Линейные модели, SVM и деревья решений.

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

1. Выберите набор данных (датасет) для решения задачи классификации или регресии.
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 одну из линейных моделей, SVM и 3 дерево решений. Оцените качество моделей с помощью трех подходящих для задачи метрик. Сравните качество полученных моделей.
5. Произведите для каждой модели подбор одного гиперпараметра с использованием GridSearchCV и кросс-валидации.
6. Повторите пункт 4 для найденных оптимальных значений гиперпараметров. Сравните качество полученных моделей с качеством моделей, полученных в пункте 4.

In [1]:

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
sns.set(style="ticks")
data = pd.read_csv('Data/lab_5/winequalityN.csv',sep=",")
data.head(5)
```

Out[1]:

	type	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulpł
0	white	7.0	0.27	0.36	20.7	0.045	45.0	170.0	1.0010	3.00	
1	white	6.3	0.30	0.34	1.6	0.049	14.0	132.0	0.9940	3.30	
2	white	8.1	0.28	0.40	6.9	0.050	30.0	97.0	0.9951	3.26	
3	white	7.2	0.23	0.32	8.5	0.058	47.0	186.0	0.9956	3.19	
4	white	7.2	0.23	0.32	8.5	0.058	47.0	186.0	0.9956	3.19	

In [2]:

```
data.shape
```

Out[2]:

```
(6497, 13)
```

In [3]:

```
# Кодирование категориального признака(тип вина: красное или белое) в столбец wine_type
_le
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
le.fit(data.type)
data['wine_type_le'] = le.transform(data.type)
data.head(2)
```

Out[3]:

	type	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphate
0	white	7.0	0.27	0.36	20.7	0.045	45.0	170.0	1.001	3.0	0.4
1	white	6.3	0.30	0.34	1.6	0.049	14.0	132.0	0.994	3.3	0.4

In [4]:

```
del data['type']
```

In [5]:

```
data.head(2)
```

Out[5]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	a
0	7.0	0.27	0.36	20.7	0.045	45.0	170.0	1.001	3.0	0.45	
1	6.3	0.30	0.34	1.6	0.049	14.0	132.0	0.994	3.3	0.49	

In [6]:

```
# Проверка на пустые значения
data.isnull().sum()
```

Out[6]:

```
fixed acidity           10
volatile acidity         8
citric acid              3
residual sugar           2
chlorides                2
free sulfur dioxide      0
total sulfur dioxide     0
density                  0
pH                       9
sulphates                4
alcohol                  0
quality                  0
wine_type_le             0
dtype: int64
```

In [7]:

```
import pandas as pd
# function to clean the dataset of nan, Inf, and missing cells (for skewed datasets)
def clean_dataset(df):
    assert isinstance(df, pd.DataFrame), "df needs to be a pd.DataFrame"
    df.dropna(inplace=True)
    indices_to_keep = ~df.isin([np.nan, np.inf, -np.inf]).any(1)
    return df[indices_to_keep].astype(np.float64)
```

In [8]:

```
clean_dataset(data)[:1]
```

Out[8]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	a
0	7.0	0.27	0.36	20.7	0.045	45.0	170.0	1.001	3.0	0.45	

In [9]:

```
# Пустых значений нет
# Перейдем к разделению выборки на обучающую и тестовую.
X = data.drop('wine_type_le',axis = 1).values
y = data['wine_type_le'].values
```

In [10]:

```
from sklearn.model_selection import train_test_split
# Функция train_test_split разделила исходную выборку таким образом,
#чтобы в обучающей и тестовой частях сохранились пропорции классов.
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.30, random_state=1)
```

In [11]:

```
# Размер обучающей выборки (70%)
print('X_train: {}  y_train: {}'.format(X_train.shape, y_train.shape))
```

```
X_train: (4524, 12)  y_train: (4524,)
```

In [12]:

```
# Размер тестовой выборки (30%)
print('X_test: {}  y_test: {}'.format(X_test.shape, y_test.shape))
```

```
X_test: (1939, 12)  y_test: (1939,)
```

In [13]:

```
# Функция train_test_split разделила исходную выборку таким образом,
#чтобы в обучающей и тестовой частях сохранились пропорции классов.
np.unique(y_train)
```

Out[13]:

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

In [14]:

```
np.unique(y_test)
```

Out[14]:

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

In [15]:

```
from sklearn.linear_model import SGDClassifier
from sklearn.svm import LinearSVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import GridSearchCV

from sklearn.metrics import accuracy_score
from sklearn.metrics import balanced_accuracy_score
from sklearn.metrics import precision_score, recall_score, f1_score
```

Сравнение качества трех линейных моделей

SGDClassifier (градиентный метод)

In [16]:

