Министерство образования и науки Российской Федерации
Федеральное государственное бюджетное образовательное учреждение
высшего профессионального образования
«Московский государственный технический университет имени Н.Э. Баумана»
(МГТУ им. Н.Э. Баумана)

ФАКУЛЬТЕТ	**«Информатики и систем управления»**
КАФЕДРА	ИУ5

Дисциплина «Технологии мультимедиа»

ОТЧЕТ
ПО ЛАБОРАТОРНОЙ РАБОТЕ №4
«Линейные модели, SVM и деревья решений.»

Студент	Группы ИУ5-62Б	Гришин Илья
Преподаватель		Гапанюк Ю.Е.

Цель лабораторной работы: изучение линейных моделей, SVM и деревьев решений.

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 следующие модели:
    - одну из линейных моделей;
    - SVM;
    - дерево решений.
5. Оцените качество моделей с помощью двух подходящих для задачи метрик. Сравните качество полученных моделей.

Дополнительные задания:

- Проведите эксперименты с важностью признаков в дереве решений.
- Визуализируйте дерево решений.

Линейные модели, SVM и деревья решений.

В качестве набора данных используется набор данных по раку груди висконсин (диагностический) Файл содержит следующие колонки:

- радиус (среднее расстояние от центра до точек по периметру)
- текстура (стандартное отклонение значений шкалы серого)
- периметр
- область
- гладкость (локальное изменение длины радиуса)
- компактность (периметр ^ 2 / площадь - 1.0)
- вогнутость (выраженность вогнутых участков контура)
- вогнутые точки (количество вогнутых участков контура)
- симметрия
- фрактальная размерность («приближение береговой линии» - 1)

Классы:

- **WDBC-**злокачественный
- **WDBC-**доброкачественный

In [215]:

```
import numpy as np
import pandas as pd
from typing import Dict, Tuple
from scipy import stats
from sklearn.datasets import load_breast_cancer
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsRegressor, KNeighborsClassifier
from sklearn.metrics import accuracy_score, balanced_accuracy_score
from sklearn.metrics import precision_score, recall_score, f1_score, classification_repor
t
from sklearn.metrics import confusion_matrix
from sklearn.metrics import mean_absolute_error, mean_squared_error, mean_squared_log_err
or, median_absolute_error, r2_score
from sklearn.metrics import roc_curve, roc_auc_score
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import SGDRegressor
from sklearn.linear_model import SGDClassifier
from sklearn.tree import DecisionTreeClassifier, DecisionTreeRegressor, export_graphviz
import seaborn as sns
import matplotlib.pyplot as plt
import graphviz
import pydotplus
%matplotlib inline
sns.set(style="ticks")
```

In [8]:

```
breast = load_breast_cancer()
```

In [9]:

```
df_breast = pd.DataFrame(breast.data,columns=breast.feature_names)
df_breast['target'] = pd.Series(breast.target)
df_breast.head()
```

Out[9]:

mean radius	mean texture	mean perimeter	mean area	mean smoothness	mean compactness	mean concavity	mean concave	mean symmetry	mean fractal	...	worst texture	w perim

	mean radius	mean texture	mean perimeter	mean area	mean smoothness	mean compactness	mean concavity	mean concave points	mean symmetry	mean fractal dimension	...	worst texture	perim
0	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.3001	0.14710	0.2419	0.07871	...	17.33	1
1	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.0869	0.07017	0.1812	0.05667	...	23.41	1
2	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.1974	0.12790	0.2069	0.05999	...	25.53	1
3	11.42	20.38	77.58	386.1	0.14250	0.28390	0.2414	0.10520	0.2597	0.09744	...	26.50	
4	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.1980	0.10430	0.1809	0.05883	...	16.67	1

5 rows × 31 columns

In [12]:

```
# Значения и наименования значений целевого признака
list(zip(np.unique(breast.target), breast.target_names))
```

Out[12]:

