### Лабораторная работа № 3.

Подготовка обучающей и тестовой выборки, кросс-валидация и подбор гиперпараметров на примере метода ближайших соседей.

**Цель** лабораторной работы: изучение способов подготовки выборки и подбора гиперпараметров на примере метода ближайших соседей.

### Задание:

- 1. Выбрать набор данных (датасет) для решения задачи классификации или регрессии.
- 2. С использованием метода train\_test\_split разделить выборку на обучающую и тестовую.
- 3. Обучить модель ближайших соседей для произвольно заданного гиперпараметра К. Оценить качество модели с помощью подходящих для задачи метрик.

In [86]:

- 4. Произвести подбор гиперпараметра К с использованием GridSearchCV и/или RandomizedSearchCV и кросс-валидации, оценить качество оптимальной модели. Желательно использование нескольких стратегий кросс-валидации.
- 5. Сравнить метрики качества исходной и оптимальной моделей.

#### Выполнение:

В качестве набора данных будем использовать датасет про вино: https://scikit-learn.org/stable/modules/generated/sklearn.datasets.load\_wine.html#sklearn.datasets.load\_wine

### Импорт библиотек

wine['feature\_names']

```
import numpy as np
import pandas as pd
from sklearn.datasets import load wine
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy score
from sklearn.metrics import confusion matrix, plot confusion matrix
from sklearn.metrics import recall score, precision score
from sklearn.model selection import cross validate
from sklearn.model_selection import KFold, LeaveOneOut, LeavePOut
from sklearn.model selection import GridSearchCV, RandomizedSearchCV
from typing import Dict
import seaborn as sns
import matplotlib.pyplot as plt
Загрузка данных
                                                                                                         In [2]:
wine = load wine()
                                                                                                        In [3]:
for x in wine:
    print(x)
data
target
frame
target_names
feature_names
                                                                                                        In [4]:
# Наименование значений целевого признака
wine['target_names']
                                                                                                       Out[4]:
array(['class_0', 'class_1', 'class_2'], dtype='<U7')
                                                                                                        In [5]:
# Признаки датасета
```

```
Out[5]:

['alcohol',
'malic_acid',
'ash',
'alcalinity_of_ash',
'magnesium',
'total_phenols',
'flavanoids',
'nonflavanoid_phenols',
'proanthocyanins',
'color_intensity',
'hue',
'od280/od315_of_diluted_wines',
'proline']

In [6]:

wine['data'].shape

Out[6]:

# Преобразование в рапсы DataFrame

w_data = pd.DataFrame(data=np.c_[wine['data'], wine['target']], columns = wine['feature_names']+['target']

w_data

Out[8]:

alcohol_maiic_acid_ash_alcalinity_of_ash_magnesium_total_phenols_flavanoids_nonflavanoid_phenols_presstype.color_intensity.
```

