# Лабораторная работа №5. Решение задач классификации с помощью байесовского классификатора и метода k-ближайших соседей.

## Часть 3. Метрический алгоритм k-ближайших соседей.

Используемый набор данных: [Iris (https://archive.ics.uci.edu/ml/datasets/Iris)](https://archive.ics.uci.edu/ml/datasets/Iris)

In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.preprocessing import label_binarize
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.multiclass import OneVsRestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import classification_report, roc_curve, roc_auc_score
import os
import requests

%matplotlib inline

pd.options.display.max_columns = None
```

In [2]:

```
def downloadFile(url, filePath):
    if not os.path.exists(filePath):
        req = requests.get(url)
        f = open(filePath, "wb")
        f.write(req.content)
        f.close

url = "https://archive.ics.uci.edu/ml/machine-learning-databases/iris"
downloadFile(url + "/iris.data", "dataset/iris.data")
downloadFile(url + "/iris.names", "dataset/iris.names")
```

In [3]:

```
headers = ["Sepal length", "Sepal width", "Petal length", "Petal width", "Class"]
data = pd.read_csv("dataset/iris.data", names=headers)
data = data.astype({"Class": "category"})
data.sample(40)
```

Out[3]:

| | Sepal length | Sepal width | Petal length | Petal width | Class |
|---|---|---|---|---|---|
| **64** | 5.6 | 2.9 | 3.6 | 1.3 | Iris-versicolor |
| **1** | 4.9 | 3.0 | 1.4 | 0.2 | Iris-setosa |
| **122** | 7.7 | 2.8 | 6.7 | 2.0 | Iris-virginica |
| **62** | 6.0 | 2.2 | 4.0 | 1.0 | Iris-versicolor |
| **99** | 5.7 | 2.8 | 4.1 | 1.3 | Iris-versicolor |
| **118** | 7.7 | 2.6 | 6.9 | 2.3 | Iris-virginica |
| **30** | 4.8 | 3.1 | 1.6 | 0.2 | Iris-setosa |
| **52** | 6.9 | 3.1 | 4.9 | 1.5 | Iris-versicolor |
| **137** | 6.4 | 3.1 | 5.5 | 1.8 | Iris-virginica |
| **73** | 6.1 | 2.8 | 4.7 | 1.2 | Iris-versicolor |
| **133** | 6.3 | 2.8 | 5.1 | 1.5 | Iris-virginica |
| **108** | 6.7 | 2.5 | 5.8 | 1.8 | Iris-virginica |
| **65** | 6.7 | 3.1 | 4.4 | 1.4 | Iris-versicolor |
| **86** | 6.7 | 3.1 | 4.7 | 1.5 | Iris-versicolor |
| **4** | 5.0 | 3.6 | 1.4 | 0.2 | Iris-setosa |
| **144** | 6.7 | 3.3 | 5.7 | 2.5 | Iris-virginica |
| **27** | 5.2 | 3.5 | 1.5 | 0.2 | Iris-setosa |
| **129** | 7.2 | 3.0 | 5.8 | 1.6 | Iris-virginica |
| **117** | 7.7 | 3.8 | 6.7 | 2.2 | Iris-virginica |
| **72** | 6.3 | 2.5 | 4.9 | 1.5 | Iris-versicolor |
| **85** | 6.0 | 3.4 | 4.5 | 1.6 | Iris-versicolor |
| **146** | 6.3 | 2.5 | 5.0 | 1.9 | Iris-virginica |
| **114** | 5.8 | 2.8 | 5.1 | 2.4 | Iris-virginica |
| **74** | 6.4 | 2.9 | 4.3 | 1.3 | Iris-versicolor |
| **56** | 6.3 | 3.3 | 4.7 | 1.6 | Iris-versicolor |
| **49** | 5.0 | 3.3 | 1.4 | 0.2 | Iris-setosa |
| **19** | 5.1 | 3.8 | 1.5 | 0.3 | Iris-setosa |
| **22** | 4.6 | 3.6 | 1.0 | 0.2 | Iris-setosa |
| **11** | 4.8 | 3.4 | 1.6 | 0.2 | Iris-setosa |
| **0** | 5.1 | 3.5 | 1.4 | 0.2 | Iris-setosa |
| **88** | 5.6 | 3.0 | 4.1 | 1.3 | Iris-versicolor |
| **37** | 4.9 | 3.1 | 1.5 | 0.1 | Iris-setosa |
| **109** | 7.2 | 3.6 | 6.1 | 2.5 | Iris-virginica |
| **69** | 5.6 | 2.5 | 3.9 | 1.1 | Iris-versicolor |
| **103** | 6.3 | 2.9 | 5.6 | 1.8 | Iris-virginica |
| **71** | 6.1 | 2.8 | 4.0 | 1.3 | Iris-versicolor |
| **119** | 6.0 | 2.2 | 5.0 | 1.5 | Iris-virginica |

| | Sepal length | Sepal width | Petal length | Petal width | Class |
|---|---|---|---|---|---|
| **87** | 6.3 | 2.3 | 4.4 | 1.3 | Iris-versicolor |
| **98** | 5.1 | 2.5 | 3.0 | 1.1 | Iris-versicolor |
| **135** | 7.7 | 3.0 | 6.1 | 2.3 | Iris-virginica |

In [4]:

```
display(data.describe())
display(data.isna().sum())
```

| | Sepal length | Sepal width | Petal length | Petal width |
|---|---|---|---|---|
| **count** | 150.000000 | 150.000000 | 150.000000 | 150.000000 |
| **mean** | 5.843333 | 3.054000 | 3.758667 | 1.198667 |
| **std** | 0.828066 | 0.433594 | 1.764420 | 0.763161 |
| **min** | 4.300000 | 2.000000 | 1.000000 | 0.100000 |
| **25%** | 5.100000 | 2.800000 | 1.600000 | 0.300000 |
| **50%** | 5.800000 | 3.000000 | 4.350000 | 1.300000 |
| **75%** | 6.400000 | 3.300000 | 5.100000 | 1.800000 |
| **max** | 7.900000 | 4.400000 | 6.900000 | 2.500000 |

```
Sepal length    0
Sepal width     0
Petal length    0
Petal width     0
Class           0
dtype: int64
```

Пропусков в данных нет.

Подготовим данные для классификации: выберем признаки и метки и сформируем тренировочные и тестовые наборы.

In [5]:

```
classes = data["Class"].unique()
y = label_binarize(data["Class"], classes=classes)
X = data.drop(columns=["Class"]).copy()

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=2
4)
```

Создадим классификатор, обучим его, а затем выполним классификацию.

In [6]:

```
y_score = OneVsRestClassifier(KNeighborsClassifier(n_neighbors=3)).fit(X_train, y_train
).predict(X_test)
```

Оценим получившуюся классификацию.

In [7]:

```
print(classification_report(y_test, y_score))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        10
           1       1.00      0.75      0.86         4
           2       0.94      1.00      0.97        16

   micro avg       0.97      0.97      0.97        30
   macro avg       0.98      0.92      0.94        30
weighted avg       0.97      0.97      0.96        30
 samples avg       0.97      0.97      0.97        30
```

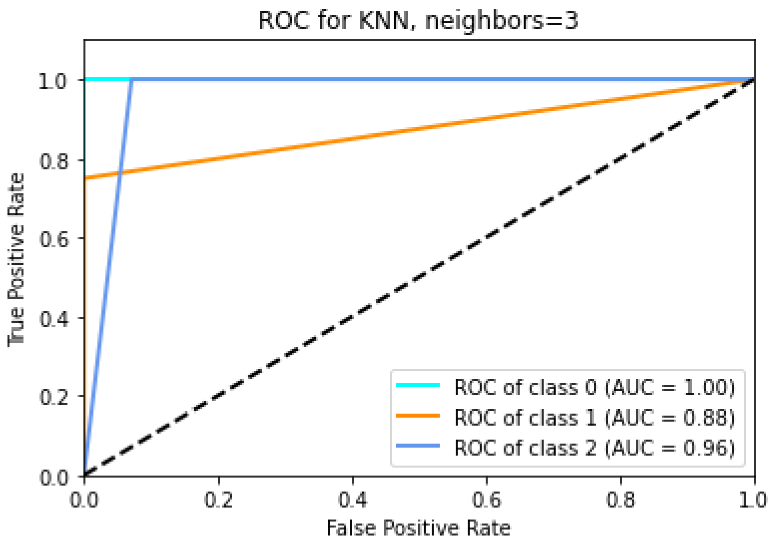
In [8]:

```
def drawROCCurve(y_test, y_score, neighbors):
    n_classes = len(classes)
    fpr, tpr, auc = dict(), dict(), dict()
    for i in range(n_classes):
        y_test_cl = y_test[:,i]
        y_score_cl = y_score[:,i]
        fpr[i], tpr[i], _ = roc_curve(y_test_cl, y_score_cl)
        auc[i] = roc_auc_score(y_test_cl, y_score_cl)

    lw = 2
    colors = ['aqua', 'darkorange', 'cornflowerblue']
    for i, color in zip(range(n_classes), colors):
        plt.plot(fpr[i], tpr[i], color=color, lw=lw, label='ROC of class {0} (AUC = {1:
0.2f})'.format(i, auc[i]))
    plt.plot([0, 1], [0, 1], 'k--', lw=lw)
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.1])
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title(f'ROC for KNN, neighbors={neighbors}')
    plt.legend(loc="lower right")
    plt.show()
```

In [9]:

```
drawROCCurve(y_test, y_score, neighbors=3)
```




Подберем оптимальное количество соседей.

In [10]:

```
params = {'n_neighbors': np.arange(1, 25)}
gscv = GridSearchCV(KNeighborsClassifier(), params)
gscv.fit(X, y)
gscv.best_params_
```

Out[10]:

```
{'n_neighbors': 1}
```

Обучим и оценим модель с оптимальным количеством соседей.

In [11]:

```
optimal_neighbors = gscv.best_params_["n_neighbors"]
y_score = OneVsRestClassifier(KNeighborsClassifier(n_neighbors=optimal_neighbors)).fit(
X_train, y_train).predict(X_test)

print(classification_report(y_test, y_score))
```

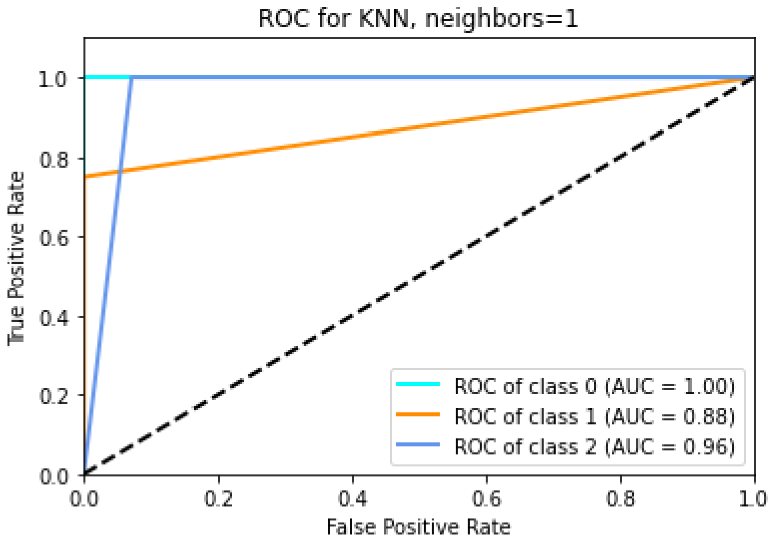
```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        10
           1       1.00      0.75      0.86         4
           2       0.94      1.00      0.97        16

   micro avg       0.97      0.97      0.97        30
   macro avg       0.98      0.92      0.94        30
weighted avg       0.97      0.97      0.96        30
 samples avg       0.97      0.97      0.97        30
```

In [12]:

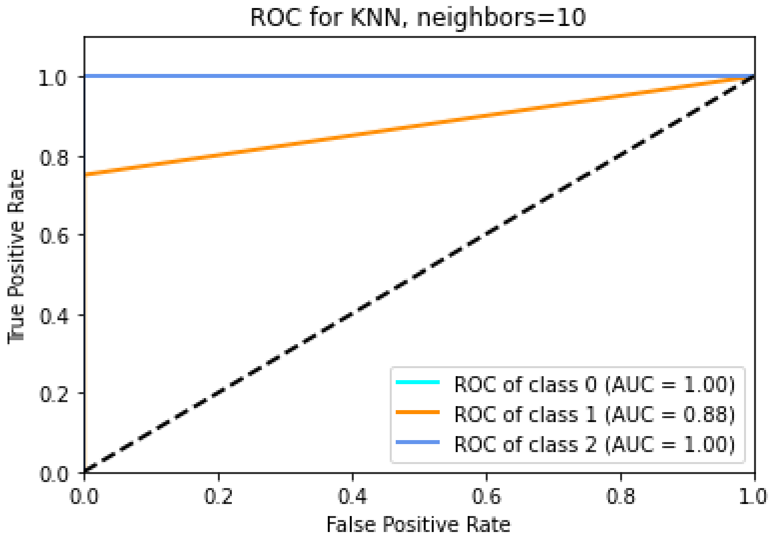
```
drawROCCurve(y_test, y_score, neighbors=optimal_neighbors)
```




Попробуем различные значения параметра k.

In [13]:

```
k = 10
y_score = OneVsRestClassifier(KNeighborsClassifier(n_neighbors=k)).fit(X_train, y_train
).predict(X_test)
drawROCCurve(y_test, y_score, neighbors=k)
```




In [14]:

```
k = 11
y_score = OneVsRestClassifier(KNeighborsClassifier(n_neighbors=k)).fit(X_train, y_train
).predict(X_test)
drawROCCurve(y_test, y_score, neighbors=k)
```