Импорт библиотек

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.preprocessing import StandardScaler

from sklearn.model_selection import train_test_split

from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier,
GradientBoostingClassifier
from xgboost import XGBClassifier
from sklearn.metrics import accuracy_score, fl_score, roc_auc_score

from sklearn.model_selection import GridSearchCV
import numpy as np
```

1. Загрузка и предварительный анализ данных

```
data = pd.read csv('WineQT.csv')
print(data.head())
print(data.info())
print(data.describe())
   fixed acidity volatile acidity citric acid residual sugar
chlorides
0
             7.4
                               0.70
                                            0.00
                                                             1.9
0.076
             7.8
                               0.88
                                            0.00
                                                             2.6
1
0.098
2
             7.8
                               0.76
                                            0.04
                                                             2.3
0.092
            11.2
                               0.28
                                            0.56
                                                             1.9
0.075
             7.4
                               0.70
                                            0.00
                                                             1.9
0.076
   free sulfur dioxide total sulfur dioxide density pH sulphates
                                                                    0.56
0
                  11.0
                                         34.0
                                                0.9978 3.51
1
                  25.0
                                         67.0
                                                0.9968 3.20
                                                                    0.68
2
                  15.0
                                         54.0
                                                0.9970 3.26
                                                                    0.65
3
                  17.0
                                         60.0
                                                0.9980 3.16
                                                                    0.58
```

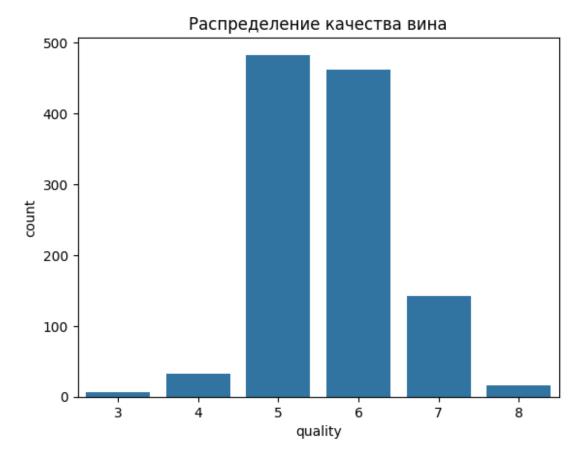
```
4
                   11.0
                                          34.0
                                                 0.9978 3.51
                                                                      0.56
   alcohol
            quality
                      Ιd
0
       9.4
                   5
                       0
                   5
1
                       1
       9.8
2
       9.8
                   5
                       2
3
       9.8
                   6
                       3
                   5
4
       9.4
                       4
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1143 entries, 0 to 1142
Data columns (total 13 columns):
                            Non-Null Count
#
     Column
                                             Dtype
- - -
 0
     fixed acidity
                            1143 non-null
                                             float64
 1
     volatile acidity
                            1143 non-null
                                             float64
 2
     citric acid
                            1143 non-null
                                             float64
 3
     residual sugar
                            1143 non-null
                                             float64
 4
     chlorides
                            1143 non-null
                                             float64
 5
     free sulfur dioxide
                            1143 non-null
                                             float64
 6
                            1143 non-null
     total sulfur dioxide
                                             float64
 7
                            1143 non-null
