
```

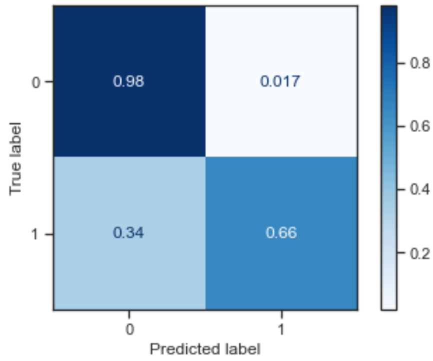
Ввод [17]:
```
def accuracy_score_for_classes(
    y_true: np.ndarray,
    y_pred: np.ndarray) -> Dict[int, float]:
    d = {'t': y_true, 'p': y_pred}
    df = pd.DataFrame(data=d)
    classes = np.unique(y_true)
    res = dict()

    for c in classes:
        temp_data_flt = df[df['t']==c]
        temp_acc = accuracy_score(
            temp_data_flt['t'].values,
            temp_data_flt['p'].values)
        res[c] = temp_acc

    return res

def print_accuracy_score_for_classes(
    y_true: np.ndarray,
    y_pred: np.ndarray):
    accs = accuracy_score_for_classes(y_true, y_pred)
    if len(accs)>0:
        print('Метка \t Accuracy')
    for i in accs:
        print('{} \t {}'.format(i, accs[i]))
```

Ввод [18]:
```
print_accuracy_score_for_classes(y_test, target10)
```

```
Метка    Accuracy
0        0.9825041006014216
1        0.6608187134502924
```

Ввод [19]:
```
plot_confusion_matrix(knn10, X_test, y_test, cmap=plt.cm.Blues, normalize='true')
```

Out[19]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7fc4e52d26a0>



Ввод [20]:
```
print(classification_report(y_test, target10))
```

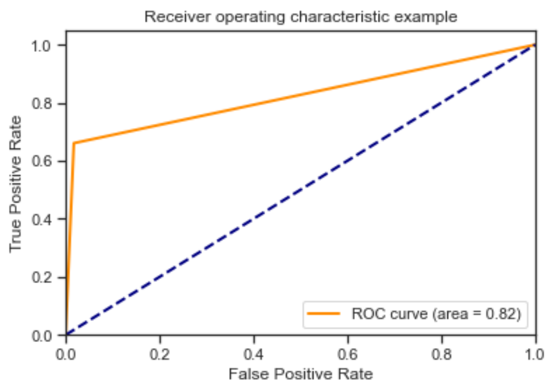
```
              precision    recall  f1-score   support

           0       0.97      0.98      0.98      9145
           1       0.78      0.66      0.72       855

    accuracy                           0.95     10000
   macro avg       0.87      0.82      0.85     10000
weighted avg       0.95      0.95      0.95     10000
```

Ввод [21]:
```
recall_score(y_test, target10)
```

Out[21]: 0.6608187134502924

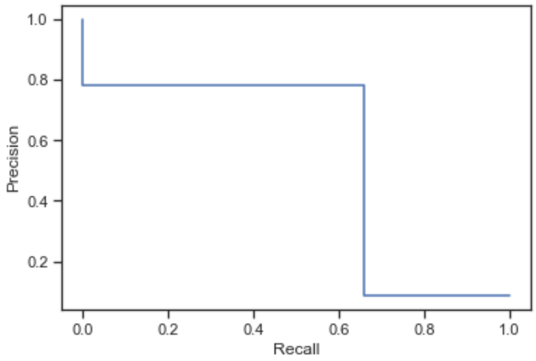
Ввод [22]:
```
# Отрисовка ROC-кривой
def draw_roc_curve(y_true, y_score, pos_label, average):
    fpr, tpr, thresholds = roc_curve(y_true, y_score, pos_label=pos_label)
    roc_auc_value = roc_auc_score(y_true, y_score, average=average)
    plt.figure()
    lw = 2
    plt.plot(fpr, tpr, color='darkorange', lw=lw, label='ROC curve (area = %0.2f)' % roc_auc_value)
    plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('Receiver operating characteristic example')
    plt.legend(loc="lower right")
    plt.show()
```

Ввод [23]:
```
# Для 10 ближайших соседей
draw_roc_curve(y_test, target10, pos_label=1, average='micro')
```



Ввод [24]:
```
precision, recall, _ = precision_recall_curve(y_test, target10)
display = PrecisionRecallDisplay(precision, recall)
display.plot()
```

Out[24]:
```
<sklearn.metrics._plot.precision_recall_curve.PrecisionRecallDisplay at 0x7fc4e584f5b0>
```



7 Подбор гиперпараметра K (к оглавлению)

7.1 K_Fold cross-validation

Ввод [25]:
```
X = df.loc[:, df.columns != 'fraud']
y = df["fraud"]
```

Ввод [26]:
```
%%time
clf_gs = GridSearchCV(KNeighborsClassifier(),
                      param_grid={'n_neighbors': range(1,10,1)},
                      cv=KFold(n_splits=5),
                      scoring='recall',
                      n_jobs=-1
)
clf_gs.fit(X, y)
```