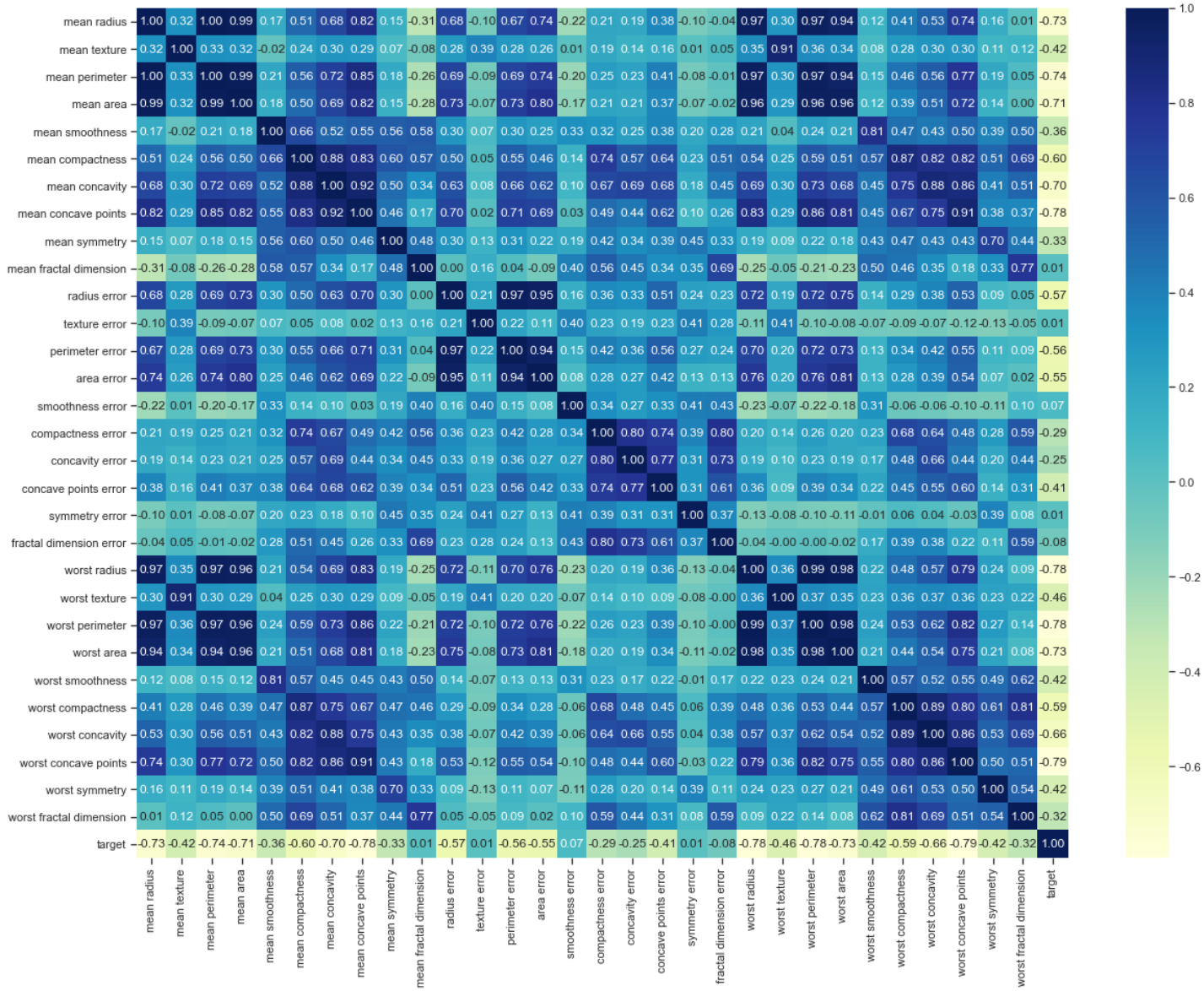
```
[(0, 'malignant'), (1, 'benign')]
```

In [206]:

```
#Построим корреляционную матрицу
fig, ax = plt.subplots(figsize=(20,15))
sns.heatmap(df_breast.corr(method='pearson'), ax=ax, annot=True, fmt='.2f', cmap="YlGnBu
")
```

Out[206]:

```
<AxesSubplot:>
```



Логистическая регрессия **(LogisticRegression)**

In [19]:

```
breast_X_train, breast_X_test, breast_y_train, breast_y_test = train_test_split(
    breast.data, breast.target, test_size=0.5, random_state=1)
```

In [34]:

```
cl1 = LogisticRegression(max_iter=10000)
```

In [35]:

```
cl1.fit(breast_X_train, breast_y_train)
```

Out[35]:

```
LogisticRegression(max_iter=10000)
```

In [24]:

```
pred_breast_y_test = cl1.predict(breast_X_test)
pred_breast_y_test
```

Out[24]:

```
array([1, 0, 1, 0, 0, 0, 0, 0, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1,
       0, 1, 0, 1, 1, 0, 0, 0, 0, 1, 0, 0, 1, 1, 0, 1, 0, 1, 1, 1, 1, 1,
       1, 0, 1, 1, 1, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 0, 1, 1,
       1, 0, 1, 1, 1, 1, 0, 0, 1, 0, 1, 1, 1, 0, 1, 0, 1, 0, 1, 1, 1, 1,
       0, 1, 1, 0, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0,
       0, 1, 0, 1, 0, 0, 1, 1, 1, 1, 1, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 1,
       1, 0, 1, 0, 0, 1, 1, 1, 0, 0, 1, 0, 1, 0, 1, 1, 1, 0, 1, 1, 0, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 0, 0, 1, 1, 1, 1, 0, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 1, 0, 1, 1, 1, 0, 0, 0, 1, 1, 0,
       0, 1, 1, 1, 1, 0, 0, 1, 1, 1, 0, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1,
       1, 1, 0, 1, 0, 1, 1, 0, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 1, 0, 1, 1, 0, 1, 0, 1, 1, 1, 1, 0,
       1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1])
```

In [25]:

```
pred_breast_y_test_proba = cl1.predict_proba(breast_X_test)
pred_breast_y_test_proba[:10]
```

Out[25]:

```
array([[1.49258350e-01, 8.50741650e-01],
       [8.53428519e-01, 1.46571481e-01],
       [6.17810193e-05, 9.99938219e-01],
       [9.99911960e-01, 8.80397272e-05],
       [5.52972743e-01, 4.47027257e-01],
       [9.99953966e-01, 4.60336276e-05],
       [9.99839687e-01, 1.60312607e-04],
       [5.85687939e-01, 4.14312061e-01],
       [7.51937022e-03, 9.92480630e-01],
       [5.46643320e-04, 9.99453357e-01]])
```

In [26]:

```
# Вероятность принадлежности к 0 классу
[round(x, 4) for x in pred_breast_y_test_proba[:10,0]]
```