```
import warnings
warnings.filterwarnings('ignore')

sgd = SGDClassifier().fit(X_train, y_train)
predicted_sgd = sgd.predict(X_test)
```

In [17]:

```
accuracy_score(y_test, predicted_sgd)
```

Out[17]:

```
0.7741103661681279
```

In [18]:

```
balanced_accuracy_score(y_test, predicted_sgd)
```

Out[18]:

```
0.8412864309603441
```

In [19]:

```
(precision_score(y_test, predicted_sgd, average='weighted'),
 recall_score(y_test, predicted_sgd, average='weighted'))
```

Out[19]:

```
(0.8730518980385593, 0.7741103661681279)
```

In [20]:

```
f1_score(y_test, predicted_sgd, average='weighted')
```

Out[20]:

```
0.7892751746523573
```

LinearSVC (линейный)

In [21]:

```
svc = LinearSVC(C=1.0).fit(X_train, y_train)
predicted_svc = svc.predict(X_test)
```

In [22]:

```
accuracy_score(y_test, predicted_svc)
```

Out[22]:

```
0.9804022692109334
```

In [23]:

```
balanced_accuracy_score(y_test, predicted_svc)
```

Out[23]:

```
0.9620461060678451
```

In [24]:

```
(precision_score(y_test, predicted_svc, average='weighted'),
 recall_score(y_test, predicted_svc, average='weighted'))
```

Out[24]:

```
(0.9807478230266101, 0.9804022692109334)
```

In [25]:

```
f1_score(y_test, predicted_svc, average='weighted')
```

Out[25]:

```
0.9801578892898227
```

DecisionTreeClassifier (дерево решений)

In [26]:

```
dtc = DecisionTreeClassifier(random_state=1).fit(X_train, y_train)
predicted_dtc = dtc.predict(X_test)
```

In [27]:

```
accuracy_score(y_test, predicted_dtc)
```

Out[27]:

```
0.9896854048478597
```

In [28]:

```
balanced_accuracy_score(y_test, predicted_dtc)
```

Out[28]:

```
0.9882893374741202
```

In [29]:

```
(precision_score(y_test, predicted_dtc, average='weighted'),
 recall_score(y_test, predicted_dtc, average='weighted'))
```

Out[29]:

```
(0.9897527301109915, 0.9896854048478597)
```

In [30]:

```
f1_score(y_test, predicted_dtc, average='weighted')
```

Out[30]:

```
0.9897065917780767
```

In [31]:

```
n_range = np.array(range(0,100,5))
n_range = n_range / 100
tuned_parameters = [{'l1_ratio': n_range}]
tuned_parameters
```

Out[31]:

```
[{'l1_ratio': array([0.  , 0.05, 0.1 , 0.15, 0.2 , 0.25, 0.3 , 0.35, 0.4 ,
0.45, 0.5 ,
         0.55, 0.6 , 0.65, 0.7 , 0.75, 0.8 , 0.85, 0.9 , 0.95])}]
```

Подбор одного гиперпараметра с использованием GridSearchCV и кросс-валидации

In [32]:

```
import warnings
warnings.filterwarnings('ignore')

clf_gs_sgd = GridSearchCV(SGDClassifier(), tuned_parameters, cv=5,
                      scoring='accuracy')
clf_gs_sgd.fit(X_train, y_train)
```

Out[32]:

```
GridSearchCV(cv=5, error_score='raise-deprecating',
       estimator=SGDClassifier(alpha=0.0001, average=False, class_weight=N
one,
       early_stopping=False, epsilon=0.1, eta0=0.0, fit_intercept=True,
       l1_ratio=0.15, learning_rate='optimal', loss='hinge', max_iter=Non
e,
       n_iter=None, n_iter_no_change=5, n_jobs=None, penalty='l2',
       power_t=0.5, random_state=None, shuffle=True, tol=None,
       validation_fraction=0.1, verbose=0, warm_start=False),
       fit_params=None, iid='warn', n_jobs=None,
       param_grid=[{'l1_ratio': array([0.  , 0.05, 0.1 , 0.15, 0.2 , 0.25,
0.3 , 0.35, 0.4 , 0.45, 0.5 ,
       0.55, 0.6 , 0.65, 0.7 , 0.75, 0.8 , 0.85, 0.9 , 0.95])}],
       pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
       scoring='accuracy', verbose=0)
```

In [33]:

```
clf_gs_sgd.best_params_
```

Out[33]:

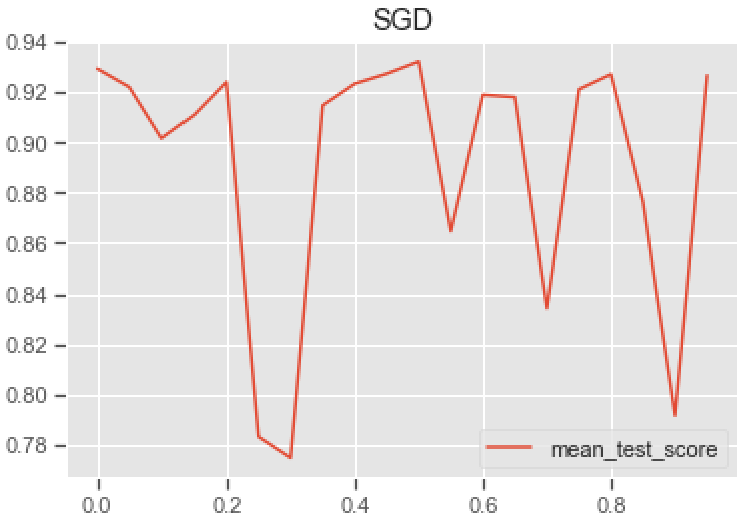
```
{'l1_ratio': 0.5}
```

In [34]:

```
import matplotlib.pyplot as plt
plt.style.use('ggplot')
```

In [35]:

```
plt.title('SGD')
plt.plot(n_range, clf_gs_sgd.cv_results_['mean_test_score'],label='mean_test_score')
plt.legend()
plt.show()
```



In [36]:

```
n_range = np.array(range(1,20,1))
tuned_parameters = [{'C': n_range}]
tuned_parameters
```

Out[36]:

```
[{'C': array([ 1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15,
16, 17,
         18, 19])}]
```

In [37]:

```
clf_gs_svm = GridSearchCV(LinearSVC(), tuned_parameters, cv=3,
                      scoring='accuracy')
clf_gs_svm.fit(X_train, y_train)
```

Out[37]:

```
GridSearchCV(cv=3, error_score='raise-deprecating',
       estimator=LinearSVC(C=1.0, class_weight=None, dual=True, fit_interc
ept=True,
     intercept_scaling=1, loss='squared_hinge', max_iter=1000,
     multi_class='ovr', penalty='l2', random_state=None, tol=0.0001,
     verbose=0),
       fit_params=None, iid='warn', n_jobs=None,
       param_grid=[{'C': array([ 1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 1
1, 12, 13, 14, 15, 16, 17,
       18, 19])}],
       pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
       scoring='accuracy', verbose=0)
```

In [38]:

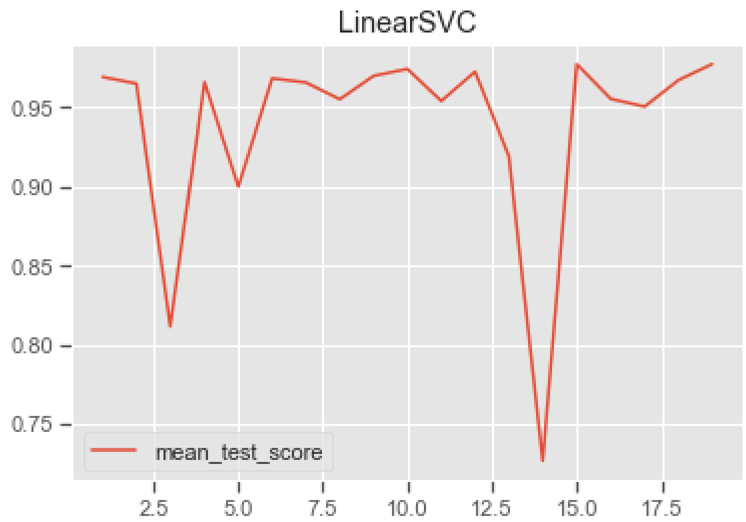
```
clf_gs_svm.best_params_
```

Out[38]:

```
{'C': 19}
```

In [39]:

```
plt.title('LinearSVC')
plt.plot(n_range, clf_gs_svm.cv_results_['mean_test_score'],label='mean_test_score')
plt.legend()
plt.show()
```



In [40]:

```
n_range = np.array(range(1,7,1))
tuned_parameters = [{'max_depth': n_range}]
tuned_parameters
```

Out[40]:

```
[{'max_depth': array([1, 2, 3, 4, 5, 6])}]
```

In [41]:

```
clf_gs_dt = GridSearchCV(DecisionTreeClassifier(random_state=1), tuned_parameters,
                          cv=5, scoring='accuracy')
clf_gs_dt.fit(X_train, y_train)
```

Out[41]:

```
GridSearchCV(cv=5, error_score='raise-deprecating',
       estimator=DecisionTreeClassifier(class_weight=None, criterion='gin
i', max_depth=None,
            max_features=None, max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, presort=False, random_state=1,
            splitter='best'),
       fit_params=None, iid='warn', n_jobs=None,
       param_grid=[{'max_depth': array([1, 2, 3, 4, 5, 6])}],
       pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
       scoring='accuracy', verbose=0)
```

In [42]:

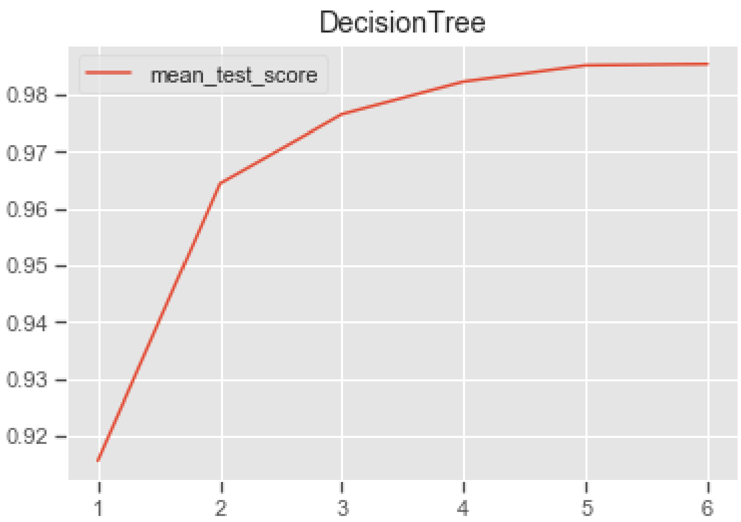
```
clf_gs_dt.best_params_
```

Out[42]:

```
{'max_depth': 6}
```

In [43]:

```
plt.title('DecisionTree')
plt.plot(n_range, clf_gs_dt.cv_results_['mean_test_score'],label='mean_test_score')
plt.legend()
plt.show()
```



Сравнение качества полученных моделей с качеством моделей, полученных ранее

SGD

In [44]:

```
sgd_optimized = SGDClassifier(l1_ratio=clf_gs_sgd.best_params_['l1_ratio']).fit(X_train
, y_train)
predicted_sgd_opt = sgd_optimized.predict(X_test)
```

In [45]:

```
accuracy_score(y_test, predicted_sgd_opt)
```

Out[45]:

```
0.9406910778751933
```

In [46]:

```
balanced_accuracy_score(y_test, predicted_sgd_opt)
```

Out[46]:

```
0.9093157748049052
```

In [47]:

```
(precision_score(y_test, predicted_sgd_opt, average='weighted'),
 recall_score(y_test, predicted_sgd_opt, average='weighted'))
```

Out[47]:

```
(0.9399862610608563, 0.9406910778751933)
```

In [48]:

```
f1_score(y_test, predicted_sgd_opt, average='weighted')
```

Out[48]:

```
0.9399744973367767
```

LinearSVC

In [49]:

```
svm_optimized = LinearSVC(C=clf_gs_svm.best_params_['C']).fit(X_train, y_train)
predicted_svm_opt = svm_optimized.predict(X_test)
```

In [50]:

```
accuracy_score(y_test, predicted_svm_opt)
```

Out[50]:

```
0.9840123775141826
```

In [51]:

```
balanced_accuracy_score(y_test, predicted_svm_opt)
```

Out[51]:

```
0.9699842729734034
```

In [52]:

```
(precision_score(y_test, predicted_svm_opt, average='weighted'),
 recall_score(y_test, predicted_svm_opt, average='weighted'))
```

Out[52]:

```
(0.9841716854842232, 0.9840123775141826)
```

In [53]:

```
f1_score(y_test, predicted_svm_opt, average='weighted')
```

Out[53]:

```
0.9838680461007199
```

DecisionTree

In [54]:

```
dt_optimized = DecisionTreeClassifier(max_depth=clf_gs_dt.best_params_['max_depth']).fi
t(X_train, y_train)
predicted_dt_opt = dt_optimized.predict(X_test)
```

In [55]:

```
accuracy_score(y_test, predicted_dt_opt)
```

Out[55]:

```
0.9896854048478597
```

In [56]:

```
balanced_accuracy_score(y_test, predicted_dt_opt)
```

Out[56]:

```
0.9848303870043
```

In [57]:

```
(precision_score(y_test, predicted_dt_opt, average='weighted'),
 recall_score(y_test, predicted_dt_opt, average='weighted'))
```

Out[57]:

```
(0.9896679065842275, 0.9896854048478597)
```

In [58]:

```
f1_score(y_test, predicted_dt_opt, average='weighted')
```

Out[58]:

```
0.9896710352653659
```

Вывод наибольшая точность у дерева решений, затем идет линейный метод, а потом SGD (стохастический градиентный метод)