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(МГТУ им. Н.Э. Баумана)

Факультет «Информатика и системы управления»

Кафедра «Системы обработки информации и управления»

Отчет по лабораторной работе №3

по теме «*Подготовка обучающей и тестовой выборки, кросс-валидация и подбор гиперпараметров на примере метода ближайших соседей*»

по дисциплине «Технологии машинного обучения»

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Проверил:
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Задание:

1. Выберите набор данных (датасет) для решения задачи классификации или регрессии.
2. В случае необходимости проведите удаление или заполнение пропусков и кодирование категориальных признаков.
3. С использованием метода train_test_split разделите выборку на обучающую и тестовую.
4. Обучите модель ближайших соседей для произвольно заданного гиперпараметра K. Оцените качество модели с помощью подходящих для задачи метрик.
5. Произведите подбор гиперпараметра K с использованием GridSearchCV и RandomizedSearchCV и кросс-валидации, оцените качество оптимальной модели. Используйте не менее двух стратегий кросс-валидации.
6. Сравните метрики качества исходной и оптимальной моделей.

Текст программы и экранные формы:

Ссылка на Colab:

https://colab.research.google.com/drive/1aPJk1PyMCODOFSIZaduePiaLThF_7iQx?usp=sharing

Ссылка на датасет: https://www.kaggle.com/datasets/brsdincer/star-type-classification

```
import numpy as np
import pandas as pd
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import cross_val_score, cross_validate
from sklearn.model_selection import KFold, RepeatedKFold, LeaveOneOut, LeavePOut, ShuffleSplit, StratifiedKFold
from sklearn.metrics import accuracy_score, balanced_accuracy_score
from sklearn.metrics import precision_score, recall_score, f1_score, classification_report
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
from sklearn.metrics import roc_curve, roc_auc_score
from sklearn.model_selection import GridSearchCV, RandomizedSearchCV
from sklearn.model_selection import learning_curve, validation_curve
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
sns.set(style="ticks")
```

```
[ ] data = pd.read_csv('Stars.csv')
    data.head()
```

	Temperature	L	R	A_M	Color	Spectral_Class	Type
0	3068	0.002400	0.1700	16.12	Red	M	0
1	3042	0.000500	0.1542	16.60	Red	M	0
2	2600	0.000300	0.1020	18.70	Red	M	0
3	2800	0.000200	0.1600	16.65	Red	M	0
4	1939	0.000138	0.1030	20.06	Red	M	0

```
[ ] categorical_cols=data.select_dtypes(include=object).columns.to_list()
    categorical_cols
```

```
['Color', 'Spectral_Class']
```

```
data.describe()
```

	Temperature	L	R	A_M	Type
count	240.000000	240.000000	240.000000	240.000000	240.000000
mean	10497.462500	107188.361635	237.157781	4.382396	2.500000
std	9552.425037	179432.244940	517.155763	10.532512	1.711394
min	1939.000000	0.000080	0.008400	-11.920000	0.000000
25%	3344.250000	0.000865	0.102750	-6.232500	1.000000
50%	5776.000000	0.070500	0.762500	8.313000	2.500000
75%	15055.500000	198050.000000	42.750000	13.697500	4.000000
max	40000.000000	849420.000000	1948.500000	20.060000	5.000000

```
[ ] data.shape
```

```
(240, 7)
```

```
[ ] data.dtypes
```

```
Temperature         int64
L                 float64
R                 float64
A_M               float64
Color              object
Spectral_Class     object
Type                int64
dtype: object
```

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

```
Temperature       0
L                 0
R                 0
A_M               0
Color             0
Spectral_Class    0
Type              0
dtype: int64
```

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 240 entries, 0 to 239
Data columns (total 7 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   Temperature     240 non-null    int64
 1   L               240 non-null    float64
 2   R               240 non-null    float64
 3   A_M             240 non-null    float64
 4   Color           240 non-null    object
 5   Spectral_Class  240 non-null    object
 6   Type            240 non-null    int64
dtypes: float64(3), int64(2), object(2)
memory usage: 13.2+ KB
```

```
[ ] total_count = data.shape[0]
    print('Всего строк: {}'.format(total_count))
```

```
Всего строк: 240
```

```
[ ] print('Color: ', data['Color'].unique())
    print('Spectral_Class: ', data['Spectral_Class'].unique())
```

