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 [7]:
```
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, KNeighborsClassi
fier
from sklearn.model_selection import GridSearchCV, RandomizedSearchC
V
from sklearn.metrics import accuracy_score, balanced_accuracy_score
from sklearn.metrics import precision_score, recall_score, f1_score
, classification_report
from sklearn.metrics import confusion_matrix
from sklearn.tree import DecisionTreeClassifier, DecisionTreeRegres
sor, export_graphviz
from sklearn.ensemble import RandomForestClassifier, RandomForestRe
gressor
from sklearn.ensemble import ExtraTreesClassifier, ExtraTreesRegres
sor
from sklearn.ensemble import GradientBoostingClassifier, GradientBo
ostingRegressor
from sklearn.ensemble import BaggingClassifier
from sklearn.ensemble import AdaBoostClassifier
from sklearn.metrics import mean_absolute_error, mean_squared_error
, mean_squared_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")
```

```
Requirement already satisfied: heamy in /usr/local/lib/python3.7/s
ite-packages (0.0.7)
Requirement already satisfied: scikit-learn>=0.17.0 in /usr/local/
lib/python3.7/site-packages (from heamy) (0.22.2.post1)
Requirement already satisfied: scipy>=0.16.0 in /usr/local/lib/pyt
hon3.7/site-packages (from heamy) (1.4.1)
Requirement already satisfied: six>=1.10.0 in /usr/local/lib/pytho
n3.7/site-packages (from heamy) (1.13.0)
Requirement already satisfied: numpy>=1.7.0 in /usr/local/lib/pyth
on3.7/site-packages (from heamy) (1.18.4)
Requirement already satisfied: pandas>=0.17.0 in /usr/local/lib/py
thon3.7/site-packages (from heamy) (1.0.1)
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/pyth
on3.7/site-packages (from scikit-learn>=0.17.0->heamy) (0.14.1)
Requirement already satisfied: pytz>=2017.2 in /usr/local/lib/pyth
on3.7/site-packages (from pandas>=0.17.0->heamy) (2019.3)
Requirement already satisfied: python-dateutil>=2.6.1 in /usr/loca
l/lib/python3.7/site-packages (from pandas>=0.17.0->heamy) (2.8.1)
```

1. Выбор набора данных для решения задачи регресии.

In [3]:
```
data = pd.read_csv('data/vgsales.csv', sep=',')
data.head()
```

Out[3]:

	Rank	Name	Platform	Year	Genre	Publisher	NA_Sales	EU_Sales	JP_Sale
0	1	Wii Sports	Wii	2006.0	Sports	Nintendo	41.49	29.02	3.7
1	2	Super Mario Bros.	NES	1985.0	Platform	Nintendo	29.08	3.58	6.8
2	3	Mario Kart Wii	Wii	2008.0	Racing	Nintendo	15.85	12.88	3.7
3	4	Wii Sports Resort	Wii	2009.0	Sports	Nintendo	15.75	11.01	3.2
4	5	Pokemon Red/Pokemon Blue	GB	1996.0	Role-Playing	Nintendo	11.27	8.89	10.2

In [4]:
```
data.shape
```

Out[4]: (16598, 11)

In [5]:
```
data.isnull().sum()
```

Out[5]:
```
Rank              0
Name              0
Platform          0
Year            271
Genre             0
Publisher        58
NA_Sales          0
EU_Sales          0
JP_Sales          0
Other_Sales       0
Global_Sales      0
dtype: int64
```

In [6]:
```
data.dtypes
```

Out[6]:
```
Rank              int64
Name             object
Platform         object
Year            float64
Genre            object
Publisher        object
NA_Sales        float64
EU_Sales        float64
JP_Sales        float64
Other_Sales     float64
Global_Sales    float64
dtype: object
```

2. Удаление и заполнение пропусков и кодирование категориальных признаков.

In [7]:
```
# Выберем числовые колонки с пропущенными значениями
# Цикл по колонкам датасета набора 1
num_cols = []
total_count = data.shape[0]
for col in data.columns:
    # Количество пустых значений
    temp_null_count = data[data[col].isnull()].shape[0]
    dt = str(data[col].dtype)
    if temp_null_count>0 and (dt=='float64' or dt=='int64'):
        num_cols.append(col)
        temp_perc = round((temp_null_count / total_count) * 100.0, 
2)
        print('Колонка {}. Тип данных {}. Количество пустых значени
й {}, {}%.'.format(col, dt, temp_null_count, temp_perc))
```

```
Колонка Year. Тип данных float64. Количество пустых значений 271,
1.63%.
```

