МОСКОВСКИЙ ГОСУДАРСТВЕННЫЙ ТЕХНИЧЕСКИЙ УНИВЕРСИТЕТ
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ОТЧЕТ

Лабораторная работа №6
по курсу «Технологии машинного обучения»

Тема: «Ансамбли моделей машинного обучения»

ИСПОЛНИТЕЛЬ: ___Меркулова Н.А.__
ФИО
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подпись
"__"_________2020 г.

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"__"_________2020 г.

Москва - 2020

1. Цель работы

Изучение ансамблей моделей машинного обучения.

2. Описание задания

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 две ансамблевые модели. Оцените качество моделей с помощью одной из подходящих для задачи метрик. Сравните качество полученных моделей.

3. Текст программы и экранные формы с примерами выполнения

См. на следующей странице

In [14]:

```
import pandas as pd
import numpy as np
from sklearn.preprocessing import LabelEncoder
```

In [4]:

```
data = pd.read_csv('../data/loans.csv')
data
```

Out[4]:

	Loan_ID	loan_status	Principal	terms	effective_date	due_date	paid_off_ti
0	xqd20166231	PAIDOFF	1000	30	9/8/2016	10/7/2016	9/14/2 19
1	xqd20168902	PAIDOFF	1000	30	9/8/2016	10/7/2016	10/7/2 9
2	xqd20160003	PAIDOFF	1000	30	9/8/2016	10/7/2016	9/25/2 16
3	xqd20160004	PAIDOFF	1000	15	9/8/2016	9/22/2016	9/22/2 20
4	xqd20160005	PAIDOFF	1000	30	9/9/2016	10/8/2016	9/23/2 21
...	...	...	...	...	...	...	
495	xqd20160496	COLLECTION_PAIDOFF	1000	30	9/12/2016	10/11/2016	10/14/2 19
496	xqd20160497	COLLECTION_PAIDOFF	1000	15	9/12/2016	9/26/2016	10/10/2 20
497	xqd20160498	COLLECTION_PAIDOFF	800	15	9/12/2016	9/26/2016	9/29/2 11
498	xqd20160499	COLLECTION_PAIDOFF	1000	30	9/12/2016	11/10/2016	11/11/2 22
499	xqd20160500	COLLECTION_PAIDOFF	1000	30	9/12/2016	10/11/2016	10/19/2 11

500 rows × 11 columns

1. Предварительная обработка

Удаляем столбцы с пустыми значениями:

In [9]:

```
data = data.dropna(axis=1, how='any')
data
```

Out[9]:

	Loan_ID	loan_status	Principal	terms	effective_date	due_date	age	edu
0	xqd20166231	PAIDOFF	1000	30	9/8/2016	10/7/2016	45	Sch
1	xqd20168902	PAIDOFF	1000	30	9/8/2016	10/7/2016	50	Be
2	xqd20160003	PAIDOFF	1000	30	9/8/2016	10/7/2016	33	Be
3	xqd20160004	PAIDOFF	1000	15	9/8/2016	9/22/2016	27	c
4	xqd20160005	PAIDOFF	1000	30	9/9/2016	10/8/2016	28	c
...	...	...	...	...	...	...	...	
495	xqd20160496	COLLECTION_PAIDOFF	1000	30	9/12/2016	10/11/2016	28	Sch
496	xqd20160497	COLLECTION_PAIDOFF	1000	15	9/12/2016	9/26/2016	26	Sch
497	xqd20160498	COLLECTION_PAIDOFF	800	15	9/12/2016	9/26/2016	30	c
498	xqd20160499	COLLECTION_PAIDOFF	1000	30	9/12/2016	11/10/2016	38	c
499	xqd20160500	COLLECTION_PAIDOFF	1000	30	9/12/2016	10/11/2016	28	Sch

500 rows × 9 columns

Удостоверимся, что пропуски отсутствуют:

In [11]:

```
for col in data.columns:
    null_count = data[data[col].isnull()].shape[0]
    if null_count == 0:
        column_type = data[col].dtype
        print('{} - {} - {}'.format(col, column_type, null_count))
```

```
Loan_ID - object - 0
loan_status - object - 0
Principal - int64 - 0
terms - int64 - 0
effective_date - object - 0
due_date - object - 0
age - int64 - 0
education - object - 0
Gender - object - 0
```

Категориальные признаки:

In [12]:

```
for col in data.columns:
    column_type = data[col].dtype
    if column_type == 'object':
        print(col)
```

```
Loan_ID
loan_status
effective_date
due_date
education
Gender
```

In [18]:

```
le1 = LabelEncoder()
data['Loan_ID'] = le1.fit_transform(data['Loan_ID']);
```

In [19]:

```
le2 = LabelEncoder()
data['loan_status'] = le2.fit_transform(data['loan_status']);
```

In [20]:

```
le3 = LabelEncoder()
data['effective_date'] = le3.fit_transform(data['effective_date']);
```

In [21]:

```
le4 = LabelEncoder()
data['due_date'] = le4.fit_transform(data['due_date']);
```

In [22]:

```
le5 = LabelEncoder()
data['education'] = le5.fit_transform(data['education']);
```

In [23]:

```
le6 = LabelEncoder()
data['Gender'] = le6.fit_transform(data['Gender']);
```

Проверим:

In [24]:

```
for col in data.columns:
    column_type = data[col].dtype
    if column_type == 'object':
        print(col)
```

Как видно, категориальных признаков не осталось

2. Разделение выборки на обучающую и тестовую

In [25]:

```
from sklearn.model_selection import train_test_split

data_x = data.loc[:, data.columns != 'due_date']
data_y = data['due_date']

train_x, test_x, train_y, test_y = train_test_split(data_x, data_y, test_size=0.3, r
```

In [27]:

```
train_x.shape
```

Out[27]:

```
(350, 8)
```

In [28]:

```
from sklearn.neighbors import KNeighborsRegressor
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import median_absolute_error, r2_score

def test_model(model):
    print('mean_absolute_error: {}'.format(round(mean_absolute_error(test_y, model.p
    print('median_absolute_error: {}'.format(round(median_absolute_error(test_y, moc
    print('r2_score: {}'.format(round(r2_score(test_y, model.predict(test_x)), 2)))
```

3. Обучение моделей

Случайный лес

In [29]:

```
from sklearn.ensemble import RandomForestRegressor

ran_80 = RandomForestRegressor(n_estimators=80)
ran_80.fit(train_x, train_y)
```

Out[29]:

```
RandomForestRegressor(bootstrap=True, ccp_alpha=0.0, criterion='mse',
                      max_depth=None, max_features='auto', max_leaf_no
des=None,
                      max_samples=None, min_impurity_decrease=0.0,
                      min_impurity_split=None, min_samples_leaf=1,
                      min_samples_split=2, min_weight_fraction_leaf=0.
0,
                      n_estimators=80, n_jobs=None, oob_score=False,
                      random_state=None, verbose=0, warm_start=False)
```

In [30]:

```
test_model(ran_80)
```

```
mean_absolute_error: 2.1
median_absolute_error: 0.32
r2_score: 0.78
```

In [33]:

```
param_range = np.arange(50, 170, 10)
tuned_parameters = [{'n_estimators': param_range}]
tuned_parameters
```

Out[33]:

```
[{'n_estimators': array([ 50,  60,  70,  80,  90, 100, 110, 120, 130,
140, 150, 160])}]
```

In [34]:

```
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import ShuffleSplit

gs = GridSearchCV(RandomForestRegressor(), tuned_parameters,
                  cv=ShuffleSplit(n_splits=10), scoring="r2",
                  return_train_score=True, n_jobs=-1)
gs.fit(data_x, data_y)
```

Out[34]:

```
GridSearchCV(cv=ShuffleSplit(n_splits=10, random_state=None, test_size
=None, train_size=None),
             error_score=nan,
             estimator=RandomForestRegressor(bootstrap=True, ccp_alpha
=0.0,
                                             criterion='mse', max_dept
h=None,
                                             max_features='auto',
                                             max_leaf_nodes=None,
                                             max_samples=None,
                                             min_impurity_decrease=0.
0,
                                             min_impurity_split=None,
                                             min_samples_leaf=1,
                                             min_samples_split=2,
                                             min_weight_fraction_leaf=
0.0,
                                             n_estimators=100, n_jobs=
None,
                                             oob_score=False, random_s
tate=None,
                                             verbose=0, warm_start=Fal
se),
             iid='deprecated', n_jobs=-1,
             param_grid=[{'n_estimators': array([ 50,  60,  70,  80,
90, 100, 110, 120, 130, 140, 150, 160])}],
             pre_dispatch='2*n_jobs', refit=True, return_train_score=T
rue,
             scoring='r2', verbose=0)
```