```
Color:  ['Red' 'Blue White' 'White' 'Yellowish White' 'Blue white'
 'Pale yellow orange' 'Blue' 'Blue-white' 'Whitish' 'yellow-white'
 'Orange' 'White-Yellow' 'white' 'yellowish' 'Yellowish' 'Orange-Red'
 'Blue-White']
Spectral_Class:  ['M' 'B' 'A' 'F' 'O' 'K' 'G']
```

```
[ ] data['Type'].unique()
```

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

```
[ ] data.shape
```

```
(240, 7)
```

```
new_data = pd.get_dummies(data, columns = ['Color', 'Spectral_Class'],  dummy_na=True)
new_data.head()
```

	Temperature	L	R	A_M	Type	Color_Blue	Color_Blue White	Color_Blue white	Color_Blue-White	Color_Blue-white	...	Color_yellowish	Color_nan	Spectral_Class_A	Spectral_Class_B	Spectral_Class_F	Spect
0	3068	0.002400	0.1700	16.12	0	0	0	0	0	0	...	0	0	0	0	0	
1	3042	0.000500	0.1542	16.60	0	0	0	0	0	0	...	0	0	0	0	0	
2	2600	0.000300	0.1020	18.70	0	0	0	0	0	0	...	0	0	0	0	0	
3	2800	0.000200	0.1600	16.65	0	0	0	0	0	0	...	0	0	0	0	0	
4	1939	0.000138	0.1030	20.06	0	0	0	0	0	0	...	0	0	0	0	0	

5 rows × 31 columns

```
[ ] new_data.shape
```

```
(240, 31)
```

```
[ ] data = new_data.copy()
```

```
[ ] data.shape
```

```
(240, 31)
```

```
data.describe()
```

	Temperature	L	R	A_M	Type	Color_Blue	Color_Blue White	Color_Blue white	Color_Blue-White	Color_Blue-white	...	Color_yellowish	Color_nan	Spectral_Class_A	Spectral_Class_
count	240.000000	240.000000	240.000000	240.000000	240.000000	240.000000	240.000000	240.000000	240.000000	240.000000	...	240.000000	240.0	240.000000	240.00000
mean	10497.462500	107188.361635	237.157781	4.382396	2.500000	0.233333	0.041667	0.016667	0.004167	0.108333	...	0.008333	0.0	0.079167	0.19166
std	9552.425037	179432.244940	517.155763	10.532512	1.711394	0.423836	0.200244	0.128287	0.064550	0.311450	...	0.091096	0.0	0.270563	0.39443
min	1939.000000	0.000080	0.008400	-11.920000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	...	0.000000	0.0	0.000000	0.00000
25%	3344.250000	0.000865	0.102750	-6.232500	1.000000	0.000000	0.000000	0.000000	0.000000	0.000000	...	0.000000	0.0	0.000000	0.00000
50%	5776.000000	0.070500	0.762500	8.313000	2.500000	0.000000	0.000000	0.000000	0.000000	0.000000	...	0.000000	0.0	0.000000	0.00000
75%	15055.500000	198050.000000	42.750000	13.697500	4.000000	0.000000	0.000000	0.000000	0.000000	0.000000	...	0.000000	0.0	0.000000	0.00000
max	40000.000000	849420.000000	1948.500000	20.060000	5.000000	1.000000	1.000000	1.000000	1.000000	1.000000	...	1.000000	0.0	1.000000	1.00000

8 rows × 31 columns

```
[ ] data
```

	Temperature	L	R	A_M	Type	Color_Blue	Color_Blue White	Color_Blue white	Color_Blue-White	Color_Blue-white	...	Color_yellowish	Color_nan	Spectral_Class_A	Spectral_Class_B	Spectral_Cla
0	3068	0.002400	0.1700	16.12	0	0	0	0	0	0	...	0	0	0	0	
1	3042	0.000500	0.1542	16.60	0	0	0	0	0	0	...	0	0	0	0	
2	2600	0.000300	0.1020	18.70	0	0	0	0	0	0	...	0	0	0	0	
3	2800	0.000200	0.1600	16.65	0	0	0	0	0	0	...	0	0	0	0	
4	1939	0.000138	0.1030	20.06	0	0	0	0	0	0	...	0	0	0	0	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
235	38940	374830.000000	1356.0000	-9.93	5	1	0	0	0	0	...	0	0	0	0	
236	30839	834042.000000	1194.0000	-10.63	5	1	0	0	0	0	...	0	0	0	0	
237	8829	537493.000000	1423.0000	-10.73	5	0	0	0	0	0	...	0	0	1	0	
238	9235	404940.000000	1112.0000	-11.23	5	0	0	0	0	0	...	0	0	1	0	
239	37882	294903.000000	1783.0000	-7.80	5	1	0	0	0	0	...	0	0	0	0	

240 rows × 31 columns

