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ОТЧЕТ
Лабораторная работа №6

«Ансамбли моделей машинного обучения»
по дисциплине «Методы машинного обучения»

Выполнил:

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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 две ансамблевые модели. Оцените качество моделей с помощью одной из подходящих для задачи метрик. Сравните качество полученных моделей.
5. Произведите для каждой модели подбор значений одного гиперпараметра. В зависимости от используемой библиотеки можно применять функцию GridSearchCV, использовать перебор параметров в цикле, или использовать другие методы.
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
from typing import Dict, Tuple
from scipy import stats
from IPython.display import Image
from sklearn.externals.six import StringIO
from IPython.display import Image
import graphviz
import pydotplus
from sklearn.datasets import load_iris, load_boston
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsRegressor, KNeighborsClassifier
from sklearn.model_selection import GridSearchCV, RandomizedSearchCV
from sklearn.metrics import accuracy_score, balanced_accuracy_score
from sklearn.metrics import precision_score, recall_score, f1_score, classificat
ion_report
from sklearn.metrics import confusion_matrix
from sklearn.tree import DecisionTreeClassifier, DecisionTreeRegressor, export_g
raphviz
from sklearn.ensemble import RandomForestClassifier, RandomForestRegressor
from sklearn.ensemble import ExtraTreesClassifier, ExtraTreesRegressor
from sklearn.ensemble import GradientBoostingClassifier, GradientBoostingRegress
or
from sklearn.ensemble import BaggingClassifier
from sklearn.ensemble import AdaBoostClassifier
from sklearn.metrics import mean_absolute_error, mean_squared_error, mean_square
d_log_error, median_absolute_error, r2_score
from sklearn.metrics import roc_curve, roc_auc_score
import seaborn as sns
!pip install heamy
from heamy.estimator import Regressor, Classifier
from heamy.pipeline import ModelsPipeline
from heamy.dataset import Dataset
import matplotlib.pyplot as plt
%matplotlib inline
sns.set(style="ticks")
```

```
/home/denis/ml/env/lib/python3.6/site-packages/sklearn/externals/si
x.py:31: FutureWarning: The module is deprecated in version 0.21 and
will be removed in version 0.23 since we've dropped support for Pyth
on 2.7. Please rely on the official version of six (https://pypi.or
g/project/six/).
  "(https://pypi.org/project/six/).", FutureWarning)


Requirement already satisfied: heamy in ./env/lib/python3.6/site-pac
kages (0.0.7)
Requirement already satisfied: numpy>=1.7.0 in ./env/lib/python3.6/s
ite-packages (from heamy) (1.18.4)
Requirement already satisfied: scipy>=0.16.0 in ./env/lib/python3.6/
site-packages (from heamy) (1.4.1)
Requirement already satisfied: six>=1.10.0 in ./env/lib/python3.6/si
te-packages (from heamy) (1.14.0)
Requirement already satisfied: scikit-learn>=0.17.0 in ./env/lib/pyt
hon3.6/site-packages (from heamy) (0.22.2)
Requirement already satisfied: pandas>=0.17.0 in ./env/lib/python3.
6/site-packages (from heamy) (1.0.3)
Requirement already satisfied: joblib>=0.11 in ./env/lib/python3.6/s
ite-packages (from scikit-learn>=0.17.0->heamy) (0.15.1)
Requirement already satisfied: python-dateutil>=2.6.1 in ./env/lib/p
ython3.6/site-packages (from pandas>=0.17.0->heamy) (2.8.1)
Requirement already satisfied: pytz>=2017.2 in ./env/lib/python3.6/s
ite-packages (from pandas>=0.17.0->heamy) (2020.1)
```

1. Выбор набора данных для решения задачи регресии.

In [2]:

```
data = pd.read_csv('winequality_red.csv', sep=',')
data.head()
```

Out[2]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcol
0	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9
1	7.8	0.88	0.00	2.6	0.098	25.0	67.0	0.9968	3.20	0.68	9
2	7.8	0.76	0.04	2.3	0.092	15.0	54.0	0.9970	3.26	0.65	9
3	11.2	0.28	0.56	1.9	0.075	17.0	60.0	0.9980	3.16	0.58	9
4	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9

In [3]:

```
data.shape
```

Out[3]:

```
(1599, 12)
```

In [4]:

```
data.isnull().sum()
```

Out[4]:

```
fixed acidity           0
volatile acidity        0
citric acid             0
residual sugar          0
chlorides               0
free sulfur dioxide     0
total sulfur dioxide    0
density                 0
pH                      0
sulphates               0
alcohol                 0
quality                 0
dtype: int64
```

In [5]:

```
data.dtypes
```

Out[5]:

```
fixed acidity           float64
volatile acidity        float64
citric acid             float64
residual sugar          float64
chlorides               float64
free sulfur dioxide     float64
total sulfur dioxide    float64
density                 float64
pH                      float64
sulphates               float64
alcohol                 float64
quality                   int64
dtype: object
```

2. Удаление и заполнение пропусков и кодирование категориальных признаков.

In [ ]:

не требуется

In [ ]:

In [6]:

```
columns = ["fixed acidity","volatile acidity","citric acid","residual sugar","ch
lorides","free sulfur dioxide","total sulfur dioxide","density","pH","sulphates"
,"alcohol"]
```

In [7]:

```
x_array = data[columns].values
y_array = data['quality'].values
```

3. Разделение с использованием метода train_test_split выборки на обучающую и тестовую.

In [8]:

```
X_train, X_test, y_train, y_test = train_test_split(x_array, y_array,
test_size=0.26, random_state=1)
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

Out[8]:

```
((1183, 11), (416, 11), (1183,), (416,))
```

4. Обучение двух ансамблевых моделей. Оценка качества моделей с помощью одной из подходящих для задачи метрик. Сравнение качества полученных моделей.

4.1. Стекинг

In [9]:

```
# Качество отдельных моделей
def val_mae(model):
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    result = mean_absolute_error(y_test, y_pred)
    print(model)
    print('MAE={}'.format(result))
```

In [10]:

```
# Точность на отдельных моделях
for model in [
    LinearRegression(),
    DecisionTreeRegressor(),
    RandomForestRegressor(n_estimators=50)
]:
    val_mae(model)
    print('==========================')
```

```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, norma
lize=False)
MAE=0.49101002617400435
==========================

DecisionTreeRegressor(ccp_alpha=0.0, criterion='mse', max_depth=Non
e,
                      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='depreca
ted',
                      random_state=None, splitter='best')
MAE=0.4375
==========================

RandomForestRegressor(bootstrap=True, ccp_alpha=0.0, criterion='ms
e',
                      max_depth=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=50, n_jobs=None, oob_score=False,
                      random_state=None, verbose=0, warm_start=Fals
e)
MAE=0.41937499999999994
==========================
```

In [11]:

```
# набор данных
dataset = Dataset(X_train, y_train, X_test)

# модели первого уровня
model_tree = Regressor(dataset=dataset, estimator=DecisionTreeRegressor, name='t
ree')
model_lr = Regressor(dataset=dataset, estimator=LinearRegression, parameters={'n
ormalize': True},name='lr')
model_rf = Regressor(dataset=dataset, estimator=RandomForestRegressor, parameter
s={'n_estimators': 50},name='rf')
```

In [12]:

```
# Эксперимент 1.1
# Первый уровень - две модели: дерево и линейная регрессия
# Второй уровень: линейная регрессия

pipeline = ModelsPipeline(model_tree, model_lr)
stack_ds = pipeline.stack(k=10, seed=1)
# модель второго уровня
stacker = Regressor(dataset=stack_ds, estimator=LinearRegression)
results = stacker.validate(k=10,scorer=mean_absolute_error)
```

```
Metric: mean_absolute_error
Folds accuracy: [0.522252793480984, 0.5204325381349485, 0.5636614213
669765, 0.46232452280050346, 0.5095639678321267, 0.4734185190755700
3, 0.47793217695331974, 0.4302567324465604, 0.44071610383028553, 0.4
90593330852405]
Mean accuracy: 0.48911521067736796
Standard Deviation: 0.03866824247419317
Variance: 0.0014952329760429968
```

In [13]:

```
# Эксперимент 1.2
# Первый уровень - две модели: дерево и линейная регрессия
# Второй уровень: случайный лес

stacker = Regressor(dataset=stack_ds, estimator=RandomForestRegressor)
results = stacker.validate(k=10,scorer=mean_absolute_error)
```

```
Metric: mean_absolute_error
Folds accuracy: [0.5707563025210081, 0.6463025210084034, 0.581680672
2689075, 0.4994915254237287, 0.5965254237288136, 0.5164406779661016,
0.5109322033898305, 0.4971186440677967, 0.5591525423728813, 0.565847
4576271187]
Mean accuracy: 0.554424797037459
Standard Deviation: 0.045839357531465785
Variance: 0.002101246698897549
```

In [14]:

```
# Эксперимент 1.3
# Первый уровень - две модели: дерево и линейная регрессия
# Второй уровень: дерево

stacker = Regressor(dataset=stack_ds, estimator=DecisionTreeRegressor)
results = stacker.validate(k=10,scorer=mean_absolute_error)
```

```
Metric: mean_absolute_error
Folds accuracy: [0.6302521008403361, 0.6722689075630253, 0.630252100
8403361, 0.5169491525423728, 0.6016949152542372, 0.5508474576271186,
0.5169491525423728, 0.559322033898305, 0.6101694915254238, 0.5847457
627118644]
Mean accuracy: 0.5873451075345393
Standard Deviation: 0.048637691252086765
Variance: 0.0023656250103333176
```