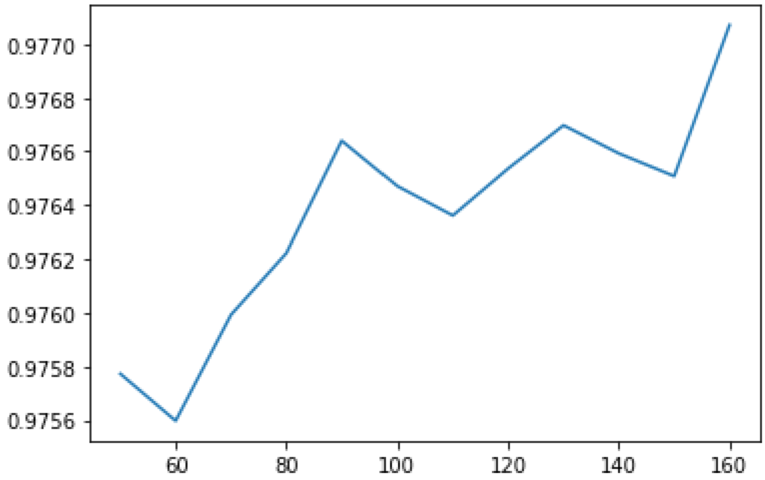
In [35]:

```
reg = gs.best_estimator_
```

In [36]:

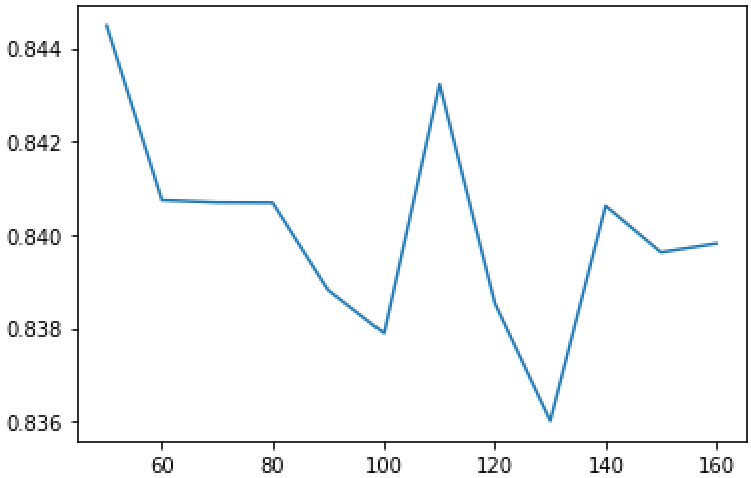
```
import matplotlib.pyplot as plt

plt.plot(param_range, gs.cv_results_["mean_train_score"]);
```



In [37]:

```
plt.plot(param_range, gs.cv_results_["mean_test_score"]);
```



In [39]:

```
reg.fit(train_x, train_y)
test_model(reg)
```

```
mean_absolute_error: 2.13
median_absolute_error: 0.45
r2_score: 0.77
```

Градиентный бустинг

In [31]:

```
from sklearn.ensemble import GradientBoostingRegressor

gr_80 = GradientBoostingRegressor(n_estimators=80)
gr_80.fit(train_x, train_y)
```

Out[31]:

```
GradientBoostingRegressor(alpha=0.9, ccp_alpha=0.0, criterion='friedma
n_mse',
                          init=None, learning_rate=0.1, loss='ls', max
_depth=3,
                          max_features=None, max_leaf_nodes=None,
                          min_impurity_decrease=0.0, min_impurity_spli
t=None,
                          min_samples_leaf=1, min_samples_split=2,
                          min_weight_fraction_leaf=0.0, n_estimators=8
0,
                          n_iter_no_change=None, presort='deprecated',
                          random_state=None, subsample=1.0, tol=0.000
1,
                          validation_fraction=0.1, verbose=0, warm_sta
rt=False)
```

In [32]:

```
test_model(gr_80)
```

```
mean_absolute_error: 2.34
median_absolute_error: 0.95
r2_score: 0.77
```