```
def class_proportions(array: np.ndarray):
    """
    Вычисляет пропорции классов
    array - массив, содержащий метки классов
    """
    # Получение меток классов и количества меток каждого класса
    labels, counts = np.unique(array, return_counts=True)
    # Превращаем количество меток в процент их встречаемости
    # делим количество меток каждого класса на общее количество меток
    counts_perc = counts/array.size
    # Теперь sum(counts_perc)==1.0
    # Создаем результирующий словарь,
    # ключом словаря является метка класса,
    # а значением словаря процент встречаемости метки
    res = dict()
    for label, count2 in zip(labels, zip(counts, counts_perc)):
        res[label] = count2
    return res

def print_class_proportions(array: np.ndarray):
    """
    Вывод пропорций классов
    """
    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 {} \t \t {}%'.format(i, val, val_perc_100))
```

```
[ ] df = data.copy()
```

```
[ ] y_df = df['Type']
    df = df.drop(columns=['Type'])
```

```
[ ] # разделение на объекты-признаки и целевой признак
    X = df.values
    y = y_df.values
```

```
print_class_proportions(y)
```

```
Метка    Количество    Процент встречаемости
0        40            16.67%
1        40            16.67%
2        40            16.67%
3        40            16.67%
4        40            16.67%
5        40            16.67%
```

```
[ ] print(X.shape, y.shape)
```

```
(240, 30) (240,)
```

```
[ ] type(y)
```

```
numpy.ndarray
```

```
[ ] np.unique(y)
```

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

```
[ ] # 1.Формирование обучающей и тестовой выборки
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state = 7)
```

```
[ ] # 2.Первичное обучение модели и оценка качества
    cl1_1 = KNeighborsClassifier(n_neighbors=9)
    cl1_1.fit(X_train, y_train)
    target1_0 = cl1_1.predict(X_train)
    target1_1 = cl1_1.predict(X_test)
    accuracy_score(y_train, target1_0), accuracy_score(y_test, target1_1)
```

```
(0.7083333333333334, 0.5208333333333334)
```

```
[ ] # 3.Оценка качества модели с использованием кросс-валидации
    scores = cross_val_score(KNeighborsClassifier(n_neighbors=9), X, y, cv=15)
    np.mean(scores)
```

```
0.6375
```

```
[ ] scoring = {'precision': 'precision_macro',
               'recall': 'recall_macro',
               'f1': 'f1_macro',
               'accuracy': 'accuracy'}
```

```
scores = cross_validate(KNeighborsClassifier(n_neighbors=11),
                        X, y, scoring=scoring,
                        cv=15, return_train_score=True)
scores
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labe
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labe
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labe
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labe
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labe
  _warn_prf(average, modifier, msg_start, len(result))
{'fit_time': array([0.00103664, 0.00375748, 0.0006237 , 0.00057602, 0.00059557,
       0.00058842, 0.00070214, 0.00101542, 0.00114322, 0.00062656,
       0.00059509, 0.00057507, 0.00061154, 0.00062656, 0.00055289]),
 'score_time': array([0.00870538, 0.00995636, 0.00762844, 0.00810528, 0.0104444 ,
```