```
CPU times: user 170 ms, sys: 79.3 ms, total: 249 ms
Wall time: 14.2 s
```

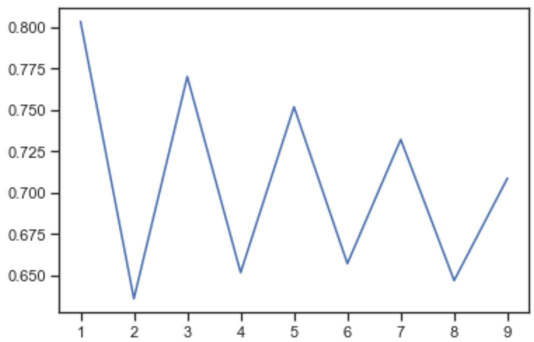
Out[26]:
```
GridSearchCV(cv=KFold(n_splits=5, random_state=None, shuffle=False),
             estimator=KNeighborsClassifier(), n_jobs=-1,
             param_grid={'n_neighbors': range(1, 10)}, scoring='recall')
```

Ввод [27]:
```
clf_gs.best_score_
```

Out[27]:
```
0.803486310666689
```

Ввод [28]:
```
plt.plot(range(1,10,1), clf_gs.cv_results_['mean_test_score'])
```

Out[28]:
```
[<matplotlib.lines.Line2D at 0x7fc4ea4ca310>]
```



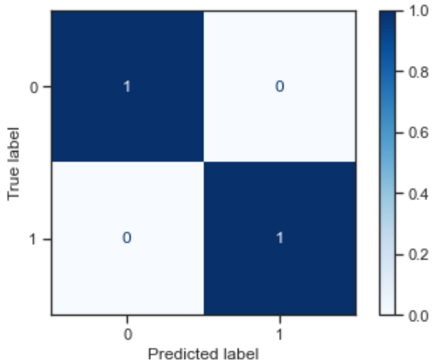
Ввод [29]:
```
target_gs = clf_gs.best_estimator_.predict(X)
```

Ввод [30]:
```
print(classification_report(y, target_gs))
```

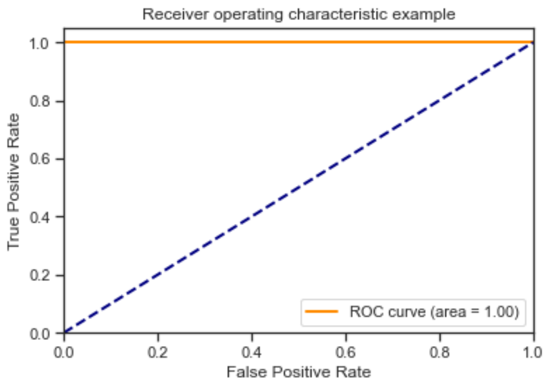
```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     45683
           1       1.00      1.00      1.00      4317

    accuracy                           1.00     50000
   macro avg       1.00      1.00      1.00     50000
weighted avg       1.00      1.00      1.00     50000
```

Ввод [31]:
```
plot_confusion_matrix(clf_gs.best_estimator_, X, y, cmap=plt.cm.Blues, normalize='true')
```

Out[31]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7fc4e53a4c40>
```



Ввод [32]:
```
draw_roc_curve(y, target_gs, pos_label=1, average='micro')
```



7.2 StratifiedKFold cross-validation

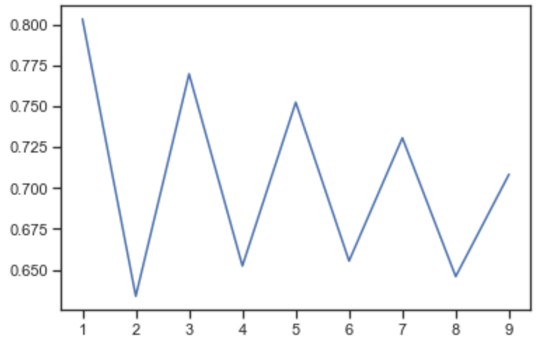
Ввод [33]:
```
%%time
clf_gs_stf = GridSearchCV(KNeighborsClassifier(),
                          param_grid={'n_neighbors': range(1,10,1)},
                          cv=StratifiedKFold(n_splits=5),
                          scoring='recall',
                          n_jobs=-1
)
clf_gs_stf.fit(X, y)
```

```
CPU times: user 219 ms, sys: 30.5 ms, total: 249 ms
Wall time: 8.6 s
```

Out[33]:
```
GridSearchCV(cv=StratifiedKFold(n_splits=5, random_state=None, shuffle=False),
             estimator=KNeighborsClassifier(), n_jobs=-1,
             param_grid={'n_neighbors': range(1, 10)}, scoring='recall')
```

Ввод [34]:
```
plt.plot(range(1,10,1), clf_gs_stf.cv_results_['mean_test_score'])
```

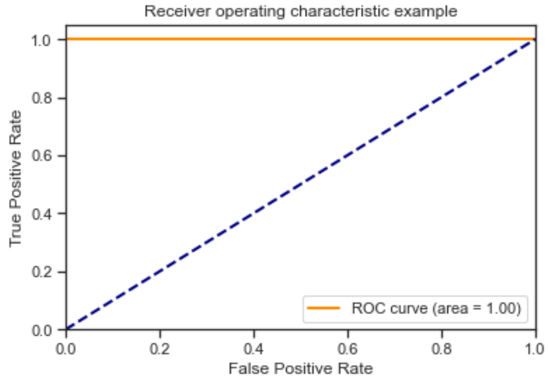
Out[34]:
```
[<matplotlib.lines.Line2D at 0x7fc4e9e0b3a0>]
```



Ввод [35]:
```
clf_gs_stf.best_score_
```

Out[35]:
```
0.8033399854083516
```

Ввод [36]:
```
target_gs_stf = clf_gs_stf.best_estimator_.predict(X)
draw_roc_curve(y, target_gs_stf, pos_label=1, average='micro')
```



7.3 Сравнение моделей

Метрика	Начальная модель K=10	Оптимальная модель (KFold)	Оптимальная модель (StratifiedKFold)
Recall	0.66	0.8	0.8
AUC	0.82	1	1