                                             float64
     density
 8
                            1143 non-null
                                             float64
     рН
 9
     sulphates
                            1143 non-null
                                             float64
 10
     alcohol
                                             float64
                            1143 non-null
 11
     quality
                            1143 non-null
                                             int64
 12
                            1143 non-null
                                             int64
     Ιd
dtypes: float64(11), int64(2)
memory usage: 116.2 KB
None
       fixed acidity
                       volatile acidity
                                          citric acid
                                                        residual sugar \
         1143.000000
                            1143.000000
                                          1143.000000
                                                           1143.000000
count
            8.311111
                                0.531339
                                             0.268364
mean
                                                              2.532152
            1.747595
                                0.179633
                                             0.196686
                                                              1.355917
std
min
            4.600000
                               0.120000
                                             0.000000
                                                              0.900000
25%
            7.100000
                               0.392500
                                             0.090000
                                                              1.900000
            7.900000
                               0.520000
                                             0.250000
50%
                                                              2.200000
75%
            9.100000
                               0.640000
                                             0.420000
                                                              2,600000
                                             1.000000
           15.900000
                               1.580000
                                                             15.500000
max
         chlorides free sulfur dioxide total sulfur dioxide
density
count 1143.000000
                                                     1143.000000
                             1143.000000
1143.000000
          0.086933
                                15.615486
mean
                                                       45.914698
0.996730
                                10.250486
std
          0.047267
                                                       32.782130
0.001925
          0.012000
                                 1.000000
                                                        6.000000
min
0.990070
```

25% 0.995570	0.070000	7.000000		21.000000	
50%	0.079000	13.000000		37.000000	
0.996680 75% 0.997845	0.090000	21.000000		61.000000	
max 1.003690	0.611000	68.000000		289.000000	
	рН	sulphates	alcohol	quality	Id
count 11	43.000000	1143.000000	1143.000000	1143.000000	1143.000000
mean	3.311015	0.657708	10.442111	5.657043	804.969379
std	0.156664	0.170399	1.082196	0.805824	463.997116
min	2.740000	0.330000	8.400000	3.000000	0.000000
25%	3.205000	0.550000	9.500000	5.000000	411.000000
50%	3.310000	0.620000	10.200000	6.000000	794.000000
75%	3.400000	0.730000	11.100000	6.000000	1209.500000
max	4.010000	2.000000	14.900000	8.000000	1597.000000

2. Разведочный анализ данных (EDA)

Распределение целевой переменной:

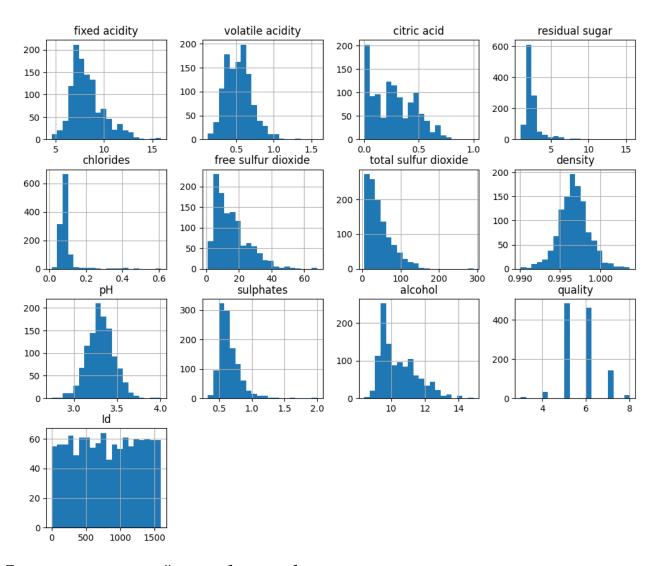
```
sns.countplot(x='quality', data=data)
plt.title('Распределение качества вина')
plt.show()
```



Наблюдается дисбаланс: большинство вин имеют оценку 5 или 6.

Гистограммы признаков:

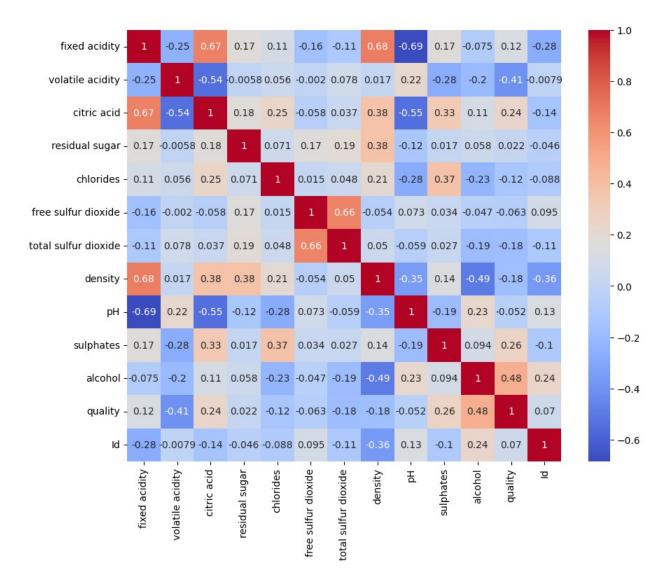
```
data.hist(bins=20, figsize=(12, 10))
plt.show()
```



Признаки имеют разный масштаб, что требует стандартизации.

Корреляционный анализ:

```
plt.figure(figsize=(10, 8))
sns.heatmap(data.corr(), annot=True, cmap='coolwarm')
plt.show()
```



Наибольшую корреляцию с quality имеют:

- alcohol (0.48)
- volatile acidity (-0.41)
- sulphates (0.26)

3. Подготовка данных

Кодирование целевой переменной (для классификации):

Преобразуем quality в 3 класса:

- Низкое (0): 0-4
- Среднее (1): 5-6
- Высокое (2): 7-10

```
data['quality_class'] = pd.cut(data['quality'], bins=[0, 4, 6, 10],
labels=[0, 1, 2])
```

```
X = data.drop(['quality', 'quality_class'], axis=1)
y = data['quality_class']
```

Масштабирование признаков:

```
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

4. Выбор метрик

Для задачи классификации с дисбалансом классов выберем:

- Accuracy (общая точность): одна из самых популярных метрик
- F1-score (среднее гармоническое precision и recall): подходит для задач с дисбалансом классов
- ROC-AUC (площадь под ROC-кривой, для многоклассовой классификации): для сравнения моделей на вероятностях, устойчива к дисбалансу

5. Разделение данных на train/test

```
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y,
test_size=0.2, random_state=42, stratify=y)
```

6. Выбор и обучение моделей (baseline)

Проверим 5 моделей:

- Логистическая регрессия (LogisticRegression)
- Метод опорных векторов (SVC)
- Случайный лес (RandomForestClassifier)
- Градиентный бустинг (GradientBoostingClassifier)
- XGBoost (XGBClassifier)

```
models = {
    'Logistic Regression': LogisticRegression(),
    'SVM': SVC(probability=True),
    'Random Forest': RandomForestClassifier(),
    'Gradient Boosting': GradientBoostingClassifier(),
    'XGBoost': XGBClassifier()
}
results = {}
for name, model in models.items():
    model.fit(X train, y train)
    y pred = model.predict(X_test)
    results[name] = {
        'Accuracy': accuracy score(y test, y pred),
        'F1-score': f1_score(y_test, y_pred, average='weighted'),
        'ROC-AUC': roc auc_score(y_test, model.predict_proba(X_test),
multi class='ovr')
```

```
}
results df = pd.DataFrame(results).T
print(results df)
                                          ROC-AUC
                     Accuracy
                               F1-score
Logistic Regression
                     0.834061
                               0.808235
                                         0.803709
SVM
                     0.851528
                               0.816625
                                         0.795464
Random Forest
                     0.903930
                              0.884047
                                         0.842532
Gradient Boosting
                     0.877729
                               0.862444
                                         0.775337
XGBoost
                     0.886463 0.870817
                                         0.787009
```

7. Подбор гиперпараметров

```
# Определим параметры для каждой модели
param_grids = {
    'Logistic Regression': {
        'C': [0.1, 1],
        'penalty': ['l2']
    },
    'SVM': {
        'C': [0.1, 1, 10],
        'kernel': ['linear', 'rbf', 'poly'],
        'gamma': ['scale', 'auto']
    },
    'Random Forest': {
        'n estimators': [75, 80, 85, 90, 95, 100, 105, 110, 115, 120],
        'max depth': [10, 15, 20, 25]
    'Gradient Boosting': {
        'n_estimators': [50, 100, 200],
        'learning rate': [0.01, 0.1, 0.2],
        'max_depth': [3, 5, 7]
   'n estimators': [50, 100, 200],
        'learning_rate': [0.01, 0.1, 0.2], 
'max_depth': [3, 5, 7],
        'subsample': [0.8, 1.0],
        'colsample_bytree': [0.8, 1.0]
    }
}
best models = {}
for name, model in models.items():
    print(f"Подбор параметров для модели: {name}")
    grid search = GridSearchCV(
        estimator=model,
        param grid=param grids[name],
        cv=5,
```

```
scoring='accuracy',
        n jobs=-1,
        verbose=1
    grid search.fit(X train, y train)
    best models[name] = grid search.best estimator
    print(f"Лучшие параметры для {name}: {qrid search.best params }\
n")
Подбор параметров для модели: Logistic Regression
Fitting 5 folds for each of 2 candidates, totalling 10 fits
Лучшие параметры для Logistic Regression: {'C': 0.1, 'penalty': 'l2'}
Подбор параметров для модели: SVM
Fitting 5 folds for each of 18 candidates, totalling 90 fits
Лучшие параметры для SVM: {'C': 10, 'gamma': 'auto', 'kernel': 'rbf'}
Подбор параметров для модели: Random Forest
Fitting 5 folds for each of 40 candidates, totalling 200 fits
Лучшие параметры для Random Forest: {'max depth': 20, 'n estimators':
105}
Подбор параметров для модели: Gradient Boosting
Fitting 5 folds for each of 27 candidates, totalling 135 fits
Лучшие параметры для Gradient Boosting: {'learning rate': 0.1,
'max depth': 7, 'n estimators': 100}
Подбор параметров для модели: XGBoost
Fitting 5 folds for each of 108 candidates, totalling 540 fits
Лучшие параметры для XGBoost: {'colsample bytree': 0.8,
'learning rate': 0.2, 'max depth': 3, 'n estimators': 200,
'subsample': 1.0}
```