In [8]:
```
# Фильтр по колонкам с пропущенными значениями  набора 1
data_num = data[num_cols].mean()
data_num
```

Out[8]:
```
Year    2006.406443
dtype: float64
```

In [9]:
```
data[num_cols] = data[num_cols].fillna(data[num_cols].mean())
```

In [10]:
```
data.isnull().sum()
```

Out[10]:
```
Rank             0
Name             0
Platform         0
Year             0
Genre            0
Publisher       58
NA_Sales         0
EU_Sales         0
JP_Sales         0
Other_Sales      0
Global_Sales     0
dtype: int64
```

In [11]:
```
data = data.fillna('')
data.isnull().sum()
```

Out[11]:
```
Rank            0
Name            0
Platform        0
Year            0
Genre           0
Publisher       0
NA_Sales        0
EU_Sales        0
JP_Sales        0
Other_Sales     0
Global_Sales    0
dtype: int64
```

In [12]:
```
data.dtypes
```

Out[12]:
```
Rank              int64
Name             object
Platform         object
Year            float64
Genre            object
Publisher        object
NA_Sales        float64
EU_Sales        float64
JP_Sales        float64
Other_Sales     float64
Global_Sales    float64
dtype: object
```

Кодирование категориальных признаков числовыми

In [13]:
```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
data['Name'] = le.fit_transform(data['Name'])
data['Platform'] = le.fit_transform(data['Platform'])
data['Genre'] = le.fit_transform(data['Genre'])
data['Publisher'] = le.fit_transform(data['Publisher'])
data.dtypes
```

Out[13]:
```
Rank              int64
Name              int64
Platform          int64
Year            float64
Genre             int64
Publisher         int64
NA_Sales        float64
EU_Sales        float64
JP_Sales        float64
Other_Sales     float64
Global_Sales    float64
dtype: object
```

In [14]:
```
data.head()
```

Out[14]:

	Rank	Name	Platform	Year	Genre	Publisher	NA_Sales	EU_Sales	JP_Sales	Other_
0	1	11007	26	2006.0	10	360	41.49	29.02	3.77	
1	2	9327	11	1985.0	4	360	29.08	3.58	6.81	
2	3	5573	26	2008.0	6	360	15.85	12.88	3.79	
3	4	11009	26	2009.0	10	360	15.75	11.01	3.28	
4	5	7346	5	1996.0	7	360	11.27	8.89	10.22	

In [17]:
```
# # # Масштабирование данных в диапазоне от 0 до 1
# sc1 = MinMaxScaler()
# sc1_data = sc1.fit_transform(data)
# X_train_1, X_test_1, y_train_1, y_test_1 = train_test_split(
#     sc1_data, data['Global_Sales'], test_size=0.26, random_state=
1)

# X_train_1.shape, X_test_1.shape
```

In [18]:
```
columns = ['Platform', 'Name', 'Year', 'Genre', 'NA_Sales',
       'EU_Sales', 'JP_Sales', 'Other_Sales', 'Global_Sales']
```

In [19]:
```
x_array = data[columns].values
y_array = data['Rank'].values
```

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

In [20]:
```
X_train, X_test, y_train, y_test = train_test_split(x_array, y_arra
y,
test_size=0.26, random_state=1)
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

Out[20]:
```
((12282, 9), (4316, 9), (12282,), (4316,))
```

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

4.1. Стекинг

In [21]:
```
# 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 [22]:
```
# Точность на отдельных моделях
for model in [
    LinearRegression(),
    DecisionTreeRegressor(),
    RandomForestRegressor(n_estimators=50)
]:
    val_mae(model)
    print('==========================')
    print()
```

```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, nor
malize=False)
MAE=3590.6105058314756
==========================

DecisionTreeRegressor(ccp_alpha=0.0, criterion='mse', max_depth=No
ne,
                      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, presort='depre
cated',
                      random_state=None, splitter='best')
MAE=100.15685820203892
==========================

RandomForestRegressor(bootstrap=True, ccp_alpha=0.0, criterion='ms
e',
                      max_depth=None, max_features='auto', max_lea
f_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_lea
f=0.0,
                      n_estimators=50, n_jobs=None, oob_score=Fals
e,
                      random_state=None, verbose=0, warm_start=Fal
se)
MAE=80.57904772937906
==========================
```