```
        0.00806093, 0.00784898, 0.00886488, 0.00756478, 0.0085156 ,
        0.00820351, 0.00885105, 0.01178479, 0.00742936, 0.00882912]),
 'test_precision': array([0.68333333, 0.60833333, 0.58333333, 0.51111111, 0.68055556,
        0.58333333, 0.61111111, 0.51111111, 0.72222222, 0.625     ,
        0.58333333, 0.45      , 0.76111111, 0.65      , 0.46111111]),
 'train_precision': array([0.69737125, 0.7319257 , 0.71832701, 0.70443119, 0.70402929,
        0.71444387, 0.69383494, 0.71768711, 0.70945698, 0.7101608 ,
        0.70379993, 0.72752777, 0.69133342, 0.72367292, 0.74792095]),
 'test_recall': array([0.63888889, 0.66666667, 0.58333333, 0.47222222, 0.66666667,
        0.58333333, 0.55555556, 0.61111111, 0.69444444, 0.63888889,
        0.63888889, 0.5       , 0.69444444, 0.61111111, 0.52777778]),
 'train_recall': array([0.69108582, 0.70851114, 0.70412518, 0.69594595, 0.68669986,
        0.70519203, 0.67828355, 0.70104315, 0.69618303, 0.70080607,
        0.68835941, 0.72368421, 0.67532006, 0.70199147, 0.7329303 ]),
 'test_f1': array([0.60833333, 0.56587302, 0.52619048, 0.46746032, 0.66507937,
        0.57222222, 0.54285714, 0.52380952, 0.66111111, 0.55753968,
        0.60634921, 0.42857143, 0.69444444, 0.59126984, 0.48134921]),
 'train_f1': array([0.68838271, 0.70278938, 0.69991653, 0.69288424, 0.68205122,
        0.70277123, 0.6737681 , 0.69684185, 0.69184917, 0.69789024,
        0.68359372, 0.72140152, 0.66792371, 0.69491139, 0.72824286]),
 'test_accuracy': array([0.625 , 0.625 , 0.5625, 0.5   , 0.6875, 0.5625, 0.5625, 0.5625,
        0.6875, 0.625 , 0.625 , 0.5625, 0.6875, 0.625 , 0.5625]),
 'train_accuracy': array([0.69196429, 0.70982143, 0.70535714, 0.69642857, 0.6875    ,
        0.70535714, 0.67857143, 0.70089286, 0.69642857, 0.70089286,
        0.6875    , 0.72321429, 0.67410714, 0.70089286, 0.73214286])}
```

+ Код + Текст

```
[ ] for i in scores:
        print(i, np.mean(scores[i]))
```

```
fit_time 0.0009084224700927734
score_time 0.008719523747762045
test_precision 0.6016666666666666
train_precision 0.7130615419548796
test_recall 0.6055555555555556
train_recall 0.6993440809230282
test_f1 0.5661640211640211
train_f1 0.695014524881888
test_accuracy 0.6041666666666666
train_accuracy 0.699404761904762
```

```
[ ] # 4.Подбор гиперпараметров на основе решетчатого поиска и кросс-валидации
    n_range = np.array(range(3,50,2))
    tuned_parameters = [{'n_neighbors': n_range}]
    tuned_parameters
```

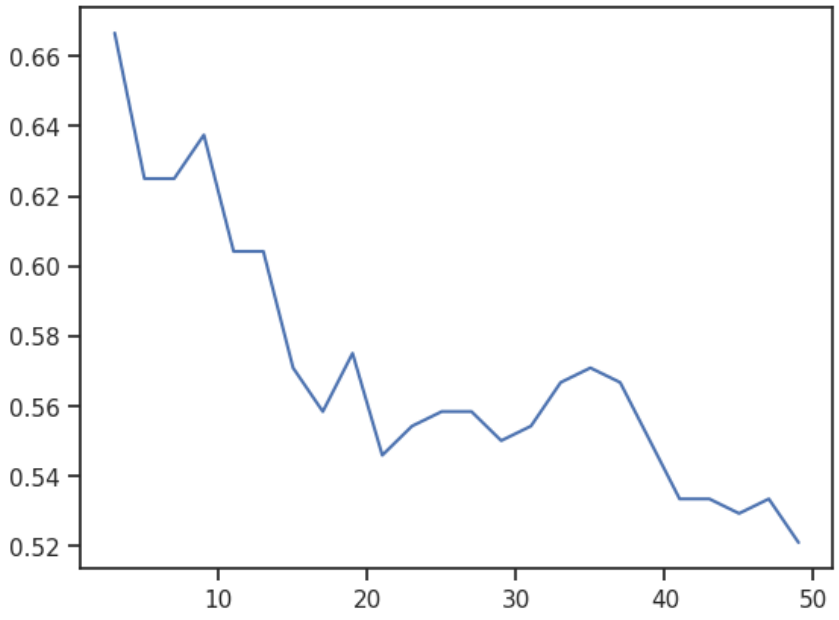
```
[{'n_neighbors': array([ 3,  5,  7,  9, 11, 13, 15, 17, 19, 21, 23, 25, 27, 29, 31, 33, 35,
         37, 39, 41, 43, 45, 47, 49])}]
```