8. Сравнение моделей с оптимальными гиперпараметрами с baseline

```
optimized_results = {}
for name, model in best_models.items():
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    optimized_results[name] = {
        'Accuracy': accuracy_score(y_test, y_pred),
        'F1-score': f1_score(y_test, y_pred, average='weighted'),
        'ROC-AUC': roc_auc_score(y_test, model.predict_proba(X_test),
multi_class='ovr')
    }
optimized_results_df = pd.DataFrame(optimized_results).T
print("\nPeзультаты после подбора гиперпараметров:")
print(optimized_results_df)
```

```
# Сравним с baseline
print("\nСравнение с baseline:")
comparison df = pd.concat([results df, optimized results df],
keys=['Baseline', 'Optimized'], axis=1)
print(comparison df)
Результаты после подбора гиперпараметров:
                    Accuracy F1-score
                                         ROC-AUC
Logistic Regression
                    0.838428
                              0.809073
                                        0.792483
SVM
                    0.877729 0.861198
                                        0.798737
                    0.908297
Random Forest
                              0.889094
                                        0.864533
Gradient Boosting
                                        0.803974
                    0.899563 0.882744
XGBoost
                    0.895197
                              0.878750
                                        0.759518
Сравнение с baseline:
                    Baseline
                                                 Optimized
/
                                         ROC-AUC Accuracy F1-score
                    Accuracy F1-score
                    0.834061 0.808235
Logistic Regression
                                        0.803709
                                                  0.838428
                                                            0.809073
SVM
                                        0.795464 0.877729 0.861198
                    0.851528 0.816625
Random Forest
                    0.903930
                              0.884047
                                        0.842532 0.908297 0.889094
Gradient Boosting
                    0.877729 0.862444
                                        0.775337 0.899563 0.882744
XGBoost
                    0.886463 0.870817 0.787009 0.895197 0.878750
                     ROC-AUC
Logistic Regression
                    0.792483
SVM
                    0.798737
Random Forest
                    0.864533
                    0.803974
Gradient Boosting
XGBoost
                    0.759518
Exception ignored in: <function ResourceTracker. del at
0 \times 107 edfb00 >
Traceback (most recent call last):
  File
"/opt/homebrew/Cellar/python@3.13/3.13.3/Frameworks/Python.framework/
Versions/3.13/lib/python3.13/multiprocessing/resource tracker.py",
line 82, in del
"/opt/homebrew/Cellar/python@3.13/3.13.3/Frameworks/Python.framework/
Versions/3.13/lib/python3.13/multiprocessing/resource tracker.py",
line 91, in stop
```

```
File
"/opt/homebrew/Cellar/python@3.13/3.13.3/Frameworks/Python.framework/
Versions/3.13/lib/python3.13/multiprocessing/resource tracker.py",
line 116, in stop locked
ChildProcessError: [Errno 10] No child processes
Exception ignored in: <function ResourceTracker. del at
0x104fe3b00>
Traceback (most recent call last):
  File
"/opt/homebrew/Cellar/python@3.13/3.13.3/Frameworks/Python.framework/
Versions/3.13/lib/python3.13/multiprocessing/resource tracker.py",
line 82, in __del__
  File
"/opt/homebrew/Cellar/python@3.13/3.13.3/Frameworks/Python.framework/
Versions/3.13/lib/python3.13/multiprocessing/resource tracker.py",
line 91, in stop
  File
"/opt/homebrew/Cellar/python@3.13/3.13.3/Frameworks/Python.framework/
Versions/3.13/lib/python3.13/multiprocessing/resource tracker.py",
line 116, in _stop_locked