alcohol	malic_acid	ash	alcalinity_of_ash	magnesium	total_phenols	flavanoids	nonflavanoid_phenols	proanthocyanins	color_intensity
14.23	1.71	2.43	15.6	127.0	2.80	3.06	0.28	2.29	5.64
13.20	1.78	2.14	11.2	100.0	2.65	2.76	0.26	1.28	4.38
13.16	2.36	2.67	18.6	101.0	2.80	3.24	0.30	2.81	5.68
14.37	1.95	2.50	16.8	113.0	3.85	3.49	0.24	2.18	7.80
13.24	2.59	2.87	21.0	118.0	2.80	2.69	0.39	1.82	4.32
13.71	5.65	2.45	20.5	95.0	1.68	0.61	0.52	1.06	7.70
13.40	3.91	2.48	23.0	102.0	1.80	0.75	0.43	1.41	7.30
13.27	4.28	2.26	20.0	120.0	1.59	0.69	0.43	1.35	10.20
13.17	2.59	2.37	20.0	120.0	1.65	0.68	0.53	1.46	9.30
14.13	4.10	2.74	24.5	96.0	2.05	0.76	0.56	1.35	9.20
	14.23 13.20 13.16 14.37 13.24  13.71 13.40 13.27 13.17	14.23     1.71       13.20     1.78       13.16     2.36       14.37     1.95       13.24     2.59           13.71     5.65       13.40     3.91       13.27     4.28       13.17     2.59	14.23     1.71     2.43       13.20     1.78     2.14       13.16     2.36     2.67       14.37     1.95     2.50       13.24     2.59     2.87            13.71     5.65     2.45       13.40     3.91     2.48       13.27     4.28     2.26       13.17     2.59     2.37	14.23       1.71       2.43       15.6         13.20       1.78       2.14       11.2         13.16       2.36       2.67       18.6         14.37       1.95       2.50       16.8         13.24       2.59       2.87       21.0               13.71       5.65       2.45       20.5         13.40       3.91       2.48       23.0         13.27       4.28       2.26       20.0         13.17       2.59       2.37       20.0	14.23       1.71       2.43       15.6       127.0         13.20       1.78       2.14       11.2       100.0         13.16       2.36       2.67       18.6       101.0         14.37       1.95       2.50       16.8       113.0         13.24       2.59       2.87       21.0       118.0                13.71       5.65       2.45       20.5       95.0         13.40       3.91       2.48       23.0       102.0         13.27       4.28       2.26       20.0       120.0         13.17       2.59       2.37       20.0       120.0	14.23       1.71       2.43       15.6       127.0       2.80         13.20       1.78       2.14       11.2       100.0       2.65         13.16       2.36       2.67       18.6       101.0       2.80         14.37       1.95       2.50       16.8       113.0       3.85         13.24       2.59       2.87       21.0       118.0       2.80                 13.71       5.65       2.45       20.5       95.0       1.68         13.40       3.91       2.48       23.0       102.0       1.80         13.27       4.28       2.26       20.0       120.0       1.59         13.17       2.59       2.37       20.0       120.0       1.65	14.23       1.71       2.43       15.6       127.0       2.80       3.06         13.20       1.78       2.14       11.2       100.0       2.65       2.76         13.16       2.36       2.67       18.6       101.0       2.80       3.24         14.37       1.95       2.50       16.8       113.0       3.85       3.49         13.24       2.59       2.87       21.0       118.0       2.80       2.69                   13.71       5.65       2.45       20.5       95.0       1.68       0.61         13.40       3.91       2.48       23.0       102.0       1.80       0.75         13.27       4.28       2.26       20.0       120.0       1.59       0.69         13.17       2.59       2.37       20.0       120.0       1.65       0.68	14.23       1.71       2.43       15.6       127.0       2.80       3.06       0.28         13.20       1.78       2.14       11.2       100.0       2.65       2.76       0.26         13.16       2.36       2.67       18.6       101.0       2.80       3.24       0.30         14.37       1.95       2.50       16.8       113.0       3.85       3.49       0.24         13.24       2.59       2.87       21.0       118.0       2.80       2.69       0.39                     13.71       5.65       2.45       20.5       95.0       1.68       0.61       0.52         13.40       3.91       2.48       23.0       102.0       1.80       0.75       0.43         13.27       4.28       2.26       20.0       120.0       1.59       0.69       0.43         13.17       2.59       2.37       20.0       120.0       1.65       0.68       0.53	14.23       1.71       2.43       15.6       127.0       2.80       3.06       0.28       2.29         13.20       1.78       2.14       11.2       100.0       2.65       2.76       0.26       1.28         13.16       2.36       2.67       18.6       101.0       2.80       3.24       0.30       2.81         14.37       1.95       2.50       16.8       113.0       3.85       3.49       0.24       2.18         13.24       2.59       2.87       21.0       118.0       2.80       2.69       0.39       1.82

178 rows × 14 columns

In [9]:

# # Статистические характеристики датасета w\_data.describe()

Out[9]:

	alcohol	malic_acid	ash	alcalinity_of_ash	magnesium	total_phenols	flavanoids	nonflavanoid_phenols	proanthocyanins	CC
count	178.000000	178.000000	178.000000	178.000000	178.000000	178.000000	178.000000	178.000000	178.000000	
mean	13.000618	2.336348	2.366517	19.494944	99.741573	2.295112	2.029270	0.361854	1.590899	
std	0.811827	1.117146	0.274344	3.339564	14.282484	0.625851	0.998859	0.124453	0.572359	
min	11.030000	0.740000	1.360000	10.600000	70.000000	0.980000	0.340000	0.130000	0.410000	
25%	12.362500	1.602500	2.210000	17.200000	88.000000	1.742500	1.205000	0.270000	1.250000	
50%	13.050000	1.865000	2.360000	19.500000	98.000000	2.355000	2.135000	0.340000	1.555000	
75%	13.677500	3.082500	2.557500	21.500000	107.000000	2.800000	2.875000	0.437500	1.950000	
max	14.830000	5.800000	3.230000	30.000000	162.000000	3.880000	5.080000	0.660000	3.580000	

In [13]:

```
Out[13]:
array([[1.423e+01, 1.710e+00, 2.430e+00, 1.560e+01, 1.270e+02, 2.800e+00,
                       2.800e-01, 2.290e+00, 5.640e+00, 1.040e+00, 3.920e+00,
          3.060e+00.
          1.065e+03],
        [1.320e+01, 1.780e+00, 2.140e+00, 1.120e+01, 1.000e+02, 2.650e+00, 2.760e+00, 2.600e-01, 1.280e+00, 4.380e+00, 1.050e+00, 3.400e+00,
          1.050e+03],
         [1.316e+01, 2.360e+00, 2.670e+00, 1.860e+01, 1.010e+02, 2.800e+00,
          3.240e+00, 3.000e-01, 2.810e+00, 5.680e+00, 1.030e+00, 3.170e+00,
          1.185e+03],
        [1.437e+01, 1.950e+00, 2.500e+00, 1.680e+01, 1.130e+02, 3.850e+00, 3.490e+00, 2.400e-01, 2.180e+00, 7.800e+00, 8.600e-01, 3.450e+00,
          1.480e+03],
        [1.324e+01, 2.590e+00, 2.870e+00, 2.100e+01, 1.180e+02, 2.800e+00, 2.690e+00, 3.900e-01, 1.820e+00, 4.320e+00, 1.040e+00, 2.930e+00,
          7.350e+02]])
                                                                                                                               In [15]:
# Отмасштабируем признаки, т.к. min и max у некоторых признаков находятся не в одном диапазоне
sc = MinMaxScaler()
sc_wine = sc.fit_transform(wine.data)
Разделение выборки на обучающую и тестовую
                                                                                                                               In [16]:
X_train, X_test, Y_train, Y_test = train_test_split(sc_wine, wine.target, test_size=0.3, random_state=1)
                                                                                                                               In [17]:
# Размер обучающей выборки
X train.shape, Y train.shape
                                                                                                                              Out[17]:
((124, 13), (124,))
                                                                                                                               In [18]:
# Размер тестовой выборки
X_test.shape, Y_test.shape
                                                                                                                              Out[18]:
((54, 13), (54,))
Функция train_test_split делит выборку так, чтобы сохранились все классы
                                                                                                                               In [19]:
np.unique(Y_train)
                                                                                                                              Out[19]:
array([0, 1, 2])
                                                                                                                               In [20]:
np.unique(Y test)
                                                                                                                              Out[20]:
array([0, 1, 2])
Построим базовую модель на основе ближайших соседей с произвольно заданным гиперпараметром К
                                                                                                                               In [94]:
# 4 ближайших соседа
cl1 = KNeighborsClassifier(n_neighbors=4)
cl1.fit(X_train, Y_train)
target1 = cl1.predict(X_test)
target11 = cl1.predict(X_train)
len(target1), target1
                                                                                                                              Out[94]:
(54,
 array([2, 1, 0, 1, 0, 2, 1, 0, 2, 1, 0, 0, 1, 0, 1, 1, 2, 0, 1, 0, 0, 1, 2, 0, 0, 2, 0, 0, 0, 2, 1, 2, 2, 0, 1, 1, 1, 1, 1, 1, 0, 0, 1, 2, 0, 0, 0, 0, 0, 0, 0, 1, 2, 2, 0]))
                                                                                                                               In [36]:
# 2 ближайших соседа
cl2 = KNeighborsClassifier(n neighbors=2)
cl2.fit(X_train, Y_train)
target2 = cl2.predict(X test)
len(target2), target2
                                                                                                                              Out[36]:
(54.
array([2, 1, 0, 1, 0, 1, 1, 0, 2, 1, 0, 0, 1, 0, 1, 1, 2, 0, 1, 0, 0, 1, 2, 0, 0, 2, 0, 0, 0, 2, 1, 2, 2, 0, 1, 1, 1, 1, 1, 1, 0, 0, 1, 2, 0, 0, 0, 1, 0, 0, 1, 2, 2, 0]))
```