In [23]:
```
# набор данных
dataset = Dataset(X_train, y_train, X_test)

# модели первого уровня
model_tree = Regressor(dataset=dataset, estimator=DecisionTreeRegre
ssor, name='tree')
model_lr = Regressor(dataset=dataset, estimator=LinearRegression, p
arameters={'normalize': True},name='lr')
model_rf = Regressor(dataset=dataset, estimator=RandomForestRegress
or, parameters={'n_estimators': 50},name='rf')
```

In [24]:
```
# 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: [101.05504753807202, 98.68054521451998, 93.1887663
479923, 102.46379170308225, 95.66529052863154, 99.32336541685724,
111.63309812884769, 101.54275570943696, 103.21560469209982, 101.55
689083889365]
Mean accuracy: 100.83251561184333
Standard Deviation: 4.670193439805995
Variance: 21.81070676520696
```

In [25]:
```
# Эксперимент 1.2
# Первый уровень - две модели: дерево и линейная регрессия
# Второй уровень: случайный лес

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

```
Metric: mean_absolute_error
Folds accuracy: [87.6426932465419, 81.69672904800653, 81.912630293
15961, 88.48411237785018, 85.58969869706837, 85.8906107491857, 94.
31790716612376, 84.81938110749184, 87.3342589576547, 85.8931026058
632]
Mean accuracy: 86.35811242489459
Standard Deviation: 3.396541919452603
Variance: 11.536497010598772
```

In [26]:
```
# Эксперимент 1.3
# Первый уровень - две модели: дерево и линейная регрессия
# Второй уровень: дерево

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

```
Metric: mean_absolute_error
Folds accuracy: [107.14890154597234, 101.77542717656631, 103.04560
26058632, 110.8013029315961, 107.71335504885994, 111.4039087947882
8, 117.74837133550488, 108.68241042345277, 110.51221498371335, 105
.79315960912052]
Mean accuracy: 108.46246544554376
Standard Deviation: 4.336713512678101
Variance: 18.807084091044835
```

In [27]:
```
# 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: [83.0022864466405, 76.7675123177237, 76.5258375137
2313, 81.3568944730721, 77.25352865690145, 75.62140435834345, 85.5
8333023773896, 79.79816510376472, 79.93518440199674, 81.4808679106
2704]
Mean accuracy: 79.73250114205317
Standard Deviation: 3.0460597672547554
Variance: 9.278480105688095
```

In [28]:
```
# Эксперимент 2.2
# Первый уровень - две модели: дерево и случайный лес
# Второй уровень: случайный лес

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

```
Metric: mean_absolute_error
Folds accuracy: [85.92564895966525, 80.87215215622456, 84.50739033
659065, 86.36403528773073, 83.96345063595473, 83.48672960291609, 8
9.7915006786102, 84.55184039087948, 83.88554440049637, 84.70701954
397394]
Mean accuracy: 84.80553119930421
Standard Deviation: 2.178821372167754
Variance: 4.747262571814974
```

In [29]:
```
# Эксперимент 2.3
# Первый уровень - две модели: дерево и случайный лес
# Второй уровень: дерево

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

```
Metric: mean_absolute_error
Folds accuracy: [107.13181448331977, 105.25223759153783, 107.13599
348534201, 103.8086319218241, 104.60342019543974, 104.458469055374
6, 110.20195439739413, 101.99837133550488, 106.76547231270358, 105
.50977198697069]
Mean accuracy: 105.68661367654113
Standard Deviation: 2.139464767551578
Variance: 4.577309491594527
```

In [30]:
```
# 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: [83.05833714764005, 76.91059773107504, 76.45827357
045583, 81.20574852665894, 76.98074637046285, 75.72574074135834, 8
5.97681235234108, 80.00097973450144, 80.0461110392515, 81.42068229
739571]
Mean accuracy: 79.77840295111409
Standard Deviation: 3.1230173156901393
Variance: 9.753237154100443
```

In [31]:
```
# Эксперимент 3.2
# Первый уровень - две модели:  линейная регрессия и случайный лес
# Второй уровень: случайный лес

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

```
Metric: mean_absolute_error
Folds accuracy: [86.46650935720096, 78.63644426362897, 78.79664495
114008, 86.08108306188926, 83.66583061889249, 80.70199511400651, 8
9.07232084690554, 83.42728827361563, 85.71984527687296, 84.2102117
2638436]
Mean accuracy: 83.67781734905368
Standard Deviation: 3.244475181915836
Variance: 10.526619206067798
```

In [32]:
```
# Эксперимент 3.3
# Первый уровень - две модели: линейная регрессия и случайный лес
# Второй уровень: дерево