In [15]:

```
# Эксперимент 2.1
# Первый уровень - две модели: дерево и случайный лес
# Второй уровень: линейная регрессия
pipeline = ModelsPipeline(model_tree, model_rf)
stack_ds = pipeline.stack(k=10, seed=1)
# модель второго уровня
stacker = Regressor(dataset=stack_ds, estimator=LinearRegression)
results = stacker.validate(k=10,scorer=mean_absolute_error)
```

```
Metric: mean_absolute_error
Folds accuracy: [0.45865438203965947, 0.4445274965685606, 0.49903909
5917168, 0.3923561183775206, 0.4185459953670375, 0.4210127246135441,
0.4157302194574986, 0.39534098846073323, 0.42439330689507, 0.4330883
699772755]
Mean accuracy: 0.43026886976740675
Standard Deviation: 0.029787026607361666
Variance: 0.0008872669541076718
```

In [16]:

```
# Эксперимент 2.2
# Первый уровень - две модели: дерево и случайный лес
# Второй уровень: случайный лес

stacker = Regressor(dataset=stack_ds, estimator=RandomForestRegressor)
results = stacker.validate(k=10,scorer=mean_absolute_error)
```

```
Metric: mean_absolute_error
Folds accuracy: [0.45074654652818813, 0.46753311845467915, 0.5358034
661009041, 0.4051528809291358, 0.43157383637781804, 0.43084850724889
817, 0.4664541324764089, 0.4440822758524653, 0.429267451416664, 0.43
466419526295225]
Mean accuracy: 0.4496126410648114
Standard Deviation: 0.03370022638152573
Variance: 0.0011357052581660828
```

In [17]:

```
# Эксперимент 2.3
# Первый уровень - две модели: дерево и случайный лес
# Второй уровень: дерево

stacker = Regressor(dataset=stack_ds, estimator=DecisionTreeRegressor)
results = stacker.validate(k=10,scorer=mean_absolute_error)
```

```
Metric: mean_absolute_error
Folds accuracy: [0.46167407970787533, 0.46985910827846994, 0.5337409
555896951, 0.3825162466117747, 0.4518668829348632, 0.439313956786539
06, 0.4561837095735401, 0.44375448617197055, 0.4135503210764269, 0.4
5238935126023855]
Mean accuracy: 0.45048490979913935
Standard Deviation: 0.03691088068516074
Variance: 0.001362413112954172
```

In [18]:

```
# Эксперимент 3.1
# Первый уровень - две модели: линейная регрессия и случайный лес
# Второй уровень: линейная регрессия
pipeline = ModelsPipeline(model_lr, model_rf)
stack_ds = pipeline.stack(k=10, seed=1)
# модель второго уровня
stacker = Regressor(dataset=stack_ds, estimator=LinearRegression)
results = stacker.validate(k=10,scorer=mean_absolute_error)
```

```
Metric: mean_absolute_error
Folds accuracy: [0.4604987665780731, 0.45081151387749263, 0.50035134
72623877, 0.39664289388098994, 0.4211657193184927, 0.422207585262129
2, 0.42170202734101114, 0.39534310172861736, 0.42218118313953923, 0.
4376346682371013]
Mean accuracy: 0.43285388066258346
Standard Deviation: 0.02978590499111804
Variance: 0.0008872001361399106
```

In [19]:

```
# Эксперимент 3.2
# Первый уровень - две модели:  линейная регрессия и случайный лес
# Второй уровень: случайный лес

stacker = Regressor(dataset=stack_ds, estimator=RandomForestRegressor)
results = stacker.validate(k=10,scorer=mean_absolute_error)
```

```
Metric: mean_absolute_error
Folds accuracy: [0.4476470588235295, 0.4726050420168067, 0.500924369
747899, 0.4836440677966102, 0.4800847457627118, 0.42601694915254246,
0.43245762711864405, 0.46915254237288123, 0.4519491525423729, 0.4773
728813559322]
Mean accuracy: 0.464185443668993
Standard Deviation: 0.022665784960144413
Variance: 0.0005137378078595087
```

In [20]:

```
# Эксперимент 3.3
# Первый уровень - две модели: линейная регрессия и случайный лес
# Второй уровень: дерево

stacker = Regressor(dataset=stack_ds, estimator=DecisionTreeRegressor)
results = stacker.validate(k=10,scorer=mean_absolute_error)
```

```
Metric: mean_absolute_error
Folds accuracy: [0.5042016806722689, 0.5294117647058824, 0.554621848
7394958, 0.5169491525423728, 0.559322033898305, 0.4576271186440678,
0.4830508474576271, 0.6186440677966102, 0.5254237288135594, 0.559322
033898305]
Mean accuracy: 0.5308574277168494
Standard Deviation: 0.04298306732922732
Variance: 0.0018475440770288891
```