In [34]:

Метрика Accuracy

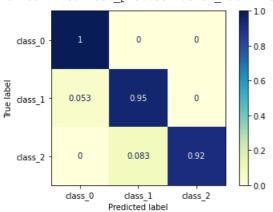
```
accuracy_score(Y_test, target1)
                                                                                                        Out[34]:
0.9629629629629629
                                                                                                         In [37]:
accuracy_score(Y_test, target2)
                                                                                                        Out[37]:
0.9629629629629
Точность в случае двух и четырех ближайших соседей составляет 96%. Однако эта метрика показывает точность по всем
классам в целом, поэтому точность в каждом отдельном классе может отличаться.
                                                                                                         In [31]:
def accuracy_score_for_classes(
    y_true: np.ndarray,
    y_pred: np.ndarray) -> Dict[int, float]:
    Вычисление метрики accuracy для каждого класса
    Возвращает словарь: ключ - метка класса,
     значение - Accuracy для данного класса
     # Для удобства фильтрации сформируем Pandas DataFrame
     d = {'t': y true, 'p': y pred}
    df = pd.DataFrame(data=d)
     # Метки классов
    classes = np.unique(y_true)
     # Результирующий словарь
    res = dict()
     # Перебор меток классов
     for c in classes:
         # отфильтруем данные, которые соответствуют текущей метке класса в истинных значениях
         temp_data_flt = df[df['t']==c]
         # расчет accuracy для заданной метки класса
         temp_acc = accuracy_score(
             temp_data_flt['t'].values,
             temp_data_flt['p'].values)
         # сохранение результата в словарь
        res[c] = temp_acc
     return res
def print_accuracy_score_for_classes(
    y_true: np.ndarray,
     y_pred: np.ndarray):
    Вывод метрики accuracy для каждого класса
    accs = accuracy_score_for_classes(y_true, y_pred)
     if len(accs)>0:
        print('Metka \t Accuracy')
     for i in accs:
        print('{} \t {}'.format(i, accs[i]))
                                                                                                         In [35]:
print_accuracy_score_for_classes(Y_test, target1)
Метка
      Accuracy
    1.0
    0.8947368421052632
Ассигасу для класса 0 и 2 составляет 100%, но для класса 1 проседает до 89%.
                                                                                                         In [38]:
print_accuracy_score_for_classes(Y_test, target2)
Метка
       Accuracy
    1.0
    0.9473684210526315
    0.916666666666666
Ассигасу для класса 0 составляет 100%, но для классов 1 и 2 - 95% и 92% соответственно.
                                                                                                         In [39]:
# Конвертация целевого признака в бинарный
def convert target to binary(array:np.ndarray, target:int) -> np.ndarray:
     # Если целевой признак совпадает с указанным, то 1 иначе 0
    res = [1 if x==target else 0 for x in array]
     return res
                                                                                                         In [40]:
# Допустим целевой признак == 2, будем считать этот случай = 1 в бинарном признаке
bin Y train = convert target to binary(Y train, 2)
list(zip(Y_train, bin_Y_train))[:10]
```

```
Out[40]:
[(1, 0),
 (1, 0),
(0, 0),
 (1, 0),
(2, 1),
 (1, 0),
 (1, 0),
 (0, 0), (2, 1),
 (1, 0)
                                                                                                                     In [41]:
bin_Y_test = convert_target_to_binary(Y_test, 2)
list(zip(Y_test, bin_Y_test))[:10]
                                                                                                                    Out[41]:
[(2, 1),
(1, 0),
(0, 0),
 (1, 0),
(0, 0),
(2, 1),
(1, 0),
 (0, 0),
(2, 1),
 (1, 0)
                                                                                                                     In [51]:
bin_target1=convert_target_to_binary(target1, 2)
bin_target2=convert_target_to_binary(target2, 2)
Матрица ошибок
                                                                                                                     In [60]:
# для 2 ближайших соседей с целевым признаком == 2
confusion_matrix(bin_Y_test, bin_target2, labels = [0, 1])
                                                                                                                    Out[60]:
array([[42, 0],
[ 1, 11]])
                                                                                                                     In [44]:
# для 4 ближайших соседей
confusion_matrix(Y_test, target1, labels = [0, 1, 2])
                                                                                                                    Out[44]:
In [48]:
# для 4 ближайших соседей
plot_confusion_matrix(cl1, X_test, Y_test,
                          display labels=wine.target names, cmap=plt.cm.YlGnBu, normalize='true')
                                                                                                                    Out[48]:
<sklearn.metrics. plot.confusion matrix.ConfusionMatrixDisplay at 0x7fc3f80510a0>
  dass_0
                       0
                                 0
                                            - 0.8
                                            0.6
                                 0
            0.11
                      0.89
  dass_1
                                            0.4
                                            0.2
             0
                       0
  dass 2
                                            0.0
           dass 0
                     dass 1
                               dass 2
                   Predicted label
                                                                                                                     In [49]:
# для 2 ближайших соседей
```