Out[26]:

```
[0.1493, 0.8534, 0.0001, 0.9999, 0.553, 1.0, 0.9998, 0.5857, 0.0075, 0.0005]
```

In [27]:

```
# Вероятность принадлежности к 1 классу
[round(x, 4) for x in pred_breast_y_test_proba[:10,1]]
```

Out[27]:

```
[0.8507, 0.1466, 0.9999, 0.0001, 0.447, 0.0, 0.0002, 0.4143, 0.9925, 0.9995]
```

In [28]:

```
# Сумма вероятностей равна 1
pred_breast_y_test_proba[:10,0] + pred_breast_y_test_proba[:10,1]
```

Out[28]:

```
array([1., 1., 1., 1., 1., 1., 1., 1., 1., 1.])
```

In [29]:

```
accuracy_score(breast_y_test, pred_breast_y_test)
```

Out[29]:

```
0.9052631578947369
```

In [30]:

```
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 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('Метка \t Accuracy')
    for i in accs:
        print('{} \t {}'.format(i, accs[i]))
```

In [31]:

```
print_accuracy_score_for_classes(breast_y_test, pred_breast_y_test)
```

```
Метка   Accuracy
0   0.8446601941747572
1   0.9395604395604396
```

Метод опорных векторов (SVC)

In [102]:

```
breast_X_a = df_breast['worst radius'].values
breast_X_b = df_breast['worst texture'].values
breast_X = np.column_stack((breast_X_a, breast_X_b))
breast_y = breast.target
```

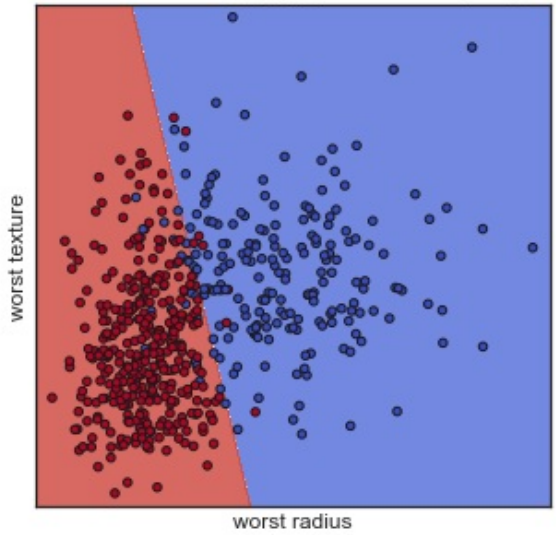
In [104]:

```
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: meshgrid 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(breast_X, breast_y)
    fig, ax = plt.subplots(figsize=(5,5))
    X0, X1 = breast_X[:, 0], breast_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=breast_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('worst radius')
    ax.set_ylabel('worst texture')
    ax.set_xticks(())
    ax.set_yticks(())
    ax.set_title(title)
    plt.show()
```

In [105]:

```
plot_cl(LinearSVC(C=1.0, max_iter=100000))
```

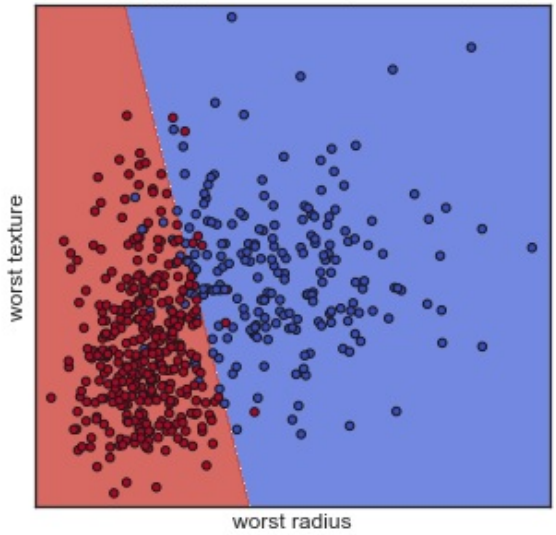
<bound method BaseEstimator.__repr__ of LinearSVC(max_iter=100000)>



In [106]:

```
plot_cl(LinearSVC(C=1.0, penalty='l1', dual=False, max_iter=10000))
```

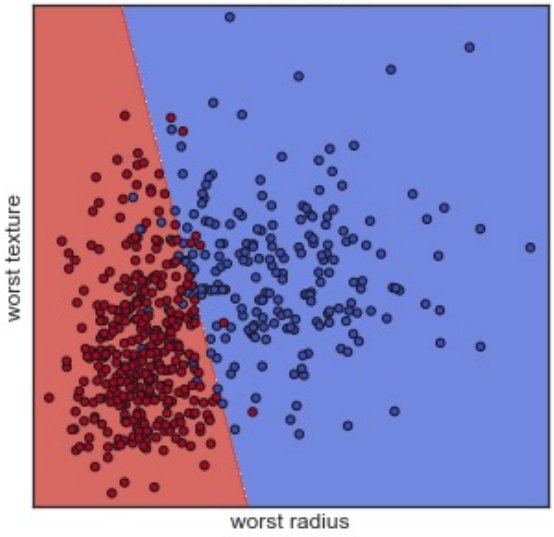
<bound method BaseEstimator.__repr__ of LinearSVC(dual=False, max_iter=10000, penalty='l1')>



