Для заданного набора данных (по Вашему варианту) постройте модели классификации или регрессии (в зависимости от конкретной задачи, рассматриваемой в наборе данных). Для построения моделей используйте методы 1 и 2 (по варианту для Вашей группы). Оцените качество моделей на основе подходящих метрик качества (не менее двух метрик). Какие метрики качества Вы использовали и почему? Какие выводы Вы можете сделать о качестве построенных моделей? Для построения моделей необходимо выполнить требуемую предобработку данных: заполнение пропусков, кодирование категориальных признаков, и т.д.

## ИУ5-65Б Бенц Ян Вариант 2

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
from sklearn.svm import SVC, NuSVC, LinearSVC
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.datasets import load wine
raw = load wine()
raw.feature names
['alcohol',
 'malic acid',
 'ash',
 'alcalinity of ash',
 'magnesium',
 'total phenols',
 'flavanoids',
 'nonflavanoid phenols',
 'proanthocyanins',
 'color intensity',
 'hue',
 'od280/od315 of diluted wines',
 'proline']
raw.target names
array(['class 0', 'class 1', 'class 2'], dtype='<U7')</pre>
data = pd.DataFrame(data= np.c_[raw['data'], raw['target']],
                     columns= raw['feature names'] + ['wine classes'])
data.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 178 entries, 0 to 177
Data columns (total 14 columns):
# Column
                                    Non-Null Count Dtype
```

```
0
    alcohol
                                  178 non-null
                                                  float64
                                                  float64
 1
    malic acid
                                  178 non-null
 2
    ash
                                  178 non-null
                                                  float64
 3
    alcalinity_of_ash
                                  178 non-null
                                                  float64
 4
    magnesium
                                  178 non-null
                                                  float64
 5
    total_phenols
                                  178 non-null
                                                  float64
    flavanoids
                                 178 non-null
                                                 float64
 6
 7
    nonflavanoid phenols
                                 178 non-null
                                                 float64
 8
    proanthocyanins
                                  178 non-null
                                                 float64
 9
    color intensity
                                  178 non-null
                                                 float64
10 hue
                                  178 non-null
                                                 float64
11 od280/od315_of_diluted_wines 178 non-null
                                                 float64
                                  178 non-null float64
12 proline
                                  178 non-null float64
13 wine classes
dtypes: float64(14)
memory usage: 19.6 KB
```

Датасет не содержит пропусков

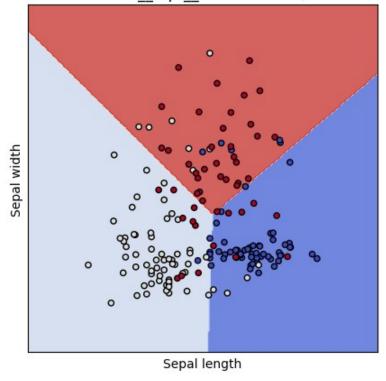
Задача классификации

Метод опорных векторов