display\_labels=wine.target\_names, cmap=plt.cm.YlGnBu, normalize='true')

plot confusion matrix(cl2, X test, Y test,

<sklearn.metrics. plot.confusion matrix.ConfusionMatrixDisplay at 0x7fc3f8051d90>



### Метрика recall (полнота), precision

scores1

```
1) Доля верно предсказанных классификатором положительных объектов, из всех действительно положительных объектов.
(TP/(TP+FN))
```

```
In [53]:
recall score(bin Y test, bin target1), recall score(bin Y test, bin target2)
                                                                                                                        Out[53]:
(1.0, 0.916666666666666)
2) Доля верно предсказанных классификатором положительных объектов, из всех объектов, которые классификатор верно или
неверно определил как положительные. (ТР/(ТР+FР))
                                                                                                                         In [55]:
precision_score(bin_Y_test, bin_target1), precision_score(bin_Y_test, bin_target2)
                                                                                                                        Out[55]:
(1.0, 1.0)
Кросс-валидация
                                                                                                                         In [62]:
# Словарь метрик качества
scoring = {'precision': 'precision_weighted',
              'recall': 'recall weighted',
              'f1': 'f1 weighted'}
                                                                                                                         In [65]:
# Кросс-валидация для 5 фолдов, на которые мы разделили обучающую и тестовую выборки
scores = cross validate(KNeighborsClassifier(n neighbors = 2),
                             sc wine, wine.target, scoring = scoring, cv = 5,
                             return_train_score = True)
scores
                                                                                                                        Out[65]:
{'fit_time': array([0.00216603, 0.00057101, 0.00048399, 0.00048113, 0.00061607])
 'score_time': array([0.00609899, 0.00359392, 0.003232 , 0.00280595, 0.0040901]),
'test_precision': array([0.80886752, 0.94910645, 1. , 1. , 0.92593407]),
'train_precision': array([0.97404032, 0.96817443, 0.97404032, 0.98027972, 0.98025504]),
 'test_recall': array([0.97183099, 0.96478873, 0.97183099, 0.97902098, 0.97902098]),
 'test f1': array([0.80041152, 0.94352462, 1. , 1. , 0.91265664]), 'train_f1': array([0.9718937 , 0.96487031, 0.9718937 , 0.9790619 , 0.97905014])}
Значения метрик precision, recall и f1 на обучающей выборке стабильнее и ближе к 100%, чем на тестовой выборке.
                                                                                                                         In [67]:
# Кросс-валидация методом LeaveOneOut: в тестовой выборке 1 элемент, а все остальные в обучающей
loo = LeaveOneOut()
                                                                                                                         In [68]:
scores1 = cross validate(KNeighborsClassifier(n neighbors = 2),
                             sc_wine, wine.target, scoring = scoring, cv = loo,
```

