# Московский государственный технический университет им. Н.Э. Баумана Факультет «Информатика и системы управления» Кафедра «Автоматизированные системы обработки информации и управления»



### Отчет Лабораторная работа № 4 По курсу «Технологии машинного обучения»

ИСПОЛНИТЕЛЬ:	
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```
In [1]:
                    import numpy as np
                    import pandas as pd
                    from sklearn.datasets import *
                    from sklearn.model selection import train test split
                    import seaborn as sns
                    import matplotlib.pyplot as plt
                    from operator import itemgetter
                    import matplotlib.ticker as ticker
                    import math
                    from sklearn.linear_model import LogisticRegression
                    from sklearn.metrics import accuracy score, balanced accuracy score
                    from sklearn.metrics import plot confusion matrix
                    from sklearn.metrics import precision score, recall score, fl score, classifi
                    from sklearn.metrics import confusion matrix
                    from sklearn.metrics import mean absolute error, mean squared error, mean squ
                    from sklearn.metrics import roc curve, roc auc score
                    from sklearn.neighbors import KNeighborsRegressor, KNeighborsClassifier
                    from sklearn.model_selection import cross_val_score, cross_validate
                    from sklearn.model selection import KFold, RepeatedKFold, LeaveOneOut, LeaveF
                    from sklearn.preprocessing import MinMaxScaler, StandardScaler, Normalizer
                    from sklearn.model selection import GridSearchCV, RandomizedSearchCV
                    from sklearn.model selection import learning curve, validation curve
                    from sklearn.metrics import confusion matrix
                    from sklearn.linear model import LinearRegression
                    from sklearn.linear model import SGDRegressor
                    from sklearn.linear model import SGDClassifier
                    from typing import Dict, Tuple
                    from scipy import stats
                    from sklearn.svm import SVC, NuSVC, LinearSVC, OneClassSVM, SVR, NuSVR, LinearSVC, OneClassSVM, SVR, OneClassSVM, OneClassSVM, SVR, OneClassSVM, OneClassS
                    from sklearn.tree import DecisionTreeClassifier, DecisionTreeRegressor, expor
                    %matplotlib inline
                    sns.set(style="ticks")
```

## Выборка датасета и ее разделение на тестовую и обучающую

```
In [2]: wine = load_wine()

In [3]: for x in wine:
    print(x)

data
    target
    frame
    target_names
```

```
In [4]:
           # Сформируем DataFrame
           wine_df = pd.DataFrame(data= np.c_[wine['data']],
                                  columns= wine['feature names'])
 In [5]:
           wine df
               alcohol malic_acid
                                 ash alcalinity_of_ash magnesium total_phenols flavanoids
                                                                                        nonflavan
 Out[5]:
                14.23
                            1.71 2.43
            0
                                                15.6
                                                           127.0
                                                                        2.80
                                                                                   3.06
            1
                13.20
                            1.78 2.14
                                                                                   2.76
                                                 11.2
                                                           100.0
                                                                        2.65
            2
                13.16
                            2.36 2.67
                                                18.6
                                                                        2.80
                                                                                   3.24
                                                           101.0
                            1.95 2.50
            3
                14.37
                                                16.8
                                                                        3.85
                                                                                   3.49
                                                           113.0
                            2.59 2.87
            4
                13.24
                                                21.0
                                                           118.0
                                                                        2.80
                                                                                   2.69
          173
                13.71
                            5.65 2.45
                                                20.5
                                                           95.0
                                                                                   0.61
                                                                        1.68
                            3.91 2.48
                                                           102.0
          174
                13.40
                                                23.0
                                                                        1.80
                                                                                   0.75
          175
                13.27
                            4.28 2.26
                                                20.0
                                                           120.0
                                                                                   0.69
                                                                        1.59
          176
                13.17
                            2.59 2.37
                                                20.0
                                                           120.0
                                                                                   0.68
                                                                        1.65
          177
                14.13
                            4.10 2.74
                                                24.5
                                                           96.0
                                                                        2.05
                                                                                   0.76
         178 rows × 13 columns
In [6]:
           X_train, X_test, Y_train, Y_test = train_test_split(
               wine.data, wine.target, test size=0.35, random state=1)
         Обучение моделей
         Обучение линейной модели
In [7]:
           reg1 = LogisticRegression(max_iter=10000).fit(X_train, Y_train)
 In [8]:
           target1 = reg1.predict(X_test)
 In [9]:
           accuracy_score(Y_test, target1), precision_score(Y_test, target1, average='mage')
          (0.9206349206349206, 0.9381499726327313)
In [10]:
           Y test
Out[10]: array([2, 1, 0, 1, 0, 2, 1, 0, 2, 1, 0, 0, 1, 0, 1, 1, 2, 0, 1, 0, 0, 1,
                  2, 1, 0, 2, 0, 0, 0, 2, 1, 2, 2, 0, 1, 1, 1, 1, 1, 0, 0, 1, 2, 0,
                 0, 0, 1, 0, 0, 0, 1, 2, 2, 0, 1, 1, 0, 1, 2, 1, 1, 0, 2])
```