ChildProcessError: [Errno 10] No child processes
Exception ignored in: <function ResourceTracker. del at
0x1054cbb00>
Traceback (most recent call last):
  File
"/opt/homebrew/Cellar/python@3.13/3.13.3/Frameworks/Python.framework/
Versions/3.13/lib/python3.13/multiprocessing/resource tracker.py",
line 82, in del
  File
"/opt/homebrew/Cellar/python@3.13/3.13.3/Frameworks/Python.framework/
Versions/3.13/lib/python3.13/multiprocessing/resource tracker.py",
line 91, in _stop
  File
"/opt/homebrew/Cellar/python@3.13/3.13.3/Frameworks/Python.framework/
Versions/3.13/lib/python3.13/multiprocessing/resource tracker.py",
line 116, in _stop_locked
ChildProcessError: [Errno 10] No child processes
Exception ignored in: <function ResourceTracker. del at
0x106d97b00>
Traceback (most recent call last):
  File
"/opt/homebrew/Cellar/python@3.13/3.13.3/Frameworks/Python.framework/
Versions/3.13/lib/python3.13/multiprocessing/resource tracker.py",
line 82, in del
"/opt/homebrew/Cellar/python@3.13/3.13.3/Frameworks/Python.framework/
Versions/3.13/lib/python3.13/multiprocessing/resource tracker.py",
line 91, in stop
  File
```

```
"/opt/homebrew/Cellar/python@3.13/3.13.3/Frameworks/Python.framework/
Versions/3.13/lib/python3.13/multiprocessing/resource tracker.py",
line 116, in _stop_locked
ChildProcessError: [Errno 10] No child processes
Exception ignored in: <function ResourceTracker. del at
0x10505bb00>
Traceback (most recent call last):
  File
"/opt/homebrew/Cellar/python@3.13/3.13.3/Frameworks/Python.framework/
Versions/3.13/lib/python3.13/multiprocessing/resource tracker.py",
line 82, in del
  File
"/opt/homebrew/Cellar/python@3.13/3.13.3/Frameworks/Python.framework/
Versions/3.13/lib/python3.13/multiprocessing/resource tracker.py",
line 91, in stop
  File
"/opt/homebrew/Cellar/python@3.13/3.13.3/Frameworks/Python.framework/
Versions/3.13/lib/python3.13/multiprocessing/resource tracker.py",
line 116, in stop locked
ChildProcessError: [Errno 10] No child processes
Exception ignored in: <function ResourceTracker. del at
0x1027dfb00>
Traceback (most recent call last):
"/opt/homebrew/Cellar/python@3.13/3.13.3/Frameworks/Python.framework/
Versions/3.13/lib/python3.13/multiprocessing/resource tracker.py",
line 82, in __del__
  File
"/opt/homebrew/Cellar/python@3.13/3.13.3/Frameworks/Python.framework/
Versions/3.13/lib/python3.13/multiprocessing/resource tracker.py",
line 91, in stop
  File
"/opt/homebrew/Cellar/python@3.13/3.13.3/Frameworks/Python.framework/
Versions/3.13/lib/python3.13/multiprocessing/resource tracker.py",
line 116, in stop locked
ChildProcessError: [Errno 10] No child processes
Exception ignored in: <function ResourceTracker. del at
0x104593b00>
Traceback (most recent call last):
"/opt/homebrew/Cellar/python@3.13/3.13.3/Frameworks/Python.framework/
Versions/3.13/lib/python3.13/multiprocessing/resource tracker.py",
line 82, in del
  File
"/opt/homebrew/Cellar/python@3.13/3.13.3/Frameworks/Python.framework/
Versions/3.13/lib/python3.13/multiprocessing/resource tracker.py",
line 91, in stop
  File
"/opt/homebrew/Cellar/python@3.13/3.13.3/Frameworks/Python.framework/
```

```
Versions/3.13/lib/python3.13/multiprocessing/resource tracker.py",
line 116, in stop locked
ChildProcessError: [Errno 10] No child processes
Exception ignored in: <function ResourceTracker. del at
0x1046bbb00>
Traceback (most recent call last):
"/opt/homebrew/Cellar/python@3.13/3.13.3/Frameworks/Python.framework/
Versions/3.13/lib/python3.13/multiprocessing/resource tracker.py",
line 82, in del
  File
"/opt/homebrew/Cellar/python@3.13/3.13.3/Frameworks/Python.framework/
Versions/3.13/lib/python3.13/multiprocessing/resource tracker.py",
line 91, in stop
  File
"/opt/homebrew/Cellar/python@3.13/3.13.3/Frameworks/Python.framework/
Versions/3.13/lib/python3.13/multiprocessing/resource tracker.py",
line 116, in _stop_locked
ChildProcessError: [Errno 10] No child processes
```