/Users/kalashnikova/opt/anaconda3/lib/python3.8/site-packages/sklearn/metrics/\_classification.py:1221: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels with no predicted

return train score = True)

samples. Use `zero\_division` parameter to control this behavior.
 \_warn\_prf(average, modifier, msg\_start, len(result))
/Users/kalashnikova/opt/anaconda3/lib/python3.8/site-packages/sklearn/metrics/\_classification.py:1221: UndefinedMetricWarning: Recall is ill-defined and being set to 0.0 in labels with no true samples. Use zero\_division` parameter to control this behavior. warn\_prf(average, modifier, msg\_start, len(result))

/Users/kalashnikova/opt/anaconda3/lib/python3.8/site-packages/sklearn/metrics/ classification.py:1221: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels with no predicted

```
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Out[68]:
   0.00037384, 0.00054407, 0.00042009, 0.00037622, 0.00037599, 0.00037503, 0.00038624, 0.00037408, 0.00037193, 0.00037098, 0.00044799, 0.00037503, 0.00037289, 0.00059009, 0.00046515, 0.00195694, 0.0004525, 0.00075102, 0.00046802, 0.00054097, 0.00048399, 0.00055313, 0.00045013, 0.00049496, 0.000489 , 0.00051308, 0.0004499 , 0.00047708, 0.00045085, 0.00046611, 0.0004909 , 0.0004518 , 0.00047779, 0.00045109, 0.00046682, 0.0004549 , 0.00044799, 0.00045729, 0.00041485, 0.0004586, 0.00052404, 0.00052214, 0.00044918, 0.00046492, 0.00060487, 0.00048923, 0.00045896, 0.00069809]), 'score_time': array([0.0070622 , 0.00250316, 0.00240588, 0.00216222, 0.00206423, 0.00209498, 0.00207996, 0.00300789, 0.00216389, 0.00213695,
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```

### Подбор гиперпараметра К с импользованием GridSearch и кросс-валидации

```
Out[73]:
[{'n neighbors': array([ 5, 10, 15, 20, 25, 30, 35, 40, 45, 50])}]
                                                                                                                                                  In [75]:
# Подбор гиперпараметра с использованием метода кросс-валидации LeavePOut(2) – 2 параметра в тестовой вы
 # остальные в обучающей, и метрики качества accurancy
lpo = LeavePOut(2)
clf_gs = GridSearchCV(KNeighborsClassifier(), tuned_params, cv = lpo, scoring = 'accuracy')
clf gs.fit(X train, Y train)
                                                                                                                                                 Out[75]:
scoring='accuracy')
                                                                                                                                                  In [76]:
clf gs.cv results
                                                                                                                                                 Out[76]:
{'mean_fit_time': array([0.00036827, 0.0003652 , 0.00036578, 0.00036527, 0.00037244,
 0.0004025, 0.00038617, 0.00038437, 0.00040303, 0.00038359]),