```
[ ] clf_gs = GridSearchCV(KNeighborsClassifier(), tuned_parameters, cv=15, scoring='accuracy')
    clf_gs.fit(X, y)
    clf_gs.best_params_
```

```
{'n_neighbors': 3}
```

```
plt.plot(n_range, clf_gs.cv_results_['mean_test_score'])
```

```
[<matplotlib.lines.Line2D at 0x7985b9bffc40>]
```

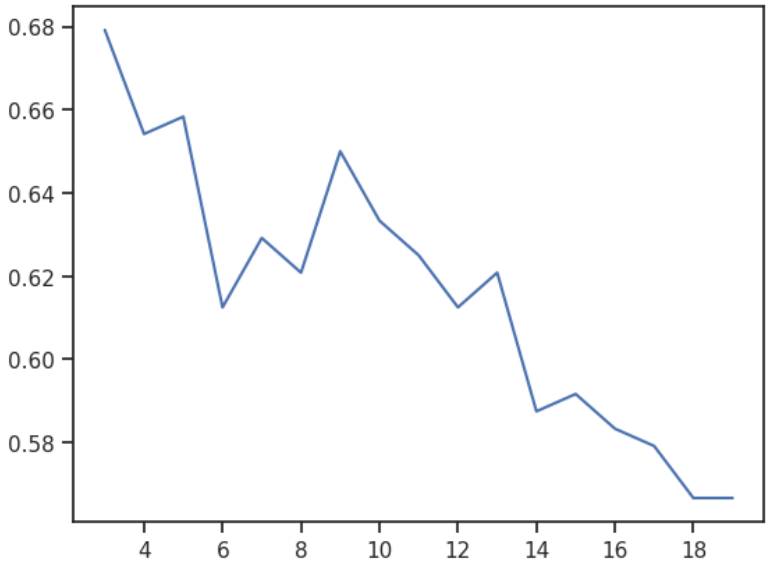


```
[ ] # Повторный подбор
    n_range = np.array(range(3,20,1))
    tuned_parameters = [{'n_neighbors': n_range}]
    clf_gs = GridSearchCV(KNeighborsClassifier(), tuned_parameters, cv=20, scoring='accuracy')
    clf_gs.fit(X, y)
    clf_gs.best_params_
```

```
{'n_neighbors': 3}
```

```
plt.plot(n_range, clf_gs.cv_results_['mean_test_score'])
```

```
[<matplotlib.lines.Line2D at 0x7985b5210dc0>]
```




```
# 5.Обучение модели и оценка качества с учетом подобранных гиперпараметров
clf_gs.best_estimator_.fit(X_train, y_train)
target2_0 = clf_gs.best_estimator_.predict(X_train)
target2_1 = clf_gs.best_estimator_.predict(X_test)
# Новое качество модели
accuracy_score(y_train, target2_0), accuracy_score(y_test, target2_1)
```

```
(0.8489583333333334, 0.5833333333333334)
```

+ Код + Текст

```
[ ] # Качество модели до подбора гиперпараметров
    accuracy_score(y_train, target1_0), accuracy_score(y_test, target1_1)
```

```
(0.7083333333333334, 0.5208333333333334)
```

```
[ ] clf_gs.classes_
```

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

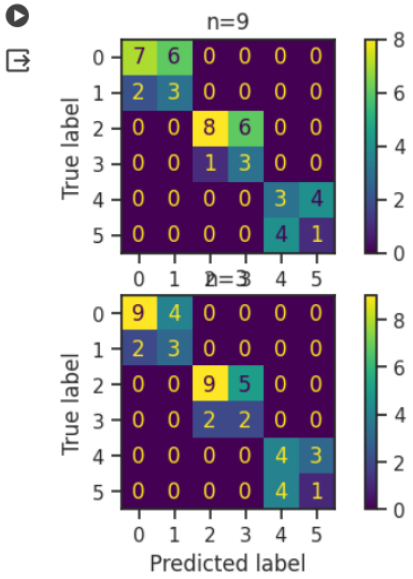
```
[ ] cl1_1.classes_
```

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