9. Выводы

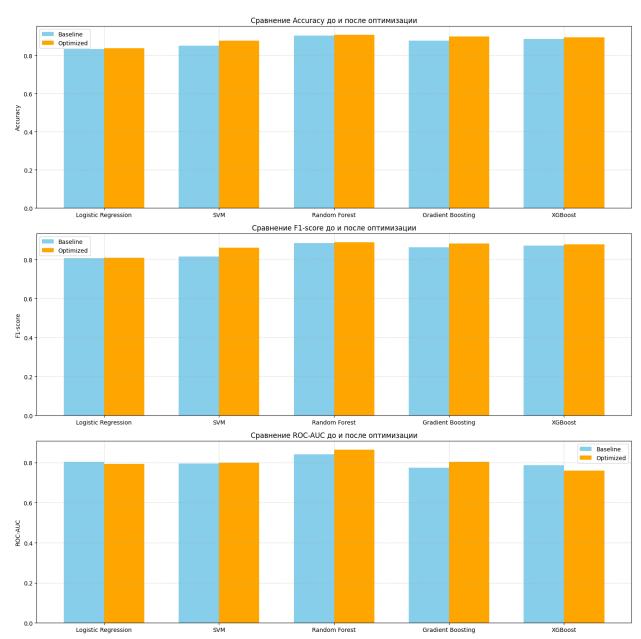
- Лучшая модель: Random Forest (F1-score = 0.889).
- Ансамблевые методы (Random Forest, Gradient Boosting, XGBoost) показали себя лучше других.
- Logistic Regression слабо реагирует на подбор параметров

Визуализация сравнения Baseline и Optimized моделей

```
metrics = ['Accuracy', 'F1-score', 'ROC-AUC']
n metrics = len(metrics)
n models = len(results df)
plt.figure(figsize=(15, 5 * n metrics))
for i, metric in enumerate(metrics, 1):
    plt.subplot(n metrics, 1, i)
    baseline values = results df[metric]
    optimized values = optimized results df[metric]
    x = range(n models)
    width = 0.35
    plt.bar(x, baseline values, width, label='Baseline',
color='skyblue')
    plt.bar([p + width for p in x], optimized values, width,
label='Optimized', color='orange')
    plt.xticks([p + width/2 for p in x], results df.index)
    plt.vlabel(metric)
    plt.title(f'Cpaвнение {metric} до и после оптимизации')
```

```
plt.legend()
  plt.grid(True, linestyle='--', alpha=0.5)

plt.tight_layout()
plt.show()
```



Влияние гиперпараметров на качество (для Random Forest)

```
param1 = 'n_estimators'
param2 = 'max_depth'

grid_values = param_grids['Random Forest']
grid_search = GridSearchCV(RandomForestClassifier(),
```

```
param_grids['Random Forest'], cv=5, scoring='accuracy')
grid search.fit(X train, y train)
results = grid search.cv results
scores =
np.array(results['mean test score']).reshape(len(grid values[param1]),
len(grid_values[param2]))
plt.figure(figsize=(10, 6))
sns.heatmap(scores, annot=True, fmt=".3f",
            xticklabels=grid values[param2],
            yticklabels=grid values[param1],
            cmap="viridis")
plt.xlabel(param2)
plt.ylabel(param1)
plt.title('Тепловая карта зависимости Accuracy от гиперпараметров
(Random Forest)')
plt.show()
```

Тепловая карта зависимости Accuracy от гиперпараметров (Random Forest)