In [21]:

```
# Эксперимент 4
# Первый уровень - три модели: дерево, линейная регрессия и случайный лес
# Второй уровень: линейная регрессия
pipeline = ModelsPipeline(model_tree, model_lr, model_rf)
stack_ds3 = pipeline.stack(k=10, seed=1)
# модель второго уровня
stacker = Regressor(dataset=stack_ds3, estimator=LinearRegression)
results = stacker.validate(k=10,scorer=mean_absolute_error)
```

```
Metric: mean_absolute_error
Folds accuracy: [0.4608321413503237, 0.45063899033624283, 0.50078531
92710473, 0.396757702659696, 0.42178476048478747, 0.4222093267878606
6, 0.4217004604267666, 0.39533382715927784, 0.4221540327193157, 0.43
850134434102656]
Mean accuracy: 0.4330697905536344
Standard Deviation: 0.029884121507574437
Variance: 0.0008930607182794731
```

In [22]:

```
# Эксперимент 5
# Первый уровень - три модели: дерево, линейная регрессия и случайный лес
# Второй уровень: дерево
stacker = Regressor(dataset=stack_ds3, estimator=RandomForestRegressor)
results = stacker.validate(k=10,scorer=mean_absolute_error)
```

```
Metric: mean_absolute_error
Folds accuracy: [0.4388235294117647, 0.49529411764705883, 0.47840336
134453776, 0.4473728813559321, 0.44966101694915245, 0.40203389830508
474, 0.43254237288135583, 0.457457627118644, 0.4461016949152542, 0.4
489830508474576]
Mean accuracy: 0.4496673550776243
Standard Deviation: 0.023804399774227755
Variance: 0.0005666494486112544
```

In [23]:

```
# Эксперимент 6
# Первый уровень - три модели: дерево, линейная регрессия и случайный лес
# Второй уровень: случайный лес
stacker = Regressor(dataset=stack_ds3, estimator=DecisionTreeRegressor)
results = stacker.validate(k=10,scorer=mean_absolute_error)
```

```
Metric: mean_absolute_error
Folds accuracy: [0.47058823529411764, 0.5882352941176471, 0.59663865
54621849, 0.559322033898305, 0.5084745762711864, 0.4491525423728814,
0.4830508474576271, 0.5677966101694916, 0.5508474576271186, 0.542372
8813559322]
Mean accuracy: 0.5316479134026492
Standard Deviation: 0.048388645127900115
Variance: 0.0023414609773138514
```

In [38]:

```
# Результаты
array_labels = ['LR','TREE', 'RF',
                'TREE+LR=>LR',  'TREE+LR=>RF','TREE+LR=>TREE',
                 'TREE+RF=>LR', 'TREE+RF=>RF','TREE+RF=>TREE',
                'LR+RF=>LR', 'LR+RF=>RF','LR+RF=>TREE',

                'TREE+LR+RF=>LR', 'TREE+LR+RF=>RF', 'TREE+LR+RF=>TREE']
array_mae = [0.4910, 0.4375, 0.4193,0.4891, 0.5544, 0.5873, 0.4302, 0.4496, 0.45
04, 0.4328, 0.4641, 0.5308, 0.4330, 0.4496, 0.5316
            ]
```

In [39]:

```
min(array_mae)
```

Out[39]:

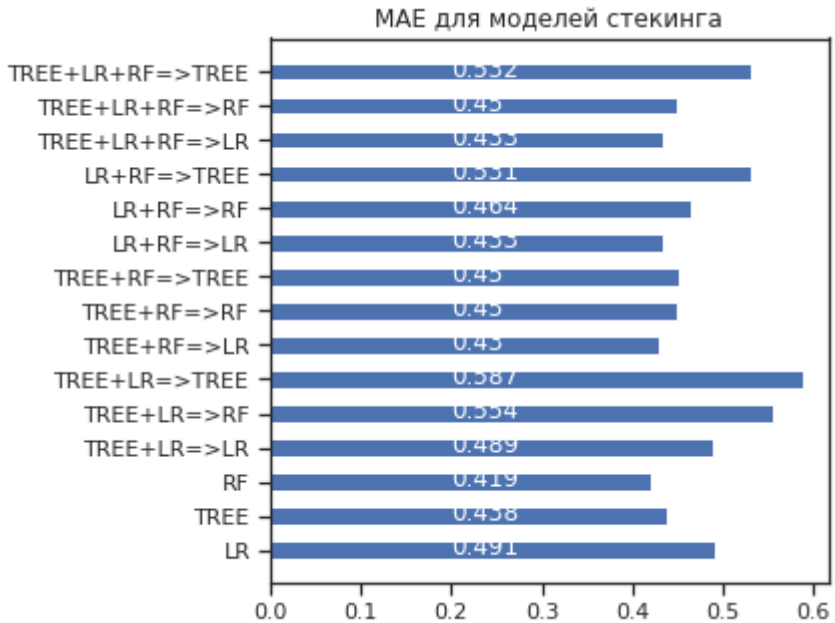
```
0.433
```

In [31]:

```
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 [32]:

```
# Визуализация результатов
vis_models_quality(array_mae, array_labels, 'MAE для моделей стекинга')
```

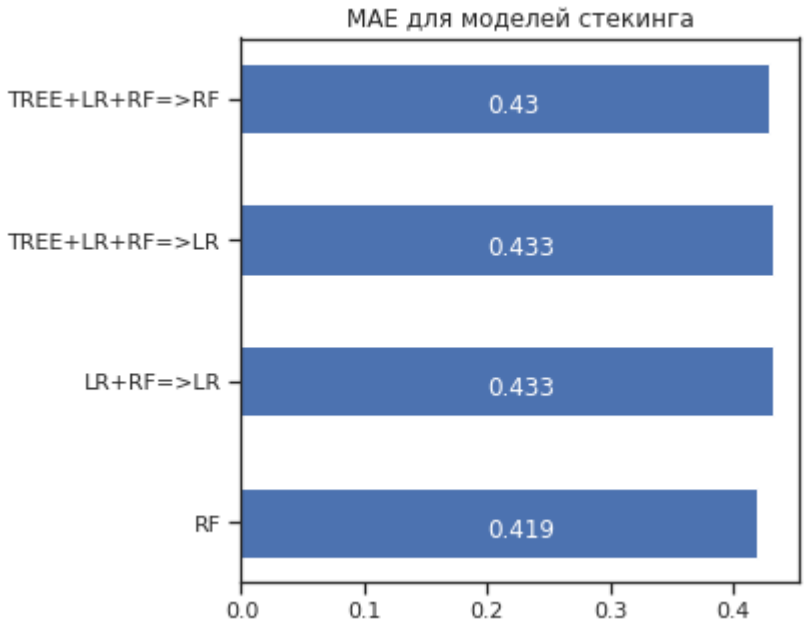


Выведем лучшие модели

In [40]:

```
# Результаты
array_labels = [ 'RF',
                 'LR+RF=>LR',
                 'TREE+LR+RF=>LR',
                 'TREE+LR+RF=>RF' ]
array_mae = [ 0.4193,
              0.4328,
              0.433,
               0.4302]

# Визуализация результатов
vis_models_quality(array_mae, array_labels, 'MAE для моделей стекинга')
```



Видим, что лучшие результаты стекинга похожи на самую сильную модель 1 уровня - случайный лес. Лучшие модели получились, если на втором уровне в большинстве случаев использовалась линейная регрессия, а на 1 применялся случайный лес.

4.2. Метод группового учета аргументов

In [41]:

```
# !pip install gmdhpy
from gmdhpy import gmdh
```

In [42]:

```
model = gmdh.MultilayerGMDH()
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
result = mean_absolute_error(y_test, y_pred)
print('MAE={}'.format(result))
```

```
train layer0 in 0.21 sec
train layer1 in 0.88 sec
train layer2 in 0.89 sec
train layer3 in 0.88 sec
train layer4 in 0.90 sec
train layer5 in 0.90 sec
train layer6 in 0.89 sec
train layer7 in 0.88 sec
train layer8 in 0.88 sec
MAE=0.49275142270917777
```

In [43]:

```
model = gmdh.MultilayerGMDH(ref_functions=('linear_cov', 'quadratic', 'cubic',
'linear'))
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
result = mean_absolute_error(y_test, y_pred)
print('MAE={}'.format(result))
```

```
train layer0 in 1.10 sec
train layer1 in 4.62 sec
train layer2 in 4.72 sec
train layer3 in 4.60 sec
train layer4 in 4.55 sec
train layer5 in 4.54 sec
train layer6 in 4.50 sec
train layer7 in 4.56 sec
MAE=0.48557106923504756
```

5. Подбор значений одного гиперпараметра для моделей.

5.1. Стекинг

In [44]:

```
DecisionTreeRegressor().get_params()
```

Out[44]:

```
{'ccp_alpha': 0.0,
 'criterion': 'mse',
 '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': 'deprecated',
 'random_state': None,
 'splitter': 'best'}
```

In [45]:

```
params = {
'min_impurity_split': [ 0, 0.5,1,1.5,2, 3]
}
```

In [46]:

```
%%time
grid_1 = GridSearchCV(estimator=DecisionTreeRegressor(),
                      param_grid=params, scoring='neg_mean_absolute_error', cv=3,
n_jobs=-1)
grid_1.fit(data, y_array)
grid_1.estimator.get_params().keys()
```