In [107]:

```
plot_cl(SVC(kernel='linear', C=1.0))
```

<bound method BaseEstimator.__repr__ of SVC(kernel='linear')>

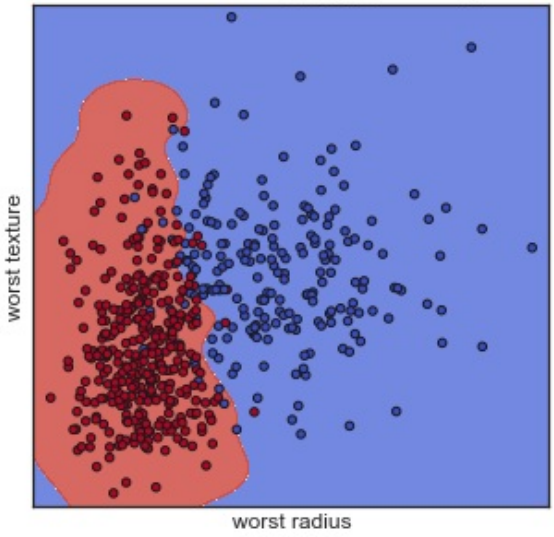


In [108]:

```
plot_cl(SVC(kernel='rbf', gamma=0.2, C=1.0))
```

<bound method BaseEstimator.__repr__ of SVC(gamma=0.2)>

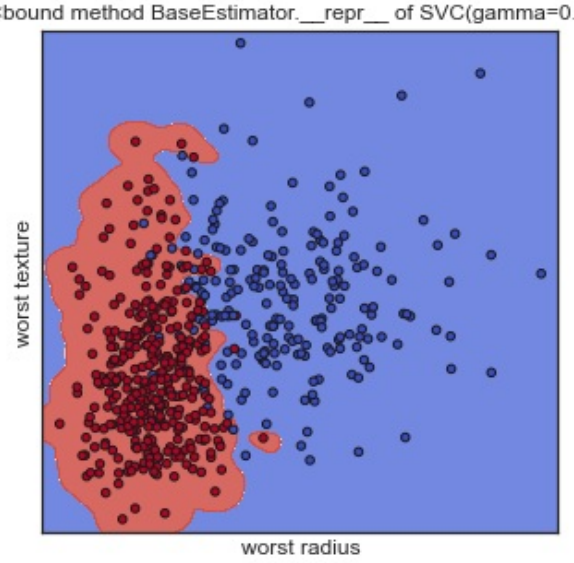
<bound method BaseEstimator.__repr__ of SVC(gamma=0.2)>



In [109]:

```
plot_cl(SVC(kernel='rbf', gamma=0.9, C=1.0))
```

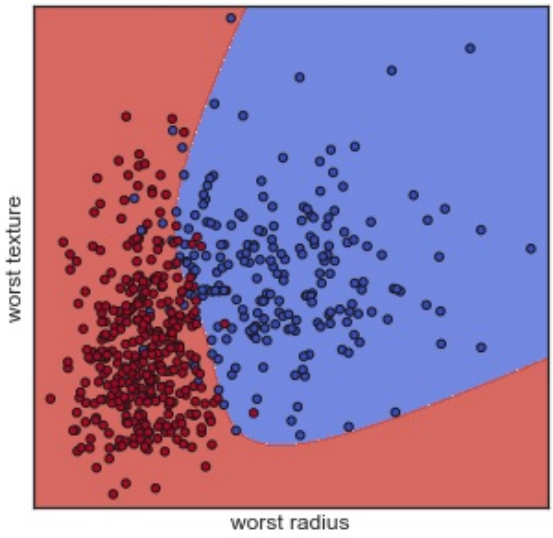
<bound method BaseEstimator.__repr__ of SVC(gamma=0.9)>



In [110]:

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

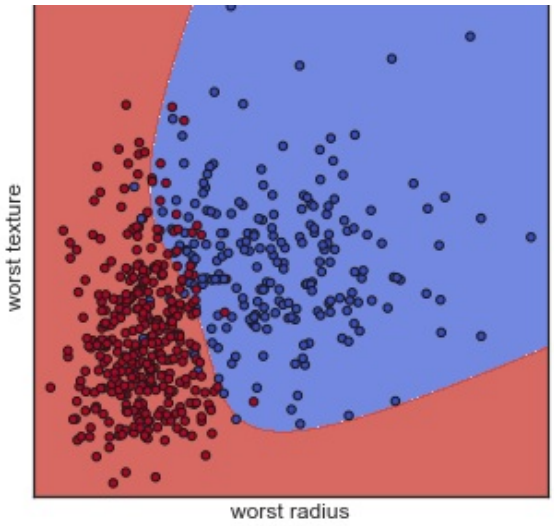
<bound method BaseEstimator.__repr__ of SVC(degree=4, gamma=0.2, kernel='poly')>



In [111]:

```
plot_cl(SVC(kernel='poly', degree=4, gamma=0.9, C=1.0))
```

<bound method BaseEstimator.__repr__ of SVC(degree=4, gamma=0.9, kernel='poly')>



In [135]:

```
breast_X_train_1, breast_X_test_1, breast_y_train_1, breast_y_test_1 = train_test_split(
    breast.data, breast.target, test_size=0.5, random_state=1)
breast_X_train_1.shape, breast_X_test_1.shape
```