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

```
Metric: mean_absolute_error
Folds accuracy: [111.66476810414972, 101.45077298616762, 101.55863
19218241, 114.38680781758957, 105.69381107491857, 100.716612377850
17, 111.40390879478828, 105.12052117263843, 107.70928338762215, 10
3.71254071661238]
Mean accuracy: 106.3417658354161
Standard Deviation: 4.558717915992085
Variance: 20.78190903758722
```

In [33]:
```
# Эксперимент 4
# Первый уровень - три модели: дерево, линейная регрессия и случайн
ый 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: [83.23089002236054, 76.79583934161822, 76.80909023
867751, 81.36725394695083, 77.34639456636724, 75.71020843187246, 8
5.71494858932246, 79.8257966603079, 80.06647360443235, 81.58660594
924592]
Mean accuracy: 79.84535013511554
Standard Deviation: 3.0524428474647856
Variance: 9.31740733703893
```

In [34]:
```
# Эксперимент 5
# Первый уровень - три модели: дерево, линейная регрессия и случайн
ый лес
# Второй уровень: дерево
stacker = Regressor(dataset=stack_ds3, estimator=RandomForestRegres
sor)
results = stacker.validate(k=10,scorer=mean_absolute_error)
```

```
Metric: mean_absolute_error
Folds accuracy: [84.5293327908869, 78.46600488201788, 78.346734527
68729, 83.81155537459284, 81.58912866449512, 80.83397394136806, 88
.85859934853421, 82.0663680781759, 82.1598697068404, 81.7132328990
228]
Mean accuracy: 82.23748002136213
Standard Deviation: 2.891915890971849
Variance: 8.363177520455505
```

In [35]:
```
# Эксперимент 6
# Первый уровень - три модели: дерево, линейная регрессия и случайн
ый лес
# Второй уровень: случайный лес
stacker = Regressor(dataset=stack_ds3, estimator=DecisionTreeRegres
sor)
results = stacker.validate(k=10,scorer=mean_absolute_error)
```

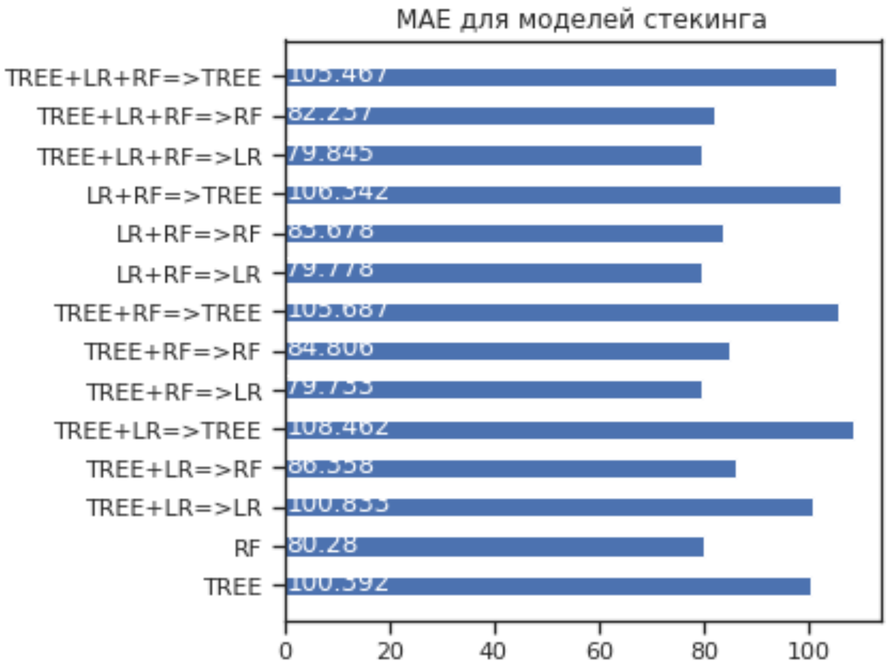
```
Metric: mean_absolute_error
Folds accuracy: [106.40683482506103, 103.02196908055329, 101.72394
136807817, 109.36482084690553, 103.3485342019544, 105.222312703583
06, 110.25895765472313, 104.52524429967427, 104.35830618892508, 10
6.435667752443]
Mean accuracy: 105.4666588921901
Standard Deviation: 2.5812789497473854
Variance: 6.663001016408964
```

Поскольку у линейной регрессии слишком большая ошибка - 3590.6105058314756, уберем ее с графика