```
In [11]: | target1
Out[11]: array([2, 1, 0, 0, 0, 2, 1, 0, 2, 1, 0, 0, 1, 0, 1, 1, 2, 0, 1, 0, 0, 1,
                1, 0, 0, 2, 0, 0, 0, 2, 1, 2, 2, 0, 1, 1, 1, 1, 1, 0, 0, 1, 2, 0,
                0, 0, 0, 0, 0, 1, 2, 2, 0, 1, 0, 0, 1, 2, 1, 1, 0, 2])
In [12]:
          def accuracy_score_for_classes(
              y true: np.ndarray,
              y_pred: np.ndarray) -> Dict[int, float]:
              Вычисление метрики accuracy для каждого класса
              y true - истинные значения классов
              y_pred - предсказанные значения классов
              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 ассигасу 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('Me⊤ka \t Accuracy')
              for i in accs:
                  print('{} \t {}'.format(i, accs[i]))
In [13]:
          print_accuracy_score_for_classes(Y_test, target1)
         Метка
                  Accuracy
         0
                  1.0
         1
                  0.8333333333333334
         2
                  0.9285714285714286
        Обучение SVM
In [14]:
          model_svc = LinearSVC(C=1.0, max_iter=10000)
          model_svc.fit(X_train, Y_train)
          target2 = model_svc.predict(X_test)
```

/home/zeus/anaconda3/envs/tml\_env/lib/python3.9/site-packages/sklearn/svm/\_base.py:985: ConvergenceWarning: Liblinear failed to converge, increase the num

In [18]: print\_accuracy\_score\_for\_classes(Y\_test, target2)

1, 1, 1, 0, 0, 0, 1, 2, 2, 0, 1, 1, 1, 1, 2, 1, 1, 1, 2])

Метка Accuracy 0 0.48 1 1.0 2 0.8571428571428571

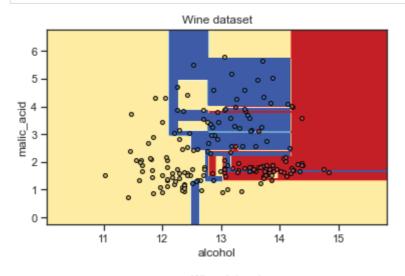
#### Обучение деревья решений

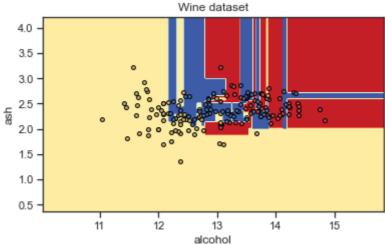
#### Классификация

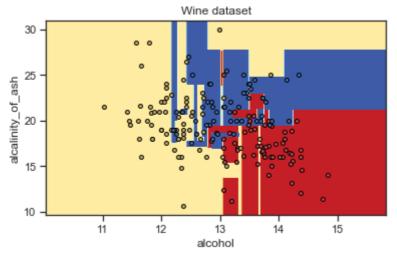
```
In [19]:
          def plot tree classification(title param, ds):
              Построение деревьев и вывод графиков для заданного датасета
              n_classes = len(np.unique(ds.target))
              plot_colors = "ryb"
              plot step = 0.02
              for pairidx, pair in enumerate([[0, 1], [0, 2], [0, 3],
                                                [1, 2], [1, 3], [2, 3]]):
                  # We only take the two corresponding features
                  X = ds.data[:, pair]
                  y = ds.target
                  # Train
                  clf = DecisionTreeClassifier(random_state=1).fit(X, y)
                  plt.title(title param)
                  x_{min}, x_{max} = X[:, 0].min() - 1, <math>X[:, 0].max() + 1
                  y \min, y \max = X[:, 1].\min() - 1, X[:, 1].\max() + 1
                  xx, yy = np.meshgrid(np.arange(x_min, x_max, plot_step),
                                        np.arange(y_min, y_max, plot_step))
                  plt.tight_layout(h_pad=0.5, w_pad=0.5, pad=2.5)
                  Z = clf.predict(np.c_[xx.ravel(), yy.ravel()])
```

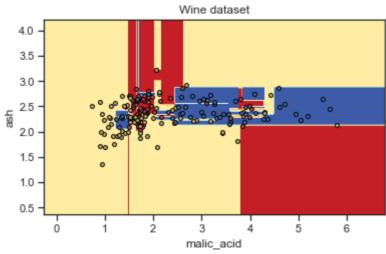
In [20]:

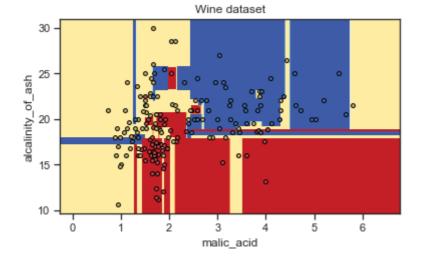
plot\_tree\_classification('Wine dataset', wine)

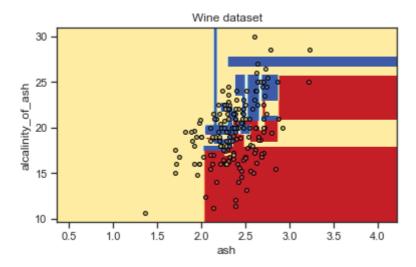