'std_fit_time': array([4.75352266e-05, 3.67897686e-05, 4.90215461e-05, 4.54180927e-05, 5.98046029e-05, 8.55278823e-05, 4.55882250e-05, 4.40962847e-05,
            5.98046029e-05, 8.55278823e-05, 4
8.89617720e-05, 4.31835096e-05]),
 'mean_score_time': array([0.00061715, 0.00063268, 0.00061605, 0.00062711, 0.00063152, 0.00070614, 0.00066285, 0.0006728, 0.00070313, 0.00066211]),
'std_score_time': array([8.77901857e-05, 1.62070956e-03, 6.98159128e-05, 8.17194101e-04,
           8.95293201e-05, 9.73635963e-04, 8.33577222e-05, 1.15841650e-03, 6.98868543e-04, 7.86441299e-05]),
 'param_n_neighbors': masked_array(data=[5, 10, 15, 20, 25, 30, 35, 40, 45, 50],
mask=[False, False, False, False, False, False, False, False, False,
                             False, False],
            fill_value='?'
                   dtype=object),
   params': [{'n_neighbors': 5}, {'n_neighbors': 10}, {'n_neighbors': 15}, {'n_neighbors': 20},
  'params':
  { n_neighbors : 20},
 {'n_neighbors': 25},
 {'n_neighbors': 30},
 {'n_neighbors': 35},
 {'n_neighbors': 40},
 {'n_neighbors': 45},
 {'n_neighbors': 50}],
 split8_test_score : array([1., 1., 1., 1., 1., 1., 1., 1., 1., 1.]),
'split9_test_score': array([1., 1., 1., 1., 1., 1., 1., 1., 1., 1.]),
'split10_test_score': array([1., 1., 1., 1., 1., 1., 1., 1., 1., 1.]),
'split12_test_score': array([1., 1., 1., 1., 1., 1., 1., 1., 1., 1.]),
'split13_test_score': array([1., 1., 1., 1., 1., 1., 1., 1., 1., 1.]),
'split14_test_score': array([1., 1., 1., 1., 1., 1., 1., 1., 1., 1.]),
'split14_test_score': array([1., 1., 1., 1., 1., 1., 1., 1., 1., 1.]),
 'split33_test_score': array([1., 1., 1., 1., 1., 1., 1., 1., 1., 1.]),
'split34_test_score': array([1., 1., 1., 1., 1., 1., 1., 1., 1., 1.]),
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                                                                                                 1.]),
  'split47_test_score': array([1., 1., 1., 1., 'split48_test_score': array([1., 1., 1., 1., 1., 1.])
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'split77_test_score': array([1., 1., 1., 1., 1., 1., 1., 1., 1., 1.]),
'split78_test_score': array([1., 1., 1., 1., 1., 1., 1., 1., 1., 1.]),
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'split80_test_score': array([1., 1., 1., 1., 1., 1., 1., 1., 1., 1.]),
'split81_test_score': array([1., 1., 1., 1., 1., 1., 1., 1., 1., 1.]),
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'split87_test_score': array([1., 1., 1., 1., 1., 1., 1., 1., 1., 1.]),
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'split89_test_score': array([1., 1., 1., 1., 1., 1., 1., 1., 1., 1.]),
'split90_test_score': array([1., 1., 1., 1., 1., 1., 1., 1., 1., 1.]),
'split91_test_score': array([1., 1., 1., 1., 1., 1., 1., 1., 1., 1.]),
'split92_test_score': array([1., 1., 1., 1., 1., 1., 1., 1., 1., 1.]),
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split10_test_score : array([1., 1., 1., 1., 1., 1., 1., 1., 1., 1.]),
'split111_test_score': array([1., 1., 1., 1., 1., 1., 1., 1., 1., 1.]),
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'split115_test_score': array([1., 1., 1., 1., 1., 1., 1., 1., 1.]),
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'split116_test_score': array([1., 1., 1., 1., 1., 1., 1., 1., 1., 1.]),
'split117_test_score': array([1., 1., 1., 1., 1., 1., 1., 1., 1., 1.]),
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'split118_test_score': array([1., 1., 1., 1., 1., 1., 1., 1., 1.]),
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split167_test_score': array([0.5, 0.5, 0.5, 0.5, 0.5, 0.5, 0.5, 0.5]), split168_test_score': array([0.5, 0.5, 0.5, 0.5, 0.5, 0.5, 0.5, 0.5]),
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           0.5,
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split251_test_score': array([1., 1., 1., 1., 1., 1., 1., 1., 1., 1.]),
split252_test_score': array([1., 1., 1., 1., 1., 1., 1., 1., 1., 1.]),
```

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                                                                                                         In [77]:
# Лучшая модель
clf_gs.best_estimator_
                                                                                                        Out[77]:
KNeighborsClassifier(n neighbors=20)
                                                                                                         In [78]:
# Лучшее значение метрики
clf gs.best score
                                                                                                        Out[78]:
0.9832153160241279
                                                                                                         In [81]:
# Лучшее значение параметров
clf gs.best params
                                                                                                        Out[81]:
{'n_neighbors': 20}
                                                                                                         In [82]:
# Изменение качества на тестовой выборке в зависимости от к-соседей
plt.plot(n_range, clf_gs.cv_results_['mean_test_score'])
                                                                                                        Out[82]:
[<matplotlib.lines.Line2D at 0x7fc3f8553ee0>]
0.98
0.97
0.96
0.95
0.94
         10
                  20
                           30
                                   40
                                            50
                                                                                                         In [85]:
lpo = LeavePOut(2)
clf_rs = RandomizedSearchCV(KNeighborsClassifier(), tuned_params, cv = lpo, scoring = 'accuracy')
clf_rs.fit(X_train, Y_train)
                                                                                                        Out[85]:
RandomizedSearchCV(cv=LeavePOut(p=2), estimator=KNeighborsClassifier(),
                    param_distributions=[{'n_neighbors': array([ 5, 10, 15, 20, 25, 30, 35, 40, 45, 50])}]
                    scoring='accuracy')
                                                                                                         In [87]:
clf_rs.best_score_, clf_rs.best_params_
                                                                                                        Out[87]:
(0.9832153160241279, {'n_neighbors': 20})
                                                                                                         In [88]:
# Подбор гиперпараметра с использованием метода кросс-валидации кFold – деление выборок на 5 фолдов,
# и метрики качества accurancy
clf_gs1 = GridSearchCV(KNeighborsClassifier(), tuned_params, cv = 5, scoring = 'accuracy')
clf_gs1.fit(X_train, Y_train)
                                                                                                        Out[88]:
scoring='accuracy')
                                                                                                         In [89]:
clf_gs1.best_score_, clf_gs1.best_params_
```

```
Out[89]:
(0.976, {'n neighbors': 15})
                                                                                                              In [90]:
plt.plot(n_range, clf_gs1.cv_results_['mean_test_score'])
                                                                                                             Out[90]:
[<matplotlib.lines.Line2D at 0x7fc3fd244430>]
0.975
0.970
0.965
0.960
0.955
0.950
0.945
                                     40
           10
                    20
                             30
                                              50
Сравнение метрик качества исходной и оптимальной моделей
                                                                                                              In [95]:
clf_gs.best_estimator_.fit(X_train, Y_train)
opt target train = clf qs.best estimator .predict(X train)
```