Out[135]:

```
((284, 30), (285, 30))
```

In [192]:

```
svc_1 = SVC()
svc_1.fit(breast_X_train_1, breast_y_train_1)
```

Out[192]:

```
SVC()
```

In [193]:

```
breast_y_pred_1 = svc_1.predict(breast_X_test_1)
```

In [194]:

```
mean_absolute_error(breast_y_test_1, breast_y_pred_1), mean_squared_error(breast_y_test_1
, breast_y_pred_1)
```

Out[194]:

```
(0.0912280701754386, 0.0912280701754386)
```

Деревья решений (DecisionTreeClassifier)

In [120]:

```
breast_x_ds = pd.DataFrame(data=breast['data'], columns=breast['feature_names'])
breast_x_ds.head()
```

Out[120]:

	mean radius	mean texture	mean perimeter	mean area	mean smoothness	mean compactness	mean concavity	mean concave points	mean symmetry	mean fractal dimension	...	worst radius	wors textur
0	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.3001	0.14710	0.2419	0.07871	...	25.38	17.3
1	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.0869	0.07017	0.1812	0.05667	...	24.99	23.4
2	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.1974	0.12790	0.2069	0.05999	...	23.57	25.5
3	11.42	20.38	77.58	386.1	0.14250	0.28390	0.2414	0.10520	0.2597	0.09744	...	14.91	26.5
4	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.1980	0.10430	0.1809	0.05883	...	22.54	16.6

5 rows × 30 columns

In [202]:

```
# Обучим дерево на всех признаках
breast_tree_cl = DecisionTreeClassifier(random_state=1)
breast_tree_cl.fit(breast_x_ds, breast.target)
breast_tree_cl
```

Out[202]:

```
DecisionTreeClassifier(random_state=1)
```

In [122]:

```
from IPython.core.display import HTML
from sklearn.tree.export import export_text
tree_rules = export_text(breast_tree_cl, feature_names=list(breast_x_ds.columns))
HTML('<pre>' + tree_rules + '</pre>')
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\utils\deprecation.py:143: FutureWarnin
g: The sklearn.tree.export module is  deprecated in version 0.22 and will be removed in v
ersion 0.24. The corresponding classes / functions should instead be imported from sklear
n.tree. Anything that cannot be imported from sklearn.tree is now part of the private API
.
  warnings.warn(message, FutureWarning)
```

Out[122]:

```
|--- worst radius <= 16.80
|   |--- worst concave points <= 0.14
|   |   |--- worst symmetry <= 0.16
|   |   |   |--- class: 0
|   |   |--- worst symmetry >  0.16
|   |   |   |--- area error <= 38.60
|   |   |   |   |--- smoothness error <= 0.00
|   |   |   |   |   |--- fractal dimension error <= 0.00
|   |   |   |   |   |   |--- class: 0
|   |   |   |   |   |--- fractal dimension error >  0.00
|   |   |   |   |   |   |--- class: 1
|   |   |   |   |--- smoothness error >  0.00
|   |   |   |   |   |--- worst texture <= 33.27
|   |   |   |   |   |   |--- class: 1
|   |   |   |   |   |--- worst texture >  33.27
|   |   |   |   |   |   |--- worst texture <= 33.56
|   |   |   |   |   |   |   |--- class: 0
|   |   |   |   |   |   |--- worst texture >  33.56
|   |   |   |   |   |   |   |--- class: 1
|   |   |   |--- area error >  38.60
|   |   |   |   |--- symmetry error <= 0.02
|   |   |   |   |   |--- class: 0
|   |   |   |   |--- symmetry error >  0.02
|   |   |   |   |   |--- area error <= 39.15
|   |   |   |   |   |   |--- class: 0
|   |   |   |   |   |--- area error >  39.15
|   |   |   |   |   |   |--- class: 1
|   |--- worst concave points >  0.14
|   |   |--- worst texture <= 25.67
|   |   |   |--- worst area <= 810.30
|   |   |   |   |--- mean smoothness <= 0.12
|   |   |   |   |   |--- class: 1
|   |   |   |   |--- mean smoothness >  0.12
|   |   |   |   |   |--- class: 0
|   |   |   |--- worst area >  810.30
```

```
|   |   |   |   |--- worst area <= 844.65
|   |   |   |   |   |--- class: 0
|   |   |   |   |--- worst area >  844.65
|   |   |   |   |   |--- class: 1
|   |   |--- worst texture >  25.67
|   |   |   |--- mean concavity <= 0.10
|   |   |   |   |--- mean texture <= 19.44
|   |   |   |   |   |--- class: 1
|   |   |   |   |--- mean texture >  19.44
|   |   |   |   |   |--- class: 0
|   |   |   |--- mean concavity >  0.10
|   |   |   |   |--- class: 0
|--- worst radius >  16.80
|   |--- worst texture <= 19.91
|   |   |--- worst concave points <= 0.15
|   |   |   |--- class: 1
|   |   |--- worst concave points >  0.15
|   |   |   |--- class: 0
|   |--- worst texture >  19.91
|   |   |--- worst smoothness <= 0.09
|   |   |   |--- class: 1
|   |   |--- worst smoothness >  0.09
|   |   |   |--- worst concavity <= 0.18
|   |   |   |   |--- compactness error <= 0.02
|   |   |   |   |   |--- class: 0
|   |   |   |   |--- compactness error >  0.02
|   |   |   |   |   |--- class: 1
|   |   |   |--- worst concavity >  0.18
|   |   |   |   |--- class: 0
```