```
In [21]:
            clf = DecisionTreeClassifier(random state=1).fit(X train, Y train)
            target3 = clf.predict(X test)
            accuracy_score(Y_test, target3), precision_score(Y test, target3, average='ma
           (0.9206349206349206, 0.9221256038647342)
Out[21]:
In [22]:
            Y test
Out[22]: array([2, 1, 0, 1, 0, 2, 1, 0, 2, 1, 0, 0, 1, 0, 1, 1, 2, 0, 1, 0, 0, 1,
                    2, 1, 0, 2, 0, 0, 0, 2, 1, 2, 2, 0, 1, 1, 1, 1, 1, 0, 0, 1, 2, 0,
                    0, 0, 1, 0, 0, 0, 1, 2, 2, 0, 1, 1, 0, 1, 2, 1, 1, 0, 2])
In [23]:
            target3
Out[23]: array([2, 1, 0, 1, 0, 2, 1, 0, 2, 1, 0, 1, 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, 2, 2, 1, 0, 0, 1, 0, 0, 0, 1, 2, 2, 0, 1, 1, 0, 1, 2, 1, 0, 0, 2])
In [24]:
            print accuracy score for classes(Y test, target3)
           Метка
                      Accuracy
           0
                      0.92
           1
                      0.875
           2
                      1.0
```

#### Итоги

```
In [25]: print('Accuracy для "Логистической регресии"', accuracy_score(Y_test, target1 print('Accuracy для "SVM"', accuracy_score(Y_test, target2)) print('Accuracy для "Дерева решений"', accuracy_score(Y_test, target3))
```

```
Accuracy для "Логистической регресии" 0.9206349206349206
Accuracy для "SVM" 0.7619047619047619
Accuracy для "Дерева решений" 0.9206349206
```