In [40]:

```
gs = GridSearchCV(GradientBoostingRegressor(), tuned_parameters,
                  cv=ShuffleSplit(n_splits=10), scoring="r2",
                  return_train_score=True, n_jobs=-1)
gs.fit(data_x, data_y)
```

Out[40]:

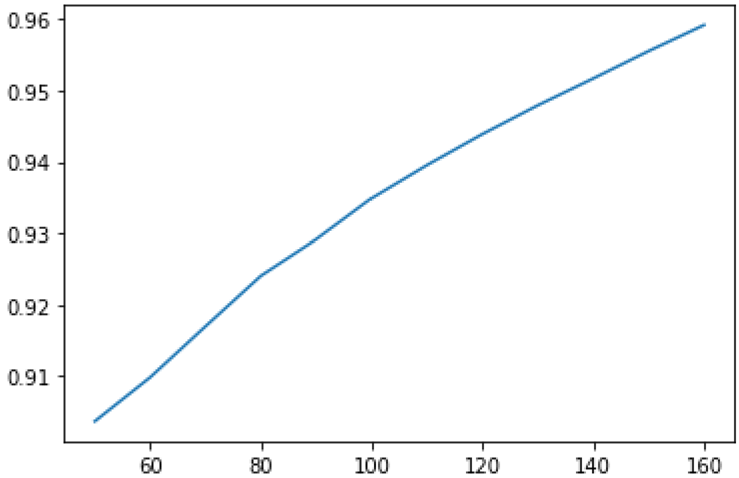
```
GridSearchCV(cv=ShuffleSplit(n_splits=10, random_state=None, test_size
=None, train_size=None),
             error_score=nan,
             estimator=GradientBoostingRegressor(alpha=0.9, ccp_alpha=
0.0,
                                                 criterion='friedman_m
se',
                                                 init=None, learning_r
ate=0.1,
                                                 loss='ls', max_depth=
3,
                                                 max_features=None,
                                                 max_leaf_nodes=None,
                                                 min_impurity_decrease
=0.0,
                                                 min_impurity_split=No
ne,
                                                 min_samples_leaf=1,
                                                 m...
                                                 min_weight_fraction_l
eaf=0.0,
                                                 n_estimators=100,
                                                 n_iter_no_change=Non
e,
                                                 presort='deprecated',
                                                 random_state=None,
                                                 subsample=1.0, tol=0.
0001,
                                                 validation_fraction=
0.1,
                                                 verbose=0, warm_start
=False),
             iid='deprecated', n_jobs=-1,
             param_grid=[{'n_estimators': array([ 50,  60,  70,  80,
90, 100, 110, 120, 130, 140, 150, 160])}],
             pre_dispatch='2*n_jobs', refit=True, return_train_score=T
rue,
             scoring='r2', verbose=0)
```

In [41]:

```
reg = gs.best_estimator_
```

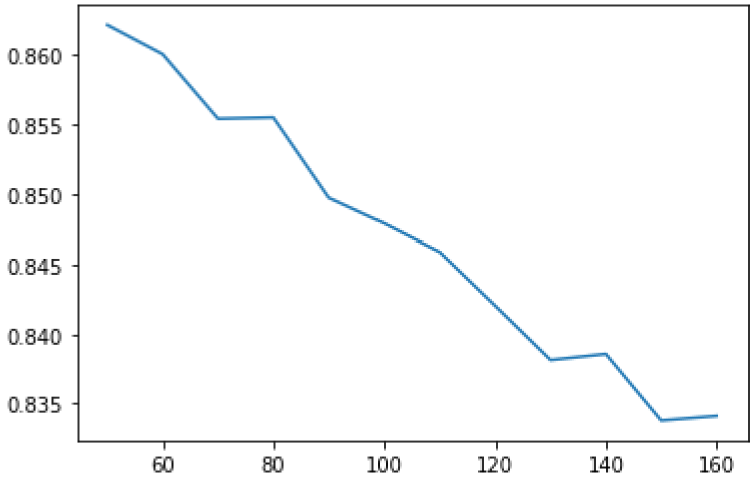
In [42]:

```
plt.plot(param_range, gs.cv_results_["mean_train_score"]);
```



In [43]:

```
plt.plot(param_range, gs.cv_results_["mean_test_score"]);
```



In [44]:

```
reg.fit(train_x, train_y)
test_model(reg)
```

```
mean_absolute_error: 2.37
median_absolute_error: 0.99
r2_score: 0.77
```