In [37]:
```
# Результаты
array_labels = ['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=>TR
EE']
array_mae = [100.39202965708989, 80.2804124189064,

              100.83251561184333,  86.35811242489459, 108.4624654455
4376,
             79.73250114205317, 84.80553119930421, 105.6866136765411
3,
             79.77840295111409, 83.67781734905368, 106.3417658354161
,

              79.84535013511554, 82.23748002136213, 105.466658892190
1
             ]
```

In [38]:
```
def vis_models_quality(array_metric, array_labels, str_header, figs
ize=(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 [39]:
```
# Визуализация результатов
vis_models_quality(array_mae, array_labels, 'MAE для моделей стекинга')
```



Выведем лучшие модели

In [40]:
```
# Результаты
array_labels = [ 'RF',
                'TREE+RF=>LR',
                'LR+RF=>LR',
                'TREE+LR+RF=>LR' ]
array_mae = [ 80.2804124189064,

             79.73250114205317,
             79.77840295111409,

              79.84535013511554]

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

Видим, что лучшие результаты стекинга сравнимы с наиболее сильной моделью 1 уровня (случайным лесом) и самые сильные модели получились, если на втором уровне использовалась линейная регрессия, а на первом одна из моделей - случайный лес.

4.2. Метод группового учета аргументов

In [41]:
```
# !pip install gmdhpy
from gmdhpy import gmdh
```

In [ ]:
```
model = gmdh.MultilayerGMDH()
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 [ ]:
```
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(model)
print('MAE={}'.format(result))
```

Видим, что для данной задачи этот метод выдает слишком большую ошибку? необходима настройка параметров.

5. Подбор значений одного гиперпараметра для моделей.

5.1. Стекинг

In [329]:
```
# # Возьмем лучшую модель: 'TREE+RF=>LR'

# # 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)
```

In [464]:
```
DecisionTreeRegressor().get_params()
```

Out[464]:
```
{'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 [495]:
```
params = {
'min_impurity_split': [ 0, 0.5,1,1.5,2, 3]
}
```

In [496]:
```
%%time
grid_1 = GridSearchCV(estimator=DecisionTreeRegressor(),
                    param_grid=params, scoring='neg_mean_absolute_e
rror', cv=3, n_jobs=-1)
grid_1.fit(data, y_array)
grid_1.estimator.get_params().keys()
```

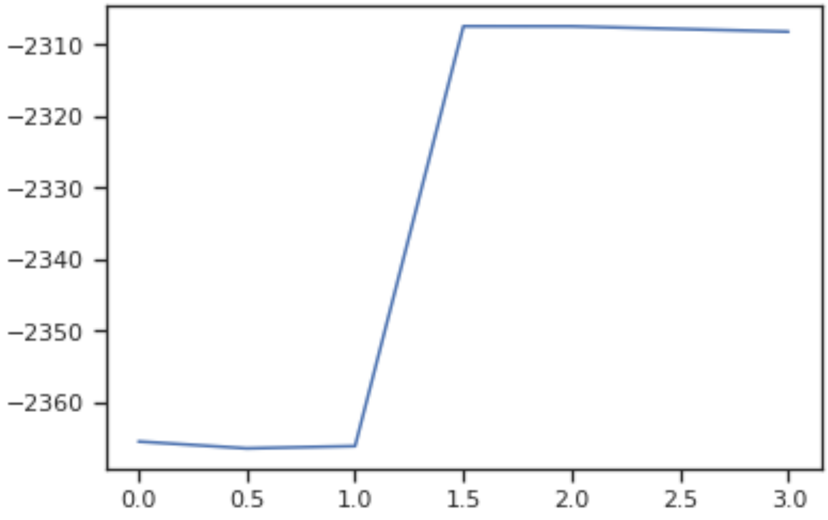
```
CPU times: user 216 ms, sys: 10.5 ms, total: 227 ms
Wall time: 897 ms

/home/lisobol/tensorflow_env/my_tensorflow/lib/python3.7/site-pack
ages/sklearn/tree/_classes.py:301: FutureWarning: The min_impurity
_split parameter is deprecated. Its default value will change from
1e-7 to 0 in version 0.23, and it will be removed in 0.25. Use the
min_impurity_decrease parameter instead.
  FutureWarning)
```

Out[496]:
```
dict_keys(['ccp_alpha', 'criterion', 'max_depth', 'max_features',
'max_leaf_nodes', 'min_impurity_decrease', 'min_impurity_split', '
min_samples_leaf', 'min_samples_split', 'min_weight_fraction_leaf'
, 'presort', 'random_state', 'splitter'])
```