```
CPU times: user 146 ms, sys: 68.5 ms, total: 214 ms
Wall time: 1.25 s
```

```
/home/denis/ml/env/lib/python3.6/site-packages/sklearn/tree/_classe
s.py:301: FutureWarning: The min_impurity_split parameter is depreca
ted. Its default value will change from 1e-7 to 0 in version 0.23, a
nd it will be removed in 0.25. Use the min_impurity_decrease paramet
er instead.
  FutureWarning)
```

Out[46]:

```
dict_keys(['ccp_alpha', 'criterion', 'max_depth', 'max_features', 'm
ax_leaf_nodes', 'min_impurity_decrease', 'min_impurity_split', 'min_
samples_leaf', 'min_samples_split', 'min_weight_fraction_leaf', 'pre
sort', 'random_state', 'splitter'])
```

In [47]:

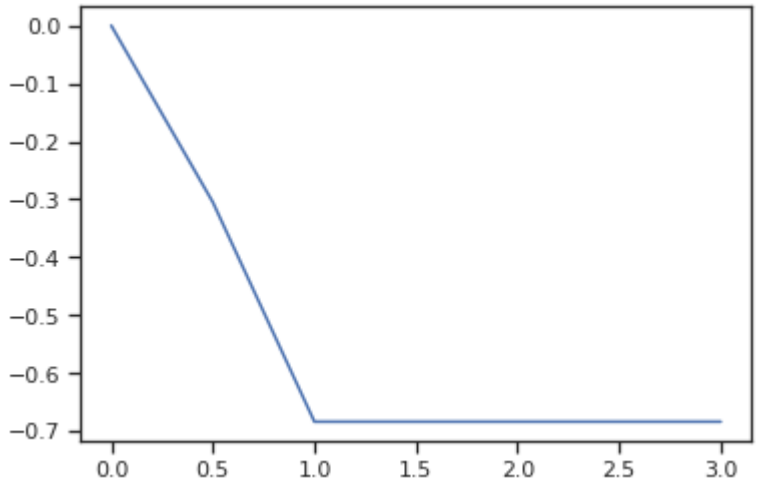
```
grid_1.best_params_
```

Out[47]:

```
{'min_impurity_split': 0}
```

In [48]:

```
plt.plot(params['min_impurity_split'], grid_1.cv_results_["mean_test_score"]);
```



5.2 Метод группового учета аргументов

In [49]:

```
model = gmdh.MultilayerGMDH(ref_functions=('linear_cov', 'quadratic',
                                           'cubic', 'linear'),
                            n_jobs=2
                            )
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
result = mean_absolute_error(y_test, y_pred)
print('MAE={}'.format(result))
```

```
train layer0 in 0.68 sec
train layer1 in 2.70 sec
train layer2 in 2.61 sec
train layer3 in 2.60 sec
train layer4 in 2.56 sec
train layer5 in 2.58 sec
train layer6 in 2.58 sec
train layer7 in 2.57 sec
MAE=0.48557106923504756
```

In [50]:

```
model = gmdh.MultilayerGMDH(ref_functions=('linear_cov', 'quadratic',
                                           'cubic', 'linear'),
                            criterion_minimum_width=5
                            )
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
result = mean_absolute_error(y_test, y_pred)
print('MAE={}'.format(result))
```

```
train layer0 in 1.14 sec
train layer1 in 4.69 sec
train layer2 in 4.65 sec
train layer3 in 4.61 sec
train layer4 in 4.59 sec
train layer5 in 4.57 sec
train layer6 in 4.09 sec
train layer7 in 4.10 sec
MAE=0.48557106923504756
```

In [51]:

```
model = gmdh.MultilayerGMDH(ref_functions=('linear_cov'),
                            max_layer_count=4)
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
result = mean_absolute_error(y_test, y_pred)
print('MAE={}'.format(result))
```

```
train layer0 in 0.21 sec
train layer1 in 0.95 sec
train layer2 in 0.91 sec
train layer3 in 0.88 sec
MAE=0.5001011616867227
```

In [52]:

```
model = gmdh.MultilayerGMDH(ref_functions=('quadratic'),
                            max_layer_count=4)
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
result = mean_absolute_error(y_test, y_pred)
print('MAE={}'.format(result))
```

```
train layer0 in 0.29 sec
train layer1 in 1.20 sec
train layer2 in 1.23 sec
train layer3 in 1.20 sec
MAE=0.4983202723714023
```

In [53]:

```
model = gmdh.MultilayerGMDH(ref_functions=('cubic'),
                            max_layer_count=4)
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
result = mean_absolute_error(y_test, y_pred)
print('MAE={}'.format(result))
```

```
train layer0 in 0.46 sec
train layer1 in 1.97 sec
train layer2 in 1.95 sec
train layer3 in 1.94 sec
MAE=0.4909035647486556
```

In [54]:

```
model = gmdh.MultilayerGMDH(ref_functions=('linear_cov', 'quadratic',
                                           'cubic', 'linear'),
                            max_layer_count=4)
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
result = mean_absolute_error(y_test, y_pred)
print('MAE={}'.format(result))
```

```
train layer0 in 1.12 sec
train layer1 in 4.70 sec
train layer2 in 4.65 sec
train layer3 in 4.62 sec
MAE=0.48724853306639215
```

In [55]:

```
params = {
    'ref_functions': ['linear_cov', 'quadratic', 'cubic', 'linear']

}
```

In [56]:

```
for param in params['ref_functions']:
    model = gmdh.MultilayerGMDH(ref_functions=(param),
                                max_layer_count=3)
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    result = mean_absolute_error(y_test, y_pred)
    print('Param value: {}, MAE={}'.format(param, result))
    print()
```

```
train layer0 in 0.21 sec
train layer1 in 0.88 sec
train layer2 in 0.93 sec
Param value: linear_cov, MAE=0.5005100535726884

train layer0 in 0.28 sec
train layer1 in 1.19 sec
train layer2 in 1.20 sec
Param value: quadratic, MAE=0.4996399148742637

train layer0 in 0.47 sec
train layer1 in 1.95 sec
train layer2 in 1.93 sec
Param value: cubic, MAE=0.48785162393161924

train layer0 in 0.17 sec
train layer1 in 0.75 sec
train layer2 in 0.74 sec
Param value: linear, MAE=0.4989142429592759
```

cubic лучше всех снизила ошибку.

In [61]:

```
params = {
    'max_layer_count': [1,2,3,4,6,8, 10],

}
```

In [62]:

```
for param in params['max_layer_count']:
    model = gmdh.MultilayerGMDH(ref_functions=('cubic'),
                                max_layer_count=param)
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    result = mean_absolute_error(y_test, y_pred)
    print('Param value: {}, MAE={}'.format(param, result))
```

```
train layer0 in 0.47 sec
Param value: 1, MAE=0.5059479855052901
train layer0 in 0.47 sec
train layer1 in 1.99 sec
Param value: 2, MAE=0.4981671446671235
train layer0 in 0.47 sec
train layer1 in 1.96 sec
train layer2 in 1.99 sec
Param value: 3, MAE=0.48785162393161924
train layer0 in 0.48 sec
train layer1 in 1.95 sec
train layer2 in 1.96 sec
train layer3 in 1.95 sec
Param value: 4, MAE=0.4909035647486556
train layer0 in 0.47 sec
train layer1 in 1.96 sec
train layer2 in 1.95 sec
train layer3 in 1.95 sec
train layer4 in 1.96 sec
train layer5 in 1.96 sec
Param value: 6, MAE=0.48579216879768594
train layer0 in 0.46 sec
train layer1 in 1.94 sec
train layer2 in 1.94 sec
train layer3 in 2.13 sec
train layer4 in 2.10 sec
train layer5 in 2.04 sec
train layer6 in 2.04 sec
Param value: 8, MAE=0.48558638121852565
train layer0 in 0.46 sec
train layer1 in 1.96 sec
train layer2 in 2.03 sec
train layer3 in 2.09 sec
train layer4 in 2.04 sec
train layer5 in 1.98 sec
train layer6 in 1.97 sec
Param value: 10, MAE=0.48558638121852565
```

6. Повтор пункта 4 для найденных оптимальных значений гиперпараметров. Сравнение качества полученных моделей с качеством моделей, полученных в пункте 4

In [63]:

```
model_tree = Regressor(dataset=dataset, estimator=DecisionTreeRegressor, paramet
ers={'min_impurity_split':1.5},name='tree')
model_lr = Regressor(dataset=dataset, estimator=LinearRegression, parameters={'n
ormalize': True},name='lr')
model_rf = Regressor(dataset=dataset, estimator=RandomForestRegressor, parameter
s={'n_estimators': 50},name='rf')

pipeline = ModelsPipeline(model_tree, model_rf)
stack_ds = pipeline.stack(k=10, seed=1)

stacker = Regressor(dataset=stack_ds, estimator=LinearRegression)
results = stacker.validate(k=10,scorer=mean_absolute_error)
```

```
Metric: mean_absolute_error
Folds accuracy: [0.4579882552127175, 0.4377693833774365, 0.489226675
53576704, 0.38921760926414134, 0.4283664559536715, 0.419131399822892
2, 0.41212175657224587, 0.39823953008713964, 0.42078538893042594, 0.
42961054068482674]
Mean accuracy: 0.42824569954412645
Standard Deviation: 0.027419240042358663
Variance: 0.0007518147245004847
```