```
wine x = raw.data[:,:2]
wine y = raw.target
def make_meshgrid(x, y, h=.02):
    """Create a mesh of points to plot in
    Parameters
    x: data to base x-axis meshgrid on
    y: data to base y-axis meshgrid on
   h: stepsize for meshgrid, optional
    Returns
    xx, yy : ndarray
    x_{min}, x_{max} = x.min() - 1, x.max() + 1
    y_{min}, y_{max} = y.min() - 1, y.max() + 1
    xx, yy = np.meshgrid(np.arange(x_min, x_max, h),
                         np.arange(y min, y max, h))
    return xx, yy
def plot contours(ax, clf, xx, yy, **params):
    """Plot the decision boundaries for a classifier.
    Parameters
```

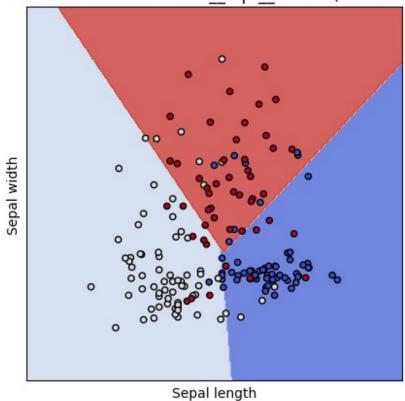
```
ax: matplotlib axes object
    clf: a classifier
    xx: meshgrid ndarray
    yy: meshqrid ndarray
    params: dictionary of params to pass to contourf, optional
    Z = clf.predict(np.c [xx.ravel(), yy.ravel()])
    Z = Z.reshape(xx.shape)
    #Можно проверить все ли метки классов предсказываются
    #print(np.unique(Z))
    out = ax.contourf(xx, yy, Z, **params)
    return out
def plot cl(clf):
    title = clf.__repr_
    clf.fit(wine x, wine y)
    fig, ax = plt.subplots(figsize=(5,5))
    X0, X1 = wine_x[:, 0], wine_x[:, 1]
    xx, yy = make meshgrid(X0, X1)
    plot contours(ax, clf, xx, yy, cmap=plt.cm.coolwarm, alpha=0.8)
    ax.scatter(X0, X1, c=wine y, cmap=plt.cm.coolwarm, s=20,
edgecolors='k')
    ax.set xlim(xx.min(), xx.max())
    ax.set_ylim(yy.min(), yy.max())
    ax.set xlabel('Sepal length')
    ax.set ylabel('Sepal width')
    ax.set xticks(())
    ax.set yticks(())
    ax.set title(title)
    plt.show()
plot cl(LinearSVC(C=1.0, penalty='l1', dual=False, max iter=1000))
C:\ml rk2\env\Lib\site-packages\sklearn\svm\ base.py:1235:
ConvergenceWarning: Liblinear failed to converge, increase the number
of iterations.
 warnings.warn(
```

<bound method BaseEstimator.\_\_repr\_\_ of LinearSVC(dual=False, penalty='l1')>



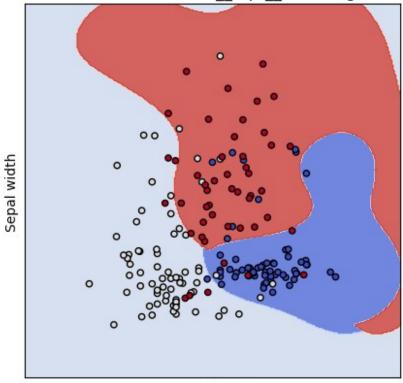
plot\_cl(SVC(kernel='linear', C=1.0))

<bound method BaseEstimator.\_\_repr\_\_ of SVC(kernel='linear')>



plot\_cl(SVC(kernel='rbf', gamma=0.9, C=1.0))

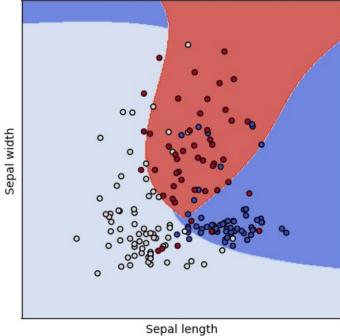
<br/><bound method BaseEstimator.\_\_repr\_\_ of SVC(gamma=0.9)>



Sepal length

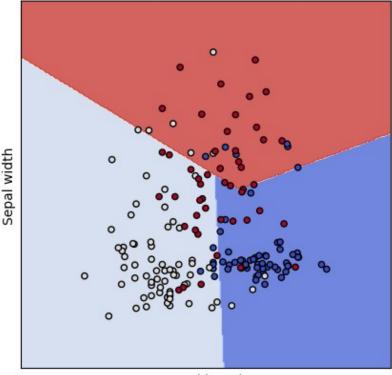
```
plot_cl(SVC(kernel='poly', degree=4, gamma=0.2, C=1.0))
```

<box><br/>d method BaseEstimator.\_\_repr\_\_ of SVC(degree=4, gamma=0.2, kernel='poly')></br>



```
plot_cl(NuSVC(kernel='linear', nu=0.8))
```

<br/>
<bound method BaseEstimator. repr of NuSVC(kernel='linear', nu=0.8)>



Sepal length

## Градиентный бустинг

```
import xgboost as xgb
from sklearn.model selection import train test split
from sklearn.metrics import accuracy score, classification report
{'LinearSVC': {'accuracy': 0.77777777778, 'f1 score':
0.7819535221496006},
 'SVC (linear kernel)': {'accuracy': 0.7777777777778,
  'f1 score': 0.7819535221496006},
 'f1 score': 0.8944855967078189},
 'SVC (poly kernel)': {'accuracy': 0.8333333333333334,
 'f1 score': 0.8435897435897436},
 'NuSVC': {'accuracy': 0.80555555555556, 'f1_score':
0.7873661459868357}}
X train, X test, y train, y test = train test split(wine x, wine y,
test size=0.2, random state=42)
model = xgb.XGBClassifier()
```

```
model.fit(X train, y train)
XGBClassifier(base score=None, booster=None, callbacks=None,
              colsample bylevel=None, colsample bynode=None,
              colsample bytree=None, device=None,
early stopping rounds=None,
              enable categorical=False, eval metric=None,
feature types=None,
              gamma=None, grow policy=None, importance type=None,
              interaction constraints=None, learning rate=None,
max bin=None,
              max cat threshold=None, max_cat_to_onehot=None,
              max delta step=None, max depth=None, max leaves=None,
              min child weight=None, missing=nan,
monotone constraints=None,
              multi strategy=None, n estimators=None, n jobs=None,
              num parallel tree=None, objective='multi:softprob', ...)
predictions = model.predict(X test)
accuracy = accuracy score(y test, predictions)
accuracy
0.80555555555556
classification_report(y_test, predictions,
target names=data.target names)
formatted report = "\n".join([line.strip() for line in
report.splitlines()])
formatted report
Accuracy: 80.6
Classification Report:
             recall f1-score
precision
                                support
              1.00
                        0.71
class 0
                                  0.83
                                              14
class 1
              0.80
                        0.86
                                  0.83
                                              14
              0.64
                        0.88
                                  0.74
                                               8
class 2
                                   0.81
                                               36
accuracy
                0.81
                          0.82
                                    0.80
                                                36
macro avg
                   0.84
                             0.81
                                       0.81
weighted avg
                                                   36
```