In [497]:
```
grid_1.best_params_
```

Out[497]:
```
{'min_impurity_split': 1.5}
```

In [498]:
```
plt.plot(params['min_impurity_split'], grid_1.cv_results_["mean_tes
t_score"]);
```



5.2 Метод группового учета аргументов

In [52]:
```
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 10.48 sec
train layer1 in 47.28 sec
train layer2 in 45.52 sec
train layer3 in 45.87 sec
train layer4 in 41.48 sec
train layer5 in 44.12 sec
train layer6 in 43.02 sec
train layer7 in 43.37 sec
train layer8 in 46.28 sec
train layer9 in 47.69 sec
train layer10 in 48.73 sec
train layer11 in 47.99 sec
train layer12 in 48.15 sec
train layer13 in 47.65 sec
train layer14 in 48.25 sec
train layer15 in 45.44 sec
train layer16 in 43.79 sec
train layer17 in 43.45 sec
train layer18 in 44.61 sec
train layer19 in 43.84 sec
train layer20 in 43.67 sec
train layer21 in 43.18 sec
train layer22 in 47.02 sec
train layer23 in 44.35 sec
train layer24 in 44.22 sec
train layer25 in 44.63 sec
MAE=6421340804610.882
```

```
Process ForkPoolWorker-5:
Process ForkPoolWorker-6:
Traceback (most recent call last):
  File "/home/lisobol/anaconda3/lib/python3.7/multiprocessing/proc
ess.py", line 297, in _bootstrap
    self.run()
  File "/home/lisobol/anaconda3/lib/python3.7/multiprocessing/proc
ess.py", line 99, in run
    self._target(*self._args, **self._kwargs)
  File "/home/lisobol/anaconda3/lib/python3.7/multiprocessing/pool
.py", line 110, in worker
    task = get()
  File "/home/lisobol/anaconda3/lib/python3.7/multiprocessing/queu
es.py", line 351, in get
    with self._rlock:
  File "/home/lisobol/anaconda3/lib/python3.7/multiprocessing/sync
hronize.py", line 95, in __enter__
    return self._semlock.__enter__()
Traceback (most recent call last):
KeyboardInterrupt
  File "/home/lisobol/anaconda3/lib/python3.7/multiprocessing/proc
ess.py", line 297, in _bootstrap
    self.run()
  File "/home/lisobol/anaconda3/lib/python3.7/multiprocessing/proc
ess.py", line 99, in run
    self._target(*self._args, **self._kwargs)
  File "/home/lisobol/anaconda3/lib/python3.7/multiprocessing/pool
.py", line 110, in worker
    task = get()
  File "/home/lisobol/anaconda3/lib/python3.7/multiprocessing/queu
es.py", line 352, in get
    res = self._reader.recv_bytes()
  File "/home/lisobol/anaconda3/lib/python3.7/multiprocessing/conn
ection.py", line 216, in recv_bytes
    buf = self._recv_bytes(maxlength)
  File "/home/lisobol/anaconda3/lib/python3.7/multiprocessing/conn
ection.py", line 407, in _recv_bytes
    buf = self._recv(4)
  File "/home/lisobol/anaconda3/lib/python3.7/multiprocessing/conn
ection.py", line 379, in _recv
    chunk = read(handle, remaining)
KeyboardInterrupt
```

In [54]:
```
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 15.88 sec
train layer1 in 66.05 sec
train layer2 in 66.15 sec
train layer3 in 66.66 sec
train layer4 in 67.51 sec
train layer5 in 68.54 sec
train layer6 in 68.09 sec
train layer7 in 68.20 sec
train layer8 in 67.01 sec
train layer9 in 67.80 sec
train layer10 in 68.10 sec
train layer11 in 68.16 sec
train layer12 in 67.78 sec
train layer13 in 67.45 sec
train layer14 in 67.30 sec
train layer15 in 67.75 sec
train layer16 in 67.57 sec
train layer17 in 67.55 sec
train layer18 in 67.47 sec
train layer19 in 66.66 sec
train layer20 in 67.82 sec
train layer21 in 68.18 sec
train layer22 in 67.93 sec
train layer23 in 67.72 sec
train layer24 in 67.99 sec
train layer25 in 67.93 sec
MAE=6421340804610.882
```

In [60]:
```
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 3.02 sec
train layer1 in 13.88 sec
train layer2 in 13.54 sec
train layer3 in 15.58 sec
MAE=2856.70534740398
```