```
[ ] cm2 = confusion_matrix(y_test, target2_1, labels = clf_gs.classes_)
```

```
[ ] cm1 = confusion_matrix(y_test, target1_1, labels = cl1_1.classes_)
```

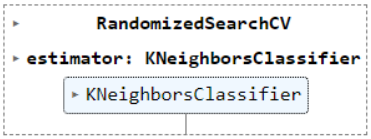
```
[ ] fig, ax = plt.subplots(2,1)
    ax[0].set_title("n=9")
    ax[1].set_title("n=3")

    ConfusionMatrixDisplay(confusion_matrix=cm1, display_labels=[0, 1, 2, 3, 4, 5]).plot(ax=ax[0])

    ConfusionMatrixDisplay(confusion_matrix=cm2, display_labels=[0, 1, 2, 3, 4, 5]).plot(ax=ax[1]);
```




```
[ ] n_range = np.array(range(3,50,2))
    tuned_parameters = [{'n_neighbors': n_range}]
    tuned_parameters
```

```
[{'n_neighbors': array([ 3,  5,  7,  9, 11, 13, 15, 17, 19, 21, 23, 25, 27, 29, 31, 33, 35,
        37, 39, 41, 43, 45, 47, 49])}]
```

```
[ ] clf_rs = RandomizedSearchCV(KNeighborsClassifier(), tuned_parameters, cv=15, scoring='accuracy')
    clf_rs.fit(X_train, y_train)
```




```
clf_rs.best_score_, clf_rs.best_params_
```

```
(0.6666666666666666, {'n_neighbors': 5})
```

+ Код + Текст

```
[ ] clf_rs.best_estimator_.fit(X_train, y_train)
    target3_0 = clf_rs.best_estimator_.predict(X_train)
    target3_1 = clf_rs.best_estimator_.predict(X_test)
    # Новое качество модели
    accuracy_score(y_train, target3_0), accuracy_score(y_test, target3_1)
```

```
(0.7708333333333334, 0.5416666666666666)
```

K-fold

```
[ ] kf = KFold(n_splits=5)
    scores = cross_val_score(KNeighborsClassifier(n_neighbors=3),
                             X, y, scoring='accuracy',
                             cv=kf)
    scores
```

```
array([0.66666667, 0.64583333, 0.58333333, 0.66666667, 0.64583333])
```

```
[ ] np.mean(scores)
```

```
0.6416666666666667
```

Repeted K-fold

```
kf = RepeatedKFold(n_splits=5, n_repeats=2)
scores = cross_val_score(KNeighborsClassifier(n_neighbors=3),
                         X, y, scoring='accuracy',
                         cv=kf)
scores
```

```
array([0.5625    , 0.6875    , 0.60416667, 0.72916667, 0.64583333,
       0.625     , 0.66666667, 0.60416667, 0.625     , 0.6875    ])
```

```
[ ] np.mean(scores)
```

```
0.64375
```

```
[ ] n_range = np.array(range(3,20,1))
    tuned_parameters = [{'n_neighbors': n_range}]
```

```
[ ] kf = KFold(n_splits=5)
```

```
[ ] clf_gs = GridSearchCV(KNeighborsClassifier(), tuned_parameters, cv=kf, scoring='accuracy')
    clf_gs.fit(X, y)
    clf_gs.best_params_
```

```
{'n_neighbors': 3}
```

```
[ ] rkf = RepeatedKFold(n_splits=5, n_repeats=2)
```

```
clf_gs = GridSearchCV(KNeighborsClassifier(), tuned_parameters, cv=rkf, scoring='accuracy')
clf_gs.fit(X, y)
clf_gs.best_params_
```

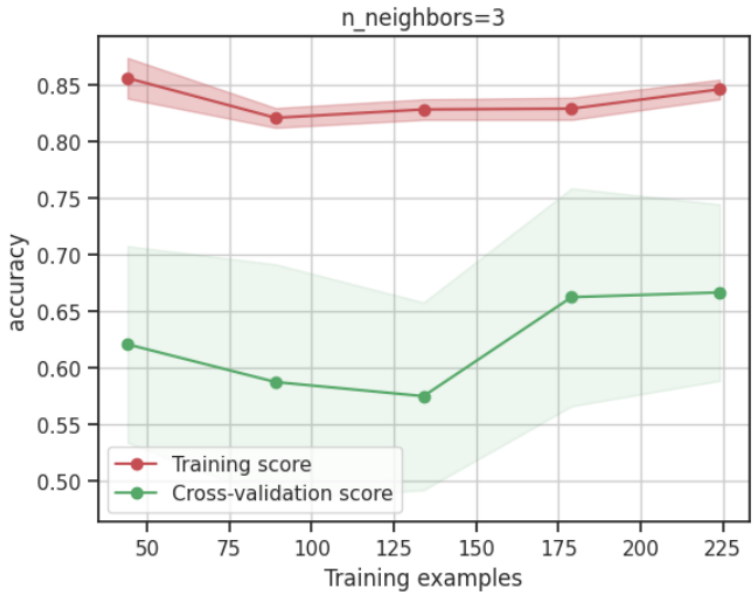
```
{'n_neighbors': 3}
```