```
/home/denis/ml/env/lib/python3.6/site-packages/sklearn/tree/_classe
s.py:301: FutureWarning: The min_impurity_split parameter is depreca
ted. Its default value will change from 1e-7 to 0 in version 0.23, a
nd it will be removed in 0.25. Use the min_impurity_decrease paramet
er instead.
  FutureWarning)
/home/denis/ml/env/lib/python3.6/site-packages/sklearn/tree/_classe
s.py:301: FutureWarning: The min_impurity_split parameter is depreca
ted. Its default value will change from 1e-7 to 0 in version 0.23, a
nd it will be removed in 0.25. Use the min_impurity_decrease paramet
er instead.
  FutureWarning)
/home/denis/ml/env/lib/python3.6/site-packages/sklearn/tree/_classe
s.py:301: FutureWarning: The min_impurity_split parameter is depreca
ted. Its default value will change from 1e-7 to 0 in version 0.23, a
nd it will be removed in 0.25. Use the min_impurity_decrease paramet
er instead.
  FutureWarning)
/home/denis/ml/env/lib/python3.6/site-packages/sklearn/tree/_classe
s.py:301: FutureWarning: The min_impurity_split parameter is depreca
ted. Its default value will change from 1e-7 to 0 in version 0.23, a
nd it will be removed in 0.25. Use the min_impurity_decrease paramet
er instead.
  FutureWarning)
/home/denis/ml/env/lib/python3.6/site-packages/sklearn/tree/_classe
s.py:301: FutureWarning: The min_impurity_split parameter is depreca
ted. Its default value will change from 1e-7 to 0 in version 0.23, a
nd it will be removed in 0.25. Use the min_impurity_decrease paramet
er instead.
  FutureWarning)
/home/denis/ml/env/lib/python3.6/site-packages/sklearn/tree/_classe
s.py:301: FutureWarning: The min_impurity_split parameter is depreca
ted. Its default value will change from 1e-7 to 0 in version 0.23, a
nd it will be removed in 0.25. Use the min_impurity_decrease paramet
er instead.
  FutureWarning)
/home/denis/ml/env/lib/python3.6/site-packages/sklearn/tree/_classe
s.py:301: FutureWarning: The min_impurity_split parameter is depreca
ted. Its default value will change from 1e-7 to 0 in version 0.23, a
nd it will be removed in 0.25. Use the min_impurity_decrease paramet
er instead.
  FutureWarning)
/home/denis/ml/env/lib/python3.6/site-packages/sklearn/tree/_classe
s.py:301: FutureWarning: The min_impurity_split parameter is depreca
ted. Its default value will change from 1e-7 to 0 in version 0.23, a
nd it will be removed in 0.25. Use the min_impurity_decrease paramet
er instead.
  FutureWarning)
/home/denis/ml/env/lib/python3.6/site-packages/sklearn/tree/_classe
s.py:301: FutureWarning: The min_impurity_split parameter is depreca
ted. Its default value will change from 1e-7 to 0 in version 0.23, a
nd it will be removed in 0.25. Use the min_impurity_decrease paramet
er instead.
  FutureWarning)
/home/denis/ml/env/lib/python3.6/site-packages/sklearn/tree/_classe
s.py:301: FutureWarning: The min_impurity_split parameter is depreca
ted. Its default value will change from 1e-7 to 0 in version 0.23, a
nd it will be removed in 0.25. Use the min_impurity_decrease paramet
er instead.
  FutureWarning)
/home/denis/ml/env/lib/python3.6/site-packages/sklearn/tree/_classe
```

```
s.py:301: FutureWarning: The min_impurity_split parameter is depreca
ted. Its default value will change from 1e-7 to 0 in version 0.23, a
nd it will be removed in 0.25. Use the min_impurity_decrease paramet
er instead.
  FutureWarning)
```

Результат немного улучшился

Метод группового учета аргументов

In [64]:

```
model = gmdh.MultilayerGMDH(ref_functions=('linear_cov', 'quadratic',
                                           'cubic', 'linear'),
                            max_layer_count=6)
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
result = mean_absolute_error(y_test, y_pred)
print('MAE={}'.format(result))
```

```
train layer0 in 1.13 sec
train layer1 in 4.58 sec
train layer2 in 4.57 sec
train layer3 in 4.56 sec
train layer4 in 4.53 sec
train layer5 in 4.54 sec
MAE=0.48498913574135594
```

Результат удалось немного улучшить.

Вывод:

- В процессе выполнения данной лабораторной работы было определено, что наилучшим образом себя показывает ансамблевая модель, где на первом уровне находятся модели случайный лес и дерево решений, а на втором- линейная регрессия. Применение линейной регрессии на первом уровне ансамблевых моделей показало себя хуже всего. Было выяснено, что модель случайный лес по точности соспоставима с лучшими ансамблевыми моделями.
- Метод группового учета оказался хуже по точности, чем ансамблевые модели.

In [ ]: