ММО ДЗ Яковлев Д. С. ИУ5-21М

Задание

Домашнее задание по дисциплине направлено на решение комплексной задачи машинного обучения. Домашнее задание включает выполнение следующих шагов:

1. Поиск и выбор набора данных для построения моделей машинного обучения. На основе выбранного набора данных студент должен построить модели машинного обучения для решения или задачи классификации, или задачи регрессии.
2. Проведение разведочного анализа данных. Построение графиков, необходимых для понимания структуры данных. Анализ и заполнение пропусков в данных.
3. Выбор признаков, подходящих для построения моделей. Кодирование категориальных признаков. Масштабирование данных. Формирование вспомогательных признаков, улучшающих качество моделей.
4. Проведение корреляционного анализа данных. Формирование промежуточных выводов о возможности построения моделей машинного обучения. В зависимости от набора данных, порядок выполнения пунктов 2, 3, 4 может быть изменен.
5. Выбор метрик для последующей оценки качества моделей. Необходимо выбрать не менее двух метрик и обосновать выбор.
6. Выбор наиболее подходящих моделей для решения задачи классификации или регрессии. Необходимо использовать не менее трех моделей, хотя бы одна из которых должна быть ансамблевой.
7. Формирование обучающей и тестовой выборок на основе исходного набора данных.
8. Построение базового решения (baseline) для выбранных моделей без подбора гиперпараметров. Производится обучение моделей на основе обучающей выборки и оценка качества моделей на основе тестовой выборки.
9. Подбор гиперпараметров для выбранных моделей. Рекомендуется подбирать не более 1-2 гиперпараметров. Рекомендуется использовать методы кросс-валидации. В зависимости от используемой библиотеки можно применять функцию GridSearchCV, использовать перебор параметров в цикле, или использовать другие методы.
10. Повторение пункта 8 для найденных оптимальных значений гиперпараметров. Сравнение качества полученных моделей с качеством baseline-моделей.
11. Формирование выводов о качестве построенных моделей на основе выбранных метрик.

Решение

In [2]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import MinMaxScaler
from sklearn.linear_model import LinearRegression, LogisticRegressi
on
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsRegressor, KNeighborsClassi
fier
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.metrics import plot_confusion_matrix
from sklearn.model_selection import GridSearchCV
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
from sklearn.svm import SVC, NuSVC, LinearSVC, OneClassSVM, SVR, Nu
SVR, LinearSVR
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.utils import shuffle
# !pip install gmdhpy
from gmdhpy import gmdh
%matplotlib inline
sns.set(style="ticks")
```

1. Поиск и выбор набора данных для построения моделей машинного обучения. На основе выбранного набора данных построение модели машинного обучения для решения или задачи регрессии.

В качестве набора данных возьмем набор с данными о песнях и их характеристиках.

Набор содержит такие колонки как:

- song_name - название песни
- song_popularity - индекс популярности песни
- song_duration_ms - длительность в мс
- acousticness - индекс акустики
- danceability - индекс танцевальности
- energy - индекс энергичности
- instrumentalness - индекс инструментальности
- key - ключ
- liveness - индекс живости
- loudness - индекс громкости
- audio_mode - режим аудио
- speechiness - индекс разговорности
- tempo - темп
- time_signature - временная метка
- audio_valence

Поставим задачу предсказания популярности песни по данным характеристикам. Построим модель машинного обучения для данного набора и решим задачу регрессии.

2. Проведение разведочного анализа данных. Построение графиков, необходимых для понимания структуры данных. Анализ и заполнение пропусков в данных.

In [4]:
```
data = pd.read_csv('data/song_data.csv', sep=',')
data.head()
```

Out[4]:

	song_name	song_popularity	song_duration_ms	acousticness	danceability	energy	inst
0	Boulevard of Broken Dreams	73	262333	0.005520	0.496	0.682	
1	In The End	66	216933	0.010300	0.542	0.853	
2	Seven Nation Army	76	231733	0.008170	0.737	0.463	
3	By The Way	74	216933	0.026400	0.451	0.970	
4	How You Remind Me	56	223826	0.000954	0.447	0.766	

In [5]:
```
data.shape
```

Out[5]:
```
(18835, 15)
```

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

Out[6]:
```
Index(['song_name', 'song_popularity', 'song_duration_ms', 'acoust
icness',
       'danceability', 'energy', 'instrumentalness', 'key', 'liven
ess',
       'loudness', 'audio_mode', 'speechiness', 'tempo', 'time_sig
nature',
       'audio_valence'],
      dtype='object')
```

In [7]:
```
data.isnull().sum()
```

Out[7]:
```
song_name           0
song_popularity     0
song_duration_ms    0
acousticness        0
danceability        0
energy              0
instrumentalness    0
key                 0
liveness            0
loudness            0
audio_mode          0
speechiness         0
tempo               0
time_signature      0
audio_valence       0
dtype: int64
```

In [9]:
```
data.dtypes
```

Out[9]:
```
song_name             object
song_popularity        int64
song_duration_ms       int64
acousticness         float64
danceability         float64
energy               float64
instrumentalness     float64
key                    int64
liveness             float64
loudness             float64
audio_mode             int64
speechiness          float64
tempo                float64
time_signature         int64
audio_valence        float64
dtype: object
```

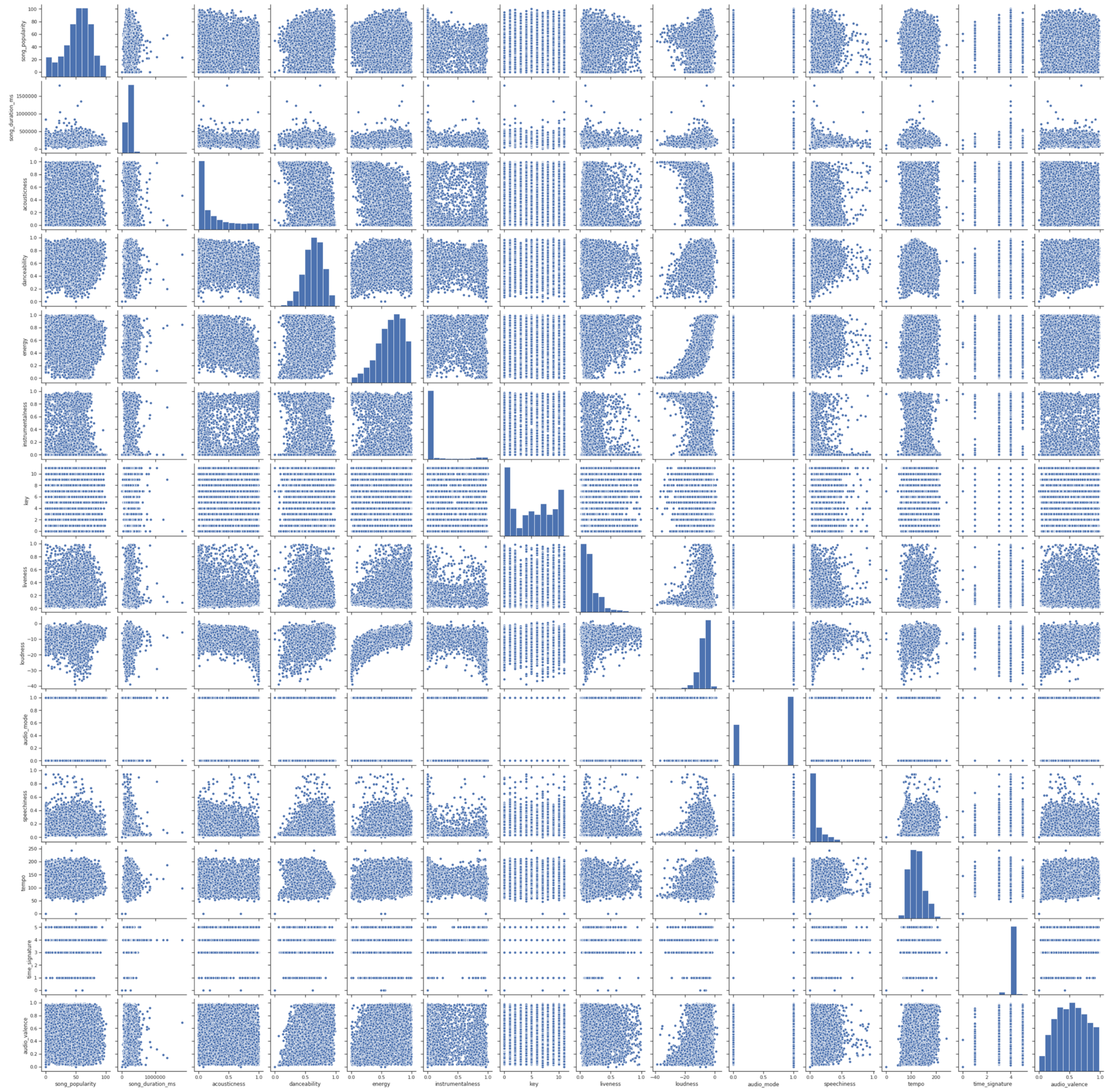
In [10]:
```
data.describe()
```

Out[10]:

	song_popularity	song_duration_ms	acousticness	danceability	energy	instr
count	18835.000000	1.883500e+04	18835.000000	18835.000000	18835.000000	1
mean	52.991877	2.182116e+05	0.258539	0.633348	0.644995	
std	21.905654	5.988754e+04	0.288719	0.156723	0.214101	
min	0.000000	1.200000e+04	0.000001	0.000000	0.001070	
25%	40.000000	1.843395e+05	0.024100	0.533000	0.510000	
50%	56.000000	2.113060e+05	0.132000	0.645000	0.674000	
75%	69.000000	2.428440e+05	0.424000	0.748000	0.815000	
max	100.000000	1.799346e+06	0.996000	0.987000	0.999000	

In [14]:
```
sns.pairplot(data)
```

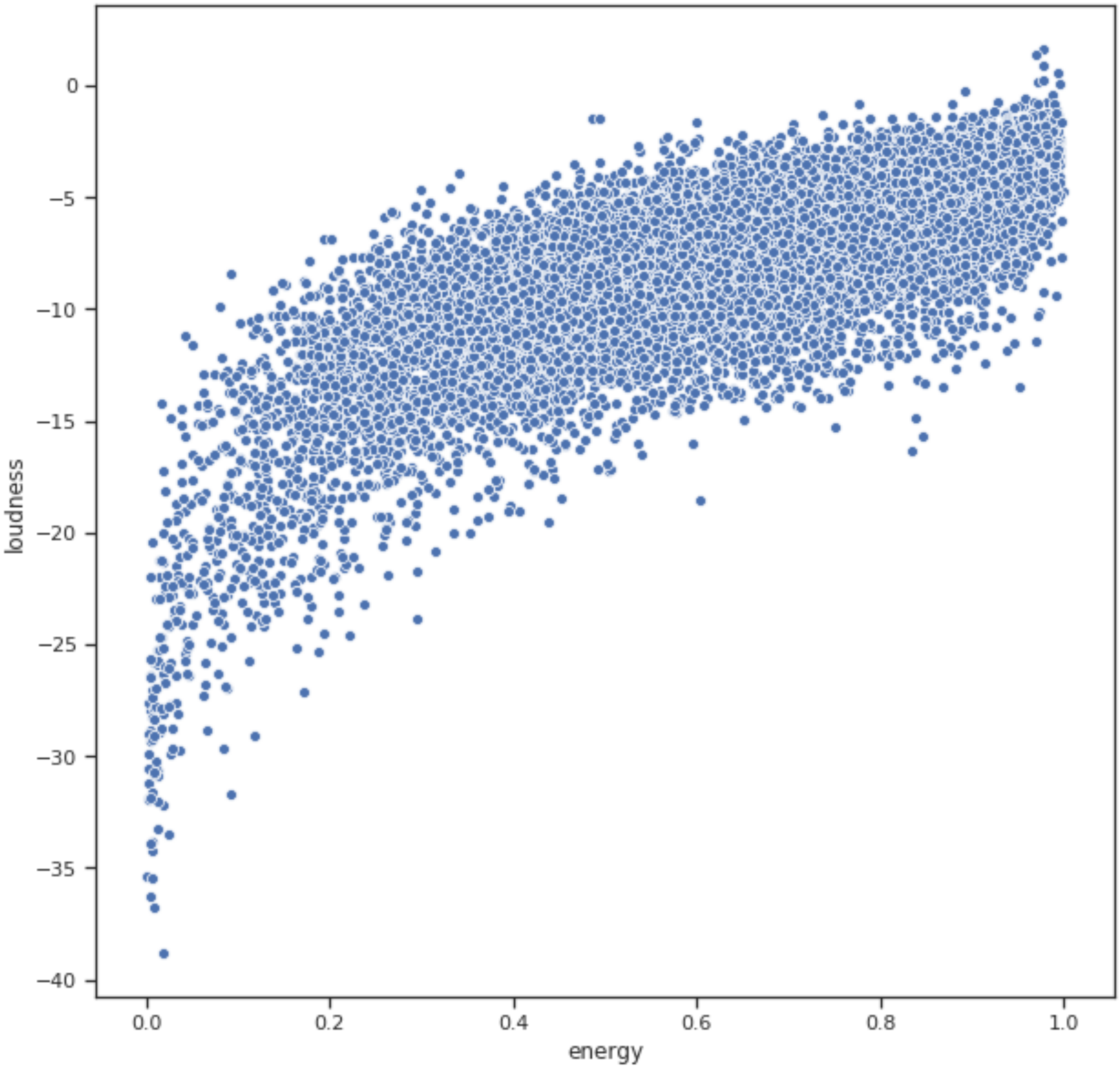
Out[14]: <seaborn.axisgrid.PairGrid at 0x7fbd3ff7a7d0>



Видим, что наиболее заметна корреляция таких характеристик как громкость и энергичность. В остальных случаях зависимости не такие очевидные.

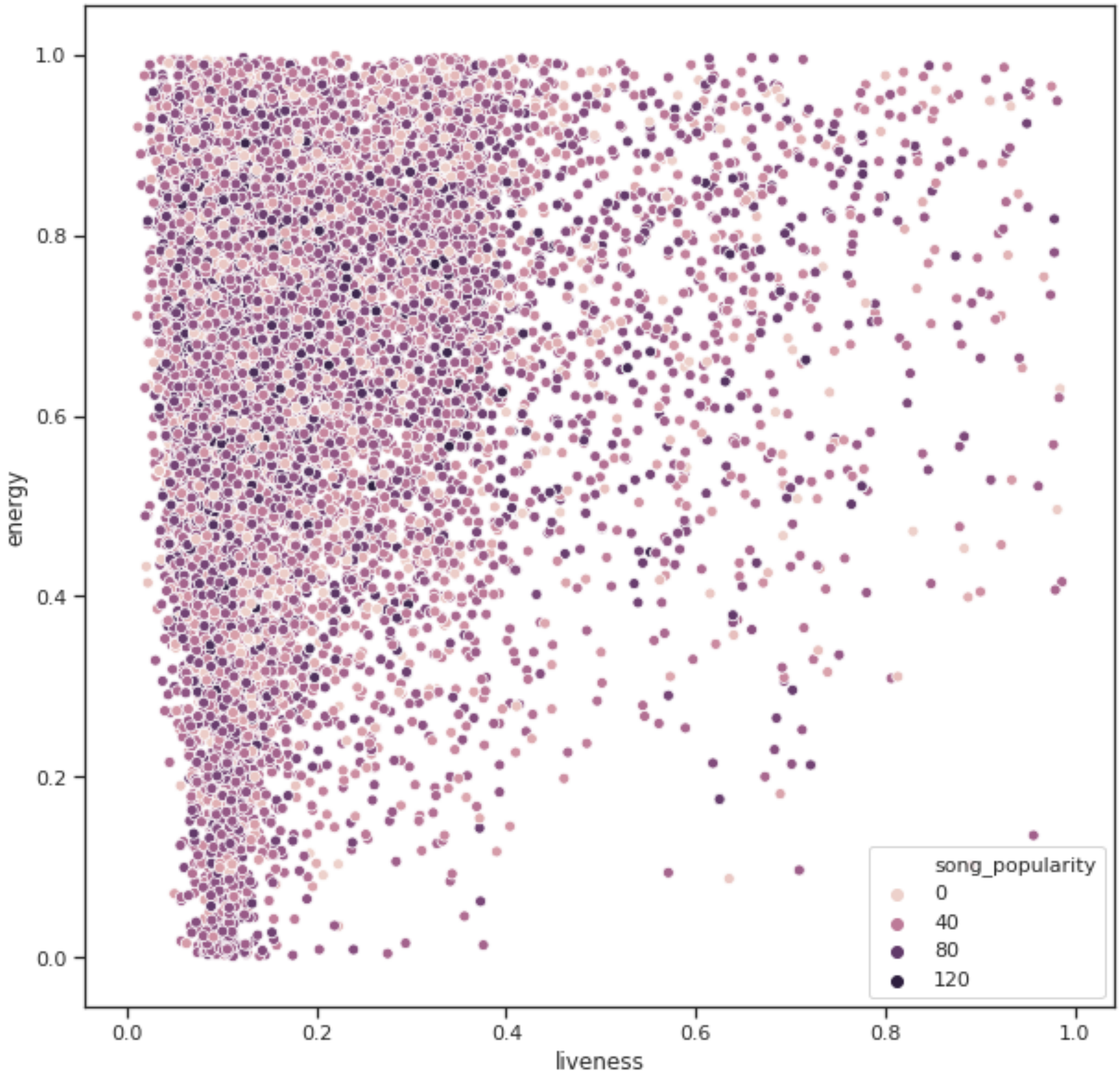
In [15]:
```
fig, ax = plt.subplots(figsize=(10,10))
sns.scatterplot(ax=ax, x='energy', y='loudness', data=data)
```

Out[15]: <matplotlib.axes._subplots.AxesSubplot at 0x7fbd3467b410>



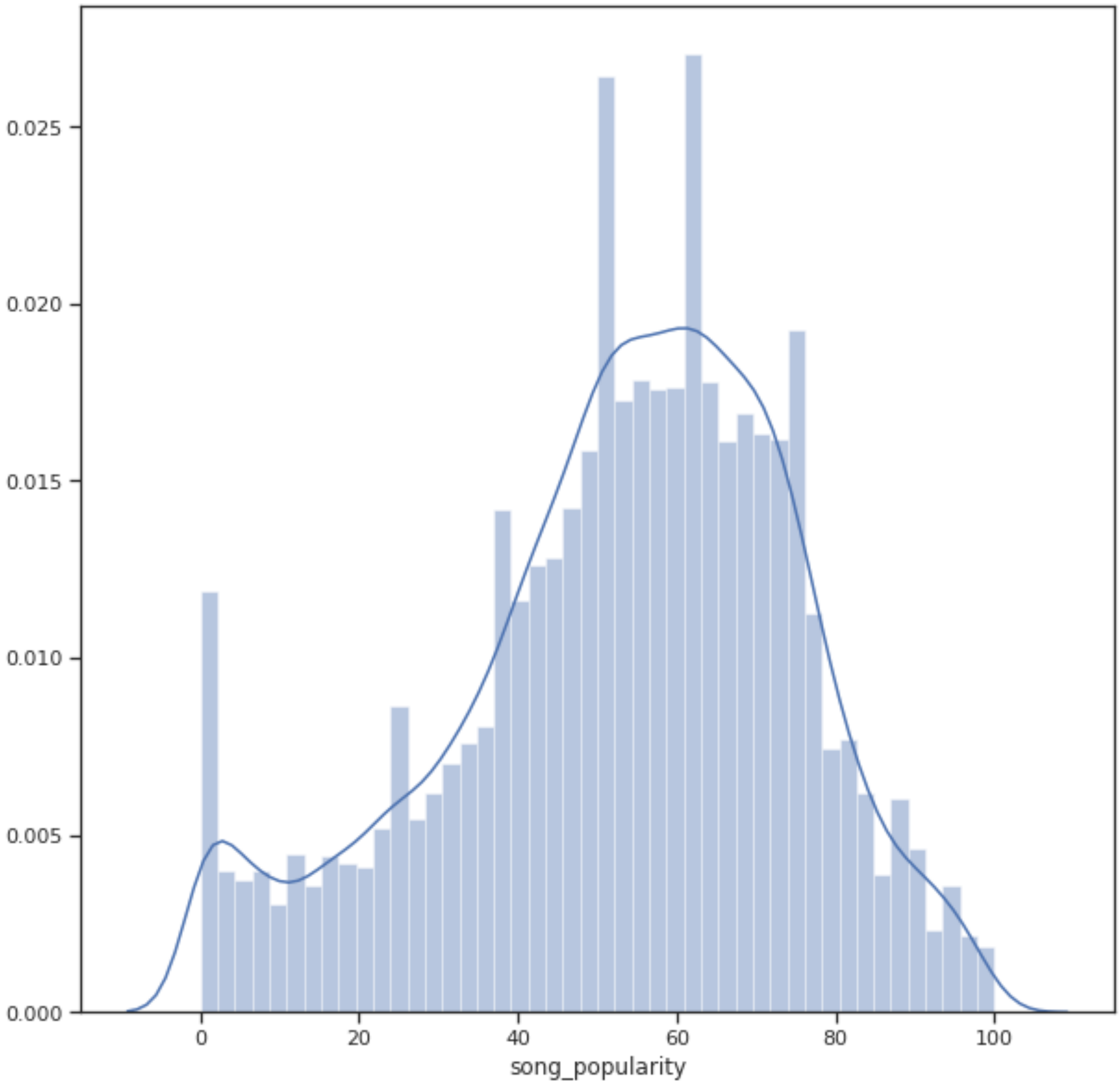
In [22]:
```
fig, ax = plt.subplots(figsize=(10,10))
sns.scatterplot(ax=ax, x='liveness', y='energy', data=data, hue='so
ng_popularity')
```

Out[22]: <matplotlib.axes._subplots.AxesSubplot at 0x7fbd32a99d90>



In [23]:
```
fig, ax = plt.subplots(figsize=(10,10))
sns.distplot(data['song_popularity'])
```

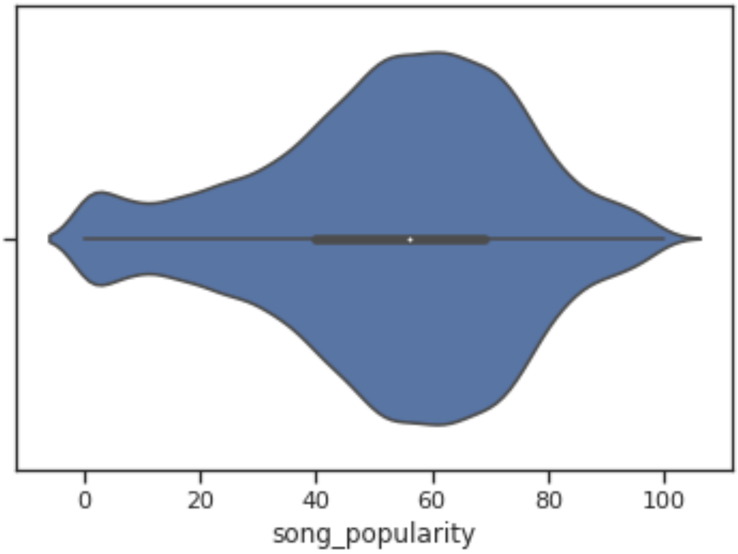
Out[23]: <matplotlib.axes._subplots.AxesSubplot at 0x7fbd32a23a50>

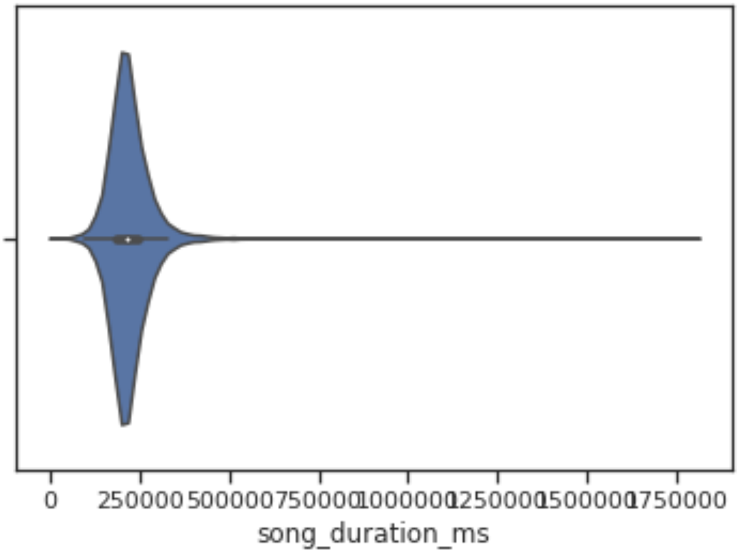


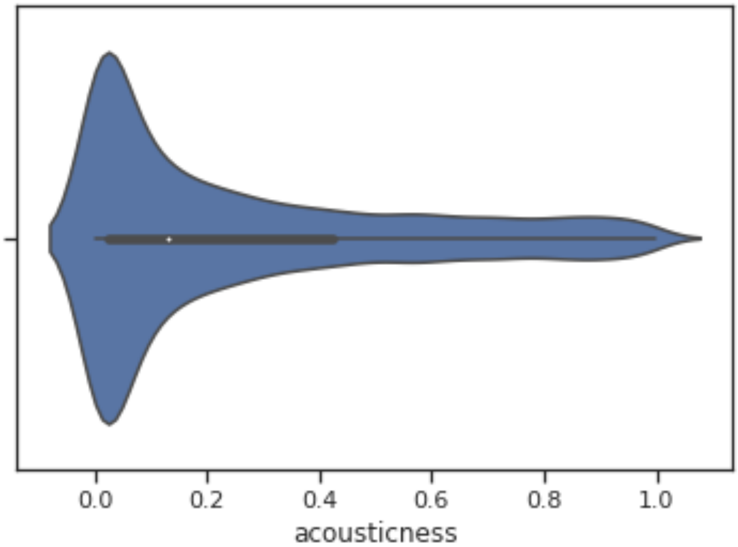
In [24]:
```
data.columns
```

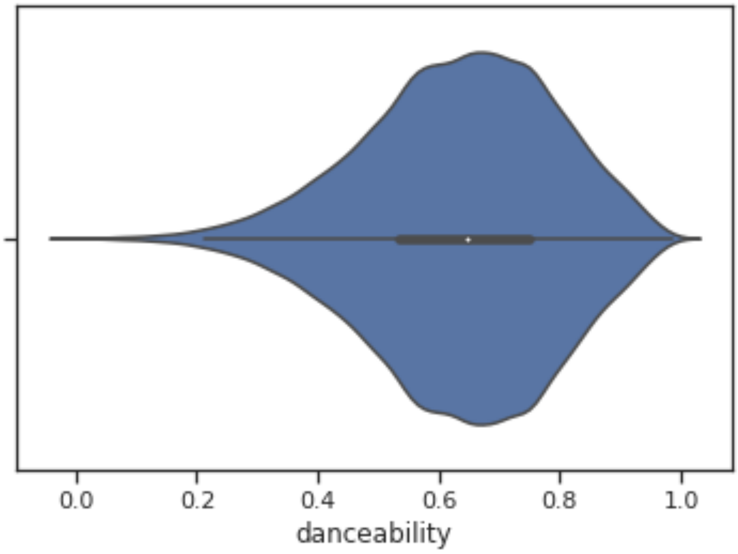
Out[24]:
```
Index(['song_name', 'song_popularity', 'song_duration_ms', 'acoust
icness',
       'danceability', 'energy', 'instrumentalness', 'key', 'liven
ess',
       'loudness', 'audio_mode', 'speechiness', 'tempo', 'time_sig
nature',
       'audio_valence'],
      dtype='object')
```

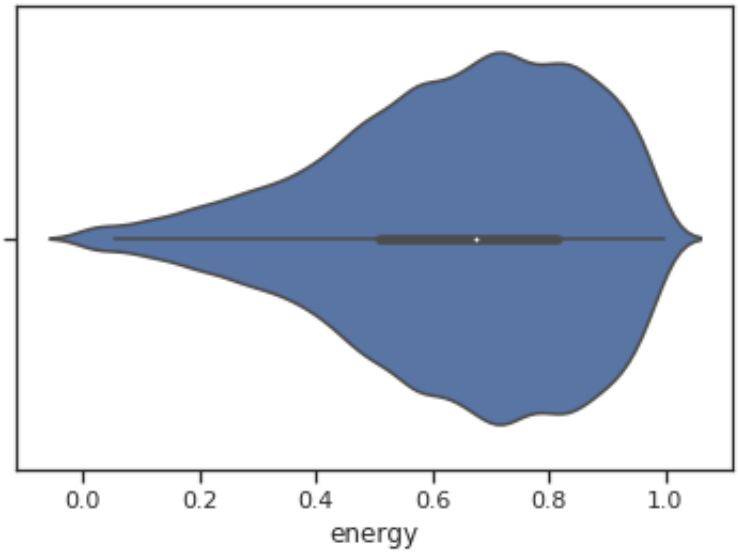
In [26]:
```
# Скрипичные диаграммы для числовых колонок
for col in [ 'song_popularity', 'song_duration_ms', 'acousticness',
        'danceability', 'energy', 'instrumentalness', 'key', 'livene
ss',
        'loudness', 'audio_mode', 'speechiness', 'tempo', 'time_sign
ature',
        'audio_valence']:

    sns.violinplot(x=data[col])
    plt.show()
```

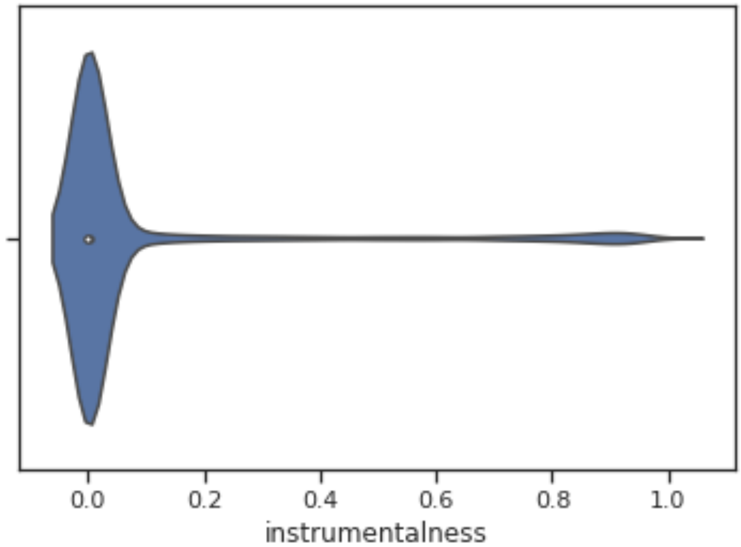


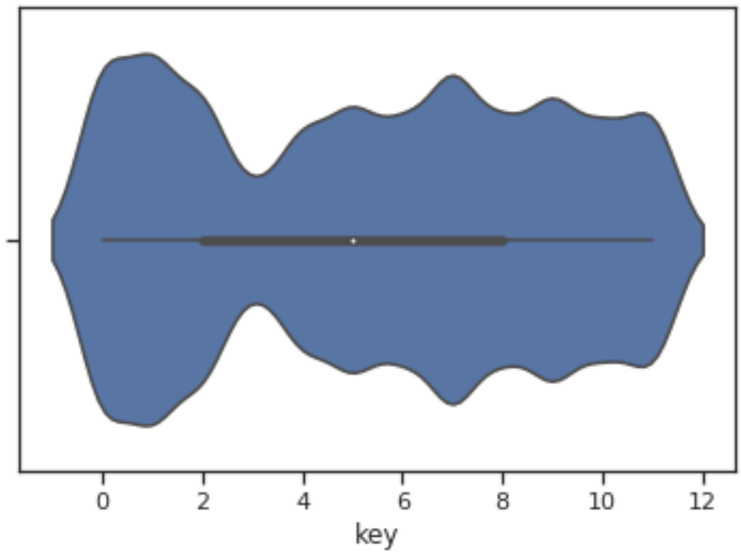


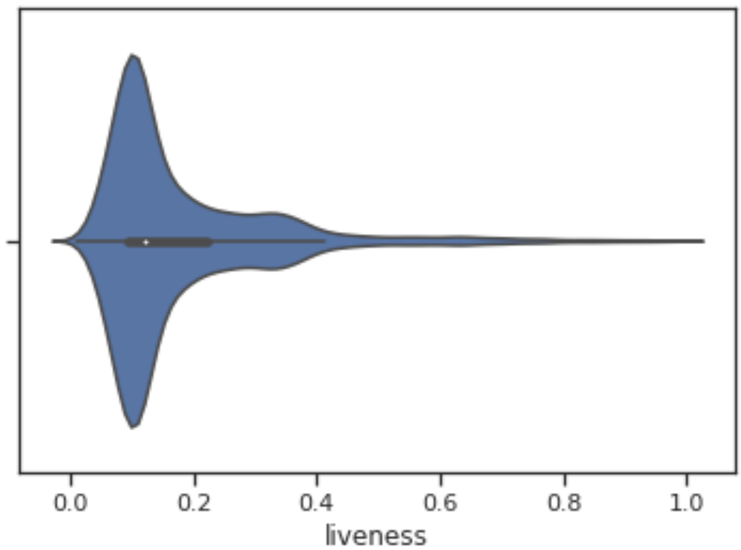

0.0
0.2
0.4
0.6
0.8
1.0
acousticness

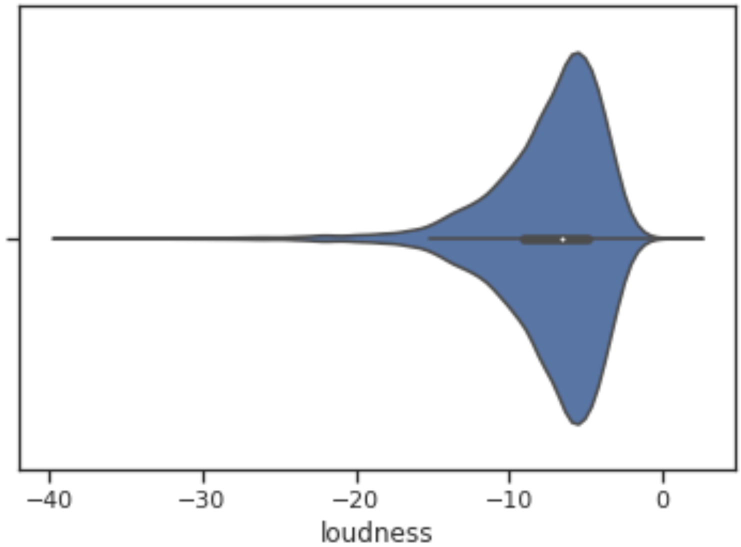

0.0
0.2
0.4
0.6
0.8
1.0
danceability

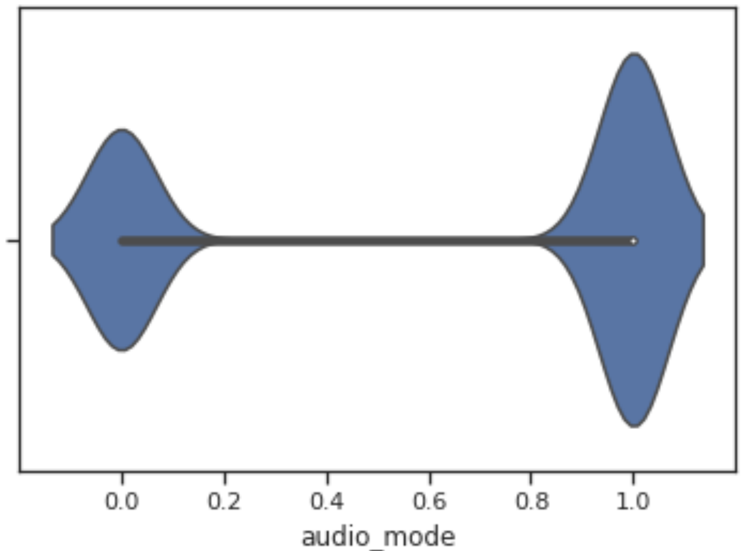

0.0
0.2
0.4
0.6
0.8
1.0
energy

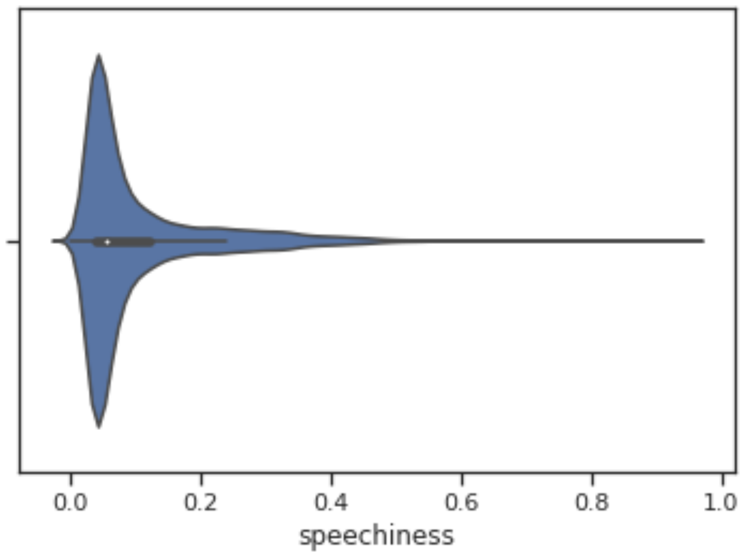

0.0
0.2
0.4
0.6
0.8
1.0
instrumentalness

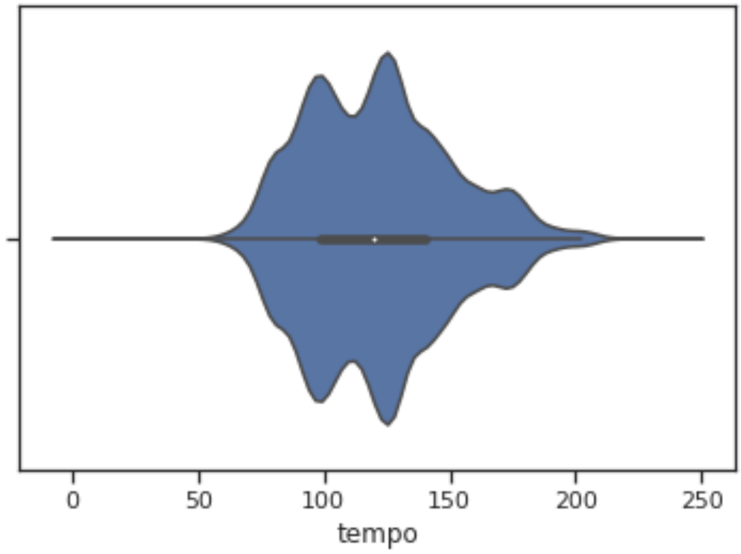

0
2
4
6
8
10
12
key

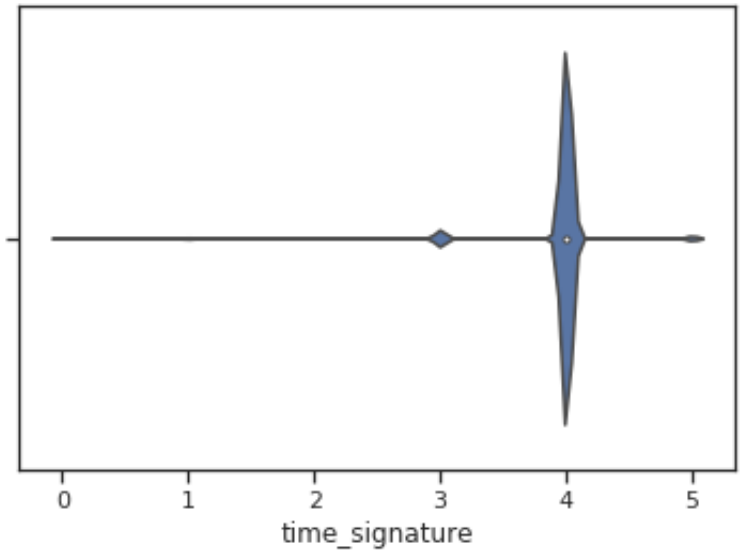

0.0
0.2
0.4
0.6
0.8
1.0
liveness

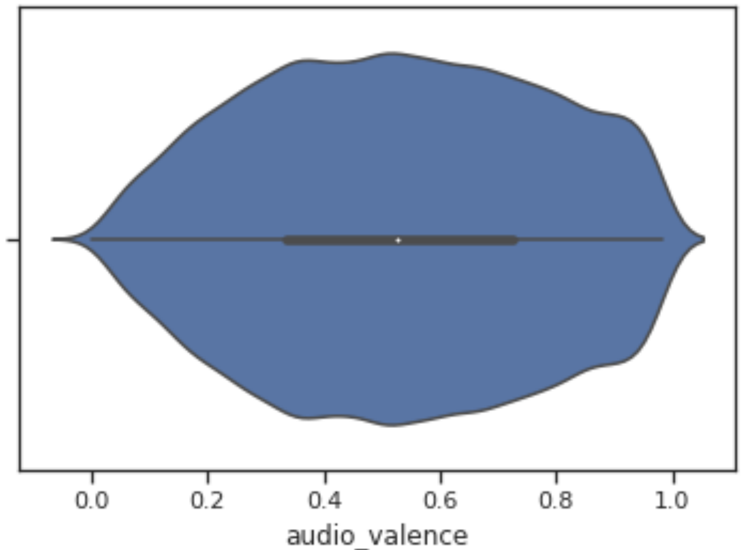

−40
−30
−20
−10
0
loudness


0.0
0.2
0.4
0.6
0.8
1.0
audio_mode


0.0
0.2
0.4
0.6
0.8
1.0
speechiness


0
50
100
150
200
250
tempo


0
1
2
3
4
5
time_signature


0.0
0.2
0.4
0.6
0.8
1.0
audio_valence

In [ ]:

In [ ]:

In [ ]:

Анализ и заполнение пропусков в данных.

Поскольку в данном наборе пустых значений нет, пропустим данный пункт.

3. Выбор признаков, подходящих для построения моделей. Кодирование категориальных признаков. Масштабирование данных. Формирование вспомогательных признаков, улучшающих качество моделей.

Кодирование категориальных признаков числовыми

In [28]:
```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
data['song_name'] = le.fit_transform(data['song_name'])
data.dtypes
```

Out[28]:
```
song_name              int64
song_popularity        int64
song_duration_ms       int64
acousticness         float64
danceability         float64
energy               float64
instrumentalness     float64
key                    int64
liveness             float64
loudness             float64
audio_mode             int64
speechiness          float64
tempo                float64
time_signature         int64
audio_valence        float64
dtype: object
```

In [29]:
```
data.head()
```

Out[29]:

	song_name	song_popularity	song_duration_ms	acousticness	danceability	energy	inst
0	1561	73	262333	0.005520	0.496	0.682	
1	5541	66	216933	0.010300	0.542	0.853	
2	9638	76	231733	0.008170	0.737	0.463	
3	1760	74	216933	0.026400	0.451	0.970	
4	4988	56	223826	0.000954	0.447	0.766	

Масштабирование данных.

In [30]:
```
scale_cols = ['song_popularity', 'song_duration_ms', 'acousticness'
,
        'danceability', 'energy', 'instrumentalness', 'key', 'livene
ss',
        'loudness', 'audio_mode', 'speechiness', 'tempo', 'time_sign
ature',
        'audio_valence']
```

In [31]:
```
data.columns
```

Out[31]:
```
Index(['song_name', 'song_popularity', 'song_duration_ms', 'acoust
icness',
       'danceability', 'energy', 'instrumentalness', 'key', 'liven
ess',
       'loudness', 'audio_mode', 'speechiness', 'tempo', 'time_sig
nature',
       'audio_valence'],
      dtype='object')
```

In [32]:
```
sc1 = MinMaxScaler()
sc1_data = sc1.fit_transform(data[scale_cols])
```

In [33]:
```
# Добавим масштабированные данные в набор данных
for i in range(len(scale_cols)):
    col = scale_cols[i]
    new_col_name = col + '_scaled'
    data[new_col_name] = sc1_data[:,i]
```

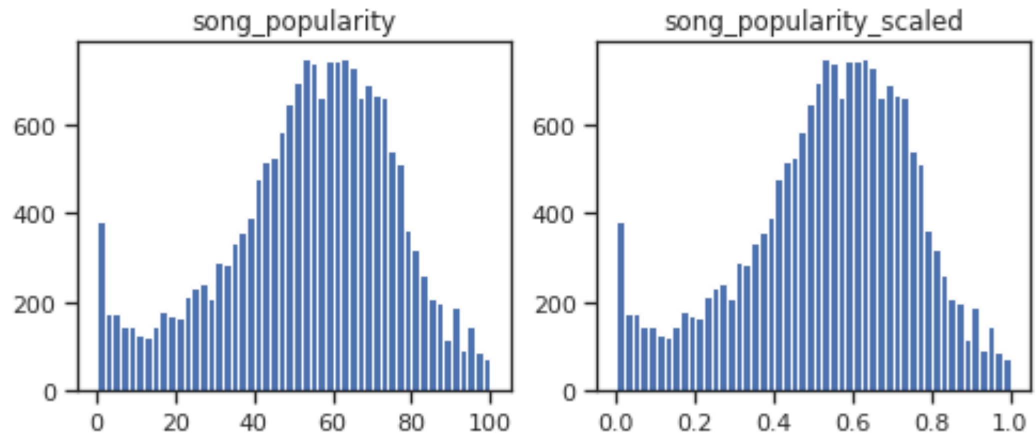
In [34]:
```
data.head()
```

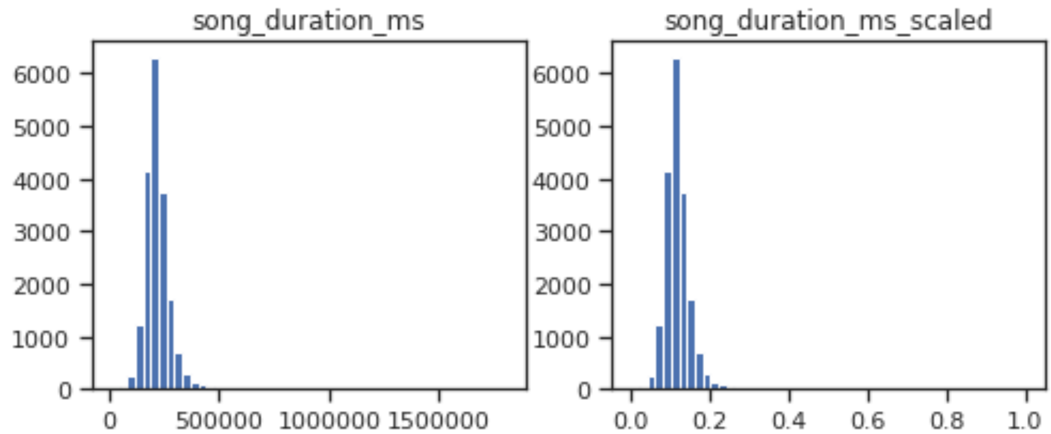
Out[34]:

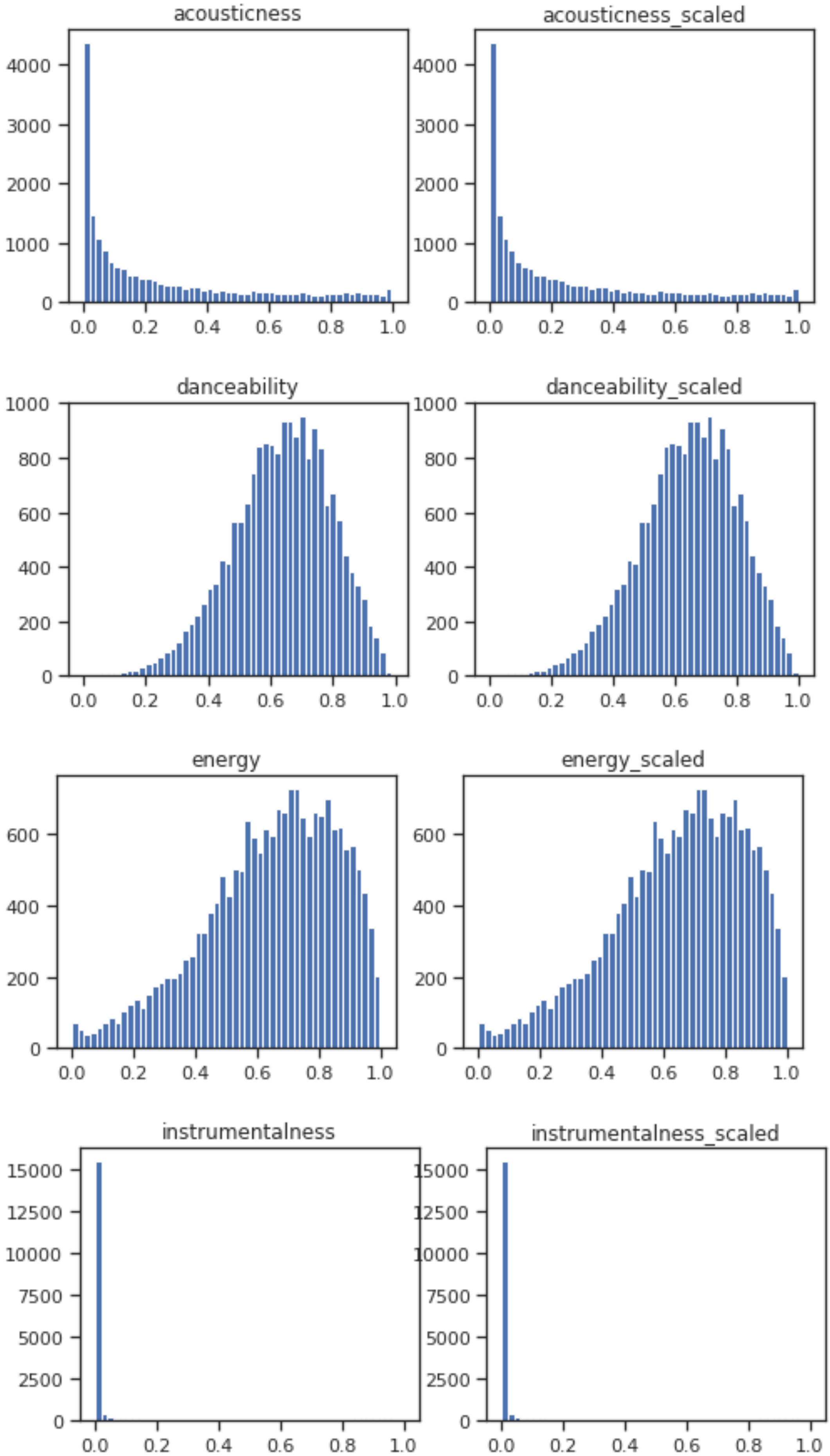
	song_name	song_popularity	song_duration_ms	acousticness	danceability	energy	inst
0	1561	73	262333	0.005520	0.496	0.682	
1	5541	66	216933	0.010300	0.542	0.853	
2	9638	76	231733	0.008170	0.737	0.463	
3	1760	74	216933	0.026400	0.451	0.970	
4	4988	56	223826	0.000954	0.447	0.766	

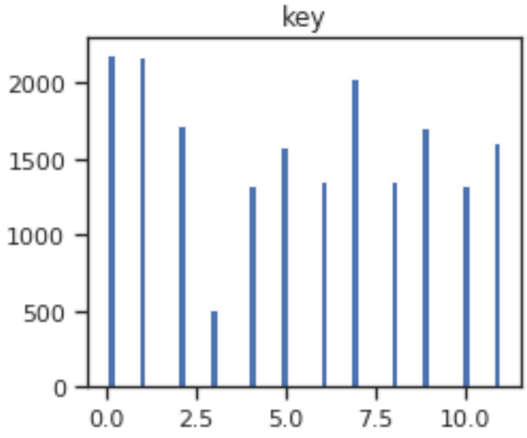
5 rows × 29 columns

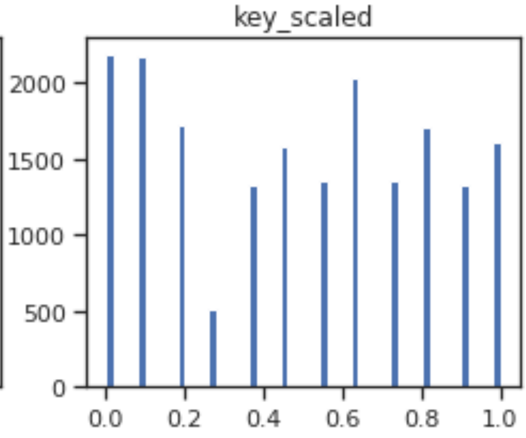
In [35]:
```
# Проверим, что масштабирование не повлияло на распределение данных
for col in scale_cols:
    col_scaled = col + '_scaled'

    fig, ax = plt.subplots(1, 2, figsize=(8,3))
    ax[0].hist(data[col], 50)
    ax[1].hist(data[col_scaled], 50)
    ax[0].title.set_text(col)
    ax[1].title.set_text(col_scaled)
    plt.show()
```

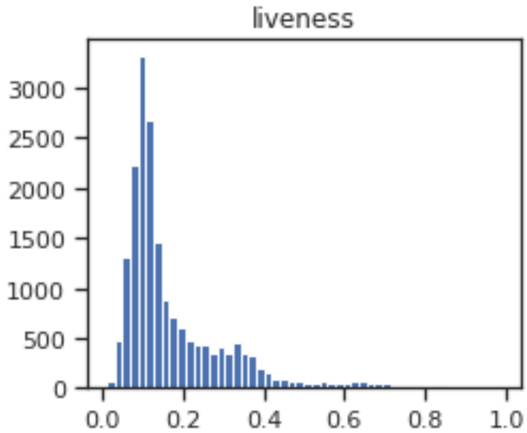


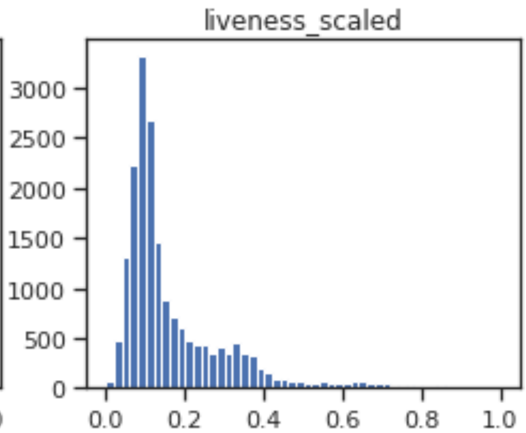


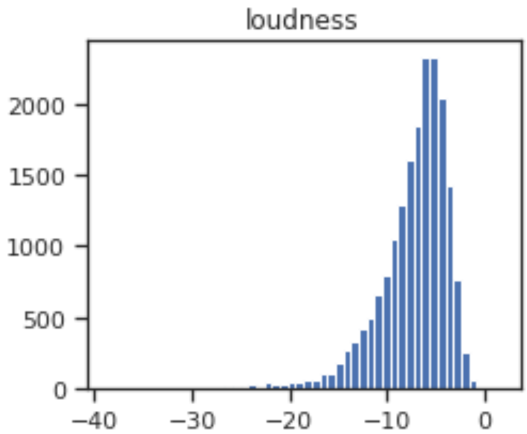

acousticness
acousticness_scaled
danceability
danceability_scaled
energy
energy_scaled
instrumentalness
instrumentalness_scaled
0.0 0.2 0.4 0.6 0.8 1.0
0 1000 2000 3000 4000
0 200 400 600 800 1000
0 200 400 600
0 2500 5000 7500 10000 12500 15000

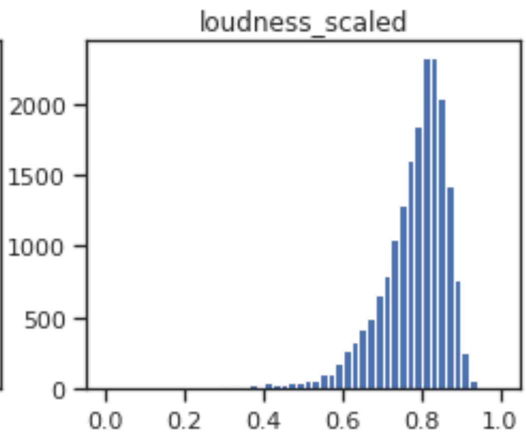

key
0 500 1000 1500 2000
0.0 2.5 5.0 7.5 10.0

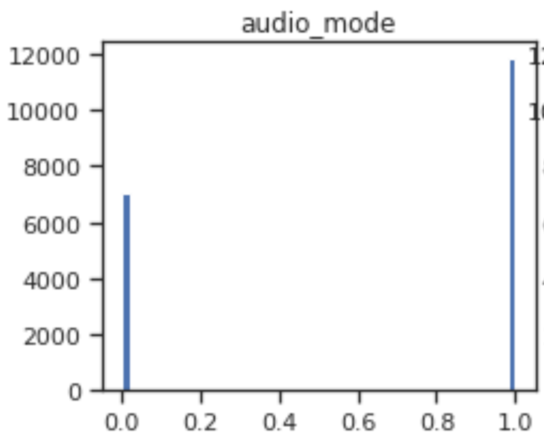

key_scaled
0 500 1000 1500 2000
0.0 0.2 0.4 0.6 0.8 1.0

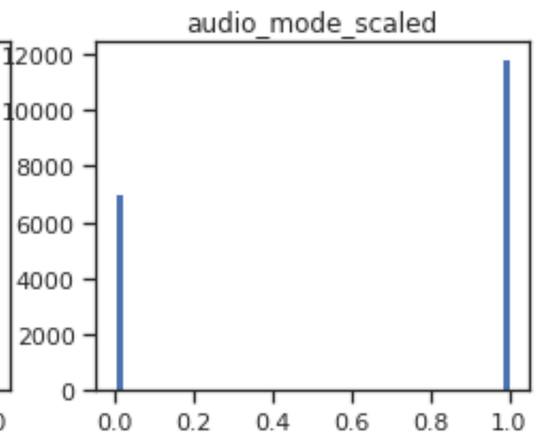

liveness
0 500 1000 1500 2000 2500 3000
0.0 0.2 0.4 0.6 0.8 1.0

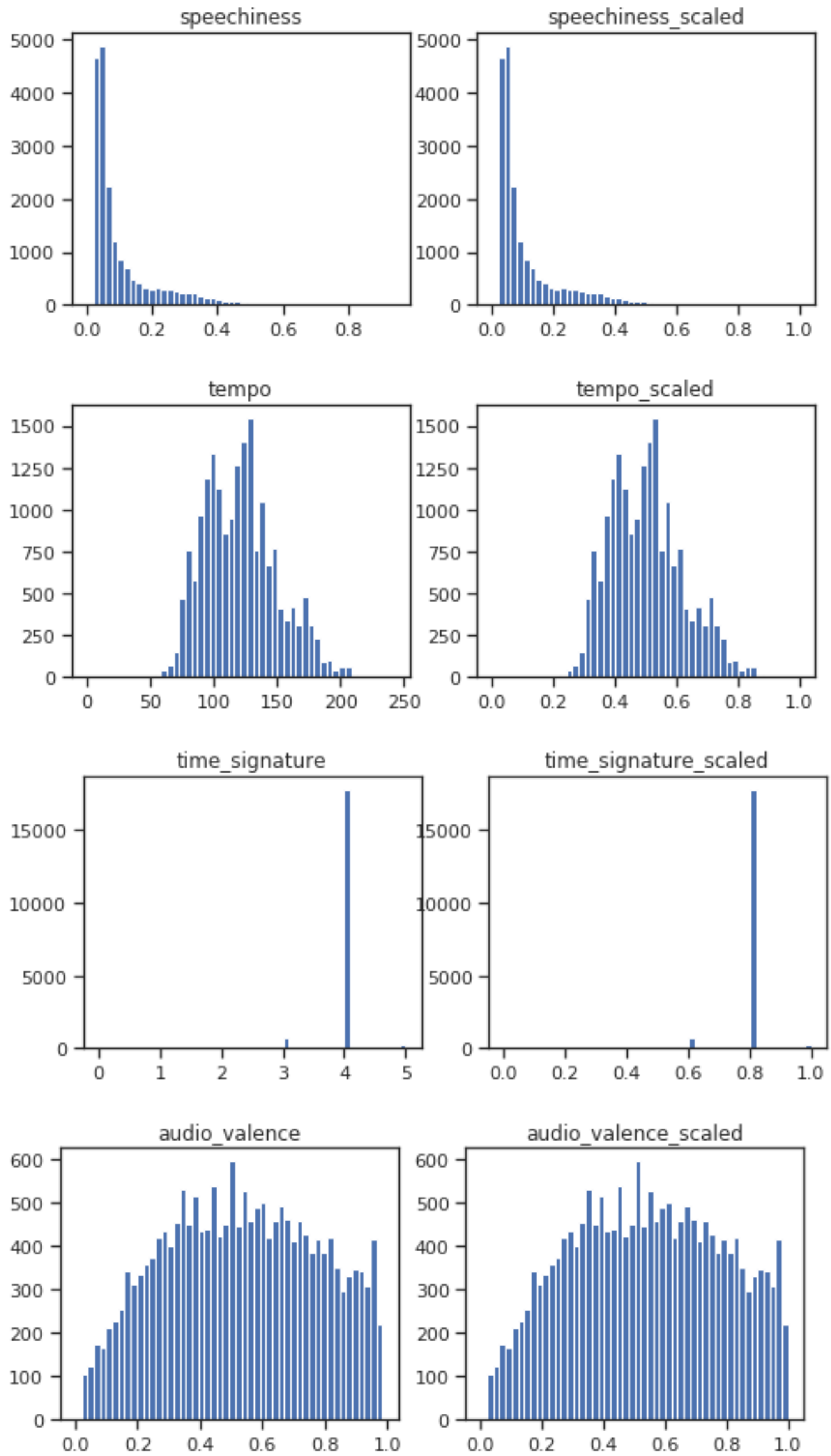

liveness_scaled
0 500 1000 1500 2000 2500 3000
0.0 0.2 0.4 0.6 0.8 1.0


loudness
0 500 1000 1500 2000
−40 −30 −20 −10 0


loudness_scaled
0 500 1000 1500 2000
0.0 0.2 0.4 0.6 0.8 1.0


audio_mode
0 2000 4000 6000 8000 10000 12000
0.0 0.2 0.4 0.6 0.8 1.0


audio_mode_scaled
0 2000 4000 6000 8000 10000 12000
0.0 0.2 0.4 0.6 0.8 1.0


speechiness
speechiness_scaled
tempo
tempo_scaled
time_signature
time_signature_scaled
audio_valence
audio_valence_scaled

4. Проведение корреляционного анализа данных. Формирование промежуточных выводов о возможности построения моделей машинного обучения.

In [36]:
```
# Воспользуемся наличием тестовых выборок,
# включив их в корреляционную матрицу
corr_cols_1 = scale_cols
corr_cols_1
```

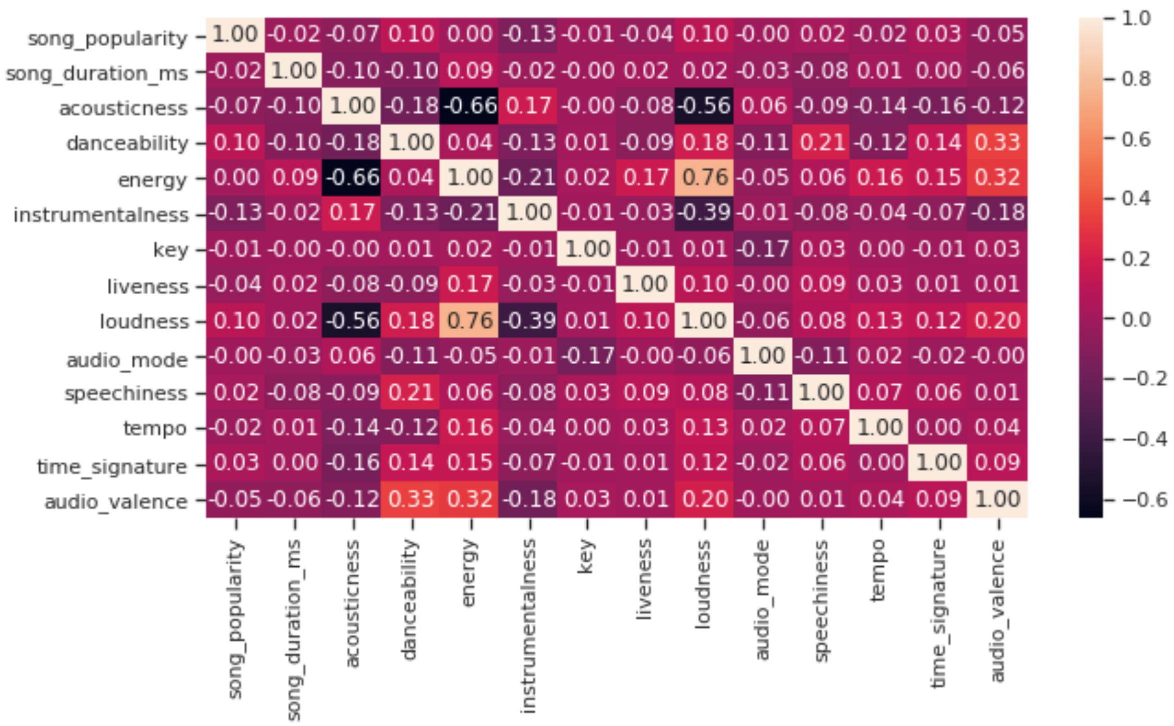
Out[36]:
```
['song_popularity',
 'song_duration_ms',
 'acousticness',
 'danceability',
 'energy',
 'instrumentalness',
 'key',
 'liveness',
 'loudness',
 'audio_mode',
 'speechiness',
 'tempo',
 'time_signature',
 'audio_valence']
```

In [37]:
```
scale_cols_postfix = [x+'_scaled' for x in scale_cols]
corr_cols_2 = scale_cols_postfix
corr_cols_2
```

Out[37]:
```
['song_popularity_scaled',
 'song_duration_ms_scaled',
 'acousticness_scaled',
 'danceability_scaled',
 'energy_scaled',
 'instrumentalness_scaled',
 'key_scaled',
 'liveness_scaled',
 'loudness_scaled',
 'audio_mode_scaled',
 'speechiness_scaled',
 'tempo_scaled',
 'time_signature_scaled',
 'audio_valence_scaled']
```

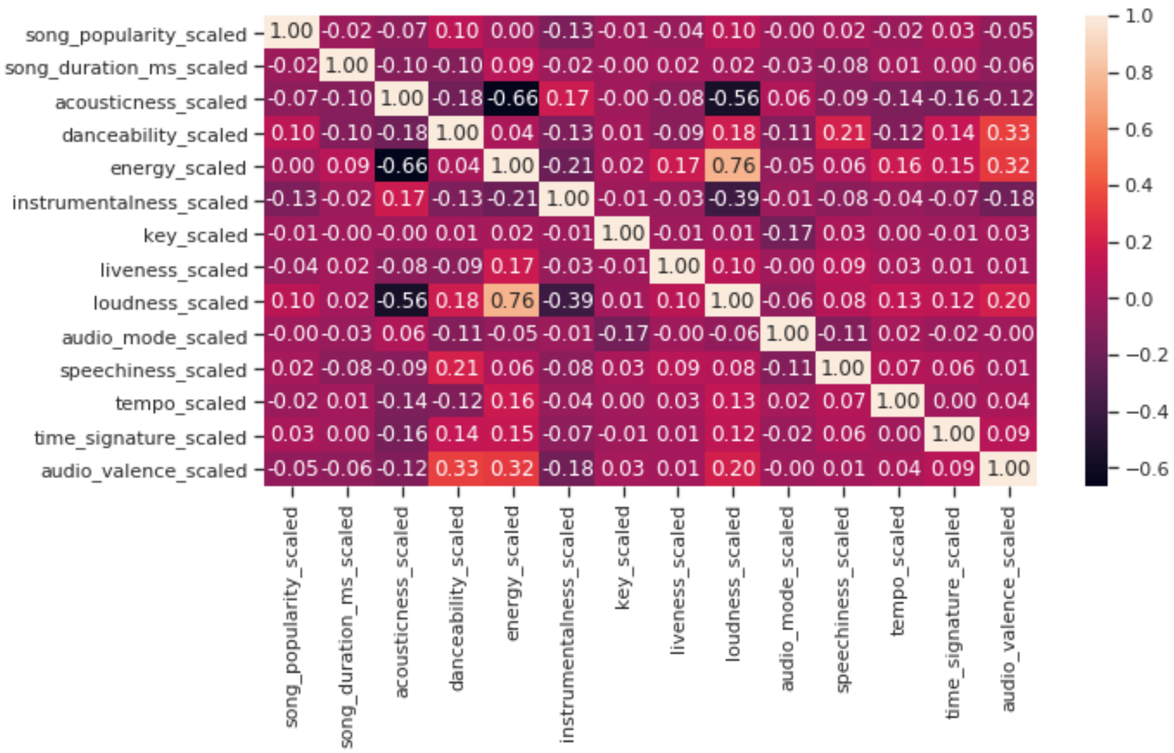
In [38]:
```
fig, ax = plt.subplots(figsize=(10,5))
sns.heatmap(data[corr_cols_1].corr(), annot=True, fmt='.2f')
```

Out[38]: <matplotlib.axes._subplots.AxesSubplot at 0x7fbd31befc90>



In [39]:
```
fig, ax = plt.subplots(figsize=(10,5))
sns.heatmap(data[corr_cols_2].corr(), annot=True, fmt='.2f')
```

Out[39]: <matplotlib.axes._subplots.AxesSubplot at 0x7fbd31da5fd0>



- Видим, что популярность песни не сильно коррелирует с данными характеристиками. Наибольшее влияние на популярность оказывают такие признаки как танцевальность трека и громкость.
- Наибольшую корреляцию видим между громкостью и энергичностью трека, как и во 2 пункте.

5. Выбор метрик для последующей оценки качества моделей. Необходимо выбрать не менее двух метрик и обосновать выбор.

Возьмем метрики MAE, Median Absolute Error и R^2.

- MAE (Mean Absolute Error) — это среднее абсолютное значение ошибки(среднее модуля ошибки). Данная метрика удобна, так как показывает среднюю ошибку, но при этом не так чувствительна к выбросам, как, например, MSE.
- Медиана абсолютного отклонения(Median Absolute Error) - это альтернатива стандартного отклонения, но она менее чувствительна к воздействию промахов, чем среднее отклонение.
- Коэффициент детерминации, или R^2 покажет насколько модель соответствует или не соответствует данным.

In [41]:
```
class MetricLogger:

    def __init__(self):
        self.df = pd.DataFrame(
            {'metric': pd.Series([], dtype='str'),
            'alg': pd.Series([], dtype='str'),
            'value': pd.Series([], dtype='float')})

    def add(self, metric, alg, value):
        """
        Добавление значения
        """
        # Удаление значения если оно уже было ранее добавлено
        self.df.drop(self.df[(self.df['metric']==metric)&(self.df['
alg']==alg)].index, inplace = True)
        # Добавление нового значения
        temp = [{'metric':metric, 'alg':alg, 'value':value}]
        self.df = self.df.append(temp, ignore_index=True)

    def get_data_for_metric(self, metric, ascending=True):
        """
        Формирование данных с фильтром по метрике
        """
        temp_data = self.df[self.df['metric']==metric]
        temp_data_2 = temp_data.sort_values(by='value', ascending=a
scending)
        return temp_data_2['alg'].values, temp_data_2['value'].valu
es

    def plot(self, str_header, metric, ascending=True, figsize=(5,
5)):
        """
        Вывод графика
        """
        array_labels, array_metric = self.get_data_for_metric(metri
c, ascending)
        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(0.5, a-0.05, str(round(b,3)), color='white')
        plt.show()
```

6. Выбор наиболее подходящих моделей для решения задачи регрессии.

- Возьмем модели случайный лес и дерево решений, поскольку в проведенных экспериментах в лабораторных работах случайный лес показал себя наилучшим образом. Результаты, которые удалось получить при помощи данной модели были соспоставимы с результатами самых сильных среди протестированных ансамблевых моделей. Дерево решений так же дает хорошие результаты по сравнению с, например, линейными моделями.
- В качестве ансамблевой модели возьмем лучшую модель, полученную при выполнении 6 лабораторной работы: 'TREE+RF=>LR', то есть на первом уровне у нас будут две модели: дерево и случайный лес, а на втором уровне - линейная регрессия.

7. Формирование обучающей и тестовой выборок на основе исходного набора данных.

In [42]:
```
data1 = shuffle(data)
data1
```

Out[42]:

	song_name	song_popularity	song_duration_ms	acousticness	danceability	energy
5764	12054	50	204213	0.8570	0.543	0.311
16725	8262	33	160693	0.0027	0.700	0.964
5593	4559	100	214289	0.1910	0.687	0.792
2612	12841	63	246186	0.0133	0.546	0.912
2528	4667	7	231800	0.0193	0.646	0.751
...	...	...	...	...	...	...
15148	45	54	228240	0.3800	0.745	0.853
7191	11719	72	233028	0.2000	0.667	0.478
12766	1204	47	119360	0.0387	0.647	0.863
3779	4837	66	307200	0.2250	0.932	0.772
3085	12698	24	161751	0.5160	0.738	0.672

18835 rows × 29 columns

In [43]:
```
len(data1)
```

Out[43]: 18835

In [46]:
```
# На основе масштабированных данных выделим
# обучающую и тестовую выборки
train_data_all = data1[:13000]
test_data_all = data1[13001:]
train_data_all.shape, test_data_all.shape
```

Out[46]:
```
((13000, 29), (5834, 29))
```

In [47]:
```
data.columns
```

Out[47]:
```
Index(['song_name', 'song_popularity', 'song_duration_ms', 'acoust
icness',
       'danceability', 'energy', 'instrumentalness', 'key', 'liven
ess',
       'loudness', 'audio_mode', 'speechiness', 'tempo', 'time_sig
nature',
       'audio_valence', 'song_popularity_scaled', 'song_duration_m
s_scaled',
       'acousticness_scaled', 'danceability_scaled', 'energy_scale
d',
       'instrumentalness_scaled', 'key_scaled', 'liveness_scaled',
       'loudness_scaled', 'audio_mode_scaled', 'speechiness_scaled
',
       'tempo_scaled', 'time_signature_scaled', 'audio_valence_sca
led'],
      dtype='object')
```

In [159]:
```
# Признаки для задачи регресии (опустим название)
task_regr_cols = ['song_duration_ms', 'acousticness',
       'danceability', 'energy', 'instrumentalness', 'key', 'livene
ss',
       'loudness', 'audio_mode', 'speechiness', 'tempo', 'time_sign
ature',
       'audio_valence', 'song_duration_ms_scaled',
       'acousticness_scaled', 'danceability_scaled', 'energy_scaled
',
       'instrumentalness_scaled', 'key_scaled', 'liveness_scaled',
       'loudness_scaled', 'audio_mode_scaled', 'speechiness_scaled'
,
       'tempo_scaled', 'time_signature_scaled', 'audio_valence_scal
ed']
```

In [160]:
```
# Выборки для задачи регресии
regr_X_train = train_data_all[task_regr_cols]
regr_X_test = test_data_all[task_regr_cols]
regr_Y_train = train_data_all['song_popularity']
regr_Y_test = test_data_all['song_popularity']
regr_X_train.shape, regr_X_test.shape, regr_Y_train.shape, regr_Y_t
est.shape
```

Out[160]:
```
((13000, 26), (5834, 26), (13000,), (5834,))
```

8. Построение базового решения (baseline) для выбранных моделей без подбора гиперпараметров. Производится обучение моделей на основе обучающей выборки и оценка качества моделей на основе тестовой выборки.

In [284]:
```
# Модели
regr_models = {'Tree':DecisionTreeRegressor(max_depth=10),
               'RF':RandomForestRegressor(max_depth=10, n_estimator
s=30),
              }
```

In [285]:
```
# Сохранение метрик
regrMetricLogger = MetricLogger()
```

In [286]:
```
def regr_train_model(model_name, model, regrMetricLogger):
    model.fit(regr_X_train, regr_Y_train)
    Y_pred = model.predict(regr_X_test)

    mae = mean_absolute_error(regr_Y_test, Y_pred)
    medae = median_absolute_error(regr_Y_test, Y_pred)
    r2 = r2_score(regr_Y_test, Y_pred)

    regrMetricLogger.add('MAE', model_name, mae)
    regrMetricLogger.add('MedAE', model_name, medae)
    regrMetricLogger.add('R2', model_name, r2)

    print('*****************************************************')
    print(model)
    print()
    print('MAE={}, MedAE={}, R2={}'.format(
        round(mae, 3), round(medae, 3), round(r2, 3)))
    print('*****************************************************')
```

In [287]:
```
for model_name, model in regr_models.items():
    regr_train_model(model_name, model, regrMetricLogger)
```

```
*****************************************************
DecisionTreeRegressor(ccp_alpha=0.0, criterion='mse', max_depth=10
,
                      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=16.609, MedAE=13.63, R2=0.034
*****************************************************
*****************************************************
RandomForestRegressor(bootstrap=True, ccp_alpha=0.0, criterion='ms
e',
                      max_depth=10, 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_lea
f=0.0,
                      n_estimators=30, n_jobs=None, oob_score=Fals
e,
                      random_state=None, verbose=0, warm_start=Fal
se)

MAE=15.211, MedAE=12.932, R2=0.222
*****************************************************
```

Ансамблевая модель

In [335]:
```
from heamy.estimator import Regressor
from heamy.pipeline import ModelsPipeline
from heamy.dataset import Dataset
# набор данных
dataset = Dataset(regr_X_train, regr_Y_train, regr_X_test)
# Возьмем лучшую модель: 'TREE+RF=>LR'
# модели первого уровня
model_tree = Regressor(dataset=dataset, estimator=DecisionTreeRegre
ssor, parameters={'max_depth':10},name='tree')
model_lr = Regressor(dataset=dataset, estimator=LinearRegression, n
ame='lr')
model_rf = Regressor(dataset=dataset, estimator=RandomForestRegress
or, parameters={'max_depth':10},name='rf')

# 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)
print()

results = stacker.validate(k=10,scorer=median_absolute_error)
```

```
Metric: mean_absolute_error
Folds accuracy: [14.89643993242869, 15.616762658202559, 14.9727884
89493295, 15.222334189473978, 15.080414157836218, 14.7590654678193
5, 15.05850462402728, 15.044001090351392, 14.8316297901197, 15.548
169842390033]
Mean accuracy: 15.103011024214249
Standard Deviation: 0.2709048887355547
Variance: 0.07338945874082325

Metric: median_absolute_error
Folds accuracy: [12.277784575440783, 13.328390040154055, 12.167663
823524233, 12.946816156161724, 13.11487250948803, 12.1117981540689
14, 12.78946051322334, 13.216714632887722, 12.85310829872179, 12.9
66059307565189]
Mean accuracy: 12.777266801123577
Standard Deviation: 0.4177398537009336
Variance: 0.1745065853700774
```

9. Подбор гиперпараметров для выбранных моделей.

Случайный лес

In [173]:
```
RandomForestRegressor().get_params()
```

Out[173]:
```
{'bootstrap': True,
 'ccp_alpha': 0.0,
 'criterion': 'mse',
 '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': 100,
 'n_jobs': None,
 'oob_score': False,
 'random_state': None,
 'verbose': 0,
 'warm_start': False}
```

In [297]:
```
n_range = np.array(range(0,50,5))
tuned_parameters = [{'max_depth': n_range}]
tuned_parameters
```

Out[297]:
```
[{'max_depth': array([ 0,  5, 10, 15, 20, 25, 30, 35, 40, 45])}]
```

In [298]:
```
%%time
rf_gs = GridSearchCV(RandomForestRegressor(), tuned_parameters, cv=
5, scoring='neg_mean_squared_error')
rf_gs.fit(regr_X_train, regr_Y_train)
```

```
/home/lisobol/tensorflow_env/my_tensorflow/lib/python3.7/site-pack
ages/sklearn/model_selection/_validation.py:536: FitFailedWarning:
Estimator fit failed. The score on this train-test partition for t
hese parameters will be set to nan. Details:
ValueError: max_depth must be greater than zero.

  FitFailedWarning)
/home/lisobol/tensorflow_env/my_tensorflow/lib/python3.7/site-pack
ages/sklearn/model_selection/_validation.py:536: FitFailedWarning:
Estimator fit failed. The score on this train-test partition for t
hese parameters will be set to nan. Details:
ValueError: max_depth must be greater than zero.

  FitFailedWarning)
/home/lisobol/tensorflow_env/my_tensorflow/lib/python3.7/site-pack
ages/sklearn/model_selection/_validation.py:536: FitFailedWarning:
Estimator fit failed. The score on this train-test partition for t
hese parameters will be set to nan. Details:
ValueError: max_depth must be greater than zero.

  FitFailedWarning)
/home/lisobol/tensorflow_env/my_tensorflow/lib/python3.7/site-pack
ages/sklearn/model_selection/_validation.py:536: FitFailedWarning:
Estimator fit failed. The score on this train-test partition for t
hese parameters will be set to nan. Details:
ValueError: max_depth must be greater than zero.

  FitFailedWarning)
/home/lisobol/tensorflow_env/my_tensorflow/lib/python3.7/site-pack
ages/sklearn/model_selection/_validation.py:536: FitFailedWarning:
Estimator fit failed. The score on this train-test partition for t
hese parameters will be set to nan. Details:
ValueError: max_depth must be greater than zero.

  FitFailedWarning)

CPU times: user 15min 41s, sys: 1.08 s, total: 15min 42s
Wall time: 15min 44s
```

Out[298]:
```
GridSearchCV(cv=5, error_score=nan,
             estimator=RandomForestRegressor(bootstrap=True, ccp_a
lpha=0.0,
                                             criterion='mse', max_
depth=None,
                                             max_features='auto',
                                             max_leaf_nodes=None,
                                             max_samples=None,
                                             min_impurity_decrease
=0.0,
                                             min_impurity_split=No
ne,
                                             min_samples_leaf=1,
                                             min_samples_split=2,
                                             min_weight_fraction_l
eaf=0.0,
                                             n_estimators=100, n_j
obs=None,
                                             oob_score=False, rand
om_state=None,
                                             verbose=0, warm_start
=False),
             iid='deprecated', n_jobs=None,
             param_grid=[{'max_depth': array([ 0,  5, 10, 15, 20,
25, 30, 35, 40, 45])}],
             pre_dispatch='2*n_jobs', refit=True, return_train_sco
re=False,
             scoring='neg_mean_squared_error', verbose=0)
```

In [299]:
```
# Лучшая модель
rf_gs.best_estimator_
```

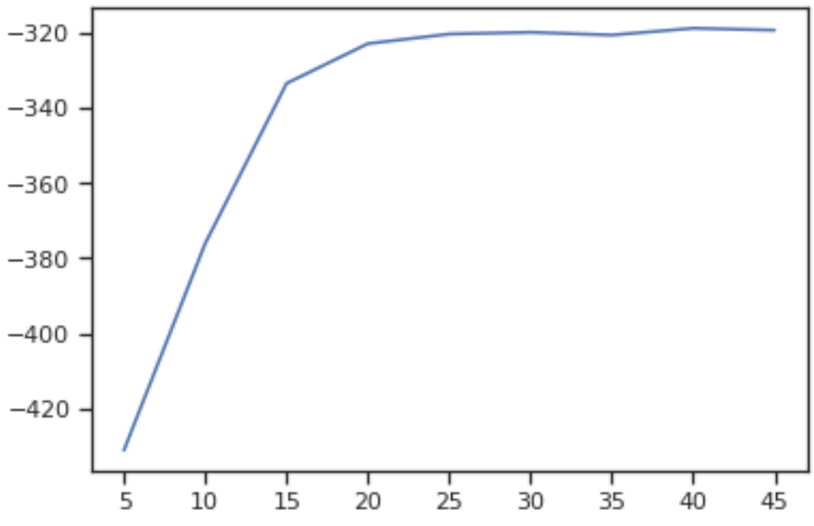
Out[299]:
```
RandomForestRegressor(bootstrap=True, ccp_alpha=0.0, criterion='ms
e',
                      max_depth=40, max_features='auto', max_leaf_
nodes=None,
                      max_samples=None, min_impurity_decrease=0.0,
                      min_impurity_split=None, min_samples_leaf=1,
                      min_samples_split=2, min_weight_fraction_lea
f=0.0,
                      n_estimators=100, n_jobs=None, oob_score=Fal
se,
                      random_state=None, verbose=0, warm_start=Fal
se)
```

In [300]:
```
# Лучшее значение параметров
rf_gs.best_params_
```

Out[300]:
```
{'max_depth': 40}
```

In [301]:
```
# Изменение качества на тестовой выборке в зависимости от К-соседей
plt.plot(n_range, rf_gs.cv_results_['mean_test_score'])
```

Out[301]:
```
[<matplotlib.lines.Line2D at 0x7fbd32307e10>]
```



Дерево

In [204]:
```
DecisionTreeRegressor().get_params()
```

Out[204]:
```
{'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 [292]:
```
n_range = np.array(range(0,50,5))

tuned_parameters = [{'max_depth': n_range}]
tuned_parameters
```

Out[292]:
```
[{'max_depth': array([ 0,  5, 10, 15, 20, 25, 30, 35, 40, 45])}]
```

In [293]:
```
%%time
dt_gs = GridSearchCV(DecisionTreeRegressor(), tuned_parameters, cv=
5, scoring='neg_mean_squared_error')
dt_gs.fit(regr_X_train, regr_Y_train)
```

```
/home/lisobol/tensorflow_env/my_tensorflow/lib/python3.7/site-pack
ages/sklearn/model_selection/_validation.py:536: FitFailedWarning:
Estimator fit failed. The score on this train-test partition for t
hese parameters will be set to nan. Details:
ValueError: max_depth must be greater than zero.

  FitFailedWarning)
/home/lisobol/tensorflow_env/my_tensorflow/lib/python3.7/site-pack
ages/sklearn/model_selection/_validation.py:536: FitFailedWarning:
Estimator fit failed. The score on this train-test partition for t
hese parameters will be set to nan. Details:
ValueError: max_depth must be greater than zero.

  FitFailedWarning)
/home/lisobol/tensorflow_env/my_tensorflow/lib/python3.7/site-pack
ages/sklearn/model_selection/_validation.py:536: FitFailedWarning:
Estimator fit failed. The score on this train-test partition for t
hese parameters will be set to nan. Details:
ValueError: max_depth must be greater than zero.

  FitFailedWarning)
/home/lisobol/tensorflow_env/my_tensorflow/lib/python3.7/site-pack
ages/sklearn/model_selection/_validation.py:536: FitFailedWarning:
Estimator fit failed. The score on this train-test partition for t
hese parameters will be set to nan. Details:
ValueError: max_depth must be greater than zero.

  FitFailedWarning)
/home/lisobol/tensorflow_env/my_tensorflow/lib/python3.7/site-pack
ages/sklearn/model_selection/_validation.py:536: FitFailedWarning:
Estimator fit failed. The score on this train-test partition for t
hese parameters will be set to nan. Details:
ValueError: max_depth must be greater than zero.

  FitFailedWarning)

CPU times: user 15.1 s, sys: 4.24 ms, total: 15.1 s
Wall time: 15.2 s
```

Out[293]:
```
GridSearchCV(cv=5, error_score=nan,
             estimator=DecisionTreeRegressor(ccp_alpha=0.0, criter
ion='mse',
                                             max_depth=None, max_f
eatures=None,
                                             max_leaf_nodes=None,
                                             min_impurity_decrease
=0.0,
                                             min_impurity_split=No
ne,
                                             min_samples_leaf=1,
                                             min_samples_split=2,
                                             min_weight_fraction_l
eaf=0.0,
                                             presort='deprecated',
                                             random_state=None,
                                             splitter='best'),
             iid='deprecated', n_jobs=None,
             param_grid=[{'max_depth': array([ 0,  5, 10, 15, 20,
25, 30, 35, 40, 45])}],
             pre_dispatch='2*n_jobs', refit=True, return_train_sco
re=False,
             scoring='neg_mean_squared_error', verbose=0)
```

In [294]:
```
# Лучшая модель
dt_gs.best_estimator_
```

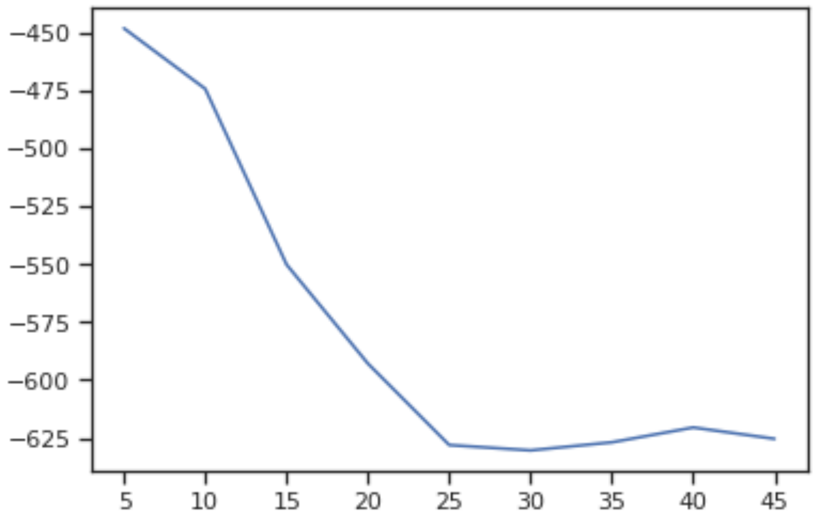
Out[294]:
```
DecisionTreeRegressor(ccp_alpha=0.0, criterion='mse', max_depth=5,
                      max_features=None, max_leaf_nodes=None,
                      min_impurity_decrease=0.0, min_impurity_spli
t=None,
                      min_samples_leaf=1, min_samples_split=2,
                      min_weight_fraction_leaf=0.0, presort='depre
cated',
                      random_state=None, splitter='best')
```

In [295]:
```
# Лучшее значение параметров
dt_gs.best_params_
```

Out[295]:
```
{'max_depth': 5}
```

In [296]:
```
# Изменение качества на тестовой выборке
plt.plot(n_range, dt_gs.cv_results_['mean_test_score'])
```

Out[296]:
```
[<matplotlib.lines.Line2D at 0x7fbd31789410>]
```



Ансамблевая модель

Поскольку параметры для случайного леса и дерева уже подобрали, то воспользуемся ими, а так же попробуем подобрать еще 2 параметра для данных моделей.

Decision tree

In [310]:
```
n_range = [0, 0.5, 1, 1.5, 2, 2.5, 3]
tuned_parameters = [{'min_impurity_split': n_range}]
tuned_parameters
```

Out[310]:
```
[{'min_impurity_split': [0, 0.5, 1, 1.5, 2, 2.5, 3]}]
```

In [320]:
```
%%time
ens_dt_gs = GridSearchCV(DecisionTreeRegressor(), tuned_parameters,
cv=5, scoring='neg_mean_squared_error')
ens_dt_gs.fit(regr_X_train, regr_Y_train)
```

```
/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)
/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)
/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)
/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)

CPU times: user 14 s, sys: 4.05 ms, total: 14 s
Wall time: 14 s
```

Out[320]:
```
GridSearchCV(cv=5, error_score=nan,
             estimator=DecisionTreeRegressor(ccp_alpha=0.0, criter
ion='mse',
                                             max_depth=None, max_f
eatures=None,
                                             max_leaf_nodes=None,
                                             min_impurity_decrease
=0.0,
                                             min_impurity_split=No
ne,
                                             min_samples_leaf=1,
                                             min_samples_split=2,
                                             min_weight_fraction_l
eaf=0.0,
                                             presort='deprecated',
                                             random_state=None,
                                             splitter='best'),
             iid='deprecated', n_jobs=None,
             param_grid=[{'min_impurity_split': [0, 0.5, 1, 1.5, 2
, 2.5, 3]}],
             pre_dispatch='2*n_jobs', refit=True, return_train_sco
re=False,
             scoring='neg_mean_squared_error', verbose=0)
```

In [321]:
```
# Лучшая модель
ens_dt_gs.best_estimator_
```

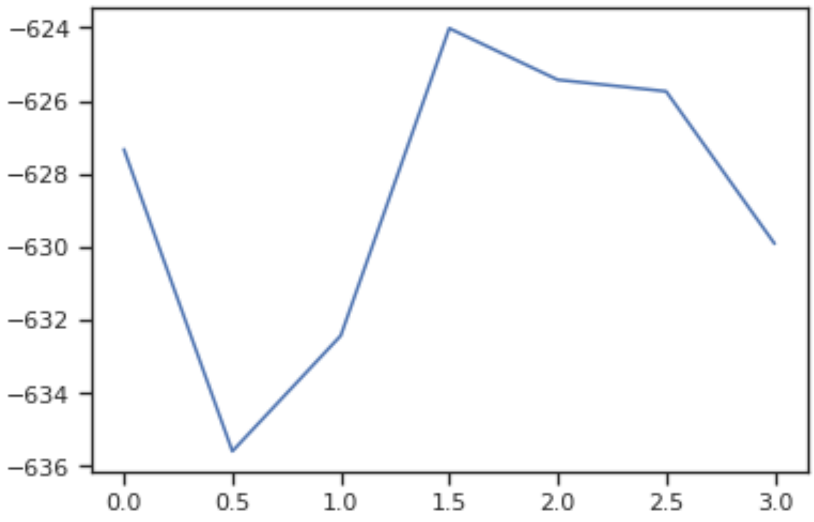
Out[321]:
```
DecisionTreeRegressor(ccp_alpha=0.0, criterion='mse', max_depth=No
ne,
                      max_features=None, max_leaf_nodes=None,
                      min_impurity_decrease=0.0, min_impurity_spli
t=1.5,
                      min_samples_leaf=1, min_samples_split=2,
                      min_weight_fraction_leaf=0.0, presort='depre
cated',
                      random_state=None, splitter='best')
```

In [322]:
```
# Лучшее значение параметров
ens_dt_gs.best_params_
```

Out[322]:
```
{'min_impurity_split': 1.5}
```

In [323]:
```
# Изменение качества на тестовой выборке
plt.plot(n_range, ens_dt_gs.cv_results_['mean_test_score'])
```

Out[323]:
```
[<matplotlib.lines.Line2D at 0x7fbd313be850>]
```



Random Forest

In [324]:
```
n_range = [1, 5, 10, 20, 30, 40 ,50 ,60]
tuned_parameters = [{'n_estimators': n_range}]
tuned_parameters
```

Out[324]:
```
[{'n_estimators': [1, 5, 10, 20, 30, 40, 50, 60]}]
```

In [326]:
```
%%time
ens_rf_gs = GridSearchCV(RandomForestRegressor(), tuned_parameters,
cv=5, scoring='neg_mean_squared_error')
ens_rf_gs.fit(regr_X_train, regr_Y_train)
```

```
CPU times: user 4min 33s, sys: 95.4 ms, total: 4min 33s
Wall time: 4min 33s
```

Out[326]:
```
GridSearchCV(cv=5, error_score=nan,
             estimator=RandomForestRegressor(bootstrap=True, ccp_a
lpha=0.0,
                                             criterion='mse', max_
depth=None,
                                             max_features='auto',
                                             max_leaf_nodes=None,
                                             max_samples=None,
                                             min_impurity_decrease
=0.0,
                                             min_impurity_split=No
ne,
                                             min_samples_leaf=1,
                                             min_samples_split=2,
                                             min_weight_fraction_l
eaf=0.0,
                                             n_estimators=100, n_j
obs=None,
                                             oob_score=False, rand
om_state=None,
                                             verbose=0, warm_start
=False),
             iid='deprecated', n_jobs=None,
             param_grid=[{'n_estimators': [1, 5, 10, 20, 30, 40, 5
0, 60]}],
             pre_dispatch='2*n_jobs', refit=True, return_train_sco
re=False,
             scoring='neg_mean_squared_error', verbose=0)
```

In [328]:
```
# Лучшая модель
ens_rf_gs.best_estimator_
```

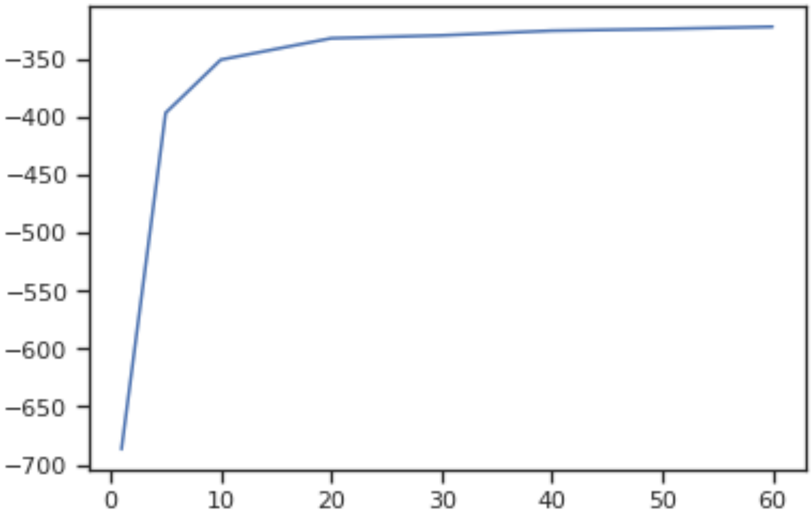
Out[328]:
```
RandomForestRegressor(bootstrap=True, ccp_alpha=0.0, criterion='ms
e',
                      max_depth=None, max_features='auto', max_lea
f_nodes=None,
                      max_samples=None, min_impurity_decrease=0.0,
                      min_impurity_split=None, min_samples_leaf=1,
                      min_samples_split=2, min_weight_fraction_lea
f=0.0,
                      n_estimators=60, n_jobs=None, oob_score=Fals
e,
                      random_state=None, verbose=0, warm_start=Fal
se)
```

In [329]:
```
# Лучшее значение параметров
ens_rf_gs.best_params_
```

Out[329]:
```
{'n_estimators': 60}
```

In [330]:
```
# Изменение качества на тестовой выборке
plt.plot(n_range, ens_rf_gs.cv_results_['mean_test_score'])
```

Out[330]:
```
[<matplotlib.lines.Line2D at 0x7fbd31511f10>]
```



10. Повторение пункта 8 для найденных оптимальных значений гиперпараметров. Сравнение качества полученных моделей с качеством baseline-моделей.

In [289]:
```
regr_models_grid = {'Tree':dt_gs.best_estimator_,
                    'RF': rf_gs.best_estimator_
                    }
```

In [290]:
```
for model_name, model in regr_models_grid.items():
    regr_train_model(model_name, model, regrMetricLogger)
```

```
*****************************************************
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=14, min_samples_split=2,
                      min_weight_fraction_leaf=0.0, presort='depre
cated',
                      random_state=None, splitter='best')

MAE=16.303, MedAE=13.375, R2=0.076
*****************************************************
*****************************************************
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=61, n_jobs=None, oob_score=Fals
e,
                      random_state=None, verbose=0, warm_start=Fal
se)

MAE=12.462, MedAE=8.665, R2=0.367
*****************************************************
```

Удалось немного улучшить модель дерева решений и достаточно неплохо улучшить модель случайный лес

Ансамблевый метод

In [333]:
```
# # # Возьмем лучшую модель: 'TREE+RF=>LR'
# # # модели первого уровня
model_tree = Regressor(dataset=dataset,
                       estimator=DecisionTreeRegressor,
                       parameters={'min_impurity_split':1.5,
                                   'max_depth':5},name='tree')
model_lr = Regressor(dataset=dataset,
                     estimator=LinearRegression,
                     name='lr')
model_rf = Regressor(dataset=dataset,
                     estimator=RandomForestRegressor,
                     parameters={'n_estimators': 60,
                                 'max_depth': 40},name='rf')

# 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)
```

In [334]:
```
results = stacker.validate(k=10,scorer=mean_absolute_error)
print()

results = stacker.validate(k=10,scorer=median_absolute_error)
```

```
Metric: mean_absolute_error
Folds accuracy: [12.80562367994027, 13.255704475940108, 13.0521689
95181646, 13.014414170510065, 12.848374721738873, 13.0161615481326
31, 12.75272305242177, 13.073417650626174, 12.619076791682607, 13.
289157092900757]
Mean accuracy: 12.97268221790749
Standard Deviation: 0.2042389455719696
Variance: 0.04171354688834995

Metric: median_absolute_error
Folds accuracy: [8.914441360926233, 9.787841717837992, 9.147558969
487442, 9.635733648259986, 8.944208849177393, 9.359388721509454, 9
.130147663254334, 9.756749380193888, 9.731591020643553, 9.74528280
351102]
Mean accuracy: 9.41529441348013
Standard Deviation: 0.3379059186286033
Variance: 0.11418040984424027
```

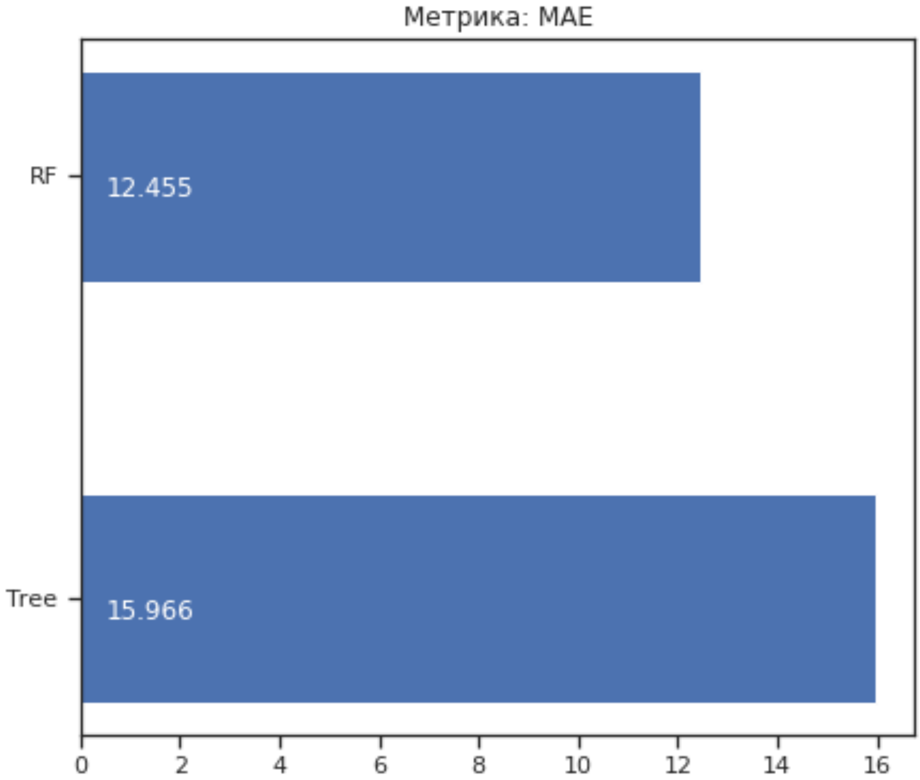
Удалось неплохо улучшить модель.

11. Формирование выводов о качестве построенных моделей на основе выбранных метрик.

In [218]:
```
# Метрики качества модели
regr_metrics = regrMetricLogger.df['metric'].unique()
regr_metrics
```

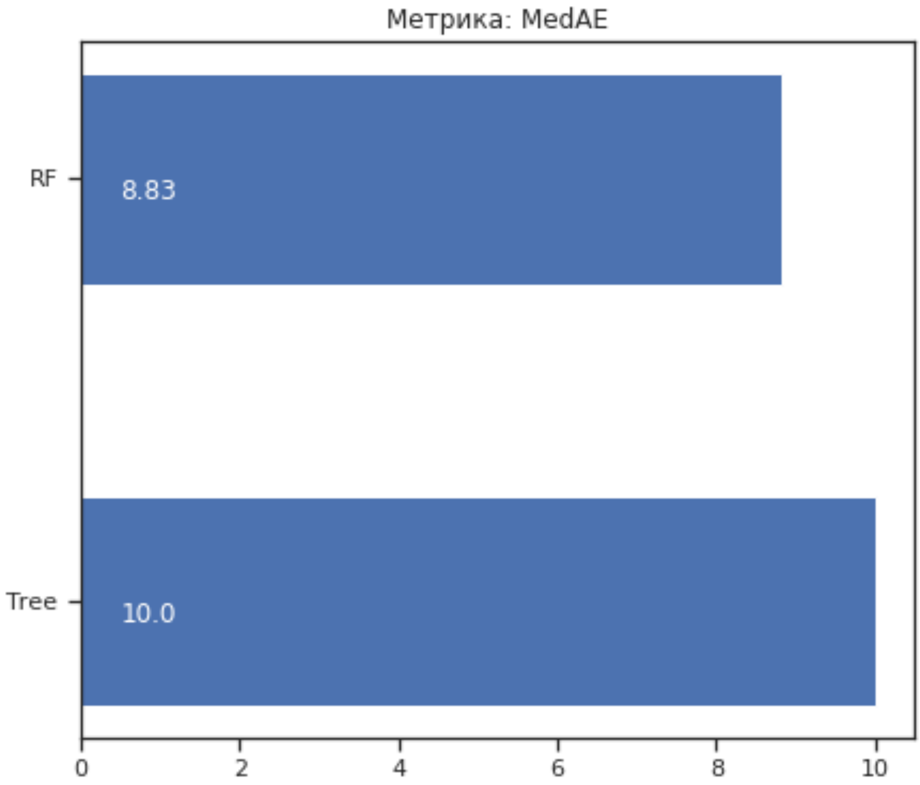
Out[218]:
```
array(['MAE', 'MedAE', 'R2'], dtype=object)
```

In [219]:
```
regrMetricLogger.plot('Метрика: ' + 'MAE', 'MAE',
                      ascending=False, figsize=(7, 6))
```



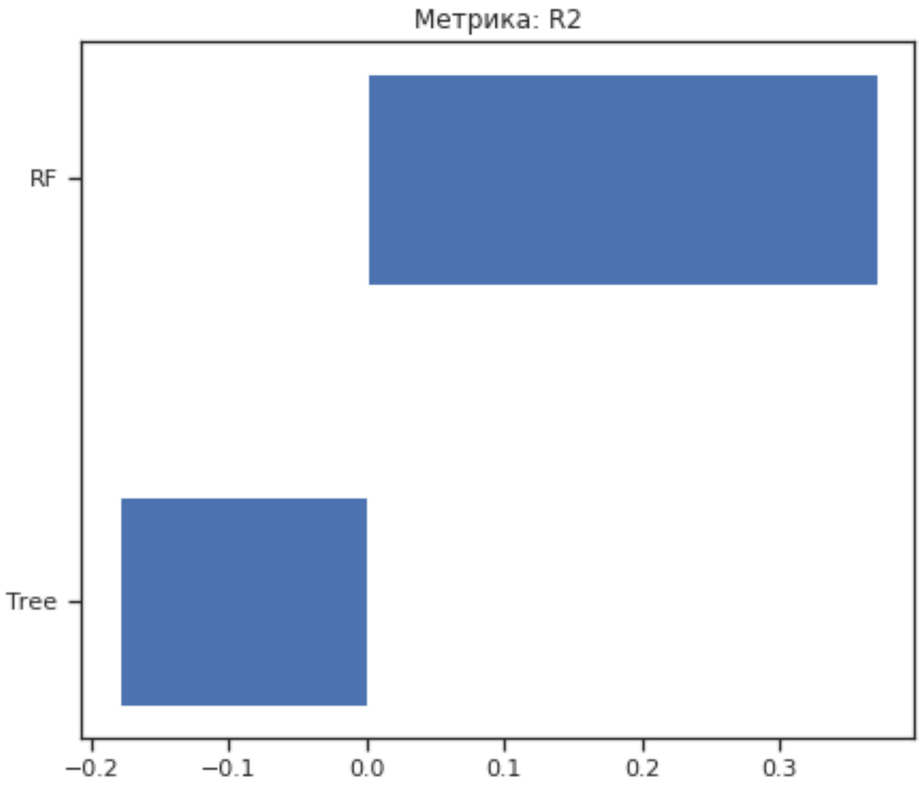
Ансамбль - 12.973

In [220]:
```
regrMetricLogger.plot('Метрика: ' + 'MedAE', 'MedAE',
                      ascending=False, figsize=(7, 6))
```



Ансамбль - 9.415

In [221]:
```
regrMetricLogger.plot('Метрика: ' + 'R2', 'R2',
                      ascending=True, figsize=(7, 6))
```



Вывод:

Лучше всего показала себя модель случайный лес, на втором месте - ансамблевая модель, на третьем - дерево решений. Однако в другой задаче в лабораторной работе лучше показала себя ансамблевая модель, так что в дальнейшем можно использовать обе эти модели и проверять, какая будет работать лучше для конкретной задачи.