In [222]:

```
dot_data = export_graphviz(breast_tree_cl, out_file=None,
                           feature_names=breast.feature_names,
                           class_names=breast.target_names,
                           filled=True, rounded=True, special_characters=True)
graph = graphviz.Source(dot_data)
graph
```

Out[222]:

In [124]:

```
# Важность признаков
list(zip(breast_x_ds.columns.values, breast_tree_cl.feature_importances_))
```

Out[124]:

```
[('mean radius', 0.0),
 ('mean texture', 0.011277152370382112),
 ('mean perimeter', 0.0),
 ('mean area', 0.0),
 ('mean smoothness', 0.007016894808237761),
 ('mean compactness', 0.0),
 ('mean concavity', 0.008771118510297198),
 ('mean concave points', 0.0),
 ('mean symmetry', 0.0),
 ('mean fractal dimension', 0.0),
 ('radius error', 0.0),
 ('texture error', 0.0),
 ('perimeter error', 0.0),
 ('area error', 0.008936807857691388),
 ('smoothness error', 0.0010038401246787545),
 ('compactness error', 0.005638576185191056),
```

```
 ('concavity error', 0.0),
 ('concave points error', 0.0),
 ('symmetry error', 0.005831348020582203),
 ('fractal dimension error', 0.006644408706878978),
 ('worst radius', 0.6955935182252058),
 ('worst texture', 0.07728413233375948),
 ('worst perimeter', 0.0),
 ('worst area', 0.016724478603093007),
 ('worst smoothness', 0.007387982534891388),
 ('worst compactness', 0.0),
 ('worst concavity', 0.0018358155021552392),
 ('worst concave points', 0.13893825016690 36),
 ('worst symmetry', 0.007315997688141106),
 ('worst fractal dimension', 0.0)]
```

In [126]:

```
# Важность признаков в сумме дает почти единицу
sum(breast_tree_cl.feature_importances_)
```

Out[126]:

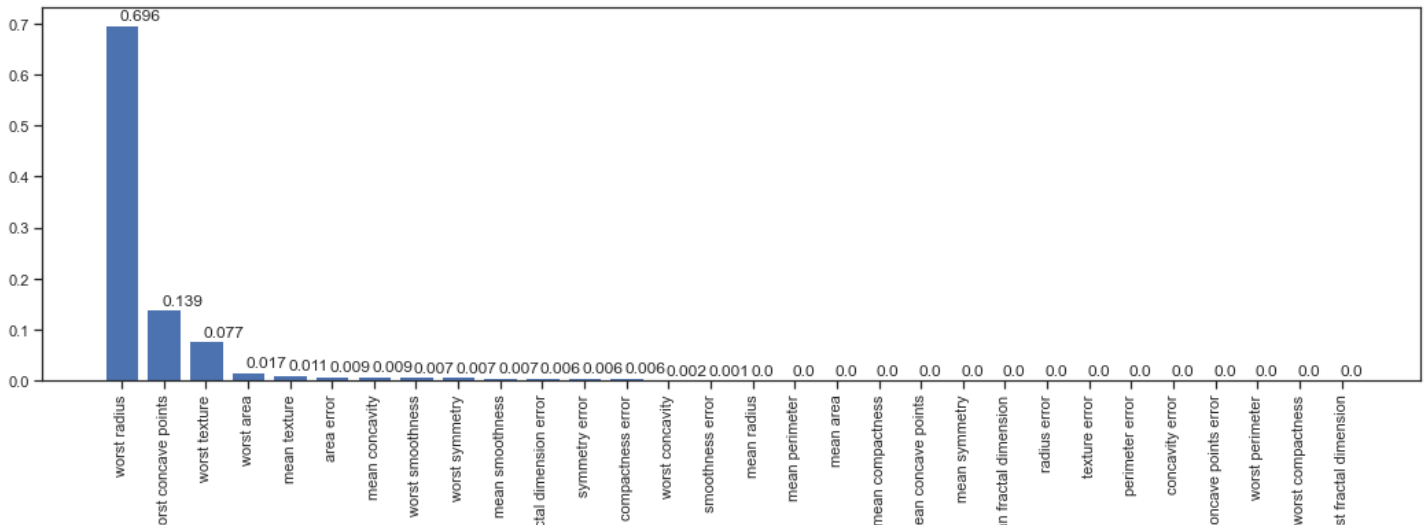
```
0.9999999999999999
```

In [127]:

```
from operator import itemgetter

def draw_feature_importances(tree_model, X_dataset, figsize=(18,5)):
    """
    Вывод важности признаков в виде графика
    """
    # Сортировка значений важности признаков по убыванию
    list_to_sort = list(zip(X_dataset.columns.values, tree_model.feature_importances_))
    sorted_list = sorted(list_to_sort, key=itemgetter(1), reverse = True)
    # Названия признаков
    labels = [x for x,_ in sorted_list]
    # Важности признаков
    data = [x for _,x in sorted_list]
    # Вывод графика
    fig, ax = plt.subplots(figsize=figsize)
    ind = np.arange(len(labels))
    plt.bar(ind, data)
    plt.xticks(ind, labels, rotation='vertical')
    # Вывод значений
    for a,b in zip(ind, data):
        plt.text(a-0.05, b+0.01, str(round(b,3)))
    plt.show()
    return labels, data
```

In [128]:

```
breast_tree_cl_fl, breast_tree_cl_fd = draw_feature_importances(breast_tree_cl, breast_x_
ds)
```