In [61]:
```
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 4.37 sec
train layer1 in 18.78 sec
train layer2 in 18.41 sec
train layer3 in 18.92 sec
MAE=3182.225760225751
```

In [62]:
```
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 6.14 sec
train layer1 in 24.60 sec
train layer2 in 24.20 sec
train layer3 in 24.45 sec
MAE=3654496.822551804
```

In [66]:
```
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 16.77 sec
train layer1 in 72.14 sec
train layer2 in 75.26 sec
train layer3 in 73.36 sec
MAE=170223.6536631281
```

In [78]:
```
params = {
    'ref_functions': ['linear_cov', 'quadratic', 'cubic', 'linear']

}
```

In [80]:
```
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 3.18 sec
train layer1 in 14.76 sec
train layer2 in 16.33 sec
Param value: linear_cov, MAE=2887.5624539528417

train layer0 in 4.82 sec
train layer1 in 18.74 sec
train layer2 in 18.27 sec
Param value: quadratic, MAE=3182.225760225751

train layer0 in 5.91 sec
train layer1 in 24.71 sec
train layer2 in 25.34 sec
Param value: cubic, MAE=3654496.822551804

train layer0 in 3.04 sec
train layer1 in 13.61 sec
train layer2 in 12.34 sec
Param value: linear, MAE=3733.7389473277804
```

Видим, что функция linear_cov лучше всех снизила ошибку.

In [73]:
```
params = {
    'max_layer_count': [1,2,3,4,6,8, 10],

}
```

In [75]:
```
for param in params['max_layer_count']:
    model = gmdh.MultilayerGMDH(ref_functions=('linear_cov'),
                                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))
    print()
```

```
train layer0 in 3.51 sec
Param value: 1, MAE=3446.9622156171276

train layer0 in 3.42 sec
train layer1 in 14.41 sec
Param value: 2, MAE=3021.9403458283196

train layer0 in 3.45 sec
train layer1 in 14.27 sec
train layer2 in 14.39 sec
Param value: 3, MAE=2887.5624539528417

train layer0 in 3.21 sec
train layer1 in 14.24 sec
train layer2 in 15.76 sec
train layer3 in 15.32 sec
Param value: 4, MAE=2856.70534740398

train layer0 in 3.30 sec
train layer1 in 16.20 sec
train layer2 in 14.49 sec
train layer3 in 14.54 sec
train layer4 in 15.00 sec
train layer5 in 15.43 sec
Param value: 6, MAE=2720.0356332397296

train layer0 in 3.27 sec
train layer1 in 14.47 sec
train layer2 in 13.71 sec
train layer3 in 15.91 sec
train layer4 in 14.78 sec
train layer5 in 14.61 sec
train layer6 in 14.66 sec
train layer7 in 14.52 sec
Param value: 8, MAE=3573.4037932916804

train layer0 in 3.47 sec
train layer1 in 15.28 sec
train layer2 in 15.36 sec
train layer3 in 14.79 sec
train layer4 in 14.10 sec
train layer5 in 14.30 sec
train layer6 in 14.31 sec
train layer7 in 14.96 sec
train layer8 in 14.41 sec
train layer9 in 16.57 sec
Param value: 10, MAE=238297.05624986373
```