```
def plot_learning_curve(estimator, title, X, y, ylim=None, cv=None,
                        n_jobs=None, train_sizes=np.linspace(.1, 1.0, 5), scoring='accuracy'):
    plt.figure()
    plt.title(title)
    if ylim is not None:
        plt.ylim(*ylim)
    plt.xlabel("Training examples")
    plt.ylabel(scoring)
    train_sizes, train_scores, test_scores = learning_curve(
        estimator, X, y, cv=cv, scoring=scoring, n_jobs=n_jobs, train_sizes=train_sizes)
    train_scores_mean = np.mean(train_scores, axis=1)
    train_scores_std = np.std(train_scores, axis=1)
    test_scores_mean = np.mean(test_scores, axis=1)
    test_scores_std = np.std(test_scores, axis=1)
    plt.grid()

    plt.fill_between(train_sizes, train_scores_mean - train_scores_std,
                     train_scores_mean + train_scores_std, alpha=0.3,
                     color="r")
    plt.fill_between(train_sizes, test_scores_mean - test_scores_std,
                     test_scores_mean + test_scores_std, alpha=0.1, color="g")
    plt.plot(train_sizes, train_scores_mean, 'o-', color="r",
             label="Training score")
    plt.plot(train_sizes, test_scores_mean, 'o-', color="g",
             label="Cross-validation score")

    plt.legend(loc="best")
    return plt
```

```
[ ]  def plot_validation_curve(estimator, title, X, y,
                               param_name, param_range, cv,
                               scoring='accuracy'):

        train_scores, test_scores = validation_curve(
            estimator, X, y, param_name=param_name, param_range=param_range,
            cv=cv, scoring=scoring, n_jobs=1)
        train_scores_mean = np.mean(train_scores, axis=1)
        train_scores_std = np.std(train_scores, axis=1)
        test_scores_mean = np.mean(test_scores, axis=1)
        test_scores_std = np.std(test_scores, axis=1)

        plt.title(title)
        plt.xlabel(param_name)
        plt.ylabel(str(scoring))
        plt.ylim(0.0, 1.1)
        lw = 2
        plt.plot(param_range, train_scores_mean, label="Training score",
                     color="darkorange", lw=lw)
        plt.fill_between(param_range, train_scores_mean - train_scores_std,
                         train_scores_mean + train_scores_std, alpha=0.4,
                         color="darkorange", lw=lw)
        plt.plot(param_range, test_scores_mean, label="Cross-validation score",
                     color="navy", lw=lw)
        plt.fill_between(param_range, test_scores_mean - test_scores_std,
                         test_scores_mean + test_scores_std, alpha=0.2,
                         color="navy", lw=lw)
        plt.legend(loc="best")
        return plt
```

```
# 6.Построение кривых обучения и валидации
plot_learning_curve(clf_gs.best_estimator_, 'n_neighbors=3', X, y, cv=15, train_sizes=np.linspace(.2, 1.0, 5))
```

```
<module 'matplotlib.pyplot' from '/usr/local/lib/python3.10/dist-packages/matplotlib/pyplot.py'>
```




```
n_range2 = np.array(range(1,16,1))
plot_validation_curve(clf_gs.best_estimator_, 'knn', X, y,
                      param_name='n_neighbors', param_range=n_range2,
                      cv=15, scoring="accuracy")
```

```
<module 'matplotlib.pyplot' from '/usr/local/lib/python3.10/dist-packages/matplotlib/pyplot.py'>
```