In [129]:

```
# Список признаков, отсортированный на основе важности, и значения важности
breast_tree_cl_fl, breast_tree_cl_fd
```

Out[129]:

```
(['worst radius',
  'worst concave points',
  'worst texture',
  'worst area',
  'mean texture',
  'area error',
  'mean concavity',
  'worst smoothness',
  'worst symmetry',
  'mean smoothness',
  'fractal dimension error',
  'symmetry error',
  'compactness error',
  'worst concavity',
  'smoothness error',
  'mean radius',
  'mean perimeter',
  'mean area',
  'mean compactness',
  'mean concave points',
  'mean symmetry',
  'mean fractal dimension',
  'radius error',
  'texture error',
  'perimeter error',
  'concavity error',
  'concave points error',
  'worst perimeter',
  'worst compactness',
  'worst fractal dimension'],
 [0.6955935182252058,
  0.1389382501669036,
  0.07728413233375948,
  0.016724478603093007,
  0.011277152370382112,
  0.008936807857691388,
  0.008771118510297198,
  0.007387982534891388,
  0.007315997688141106,
  0.007016894808237761,
  0.00644408706878978,
  0.005831348020582203,
  0.005638576185191056,
  0.0018358155021552392,
  0.0010038401246787545,
  0.0,
  0.0,
  0.0,
  0.0,
  0.0,
  0.0,
  0.0,
  0.0,
  0.0,
  0.0,
  0.0,
  0.0,
  0.0,
  0.0,
  0.0])
```

In [130]:

```
# Пересортируем признаки на основе важности
breast_x_ds_sorted = breast_x_ds[breast_tree_cl_fl]
breast_x_ds_sorted.head()
```

Out[130]:

	worst radius	worst concave points	worst texture	worst area	mean texture	area error	mean concavity	worst smoothness	worst symmetry	mean smoothness	...	mean symmetry	mean fractal dimension
0	25.38	0.2654	17.33	2019.0	10.38	153.40	0.3001	0.1622	0.4601	0.11840	...	0.2419	0.07871
1	24.99	0.1860	23.41	1956.0	17.77	74.08	0.0869	0.1238	0.2750	0.08474	...	0.1812	0.05667
2	23.57	0.2430	25.53	1709.0	21.25	94.03	0.1974	0.1444	0.3613	0.10960	...	0.2069	0.05999
3	14.91	0.2575	26.50	567.7	20.38	27.23	0.2414	0.2098	0.6638	0.14250	...	0.2597	0.09744
4	22.54	0.1625	16.67	1575.0	14.34	94.44	0.1980	0.1374	0.2364	0.10030	...	0.1809	0.05883

5 rows × 30 columns

In [149]:

```
breast_X_train_2, breast_X_test_2, breast_y_train_2, breast_y_test_2 = train_test_split(
    breast_x_ds_sorted, breast.target, test_size=0.5, random_state=1)
breast_X_train_2.shape, breast_X_test_2.shape
```

Out[149]:

```
((284, 30), (285, 30))
```

In [150]:

```
# Обучим дерево и предскажем результаты на всех признаках
breast_tree_cl_feat_1 = DecisionTreeClassifier(random_state=1).fit(breast_X_train_2, bre
ast_y_train_2)
breast_y_test_predict = breast_tree_cl_feat_1.predict(breast_X_test_2)
breast_y_test_predict.shape
```

Out[150]:

```
(285,)
```

In [151]:

```
# Проверим точность по классам
print_accuracy_score_for_classes(breast_y_test_2, breast_y_test_predict)
```

```
Метка   Accuracy
0   0.8737864077669902
1   0.9010989010989011
```

In [152]:

```
# Обучим дерево и предскажем результаты на единственном самом важном признаке
breast_tree_cl_feat_2 = DecisionTreeClassifier(random_state=1).fit(breast_X_train_2[[bre
ast_tree_cl_fl[0]]], breast_y_train_2)
breast_y_test_predict_2 = breast_tree_cl_feat_2.predict(breast_X_test_2[[breast_tree_cl_f
l[0]]])
breast_y_test_predict_2.shape
```

Out[152]:

```
(285,)
```

In [153]:

```
# Проверим точность по классам
print_accuracy_score_for_classes(breast_y_test_2, breast_y_test_predict_2)
```

```
Метка   Accuracy
0   0.7766990291262136
1   0.8956043956043956
```

1 0.8956043956043956

Качество моделей с помощью двух подходящих для задачи метрик. Сравнение качеств полученных моделей.

В качестве метрик для решения задачи классификации будем использовать:

- Метрика **precision:** $precision = \frac{TP}{TP+FP}$
- Метрика **recall (полнота):** $recall = \frac{TP}{TP+FN}$

In [207]:

```
def vis_models_quality(array_metric, array_labels, str_header, figsize=(5, 5)):
    fig, ax1 = plt.subplots(figsize=figsize)
    pos = np.arange(len(array_metric))
    rects = ax1.barh(pos, array_metric,
                     align='center',
                     height=0.5,
                     tick_label=array_labels)
    ax1.set_title(str_header)
    for a,b in zip(pos, array_metric):
        plt.text(0.2, a-0.1, str(round(b,3)), color='white')
    plt.show()
```

In [200]:

```
# Логистическая регрессия (LogisticRegression)
precision_score(breast_y_test, pred_breast_y_test), recall_score(breast_y_test, pred_brea
st_y_test)
```