## opt\_target\_test = clf\_gs.best\_estimator\_.predict(X\_test) In [98]: # Точность для оптимальной модели accuracy score(Y train, opt target train), accuracy score(Y test, opt target test) Out[98]: (0.9838709677419355, 0.9814814814814815) In [99]: # Точность для исходной модели accuracy\_score(Y\_train, target11), accuracy\_score(Y\_test, target1) Out[99]: (0.967741935483871, 0.9629629629629629) Точность у оптимальной модели выше и разница в точности между обучающей и тестовой выборками уменьшилась с 0.0048 до 0.0023

In [101]:

# Precision для оптимальной модели precision\_score(Y\_train, opt\_target\_train, average='macro'), precision\_score(Y\_test, opt\_target\_test, ave Out[101]: (0.981981981981982, 0.9861111111111112)

In [102]: # Precision для исходной модели

precision score(Y train, target11, average='macro'), precision score(Y test, target1, average='macro') Out[102]:

(0.9653499653499654, 0.9733333333333333)

Разница метрики между выборками уменьшилась с 0.0079 до 0.0041

# Полнота для оптимальной модели, учитывается вес классов recall\_score(Y\_train, opt\_target\_train, average='weighted'), recall\_score(Y\_test, opt\_target\_test, averag

In [103]:

In [104]:

Out[103]: (0.9838709677419355, 0.9814814814814815)

# Полнота для исходной модели, учитывается вес классов recall\_score(Y\_train, target11, average='weighted'), recall\_score(Y\_test, target1, average='weighted')

Out[104]: (0.967741935483871, 0.9629629629629629)

Разница полноты между выборками уменьшилась с 0.0047 до 0.0023