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

In [494]:
```
# Возьмем лучшую модель: 'TREE+RF=>LR'
# модели первого уровня
model_tree = Regressor(dataset=dataset, estimator=DecisionTreeRegre
ssor, parameters={'min_impurity_split':1.5},name='tree')
model_lr = Regressor(dataset=dataset, estimator=LinearRegression, p
arameters={'normalize': True},name='lr')
model_rf = Regressor(dataset=dataset, estimator=RandomForestRegress
or, parameters={'n_estimators': 50},name='rf')

# 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)
```

```
/home/lisobol/tensorflow_env/my_tensorflow/lib/python3.7/site-pack
ages/sklearn/tree/_classes.py:301: FutureWarning: The min_impurity
_split parameter is deprecated. Its default value will change from
1e-7 to 0 in version 0.23, and it will be removed in 0.25. Use the
min_impurity_decrease parameter instead.
  FutureWarning)
/home/lisobol/tensorflow_env/my_tensorflow/lib/python3.7/site-pack
ages/sklearn/tree/_classes.py:301: FutureWarning: The min_impurity
_split parameter is deprecated. Its default value will change from
1e-7 to 0 in version 0.23, and it will be removed in 0.25. Use the
min_impurity_decrease parameter instead.
  FutureWarning)
/home/lisobol/tensorflow_env/my_tensorflow/lib/python3.7/site-pack
ages/sklearn/tree/_classes.py:301: FutureWarning: The min_impurity
_split parameter is deprecated. Its default value will change from
1e-7 to 0 in version 0.23, and it will be removed in 0.25. Use the
min_impurity_decrease parameter instead.
  FutureWarning)
/home/lisobol/tensorflow_env/my_tensorflow/lib/python3.7/site-pack
ages/sklearn/tree/_classes.py:301: FutureWarning: The min_impurity
_split parameter is deprecated. Its default value will change from
1e-7 to 0 in version 0.23, and it will be removed in 0.25. Use the
min_impurity_decrease parameter instead.
  FutureWarning)
/home/lisobol/tensorflow_env/my_tensorflow/lib/python3.7/site-pack
ages/sklearn/tree/_classes.py:301: FutureWarning: The min_impurity
_split parameter is deprecated. Its default value will change from
1e-7 to 0 in version 0.23, and it will be removed in 0.25. Use the
min_impurity_decrease parameter instead.
```

```
  FutureWarning)
/home/lisobol/tensorflow_env/my_tensorflow/lib/python3.7/site-pack
ages/sklearn/tree/_classes.py:301: FutureWarning: The min_impurity
_split parameter is deprecated. Its default value will change from
1e-7 to 0 in version 0.23, and it will be removed in 0.25. Use the
min_impurity_decrease parameter instead.
  FutureWarning)
/home/lisobol/tensorflow_env/my_tensorflow/lib/python3.7/site-pack
ages/sklearn/tree/_classes.py:301: FutureWarning: The min_impurity
_split parameter is deprecated. Its default value will change from
1e-7 to 0 in version 0.23, and it will be removed in 0.25. Use the
min_impurity_decrease parameter instead.
  FutureWarning)
/home/lisobol/tensorflow_env/my_tensorflow/lib/python3.7/site-pack
ages/sklearn/tree/_classes.py:301: FutureWarning: The min_impurity
_split parameter is deprecated. Its default value will change from
1e-7 to 0 in version 0.23, and it will be removed in 0.25. Use the
min_impurity_decrease parameter instead.
  FutureWarning)
/home/lisobol/tensorflow_env/my_tensorflow/lib/python3.7/site-pack
ages/sklearn/tree/_classes.py:301: FutureWarning: The min_impurity
_split parameter is deprecated. Its default value will change from
1e-7 to 0 in version 0.23, and it will be removed in 0.25. Use the
min_impurity_decrease parameter instead.
  FutureWarning)
/home/lisobol/tensorflow_env/my_tensorflow/lib/python3.7/site-pack
ages/sklearn/tree/_classes.py:301: FutureWarning: The min_impurity
_split parameter is deprecated. Its default value will change from
1e-7 to 0 in version 0.23, and it will be removed in 0.25. Use the
min_impurity_decrease parameter instead.
  FutureWarning)
/home/lisobol/tensorflow_env/my_tensorflow/lib/python3.7/site-pack
ages/sklearn/tree/_classes.py:301: FutureWarning: The min_impurity
_split parameter is deprecated. Its default value will change from
1e-7 to 0 in version 0.23, and it will be removed in 0.25. Use the
min_impurity_decrease parameter instead.
  FutureWarning)

Metric: mean_absolute_error
Folds accuracy: [82.93794770962629, 76.72190307693761, 76.38549607
849212, 81.42345670530885, 77.26296958822235, 75.66363891065595, 8
5.54545956892413, 79.799864867851, 79.92263363066833, 81.327496397
69646]
Mean accuracy: 79.6990866534383
Standard Deviation: 3.0400428691952763
Variance: 9.241860646545048
```

Удалось немного улучшить результат

Метод группового учета аргументов

In [81]:
```
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 17.21 sec
train layer1 in 70.49 sec
train layer2 in 70.70 sec
train layer3 in 71.41 sec
train layer4 in 75.24 sec
train layer5 in 72.57 sec
MAE=1111093477670.3252
```

Результат удалось существенно улучшить, однако ошибка все еще очень большая, модель требует дальнейшего исследования, пока она к данной задаче не применима.

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. Ансамблевые методы с линейной регрессией на первом уровне показали себя хуже всего. Так же было выяснено, что модель случайный лес по тосности соспоставима с лучшими ансамблевыми моделями, хотя все же совсем немного им уступает.
- Метод группового учета оказался сложнее в настройке и хотя и удалось значительно улучшить результат, этого оказалось недостаточно, поскольку ошибка все еще слишком большая.

In [ ]:
```

```