Out[200]:

```
(0.9144385026737968, 0.9395604395604396)
```

In [201]:

```
# Метод опорных векторов (SVC)
precision_score(breast_y_test_1, breast_y_pred_1), recall_score(breast_y_test_1, breast_y
_pred_1)
```

Out[201]:

```
(0.89, 0.978021978021978)
```

In [203]:

```
# Деревья решений (DecisionTreeClassifier)
precision_score(breast_y_test_2, breast_y_test_predict_2), recall_score(breast_y_test_2,
breast_y_test_predict_2)
```

Out[203]:

```
(0.8763440860215054, 0.8956043956043956)
```

In [199]:

```
# Логистическая регрессия
accuracy_score(breast_y_test, pred_breast_y_test)
```

Out[199]:

```
0.9052631578947369
```

In [205]:

```
# Метод опорных векторов (SVC)
```

```
accuracy_score(breast_y_test_1, breast_y_pred_1)
```

Out[205]:

```
0.9087719298245615
```

In [204]:

```
# Деревья решений (DecisionTreeClassifier)
accuracy_score(breast_y_test_2, breast_y_test_predict_2)
```

Out[204]:

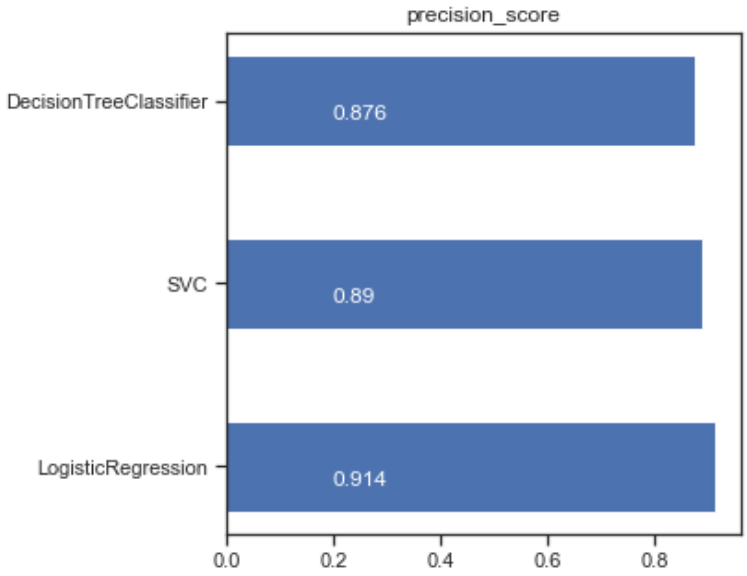
```
0.8526315789473684
```

In [231]:

```
# Результаты
array_labels = ['LogisticRegression','SVC', 'DecisionTreeClassifier']
array_mae = [precision_score(breast_y_test, pred_breast_y_test),
             precision_score(breast_y_test_1, breast_y_pred_1),
             precision_score(breast_y_test_2, breast_y_test_predict_2)]
```

In [232]:

```
# Визуализация результатов
vis_models_quality(array_mae, array_labels, 'precision_score')
```

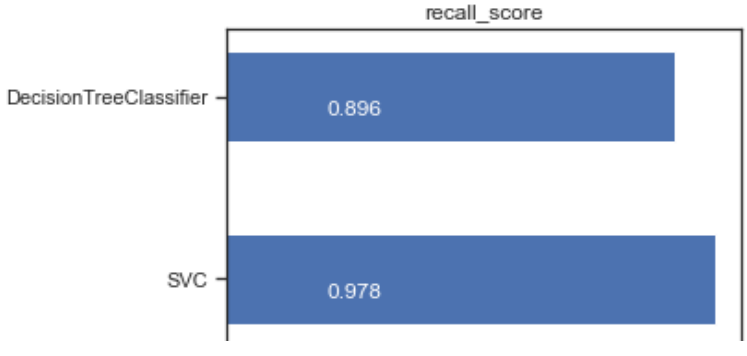


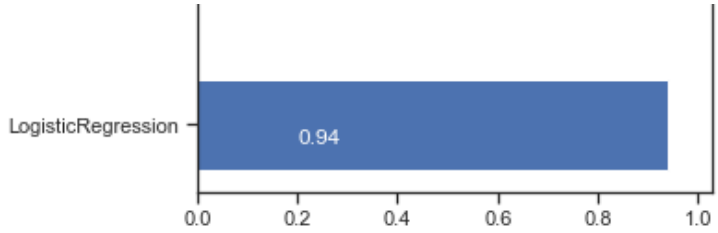
In [233]:

```
# Результаты
array_labels = ['LogisticRegression','SVC', 'DecisionTreeClassifier']
array_mae = [recall_score(breast_y_test, pred_breast_y_test),
             recall_score(breast_y_test_1, breast_y_pred_1),
             recall_score(breast_y_test_2, breast_y_test_predict_2)]
```

In [234]:

```
# Визуализация результатов
vis_models_quality(array_mae, array_labels, 'recall_score')
```





In [235]:

```
# Результаты
array_labels = ['LogisticRegression','SVC', 'DecisionTreeClassifier']
array_mae = [accuracy_score(breast_y_test, pred_breast_y_test),
             accuracy_score(breast_y_test_1, breast_y_pred_1),
             accuracy_score(breast_y_test_2, breast_y_test_predict_2)]
```

In [236]:

```
# Визуализация результатов
vis_models_quality(array_mae, array_labels, 'accuracy_score')
```