Московский государственный технический университет им. Н.Э.Баумана

Утверждаю:

Гапанюк Ю.Е.

"__"____________2019 г.

Курсовая работа по курсу
“Технологии машинного обучения”
“Бинарная классификация”

Вариант №_1_

Пояснительная записка
(вид документа)

писчая бумага
(вид носителя)

22
(количество листов)

ИСПОЛНИТЕЛЬ:

студент группы ИУ5-62 ______________________
Андреев А.С.

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Содержание

Задание

В данной курсовой работе необходимо предпринять следующие шаги:

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 трех метрик и обосновать выбор.
6. Выбор наиболее подходящих моделей для решения задачи классификации или регрессии. Необходимо использовать не менее пяти моделей, две из которых должны быть ансамблевыми.
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 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. Результаты сравнения качества рекомендуется отобразить в виде графиков и сделать выводы в форме текстового описания. Рекомендуется постройение графиков обучения и валидации, влияния значений гиперпарметров на качество моделей и т.д.

Приведенная схема исследования является рекомендуемой. Возможно выполнение курсовой работы на нестандартную тему, которая должна быть предварительно согласована с ответственным за прием курсовой работы.

Введение

Курсовая работа – самостоятельная часть учебной дисциплины «Технологии машинного обучения» – учебная и практическая исследовательская студенческая работа, направленная на решение комплексной задачи машинного обучения. Результатом курсовой работы является отчет, содержащий описания моделей, тексты программ и результаты экспериментов.

Курсовая работа опирается на знания, умения и владения, полученные студентом в рамках лекций и лабораторных работ по дисциплине.

В рамках данной курсовой работы необходимо применить навыки, полученные в течение курса «Технологии машинного обучения», и обосновать полученные результаты.

Основная часть

Постановка задачи

Датасет представляет собой описание дома и его стоимость. В нем 19 признаков, среди которых количество спален, ванн, площадь, по которым предсказывается стоимость (это целевой признак). Это классическая задача регрессии. Разделительная плоскость, описанная выше, была получена с использованием Multisurface Method-Tree (MSM-T) [K. П. Беннетт, "Построение дерева решений с помощью линейного программирования". Труды 4-го Среднего Запада Общества искусственного интеллекта и когнитивной науки, стр. 97-101, 1992], метод классификации, который использует линейное программирование для построения дерева решений. Соответствующие элементы были выбраны с использованием исчерпывающего поиска в пространстве 1-4 элементов и 1-3 разделительных плоскостей. Фактическая линейная программа, используемая для получения разделяющей плоскости в трехмерном пространстве, описана в: [K. П. Беннетт и О. Л. Мангасарян: «Надежное распознавание линейного программирования двух линейно неразделимых множеств», Методы оптимизации и программное обеспечение 1, 1992, 23-34].

Описание выбранного датасета

Информация об атрибутах:

id a notation for a house
date Date house was sold
price Price is prediction target
bedrooms Number of Bedrooms/House
bathrooms Number of bathrooms/House
sqft_living square footage of the home
sqft_lot square footage of the lot
floors Total floors (levels) in house
water frontHouse which has a view to a waterfront
viewHas been viewed
conditionHow good the condition is (Overall)
gradeoverall grade given to the housing unit, based on King County grading system
sqft_abovesquare footage of house apart from basement
sqft_basementsquare footage of the basement
yr_builtBuilt Year
yr_renovatedYear when house was renovated
zipcodezip
latLatitude coordinate
longLongitude coordinate
sqft_living15Living room area in 2015(implies-- some renovations) This might or might not have affected the lotsize area
sqft_lot15lotSize area in 2015(implies-- some renovations)

In [311]:
```
import numpy as np
import pandas as pd
pd.set_option('display.max.rows', 1000)
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
sns.set(style='ticks')
```

1) Поиск и выбор набора данных для построения моделей машинного обучения.

In [312]:
```
data = pd.read_csv('data/kc_house_data.csv')
```

House Sales in King County, USA

Predict house price using regression

https://www.kaggle.com/harlfoxem/housesalesprediction
(https://www.kaggle.com/harlfoxem/housesalesprediction)

This dataset contains house sale prices for King County, which includes Seattle. It includes homes sold between May 2014 and May 2015.

It's a great dataset for evaluating simple regression models.

19 house features plus the price and the id columns, along with 21613 observations:

- id – a notation for a house
- date – Date house was sold
- price – Price is prediction target
- bedrooms – Number of Bedrooms/House
- bathrooms – Number of bathrooms/House
- sqft_living – square footage of the home
- sqft_lot – square footage of the lot
- floors – Total floors (levels) in house
- waterfront – House which has a view to a waterfront
- view – Has been viewed
- condition – How good the condition is (Overall)
- grade – overall grade given to the housing unit, based on King County grading system
- sqft_above – square footage of house apart from basement
- sqft_basement – square footage of the basement
- yr_built – Built Year
- yr_renovated – Year when house was renovated
- zipcode – zip
- lat – Latitude coordinate
- long – Longitude coordinate
- sqft_living15 – Living room area in 2015(implies-- some renovations) This might or might not have affected the lotsize area
- sqft_lot15 – lotSize area in 2015(implies-- some renovations)

In [313]:
```
data.head()
```

Out[313]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floo
0	7129300520	20141013T000000	221900.0	3	1.00	1180	5650	
1	6414100192	20141209T000000	538000.0	3	2.25	2570	7242	
2	5631500400	20150225T000000	180000.0	2	1.00	770	10000	
3	2487200875	20141209T000000	604000.0	4	3.00	1960	5000	
4	1954400510	20150218T000000	510000.0	3	2.00	1680	8080	

5 rows × 21 columns

In [314]:
```
data.shape
```

Out[314]:
```
(21613, 21)
```

In [315]:
```
data.dtypes
```

Out[315]:
```
id                 int64
date              object
price            float64
bedrooms           int64
bathrooms        float64
sqft_living        int64
sqft_lot           int64
floors           float64
waterfront         int64
view               int64
condition          int64
grade              int64
sqft_above         int64
sqft_basement      int64
yr_built           int64
yr_renovated       int64
zipcode            int64
lat              float64
long             float64
sqft_living15      int64
sqft_lot15         int64
dtype: object
```

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

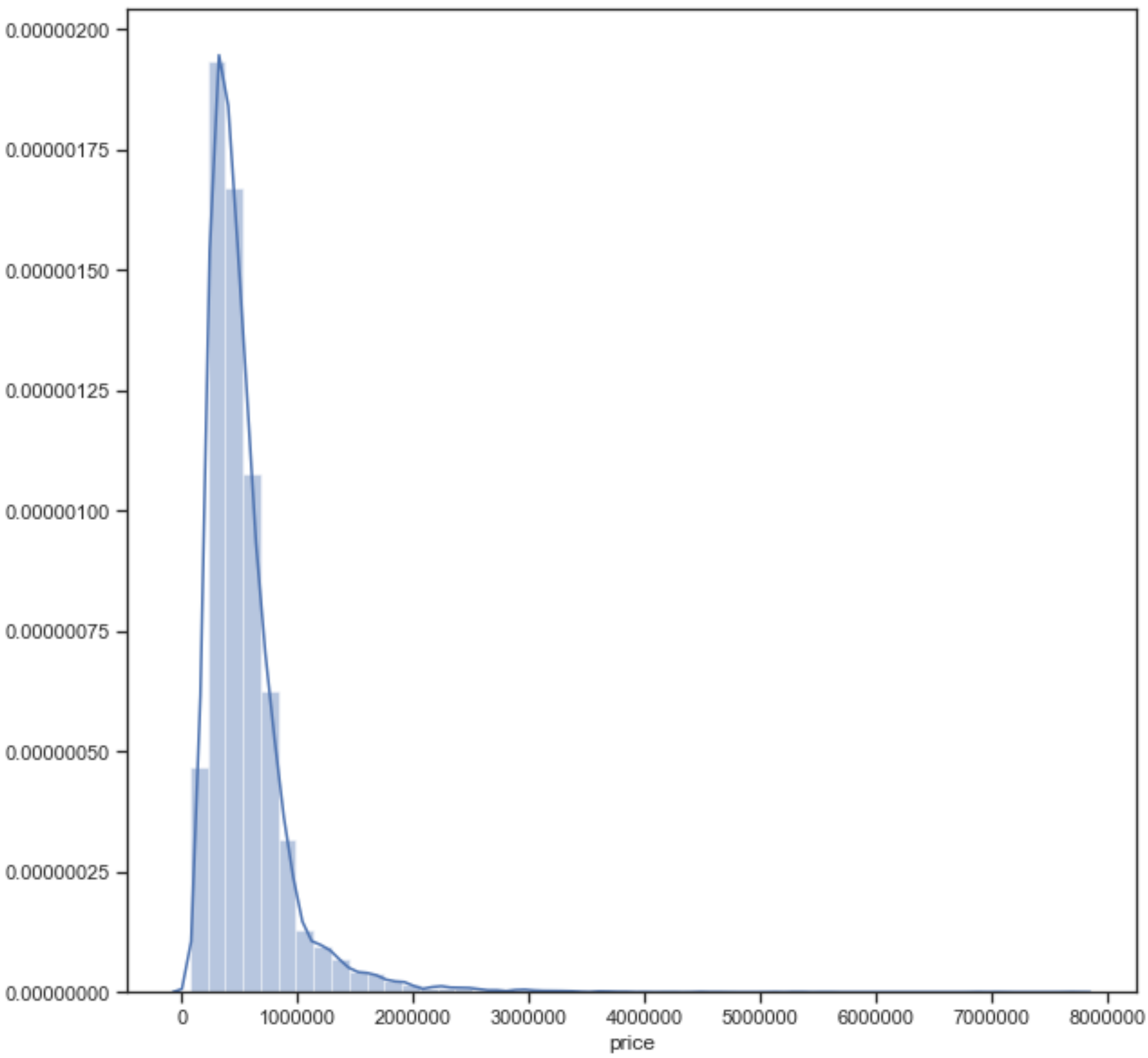
In [316]:
```
data.describe()
```

Out[316]:

	id	price	bedrooms	bathrooms	sqft_living	sqft_l(
count	2.161300e+04	2.161300e+04	21613.000000	21613.000000	21613.000000	2.161300e+(
mean	4.580302e+09	5.400881e+05	3.370842	2.114757	2079.899736	1.510697e+(
std	2.876566e+09	3.671272e+05	0.930062	0.770163	918.440897	4.142051e+(
min	1.000102e+06	7.500000e+04	0.000000	0.000000	290.000000	5.200000e+(
25%	2.123049e+09	3.219500e+05	3.000000	1.750000	1427.000000	5.040000e+(
50%	3.904930e+09	4.500000e+05	3.000000	2.250000	1910.000000	7.618000e+(
75%	7.308900e+09	6.450000e+05	4.000000	2.500000	2550.000000	1.068800e+(
max	9.900000e+09	7.700000e+06	33.000000	8.000000	13540.000000	1.651359e+(

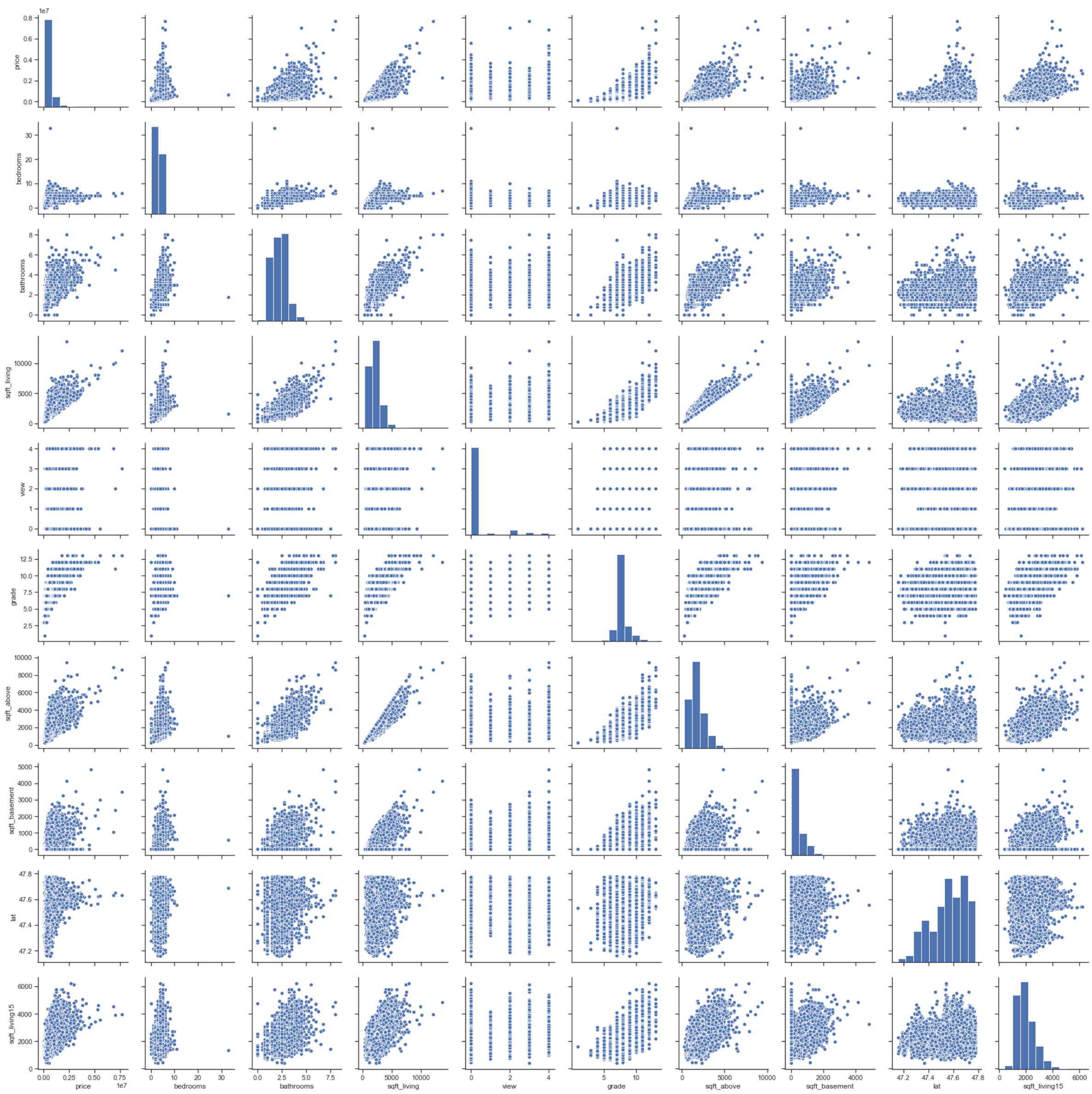
In [317]:
```
fig, ax = plt.subplots(figsize=(10,10))
sns.distplot(data['price'])
```

Out[317]: <matplotlib.axes._subplots.AxesSubplot at 0x12d6d0748>



In [424]:
```
sns.pairplot(data)  # парные диаграммы
```

Out[424]: <seaborn.axisgrid.PairGrid at 0x1401c5278>



In [319]:
```
data.isnull().sum()
```

Out[319]:
```
id               0
date             0
price            0
bedrooms         0
bathrooms        0
sqft_living      0
sqft_lot         0
floors           0
waterfront       0
view             0
condition        0
grade            0
sqft_above       0
sqft_basement    0
yr_built         0
yr_renovated     0
zipcode          0
lat              0
long             0
sqft_living15    0
sqft_lot15       0
dtype: int64
```

Пропусков нет, заполнять нечего.

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

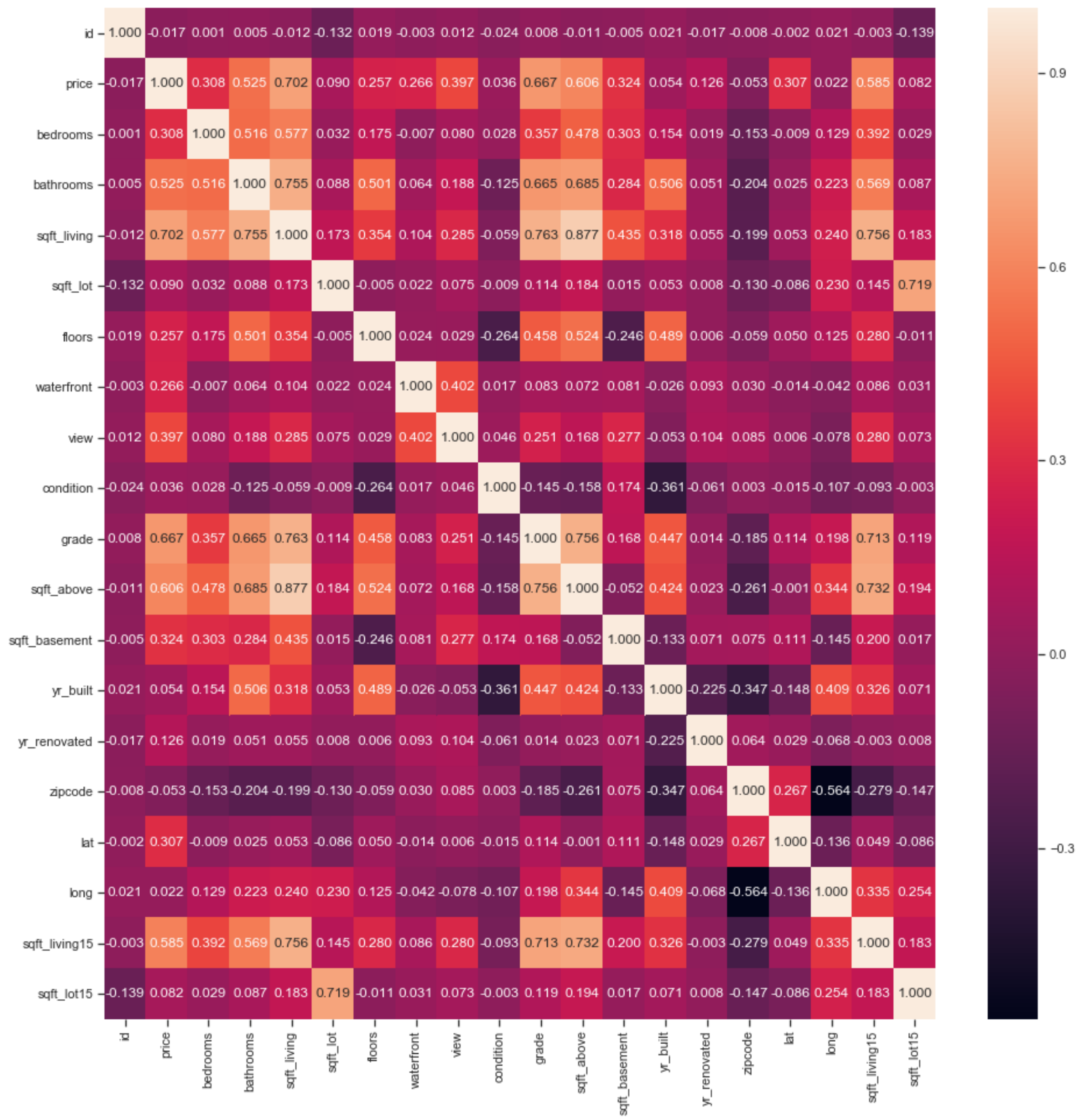
In [320]:
```
data.corr()
```

Out[320]:

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floor
id	1.000000	-0.016762	0.001286	0.005160	-0.012258	-0.132109	0.01852
price	-0.016762	1.000000	0.308350	0.525138	0.702035	0.089661	0.25679
bedrooms	0.001286	0.308350	1.000000	0.515884	0.576671	0.031703	0.17542
bathrooms	0.005160	0.525138	0.515884	1.000000	0.754665	0.087740	0.50065
sqft_living	-0.012258	0.702035	0.576671	0.754665	1.000000	0.172826	0.35394
sqft_lot	-0.132109	0.089661	0.031703	0.087740	0.172826	1.000000	-0.00520
floors	0.018525	0.256794	0.175429	0.500653	0.353949	-0.005201	1.00000
waterfront	-0.002721	0.266369	-0.006582	0.063744	0.103818	0.021604	0.02369
view	0.011592	0.397293	0.079532	0.187737	0.284611	0.074710	0.02944
condition	-0.023783	0.036362	0.028472	-0.124982	-0.058753	-0.008958	-0.26376
grade	0.008130	0.667434	0.356967	0.664983	0.762704	0.113621	0.45818
sqft_above	-0.010842	0.605567	0.477600	0.685342	0.876597	0.183512	0.52388
sqft_basement	-0.005151	0.323816	0.303093	0.283770	0.435043	0.015286	-0.24570
yr_built	0.021380	0.054012	0.154178	0.506019	0.318049	0.053080	0.48931
yr_renovated	-0.016907	0.126434	0.018841	0.050739	0.055363	0.007644	0.00633
zipcode	-0.008224	-0.053203	-0.152668	-0.203866	-0.199430	-0.129574	-0.05912
lat	-0.001891	0.307003	-0.008931	0.024573	0.052529	-0.085683	0.04961
long	0.020799	0.021626	0.129473	0.223042	0.240223	0.229521	0.12541
sqft_living15	-0.002901	0.585379	0.391638	0.568634	0.756420	0.144608	0.27988
sqft_lot15	-0.138798	0.082447	0.029244	0.087175	0.183286	0.718557	-0.01126

```
In [321]: plt.figure(figsize=(16, 16))
          sns.heatmap(data.corr(), annot=True, fmt='.3f')
```

```
Out[321]: <matplotlib.axes._subplots.AxesSubplot at 0x143827358>
```

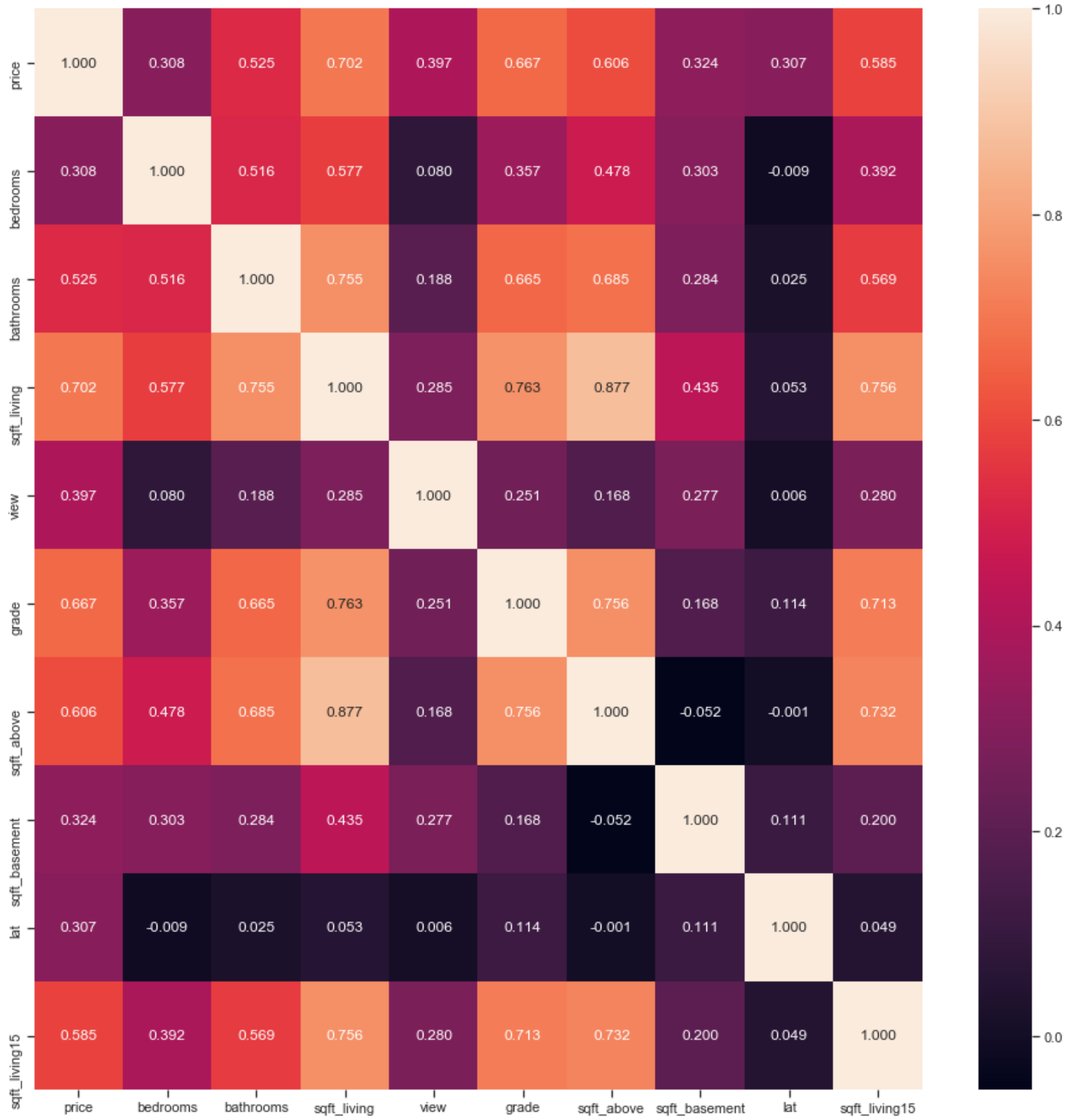


Целевой признак – `price` (цена). Возьмем только те фичи, которые коррелируют с целевым признаком средне и сильно (≥ 0.3 по модулю)

```
In [322]: # уберем ID
          data = data.drop(columns='id')
          # ≤ 0.3
          data = data.drop(columns=['sqft_lot', 'floors', 'waterfront', 'cond
          ition', 'yr_built', 'yr_renovated',
                                     'zipcode', 'long', 'sqft_lot15'])
```

In [323]:
```
plt.figure(figsize=(16, 16))
sns.heatmap(data.corr(), annot=True, fmt='.3f')
```

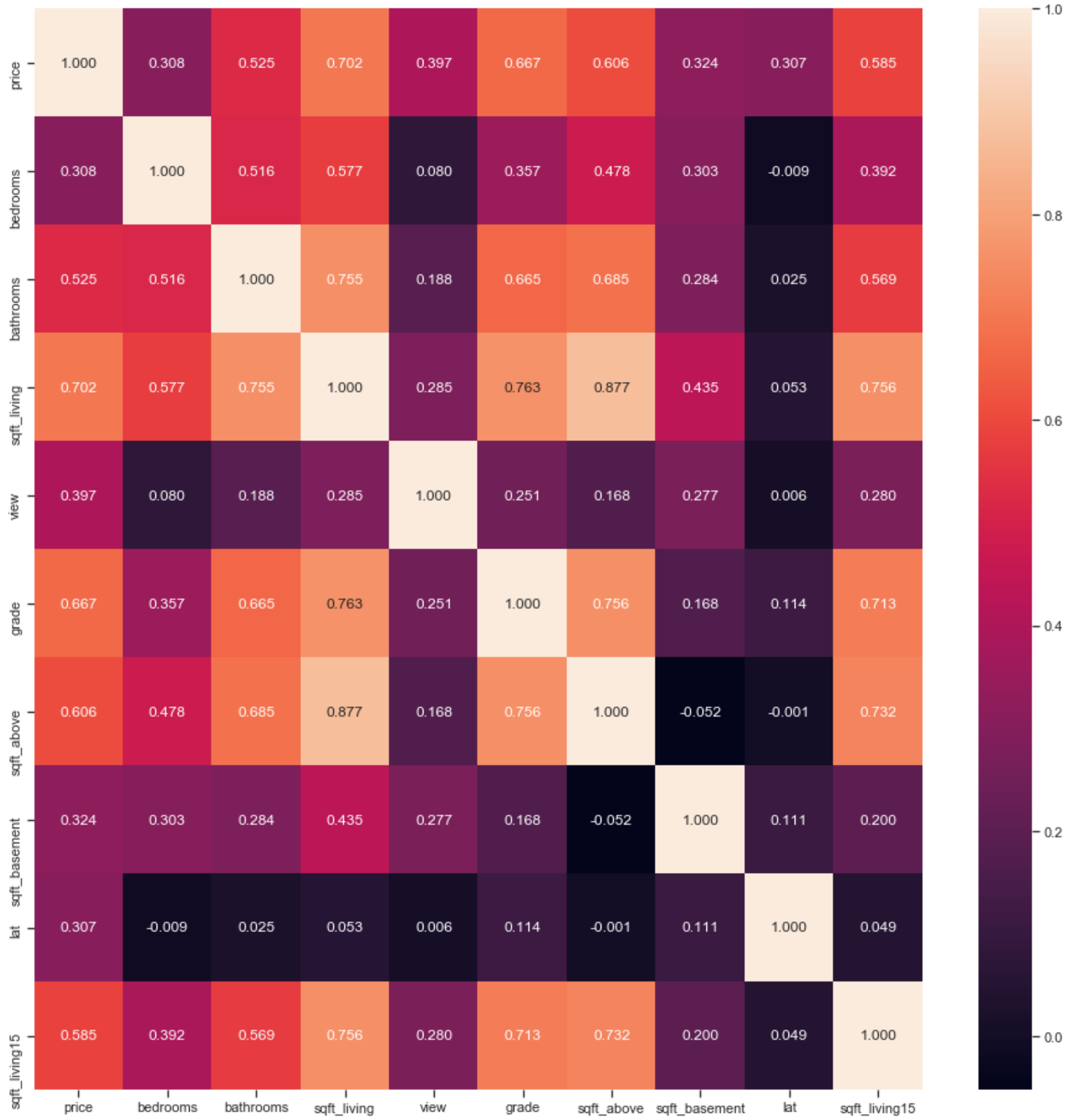
Out[323]: <matplotlib.axes._subplots.AxesSubplot at 0x143548908>



In [324]:
```
# дропнем коллинеарные фичи:
# data = data.drop(columns=['grade', 'sqft_above', 'bathrooms'])
```

In [325]:
```python
plt.figure(figsize=(16, 16))
sns.heatmap(data.corr(), annot=True, fmt='.3f')
```

Out[325]: <matplotlib.axes._subplots.AxesSubplot at 0x142f6f748>



Кодирование категориальных признаков

In [326]:
```python
cat_cols = []
for col in data.columns:
    if data[col].dtype == 'object':
        cat_cols.append(col)
cat_cols
```

Out[326]: ['date']

In [327]:
```
for col in cat_cols:
    print('`{}`: {} unique values'.format(col, len(data[col].unique
())))
```

```
`date`: 372 unique values
```

In [328]:
```
from sklearn.preprocessing import LabelEncoder
```

In [329]:
```
encoding_of_cat = {}
for col in cat_cols:
    le = LabelEncoder()
    data[[col]] = le.fit_transform(data[col])
    encoding_of_cat[col] = le
```

In [330]:
```
data.corr()
```

Out[330]:

	date	price	bedrooms	bathrooms	sqft_living	view	grad
date	1.000000	-0.004649	-0.016964	-0.034481	-0.034570	-0.001837	-0.04004
price	-0.004649	1.000000	0.308350	0.525138	0.702035	0.397293	0.66743
bedrooms	-0.016964	0.308350	1.000000	0.515884	0.576671	0.079532	0.35696
bathrooms	-0.034481	0.525138	0.515884	1.000000	0.754665	0.187737	0.66498
sqft_living	-0.034570	0.702035	0.576671	0.754665	1.000000	0.284611	0.76270
view	-0.001837	0.397293	0.079532	0.187737	0.284611	1.000000	0.25132
grade	-0.040040	0.667434	0.356967	0.664983	0.762704	0.251321	1.00000
sqft_above	-0.027890	0.605567	0.477600	0.685342	0.876597	0.167649	0.75592
sqft_basement	-0.019554	0.323816	0.303093	0.283770	0.435043	0.276947	0.16839
lat	-0.032851	0.307003	-0.008931	0.024573	0.052529	0.006157	0.11408
sqft_living15	-0.031653	0.585379	0.391638	0.568634	0.756420	0.280439	0.71320

In [331]:
```
print('`date` corr:', data.corr()['price']['date'])
```

```
`date` corr: -0.0046490362965513525
```

Целевой признак `price` слабо коррелирует с `date` , удалим `date`

In [332]:
```
data = data.drop(columns='date')
```

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

In [333]:
```
data.corr()
```

Out[333]:

	price	bedrooms	bathrooms	sqft_living	view	grade	sqft_above
price	1.000000	0.308350	0.525138	0.702035	0.397293	0.667434	0.605567
bedrooms	0.308350	1.000000	0.515884	0.576671	0.079532	0.356967	0.477600
bathrooms	0.525138	0.515884	1.000000	0.754665	0.187737	0.664983	0.685342
sqft_living	0.702035	0.576671	0.754665	1.000000	0.284611	0.762704	0.876597
view	0.397293	0.079532	0.187737	0.284611	1.000000	0.251321	0.167649
grade	0.667434	0.356967	0.664983	0.762704	0.251321	1.000000	0.755923
sqft_above	0.605567	0.477600	0.685342	0.876597	0.167649	0.755923	1.000000
sqft_basement	0.323816	0.303093	0.283770	0.435043	0.276947	0.168392	-0.051943
lat	0.307003	-0.008931	0.024573	0.052529	0.006157	0.114084	-0.000816
sqft_living15	0.585379	0.391638	0.568634	0.756420	0.280439	0.713202	0.731870

Корреляция была проанализирована выше (тут-Выбор-признаков,-подходящих-для-построения-моделей.-Кодирование-категориальных-признаков-Масштабирование-данных.-Формирование-вспомогательных-признаков,-улучшающих-качество-моделей.)), выброшены признаки с слабой зависимостью с целевым признаком `price` , он имеет сильную зависимость с `sqft_living` , с остальными – среднюю.

5) Выбор метрик для последующей оценки качества моделей.

Перед нами стоит задача регрессии, необходимо выбрать 3 метрики, подходящие для регрессии.

In [334]:
```
from sklearn.metrics import mean_absolute_error, median_absolute_er
ror, r2_score
my_metrics = (mean_absolute_error, median_absolute_error, r2_score)

from sklearn.model_selection import cross_validate, KFold, ShuffleS
plit
cross_val_names = ('neg_mean_absolute_error', 'neg_median_absolute_
error', 'r2')
```

Выбрана метрика `mean_absolute_error` , поскольку она проста и очевидна, так как отражает разницу в среднем промахе модели (|y - y'| для 1 случая, суммируем N случаев, усредняем, деля на N).

Выбрана метрика `median_absolute_error` , поскольку она устойчива к выбросам (медиана из всех случаев |y - y'|).

Выбрана метрика `r2_score` , поскольку она представляет собой универсальную меру зависимости одной случайной величины от множества других.

In [335]:
```
def print_metrics(y_true, y_pred):
    for m in my_metrics:
        print('Metric {}: {}'.format(m.__name__, m(y_true, y_pred))
)

def print_cross_val_scores(model, X_, y_, cv):
    print(cross_validate(model(), X_, y_, scoring=cross_val_names,
cv=cv, return_train_score=True))
```

6) Выбор наиболее подходящих моделей для решения задачи классификации или регрессии.

Перед нами задача регрессии, выбраны следующие модели:

- LinearRegression
- LinearSVR
- DecisionTreeRegressor
- Ensemble: BaggingRegressor with DecisionTreeRegressor
- Ensemble: Gradient boosting (XGBRegressor from xgboost library)

In [336]:
```
from sklearn.linear_model import LinearRegression
from sklearn.svm import LinearSVR
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import BaggingRegressor
from xgboost import XGBRegressor
```

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

In [337]:
```
from sklearn.model_selection import train_test_split
```

In [338]:
```
data.columns
```

Out[338]:
```
Index(['price', 'bedrooms', 'bathrooms', 'sqft_living', 'view', 'g
rade',
       'sqft_above', 'sqft_basement', 'lat', 'sqft_living15'],
      dtype='object')
```

In [339]:
```
test_size = 0.3
state = 42
X, y = data[data.columns[range(1, data.shape[1])]], data[data.colum
ns[[0]]]
xTrain, xTest, yTrain, yTest = train_test_split(X, y, test_size=tes
t_size, random_state=state)
len(xTrain), len(xTest), len(yTrain), len(yTest)
```

Out[339]:
```
(15129, 6484, 15129, 6484)
```

In [340]:
```
X.columns
```

Out[340]:
```
Index(['bedrooms', 'bathrooms', 'sqft_living', 'view', 'grade', 's
qft_above',
       'sqft_basement', 'lat', 'sqft_living15'],
      dtype='object')
```

In [341]:
```
y.columns
```

Out[341]:
```
Index(['price'], dtype='object')
```

Решение задачи регрессии

8) Построение базового решения (baseline) для выбранных моделей без подбора гиперпараметров.

LinearRegression

In [342]:
```
lin_reg = LinearRegression(n_jobs=-1)  # no hyperparams
lin_reg.fit(xTrain, yTrain)
```

Out[342]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=-1, norma
lize=False)
```

In [343]:
```
yPredicted_lin_reg = lin_reg.predict(xTest)
```

In [344]:
```
print_metrics(yTest, yPredicted_lin_reg)
```

```
Metric mean_absolute_error: 139654.25998331458
Metric median_absolute_error: 93998.91289327666
Metric r2_score: 0.6331075681984636
```

LinearSVR

In [368]:
```
from sklearn.preprocessing import Normalizer
normalizerX = Normalizer().fit(X)
X_n = normalizerX.transform(X)

test_size = 0.3
state = 42
xTrain_n, xTest_n = train_test_split(X_n, test_size=test_size, rand
om_state=state)
print(len(xTrain_n), len(xTest_n))

lin_svr = LinearSVR(C=1.0, max_iter=1000)
lin_svr.fit(xTrain_n, yTrain.values.ravel())
```

```
15129 6484
```

Out[368]:
```
LinearSVR(C=1.0, dual=True, epsilon=0.0, fit_intercept=True,
     intercept_scaling=1.0, loss='epsilon_insensitive', max_iter=1
000,
     random_state=None, tol=0.0001, verbose=0)
```

In [369]:
```
yPredicted_lin_svr = lin_svr.predict(xTest)
```

In [370]:
```
print_metrics(yTest, yPredicted_lin_svr)
```

```
Metric mean_absolute_error: 50270369.62206803
Metric median_absolute_error: 45918359.11039731
Metric r2_score: -20096.001594459798
```

DecisionTreeRegressor

In [348]:
```
tree = DecisionTreeRegressor(random_state=state)  # with default hy
perparams
tree.fit(xTrain, yTrain.values.ravel())
```

Out[348]:
```
DecisionTreeRegressor(criterion='mse', max_depth=None, max_feature
s=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=False, random_state=42, splitter='best')
```

In [349]:
```
yPredicted_tree = tree.predict(xTest)
```

In [350]:
```
print_metrics(yTest, yPredicted_tree)
```

```
Metric mean_absolute_error: 129773.90270923298
Metric median_absolute_error: 70000.5
Metric r2_score: 0.5664820790736267
```

Ensemble: BaggingRegressor with DecisionTreeRegressor

In [351]:
```
bagreg_treereg = BaggingRegressor(DecisionTreeRegressor(random_stat
e=state), n_estimators=100)
bagreg_treereg.fit(xTrain, yTrain.values.ravel())
```

Out[351]:
```
BaggingRegressor(base_estimator=DecisionTreeRegressor(criterion='m
se', 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=False, random_state=42, splitter='best'),
         bootstrap=True, bootstrap_features=False, max_features=1.
0,
         max_samples=1.0, n_estimators=100, n_jobs=None, oob_score
=False,
         random_state=None, verbose=0, warm_start=False)
```

In [352]:
```
yPredicted_bagreg_treereg = bagreg_treereg.predict(xTest)
```

In [353]:
```
print_metrics(yTest, yPredicted_bagreg_treereg)
```

```
Metric mean_absolute_error: 94834.9737203201
Metric median_absolute_error: 51491.19999999995
Metric r2_score: 0.7686480983618686
```

Ensemble: Gradient boosting (XGBRegressor from xgboost library)

In [354]:
```
xgbreg_treereg = XGBRegressor(n_jobs=-1)
xgbreg_treereg.fit(xTrain, yTrain.values.ravel())
```

```
[14:21:11] WARNING: src/objective/regression_obj.cu:152: reg:linea
r is now deprecated in favor of reg:squarederror.
```

Out[354]:
```
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1
,
             colsample_bynode=1, colsample_bytree=1, gamma=0,
             importance_type='gain', learning_rate=0.1, max_delta_step=0
,
             max_depth=3, min_child_weight=1, missing=None, n_estimators
=100,
             n_jobs=-1, nthread=None, objective='reg:linear', random_sta
te=0,
             reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
             silent=None, subsample=1, verbosity=1)
```

In [355]:
```
yPredicted_xgbreg_treereg = xgbreg_treereg.predict(xTest)
```

In [356]:
```
print_metrics(yTest, yPredicted_xgbreg_treereg)
```

```
Metric mean_absolute_error: 99196.6039096237
Metric median_absolute_error: 56986.390625
Metric r2_score: 0.7605725228859841
```

9) Подбор гиперпараметров для выбранных моделей.

In [359]:
```
from sklearn.model_selection import GridSearchCV, KFold, ShuffleSpl
it
```

LinearSVR

In [381]:
```
parameters = [{'C': np.array(np.arange(0.1, 20.1, 0.1)),
               'max_iter': np.array([1000, 5000, 10000, 25000, 5000
0, 100000, 250000, 500000, 1000000])}]
lin_svr_grid = GridSearchCV(LinearSVR(), parameters, cv=ShuffleSpli
t(n_splits=10, test_size=test_size),
                            scoring='neg_median_absolute_error',
                            n_jobs=-1,
                            verbose=10
                           )
lin_svr_grid.fit(X_n, y.values.ravel())
```

```
Fitting 10 folds for each of 1800 candidates, totalling 18000 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent
workers.
[Parallel(n_jobs=-1)]: Done   2 tasks      | elapsed:    0.9s
```

```
[Parallel(n_jobs=-1)]: Done   9 tasks      | elapsed:    1.0s
[Parallel(n_jobs=-1)]: Done  16 tasks      | elapsed:    1.0s
[Parallel(n_jobs=-1)]: Done  25 tasks      | elapsed:    1.0s
[Parallel(n_jobs=-1)]: Batch computation too fast (0.1710s.) Setti
ng batch_size=2.
[Parallel(n_jobs=-1)]: Done  34 tasks      | elapsed:    1.1s
[Parallel(n_jobs=-1)]: Batch computation too fast (0.0703s.) Setti
ng batch_size=10.
[Parallel(n_jobs=-1)]: Done  50 tasks      | elapsed:    1.1s
[Parallel(n_jobs=-1)]: Done  72 tasks      | elapsed:    1.2s
[Parallel(n_jobs=-1)]: Done 202 tasks      | elapsed:    1.6s
[Parallel(n_jobs=-1)]: Done 332 tasks      | elapsed:    1.9s
[Parallel(n_jobs=-1)]: Done 482 tasks      | elapsed:    2.3s
[Parallel(n_jobs=-1)]: Done 632 tasks      | elapsed:    2.7s
[Parallel(n_jobs=-1)]: Done 802 tasks      | elapsed:    3.1s
[Parallel(n_jobs=-1)]: Done 972 tasks      | elapsed:    3.6s
[Parallel(n_jobs=-1)]: Done 1162 tasks      | elapsed:    4.2s
[Parallel(n_jobs=-1)]: Done 1352 tasks      | elapsed:    4.6s
[Parallel(n_jobs=-1)]: Done 1562 tasks      | elapsed:    5.2s
[Parallel(n_jobs=-1)]: Done 1772 tasks      | elapsed:    5.8s
[Parallel(n_jobs=-1)]: Done 2002 tasks      | elapsed:    6.5s
[Parallel(n_jobs=-1)]: Done 2232 tasks      | elapsed:    7.2s
[Parallel(n_jobs=-1)]: Done 2482 tasks      | elapsed:    7.8s
[Parallel(n_jobs=-1)]: Done 2732 tasks      | elapsed:    8.5s
[Parallel(n_jobs=-1)]: Done 3002 tasks      | elapsed:    9.2s
[Parallel(n_jobs=-1)]: Done 3272 tasks      | elapsed:    9.9s
[Parallel(n_jobs=-1)]: Done 3562 tasks      | elapsed:   10.6s
[Parallel(n_jobs=-1)]: Done 3852 tasks      | elapsed:   11.6s
[Parallel(n_jobs=-1)]: Done 4162 tasks      | elapsed:   12.9s
[Parallel(n_jobs=-1)]: Done 4472 tasks      | elapsed:   13.9s
[Parallel(n_jobs=-1)]: Done 4802 tasks      | elapsed:   15.1s
[Parallel(n_jobs=-1)]: Done 5132 tasks      | elapsed:   16.3s
[Parallel(n_jobs=-1)]: Done 5482 tasks      | elapsed:   17.6s
[Parallel(n_jobs=-1)]: Done 5832 tasks      | elapsed:   18.9s
[Parallel(n_jobs=-1)]: Done 6202 tasks      | elapsed:   20.3s
[Parallel(n_jobs=-1)]: Done 6572 tasks      | elapsed:   21.7s
[Parallel(n_jobs=-1)]: Done 6962 tasks      | elapsed:   23.1s
[Parallel(n_jobs=-1)]: Done 7352 tasks      | elapsed:   24.5s
[Parallel(n_jobs=-1)]: Done 7762 tasks      | elapsed:   26.0s
[Parallel(n_jobs=-1)]: Done 8172 tasks      | elapsed:   27.6s
[Parallel(n_jobs=-1)]: Done 8602 tasks      | elapsed:   29.2s
[Parallel(n_jobs=-1)]: Done 9032 tasks      | elapsed:   30.7s
[Parallel(n_jobs=-1)]: Done 9482 tasks      | elapsed:   32.4s
[Parallel(n_jobs=-1)]: Done 9932 tasks      | elapsed:   34.1s
[Parallel(n_jobs=-1)]: Done 10402 tasks      | elapsed:   36.0s
[Parallel(n_jobs=-1)]: Done 10872 tasks      | elapsed:   37.8s
[Parallel(n_jobs=-1)]: Done 11362 tasks      | elapsed:   39.6s
[Parallel(n_jobs=-1)]: Done 11852 tasks      | elapsed:   41.5s
[Parallel(n_jobs=-1)]: Done 12362 tasks      | elapsed:   43.4s
[Parallel(n_jobs=-1)]: Done 12872 tasks      | elapsed:   45.3s
[Parallel(n_jobs=-1)]: Done 13402 tasks      | elapsed:   47.4s
[Parallel(n_jobs=-1)]: Done 13932 tasks      | elapsed:   49.6s
[Parallel(n_jobs=-1)]: Done 14482 tasks      | elapsed:   51.7s
[Parallel(n_jobs=-1)]: Done 15032 tasks      | elapsed:   53.9s
[Parallel(n_jobs=-1)]: Done 15602 tasks      | elapsed:   56.0s
[Parallel(n_jobs=-1)]: Done 16172 tasks      | elapsed:   58.2s
[Parallel(n_jobs=-1)]: Done 16762 tasks      | elapsed:  1.0min
```

```
[Parallel(n_jobs=-1)]: Done 17352 tasks      | elapsed:  1.0min
[Parallel(n_jobs=-1)]: Done 18000 out of 18000 | elapsed:  1.1min
finished
```

Out[381]:
```
GridSearchCV(cv=ShuffleSplit(n_splits=10, random_state=None, test_
size=0.3, train_size=None),
       error_score='raise-deprecating',
       estimator=LinearSVR(C=1.0, dual=True, epsilon=0.0, fit_inte
rcept=True,
     intercept_scaling=1.0, loss='epsilon_insensitive', max_iter=1
000,
     random_state=None, tol=0.0001, verbose=0),
       fit_params=None, iid='warn', n_jobs=-1,
       param_grid=[{'C': array([ 0.1,  0.2, ..., 19.9, 20. ]), 'ma
x_iter': array([   1000,    5000,   10000,   25000,   50000,  1000
00,  250000,
        500000, 1000000])}],
       pre_dispatch='2*n_jobs', refit=True, return_train_score='wa
rn',
       scoring='neg_median_absolute_error', verbose=10)
```

In [390]:
```
lin_svr_grid.best_estimator_
```

Out[390]:
```
LinearSVR(C=20.000000000000004, dual=True, epsilon=0.0, fit_interc
ept=True,
     intercept_scaling=1.0, loss='epsilon_insensitive', max_iter=1
00000,
     random_state=None, tol=0.0001, verbose=0)
```

In [391]:
```
lin_svr_grid.best_score_
```

Out[391]:
```
-146027.5578859402
```

In [392]:
```
lin_svr_grid.best_params_
```

Out[392]:
```
{'C': 20.000000000000004, 'max_iter': 100000}
```

DecisionTreeRegressor

In [396]:
```
parameters = [{'random_state': np.array([state]),
               'max_depth': np.array([None, 10, 50, 100, 500, 1000,
5000, 10000]),
               'min_samples_split': np.array(range(2, 11)),
               'min_samples_leaf': np.array(range(1, 11))
             }]
tree_grid = GridSearchCV(DecisionTreeRegressor(), parameters, cv=Sh
uffleSplit(n_splits=10, test_size=0.2),
                         scoring='neg_median_absolute_error',
                         n_jobs=-1,
                         verbose=10
                        )
tree_grid.fit(X, y.values.ravel())
```

```
Fitting 10 folds for each of 720 candidates, totalling 7200 fits
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent
workers.
[Parallel(n_jobs=-1)]: Done   2 tasks      | elapsed:    0.7s
[Parallel(n_jobs=-1)]: Done   9 tasks      | elapsed:    0.9s
[Parallel(n_jobs=-1)]: Done  16 tasks      | elapsed:    0.9s
[Parallel(n_jobs=-1)]: Done  25 tasks      | elapsed:    1.2s
[Parallel(n_jobs=-1)]: Done  34 tasks      | elapsed:    1.3s
[Parallel(n_jobs=-1)]: Done  45 tasks      | elapsed:    1.5s
[Parallel(n_jobs=-1)]: Done  56 tasks      | elapsed:    1.6s
[Parallel(n_jobs=-1)]: Done  69 tasks      | elapsed:    1.9s
[Parallel(n_jobs=-1)]: Done  82 tasks      | elapsed:    2.2s
[Parallel(n_jobs=-1)]: Done  97 tasks      | elapsed:    2.5s
[Parallel(n_jobs=-1)]: Done 112 tasks      | elapsed:    2.8s
[Parallel(n_jobs=-1)]: Done 129 tasks      | elapsed:    3.1s
[Parallel(n_jobs=-1)]: Done 146 tasks      | elapsed:    3.4s
[Parallel(n_jobs=-1)]: Done 165 tasks      | elapsed:    3.8s
[Parallel(n_jobs=-1)]: Done 184 tasks      | elapsed:    4.0s
[Parallel(n_jobs=-1)]: Done 205 tasks      | elapsed:    4.4s
[Parallel(n_jobs=-1)]: Done 226 tasks      | elapsed:    4.8s
[Parallel(n_jobs=-1)]: Done 249 tasks      | elapsed:    5.2s
[Parallel(n_jobs=-1)]: Done 272 tasks      | elapsed:    5.5s
[Parallel(n_jobs=-1)]: Done 297 tasks      | elapsed:    5.9s
[Parallel(n_jobs=-1)]: Done 322 tasks      | elapsed:    6.3s
[Parallel(n_jobs=-1)]: Done 349 tasks      | elapsed:    6.7s
[Parallel(n_jobs=-1)]: Done 376 tasks      | elapsed:    7.1s
[Parallel(n_jobs=-1)]: Done 405 tasks      | elapsed:    7.6s
[Parallel(n_jobs=-1)]: Done 434 tasks      | elapsed:    8.0s
[Parallel(n_jobs=-1)]: Done 465 tasks      | elapsed:    8.5s
[Parallel(n_jobs=-1)]: Done 496 tasks      | elapsed:    8.9s
[Parallel(n_jobs=-1)]: Done 529 tasks      | elapsed:    9.4s
[Parallel(n_jobs=-1)]: Done 562 tasks      | elapsed:    9.9s
[Parallel(n_jobs=-1)]: Done 597 tasks      | elapsed:   10.4s
[Parallel(n_jobs=-1)]: Done 632 tasks      | elapsed:   10.9s
[Parallel(n_jobs=-1)]: Done 669 tasks      | elapsed:   11.4s
[Parallel(n_jobs=-1)]: Done 706 tasks      | elapsed:   12.0s
[Parallel(n_jobs=-1)]: Done 745 tasks      | elapsed:   12.6s
[Parallel(n_jobs=-1)]: Done 784 tasks      | elapsed:   13.1s
[Parallel(n_jobs=-1)]: Done 825 tasks      | elapsed:   13.7s
[Parallel(n_jobs=-1)]: Done 866 tasks      | elapsed:   14.3s
[Parallel(n_jobs=-1)]: Done 909 tasks      | elapsed:   14.8s
[Parallel(n_jobs=-1)]: Done 952 tasks      | elapsed:   15.4s
[Parallel(n_jobs=-1)]: Batch computation too fast (0.1975s.) Setti
ng batch_size=2.
[Parallel(n_jobs=-1)]: Done 997 tasks      | elapsed:   16.0s
[Parallel(n_jobs=-1)]: Done 1085 tasks      | elapsed:   17.0s
[Parallel(n_jobs=-1)]: Done 1179 tasks      | elapsed:   18.0s
[Parallel(n_jobs=-1)]: Done 1273 tasks      | elapsed:   19.1s
[Parallel(n_jobs=-1)]: Done 1371 tasks      | elapsed:   20.3s
[Parallel(n_jobs=-1)]: Done 1469 tasks      | elapsed:   21.5s
[Parallel(n_jobs=-1)]: Done 1571 tasks      | elapsed:   22.7s
[Parallel(n_jobs=-1)]: Done 1673 tasks      | elapsed:   23.9s
[Parallel(n_jobs=-1)]: Done 1779 tasks      | elapsed:   25.1s
[Parallel(n_jobs=-1)]: Done 1885 tasks      | elapsed:   27.2s
[Parallel(n_jobs=-1)]: Done 1995 tasks      | elapsed:   29.3s
[Parallel(n_jobs=-1)]: Done 2105 tasks      | elapsed:   31.3s
[Parallel(n_jobs=-1)]: Done 2219 tasks      | elapsed:   33.1s
[Parallel(n_jobs=-1)]: Done 2333 tasks      | elapsed:   35.0s
```

```
[Parallel(n_jobs=-1)]: Done 2451 tasks      | elapsed:   36.7s
[Parallel(n_jobs=-1)]: Done 2569 tasks      | elapsed:   38.6s
[Parallel(n_jobs=-1)]: Done 2691 tasks      | elapsed:   40.2s
[Parallel(n_jobs=-1)]: Done 2813 tasks      | elapsed:   42.6s
[Parallel(n_jobs=-1)]: Done 2939 tasks      | elapsed:   44.8s
[Parallel(n_jobs=-1)]: Done 3065 tasks      | elapsed:   46.9s
[Parallel(n_jobs=-1)]: Done 3195 tasks      | elapsed:   49.1s
[Parallel(n_jobs=-1)]: Done 3325 tasks      | elapsed:   51.2s
[Parallel(n_jobs=-1)]: Done 3459 tasks      | elapsed:   53.3s
[Parallel(n_jobs=-1)]: Done 3593 tasks      | elapsed:   55.6s
[Parallel(n_jobs=-1)]: Done 3731 tasks      | elapsed:   58.5s
[Parallel(n_jobs=-1)]: Done 3869 tasks      | elapsed:  1.0min
[Parallel(n_jobs=-1)]: Done 4011 tasks      | elapsed:  1.1min
[Parallel(n_jobs=-1)]: Done 4153 tasks      | elapsed:  1.1min
[Parallel(n_jobs=-1)]: Done 4299 tasks      | elapsed:  1.1min
[Parallel(n_jobs=-1)]: Done 4445 tasks      | elapsed:  1.2min
[Parallel(n_jobs=-1)]: Done 4595 tasks      | elapsed:  1.2min
[Parallel(n_jobs=-1)]: Done 4745 tasks      | elapsed:  1.3min
[Parallel(n_jobs=-1)]: Done 4899 tasks      | elapsed:  1.3min
[Parallel(n_jobs=-1)]: Done 5053 tasks      | elapsed:  1.4min
[Parallel(n_jobs=-1)]: Done 5211 tasks      | elapsed:  1.4min
[Parallel(n_jobs=-1)]: Done 5369 tasks      | elapsed:  1.4min
[Parallel(n_jobs=-1)]: Done 5531 tasks      | elapsed:  1.5min
[Parallel(n_jobs=-1)]: Done 5693 tasks      | elapsed:  1.5min
[Parallel(n_jobs=-1)]: Done 5859 tasks      | elapsed:  1.6min
[Parallel(n_jobs=-1)]: Done 6025 tasks      | elapsed:  1.6min
[Parallel(n_jobs=-1)]: Done 6195 tasks      | elapsed:  1.7min
[Parallel(n_jobs=-1)]: Done 6365 tasks      | elapsed:  1.7min
[Parallel(n_jobs=-1)]: Done 6539 tasks      | elapsed:  1.8min
[Parallel(n_jobs=-1)]: Done 6713 tasks      | elapsed:  1.8min
[Parallel(n_jobs=-1)]: Done 6891 tasks      | elapsed:  1.9min
[Parallel(n_jobs=-1)]: Done 7069 tasks      | elapsed:  1.9min
[Parallel(n_jobs=-1)]: Done 7185 out of 7200 | elapsed:  2.0min re
maining:    0.2s
[Parallel(n_jobs=-1)]: Done 7200 out of 7200 | elapsed:  2.0min fi
nished
```

Out[396]:

```
GridSearchCV(cv=ShuffleSplit(n_splits=10, random_state=None, test_
size=0.2, train_size=None),
       error_score='raise-deprecating',
       estimator=DecisionTreeRegressor(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=False, random_state=None, splitter='best'),
       fit_params=None, iid='warn', n_jobs=-1,
       param_grid=[{'random_state': array([42]), 'max_depth': arra
y([None, 10, 50, 100, 500, 1000, 5000, 10000], dtype=object), 'min
_samples_split': array([ 2,  3,  4,  5,  6,  7,  8,  9, 10]), 'min
_samples_leaf': array([ 1,  2,  3,  4,  5,  6,  7,  8,  9, 10])}],
       pre_dispatch='2*n_jobs', refit=True, return_train_score='wa
rn',
       scoring='neg_median_absolute_error', verbose=10)
```

In [397]:
```
tree_grid.best_estimator_
```

Out[397]:
```
DecisionTreeRegressor(criterion='mse', max_depth=10, max_features=
None,
           max_leaf_nodes=None, min_impurity_decrease=0.0,
           min_impurity_split=None, min_samples_leaf=3,
           min_samples_split=2, min_weight_fraction_leaf=0.0,
           presort=False, random_state=42, splitter='best')
```

In [398]:
```
tree_grid.best_score_
```

Out[398]:
```
-58160.48411132714
```

In [399]:
```
tree_grid.best_params_
```

Out[399]:
```
{'max_depth': 10,
 'min_samples_leaf': 3,
 'min_samples_split': 2,
 'random_state': 42}
```

Ensemble: BaggingRegressor with DecisionTreeRegressor

In [401]:
```
from sklearn.model_selection import GridSearchCV, KFold, ShuffleSpl
it
parameters = [{'n_estimators': np.array(range(1, 101, 5))}]
bagreg_grid = GridSearchCV(BaggingRegressor(DecisionTreeRegressor(r
andom_state=state)), parameters, cv=ShuffleSplit(n_splits=10, test_
size=0.2),
                           scoring='neg_median_absolute_error',
                           n_jobs=-1,
                           verbose=10,
                          )
bagreg_grid.fit(X, y.values.ravel())
```

```
Fitting 10 folds for each of 20 candidates, totalling 200 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent
workers.
[Parallel(n_jobs=-1)]: Done   2 tasks      | elapsed:    1.5s
[Parallel(n_jobs=-1)]: Done   9 tasks      | elapsed:    1.7s
[Parallel(n_jobs=-1)]: Done  16 tasks      | elapsed:    2.2s
[Parallel(n_jobs=-1)]: Done  25 tasks      | elapsed:    3.3s
[Parallel(n_jobs=-1)]: Done  34 tasks      | elapsed:    4.8s
[Parallel(n_jobs=-1)]: Done  45 tasks      | elapsed:    7.8s
[Parallel(n_jobs=-1)]: Done  56 tasks      | elapsed:   10.8s
[Parallel(n_jobs=-1)]: Done  69 tasks      | elapsed:   17.5s
[Parallel(n_jobs=-1)]: Done  82 tasks      | elapsed:   23.3s
[Parallel(n_jobs=-1)]: Done  97 tasks      | elapsed:   31.6s
[Parallel(n_jobs=-1)]: Done 112 tasks      | elapsed:   41.5s
[Parallel(n_jobs=-1)]: Done 129 tasks      | elapsed:   55.2s
[Parallel(n_jobs=-1)]: Done 146 tasks      | elapsed:  1.2min
[Parallel(n_jobs=-1)]: Done 165 tasks      | elapsed:  1.5min
[Parallel(n_jobs=-1)]: Done 184 tasks      | elapsed:  1.8min
[Parallel(n_jobs=-1)]: Done 200 out of 200 | elapsed:  2.1min fini
shed
```

Out[401]:
```
GridSearchCV(cv=ShuffleSplit(n_splits=10, random_state=None, test_
size=0.2, train_size=None),
       error_score='raise-deprecating',

estimator=BaggingRegressor(base_estimator=DecisionTreeRegressor(cr
iterion='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,
       ...stimators=10, n_jobs=None, oob_score=False,
         random_state=None, verbose=0, warm_start=False),
       fit_params=None, iid='warn', n_jobs=-1,
       param_grid=[{'n_estimators': array([ 1,  6, 11, 16, 21, 26,
31, 36, 41, 46, 51, 56, 61, 66, 71, 76, 81,
       86, 91, 96])}],
       pre_dispatch='2*n_jobs', refit=True, return_train_score='wa
rn',
       scoring='neg_median_absolute_error', verbose=10)
```

In [403]:
```
bagreg_grid.best_estimator_
```

Out[403]:
```
BaggingRegressor(base_estimator=DecisionTreeRegressor(criterion='m
se', 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=False, random_state=42, splitter='best'),
         bootstrap=True, bootstrap_features=False, max_features=1.
0,
         max_samples=1.0, n_estimators=71, n_jobs=None, oob_score=
False,
         random_state=None, verbose=0, warm_start=False)
```

In [404]:
```
bagreg_grid.best_score_
```
Out[404]:
```
-50558.99342723005
```
In [405]:
```
bagreg_grid.best_params_
```
Out[405]:
```
{'n_estimators': 71}
```

Ensemble: Gradient boosting (XGBRegressor from xgboost library)

In [406]:
```
parameters = [{"colsample_bytree": [1.0], "min_child_weight": [0.8, 1.0, 1.2],
               'max_depth': range(3, 11), 'n_estimators': [25, 50, 75, 100]}]
xgbreg_grid = GridSearchCV(XGBRegressor(), parameters, cv=ShuffleSplit(n_splits=10, test_size=0.2),
                           scoring='neg_median_absolute_error',
                           n_jobs=-1,
                           verbose=10,
                          )
xgbreg_grid.fit(X, y.values.ravel())
```
```
Fitting 10 folds for each of 96 candidates, totalling 960 fits
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent
workers.
[Parallel(n_jobs=-1)]: Done   2 tasks      | elapsed:    0.4s
[Parallel(n_jobs=-1)]: Done   9 tasks      | elapsed:    0.8s
[Parallel(n_jobs=-1)]: Done  16 tasks      | elapsed:    1.3s
[Parallel(n_jobs=-1)]: Done  25 tasks      | elapsed:    2.8s
[Parallel(n_jobs=-1)]: Done  34 tasks      | elapsed:    4.3s
[Parallel(n_jobs=-1)]: Done  45 tasks      | elapsed:    5.4s
[Parallel(n_jobs=-1)]: Done  56 tasks      | elapsed:    6.2s
[Parallel(n_jobs=-1)]: Done  69 tasks      | elapsed:    8.3s
[Parallel(n_jobs=-1)]: Done  82 tasks      | elapsed:    9.7s
[Parallel(n_jobs=-1)]: Done  97 tasks      | elapsed:   11.2s
[Parallel(n_jobs=-1)]: Done 112 tasks      | elapsed:   13.6s
[Parallel(n_jobs=-1)]: Done 129 tasks      | elapsed:   15.4s
[Parallel(n_jobs=-1)]: Done 146 tasks      | elapsed:   17.7s
[Parallel(n_jobs=-1)]: Done 165 tasks      | elapsed:   21.1s
[Parallel(n_jobs=-1)]: Done 184 tasks      | elapsed:   23.5s
[Parallel(n_jobs=-1)]: Done 205 tasks      | elapsed:   27.0s
[Parallel(n_jobs=-1)]: Done 226 tasks      | elapsed:   29.6s
[Parallel(n_jobs=-1)]: Done 249 tasks      | elapsed:   33.4s
[Parallel(n_jobs=-1)]: Done 272 tasks      | elapsed:   39.0s
[Parallel(n_jobs=-1)]: Done 297 tasks      | elapsed:   42.8s
[Parallel(n_jobs=-1)]: Done 322 tasks      | elapsed:   48.3s
[Parallel(n_jobs=-1)]: Done 349 tasks      | elapsed:   53.7s
[Parallel(n_jobs=-1)]: Done 376 tasks      | elapsed:   58.3s
[Parallel(n_jobs=-1)]: Done 405 tasks      | elapsed:  1.1min
[Parallel(n_jobs=-1)]: Done 434 tasks      | elapsed:  1.2min
[Parallel(n_jobs=-1)]: Done 465 tasks      | elapsed:  1.3min
[Parallel(n_jobs=-1)]: Done 496 tasks      | elapsed:  1.4min
[Parallel(n_jobs=-1)]: Done 529 tasks      | elapsed:  1.6min
[Parallel(n_jobs=-1)]: Done 562 tasks      | elapsed:  1.7min
[Parallel(n_jobs=-1)]: Done 597 tasks      | elapsed:  1.9min
[Parallel(n_jobs=-1)]: Done 632 tasks      | elapsed:  2.0min
[Parallel(n_jobs=-1)]: Done 669 tasks      | elapsed:  2.2min
[Parallel(n_jobs=-1)]: Done 706 tasks      | elapsed:  2.4min
[Parallel(n_jobs=-1)]: Done 745 tasks      | elapsed:  2.6min
[Parallel(n_jobs=-1)]: Done 784 tasks      | elapsed:  2.8min
[Parallel(n_jobs=-1)]: Done 825 tasks      | elapsed:  3.0min
[Parallel(n_jobs=-1)]: Done 866 tasks      | elapsed:  3.2min
[Parallel(n_jobs=-1)]: Done 909 tasks      | elapsed:  3.5min
[Parallel(n_jobs=-1)]: Done 960 out of 960 | elapsed:  3.8min fini
shed

[14:58:22] WARNING: src/objective/regression_obj.cu:152: reg:linea
r is now deprecated in favor of reg:squarederror.
```

```
Out[406]: GridSearchCV(cv=ShuffleSplit(n_splits=10, random_state=None, test_
size=0.2, train_size=None),
       error_score='raise-deprecating',
       estimator=XGBRegressor(base_score=0.5, booster='gbtree', co
lsample_bylevel=1,
       colsample_bynode=1, colsample_bytree=1, gamma=0,
       importance_type='gain', learning_rate=0.1, max_delta_step=0
,
       max_depth=3, min_child_weight=1, missing=None, n_estimators
=100,
       n_jobs=1, nthread=None, objective='reg:linear', random_stat
e=0,
       reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
       silent=None, subsample=1, verbosity=1),
       fit_params=None, iid='warn', n_jobs=-1,
       param_grid=[{'colsample_bytree': [1.0], 'min_child_weight':
[0.8, 1.0, 1.2], 'max_depth': range(3, 11), 'n_estimators': [25, 5
0, 75, 100]}],
       pre_dispatch='2*n_jobs', refit=True, return_train_score='wa
rn',
       scoring='neg_median_absolute_error', verbose=10)
```

```
In [407]: xgbreg_grid.best_estimator_
```

```
Out[407]: XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1
,
       colsample_bynode=1, colsample_bytree=1.0, gamma=0,
       importance_type='gain', learning_rate=0.1, max_delta_step=0
,
       max_depth=10, min_child_weight=0.8, missing=None, n_estimat
ors=50,
       n_jobs=1, nthread=None, objective='reg:linear', random_stat
e=0,
       reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
       silent=None, subsample=1, verbosity=1)
```

```
In [408]: xgbreg_grid.best_score_
```

```
Out[408]: -49993.25625
```

```
In [409]: xgbreg_grid.best_params_
```

```
Out[409]: {'colsample_bytree': 1.0,
 'max_depth': 10,
 'min_child_weight': 0.8,
 'n_estimators': 50}
```

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

LinearSVR

In [410]:
```
lin_svr_grid.best_estimator_.fit(xTrain_n, yTrain.values.ravel())

yPredicted_lin_svr_new = lin_svr_grid.best_estimator_.predict(xTest
_n)
print('old:')
print_metrics(yTest, yPredicted_lin_svr)

print('\nnew:')
print_metrics(yTest, yPredicted_lin_svr_new)
```

```
old:
Metric mean_absolute_error: 50270369.62206803
Metric median_absolute_error: 45918359.11039731
Metric r2_score: -20096.001594459798

new:
Metric mean_absolute_error: 262271.02348911285
Metric median_absolute_error: 147450.00928251055
Metric r2_score: -0.3718708004825009
```

DecisionTreeRegressor

In [414]:
```
tree_grid.best_estimator_.fit(xTrain, yTrain.values.ravel())

yPredicted_tree_new = tree_grid.best_estimator_.predict(xTest)
print('old:')
print_metrics(yTest, yPredicted_tree)

print('\nnew:')
print_metrics(yTest, yPredicted_tree_new)
```

```
old:
Metric mean_absolute_error: 129773.90270923298
Metric median_absolute_error: 70000.5
Metric r2_score: 0.5664820790736267

new:
Metric mean_absolute_error: 109969.3788295769
Metric median_absolute_error: 59306.32438316394
Metric r2_score: 0.6733312258690927
```

Ensemble: BaggingRegressor with DecisionTreeRegressor

In [412]:
```
bagreg_grid.best_estimator_.fit(xTrain, yTrain.values.ravel())

yPredicted_bagreg_treereg_new = bagreg_grid.best_estimator_.predict
(xTest)
print('old:')
print_metrics(yTest, yPredicted_bagreg_treereg)

print('\nnew:')
print_metrics(yTest, yPredicted_bagreg_treereg_new)
```

```
old:
Metric mean_absolute_error: 94834.9737203201
Metric median_absolute_error: 51491.19999999995
Metric r2_score: 0.7686480983618686

new:
Metric mean_absolute_error: 94800.05277012683
Metric median_absolute_error: 51570.542253521126
Metric r2_score: 0.7697305739843688
```

Ensemble: Gradient boosting (XGBRegressor from xgboost library)

In [413]:
```
xgbreg_grid.best_estimator_.fit(xTrain, yTrain.values.ravel())

yPredicted_xgbreg_treereg_new = xgbreg_grid.best_estimator_.predict
(xTest)
print('old:')
print_metrics(yTest, yPredicted_xgbreg_treereg)

print('\nnew:')
print_metrics(yTest, yPredicted_xgbreg_treereg_new)
```

```
[14:59:08] WARNING: src/objective/regression_obj.cu:152: reg:linea
r is now deprecated in favor of reg:squarederror.
old:
Metric mean_absolute_error: 99196.6039096237
Metric median_absolute_error: 56986.390625
Metric r2_score: 0.7605725228859841

new:
Metric mean_absolute_error: 93738.3927745219
Metric median_absolute_error: 51429.953125
Metric r2_score: 0.7570938895100083
```

Графическая реализация

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

In [415]:
```
from sklearn.model_selection import learning_curve, validation_curv
e
```

In [416]:
```
def plot_learning_curve(estimator, title, X, y, ylim=None, cv=None,
                        n_jobs=-1, train_sizes=np.linspace(.1, 1.0,
5)):
    """
    Generate a simple plot of the test and training learning curve.

    Parameters
    ----------
    estimator : object type that implements the "fit" and "predict"
methods
        An object of that type which is cloned for each validation.

    title : string
        Title for the chart.

    X : array-like, shape (n_samples, n_features)
        Training vector, where n_samples is the number of samples a
nd
        n_features is the number of features.

    y : array-like, shape (n_samples) or (n_samples, n_features), o
ptional
        Target relative to X for classification or regression;
        None for unsupervised learning.

    ylim : tuple, shape (ymin, ymax), optional
        Defines minimum and maximum yvalues plotted.

    cv : int, cross-validation generator or an iterable, optional
        Determines the cross-validation splitting strategy.
        Possible inputs for cv are:
          - None, to use the default 3-fold cross-validation,
          - integer, to specify the number of folds.
          - :term:`CV splitter`,
          - An iterable yielding (train, test) splits as arrays of
indices.

        For integer/None inputs, if ``y`` is binary or multiclass,
        :class:`StratifiedKFold` used. If the estimator is not a cl
assifier
        or if ``y`` is neither binary nor multiclass, :class:`KFold
` is used.

        Refer :ref:`User Guide <cross_validation>` for the various
        cross-validators that can be used here.
```

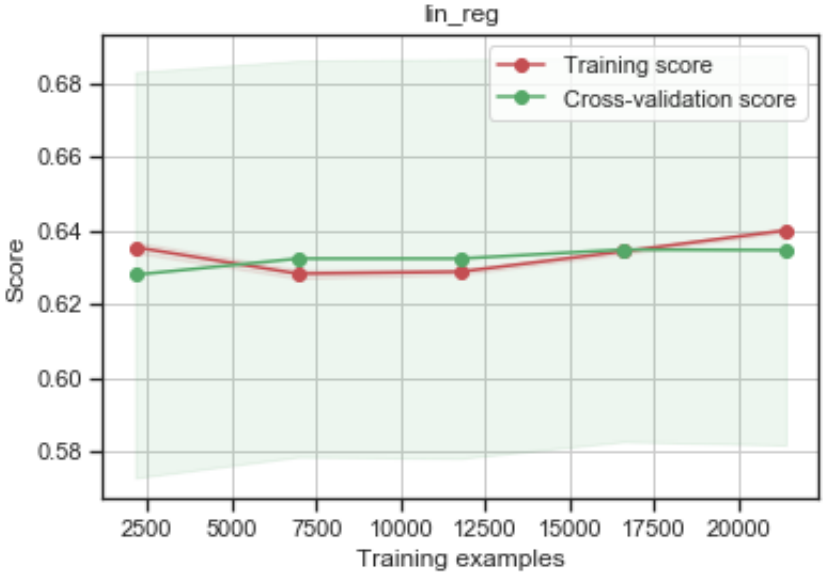
```
    n_jobs : int or None, optional (default=None)
        Number of jobs to run in parallel.
        ``None`` means 1 unless in a :obj:`joblib.parallel_backend`
context.
        ``-1`` means using all processors. See :term:`Glossary <n_j
obs>`
        for more details.

    train_sizes : array-like, shape (n_ticks,), dtype float or int
        Relative or absolute numbers of training examples that will
be used to
        generate the learning curve. If the dtype is float, it is r
egarded as a
        fraction of the maximum size of the training set (that is d
etermined
        by the selected validation method), i.e. it has to be withi
n (0, 1].
        Otherwise it is interpreted as absolute sizes of the traini
ng sets.
        Note that for classification the number of samples usually
have to
        be big enough to contain at least one sample from each clas
s.
        (default: np.linspace(0.1, 1.0, 5))
    """
    plt.figure()
    plt.title(title)
    if ylim is not None:
        plt.ylim(*ylim)
    plt.xlabel("Training examples")
    plt.ylabel("Score")
    train_sizes, train_scores, test_scores = learning_curve(
        estimator, X, y, cv=cv, n_jobs=n_jobs, train_sizes=train_si
zes)
    train_scores_mean = np.mean(train_scores, axis=1)
    train_scores_std = np.std(train_scores, axis=1)
    test_scores_mean = np.mean(test_scores, axis=1)
    test_scores_std = np.std(test_scores, axis=1)
    plt.grid()

    plt.fill_between(train_sizes, train_scores_mean - train_scores_
std,
                     train_scores_mean + train_scores_std, alpha=0.
1,
                     color="r")
    plt.fill_between(train_sizes, test_scores_mean - test_scores_st
d,
                     test_scores_mean + test_scores_std, alpha=0.1,
color="g")
    plt.plot(train_sizes, train_scores_mean, 'o-', color="r",
             label="Training score")
    plt.plot(train_sizes, test_scores_mean, 'o-', color="g",
             label="Cross-validation score")

    plt.legend(loc="best")
    return plt
```

In [417]:
```python
def plot_validation_curve(estimator, title, X, y,
                          param_name, param_range, cv,
                          scoring="accuracy"):

    train_scores, test_scores = validation_curve(
        estimator, X, y, param_name=param_name, param_range=param_r
ange,
        cv=cv, scoring=scoring,
        n_jobs=-1
    )
    train_scores_mean = np.mean(train_scores, axis=1)
    train_scores_std = np.std(train_scores, axis=1)
    test_scores_mean = np.mean(test_scores, axis=1)
    test_scores_std = np.std(test_scores, axis=1)

    plt.title(title)
    plt.xlabel(param_name)
    plt.ylabel("Score")
    plt.ylim(0.0, 1.1)
    lw = 2
    plt.plot(param_range, train_scores_mean, label="Training score"
,
                 color="darkorange", lw=lw)
    plt.fill_between(param_range, train_scores_mean - train_scores_
std,
                     train_scores_mean + train_scores_std, alpha=0.
2,
                     color="darkorange", lw=lw)
    plt.plot(param_range, test_scores_mean, label="Cross-validation
score",
                 color="navy", lw=lw)
    plt.fill_between(param_range, test_scores_mean - test_scores_st
d,
                     test_scores_mean + test_scores_std, alpha=0.2,
                     color="navy", lw=lw)
    plt.legend(loc="best")
    return plt
```

LinearRegression

In [433]:
```
plot_learning_curve(lin_reg, 'lin_reg',
                    X, y.values.ravel(), cv=KFold(n_splits=100))
```

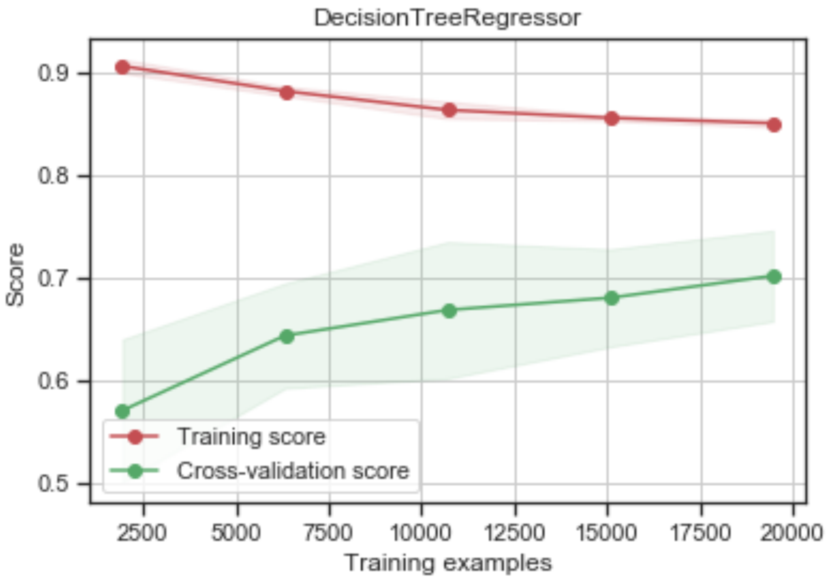
Out[433]: <module 'matplotlib.pyplot' from '/Users/artyom.andreev/Study/.venv/lib/python3.7/site-packages/matplotlib/pyplot.py'>



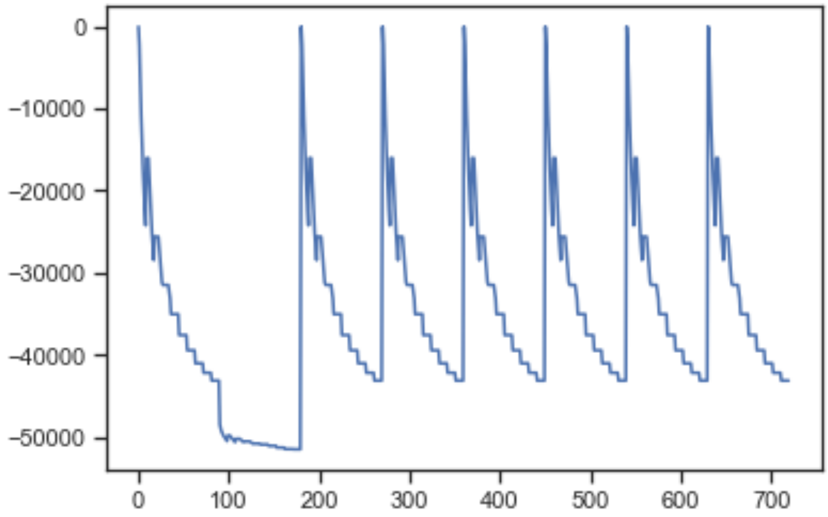
DecisionTreeRegressor

In [430]:
```
plot_learning_curve(tree_grid.best_estimator_, 'DecisionTreeRegressor',
                    X, y.values.ravel(), cv=KFold(n_splits=10))
```

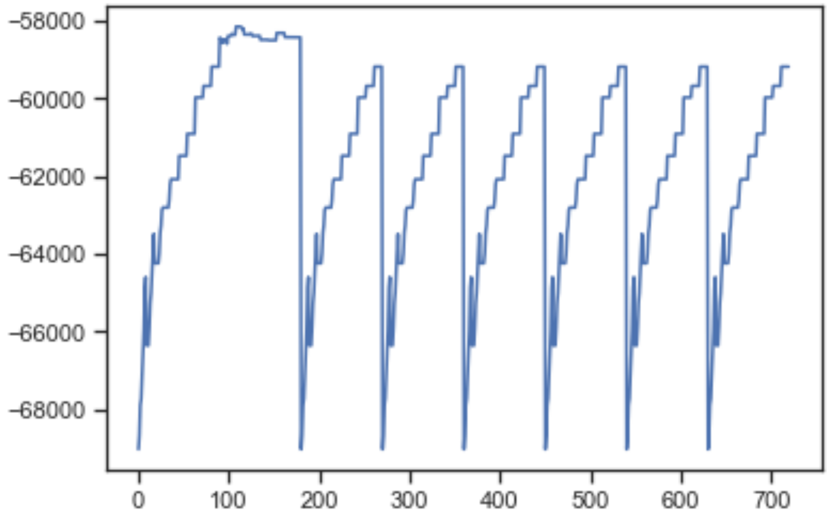
Out[430]: <module 'matplotlib.pyplot' from '/Users/artyom.andreev/Study/.venv/lib/python3.7/site-packages/matplotlib/pyplot.py'>



In [453]:
```
plt.plot(range(720), tree_grid.cv_results_['mean_train_score'])
```
Out[453]: [<matplotlib.lines.Line2D at 0x17099bcc0>]

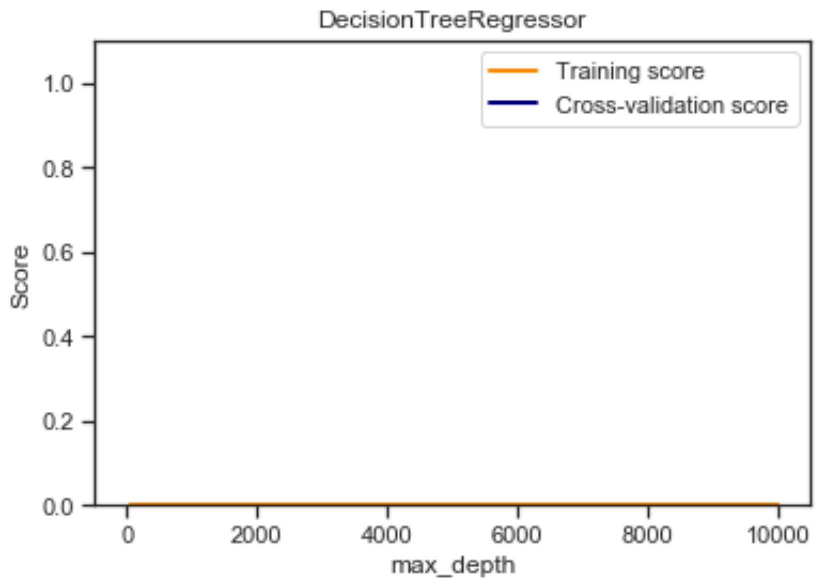


In [454]:
```
plt.plot(range(720), tree_grid.cv_results_['mean_test_score'])
```
Out[454]: [<matplotlib.lines.Line2D at 0x1706b1160>]



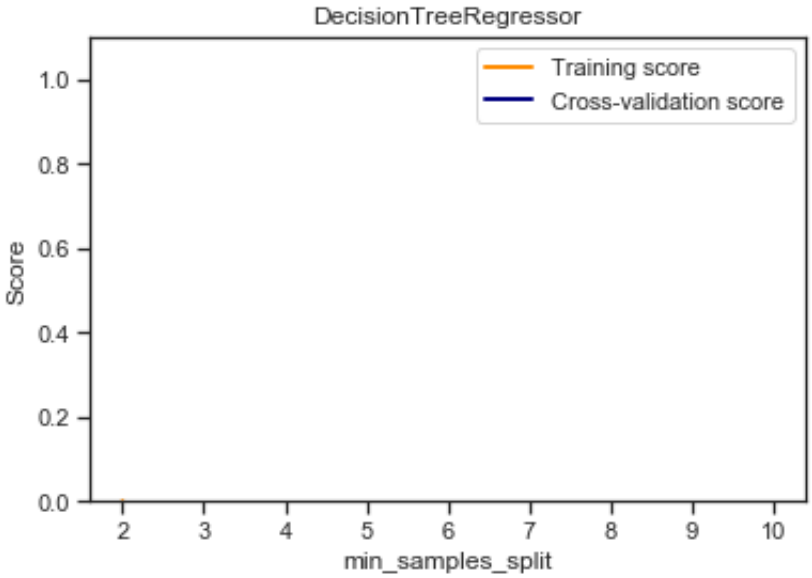
In [440]:
```
parameters_tree = [{'random_state': np.array([state]),
                    'max_depth': np.array([None, 10, 50, 100, 500,
1000, 5000, 10000]),
                    'min_samples_split': np.array(range(2, 11)),
                    'min_samples_leaf': np.array(range(1, 11))
                   }]

plot_validation_curve(DecisionTreeRegressor(random_state=state), 'D
ecisionTreeRegressor',
                      X, y.values.ravel(),
                      param_name='max_depth', param_range=[10, 50,
100, 500, 1000, 5000, 10000],
                      cv=KFold(n_splits=10), scoring="neg_median_ab
solute_error")
```

Out[440]:
```
<module 'matplotlib.pyplot' from '/Users/artyom.andreev/Study/.ven
v/lib/python3.7/site-packages/matplotlib/pyplot.py'>
```



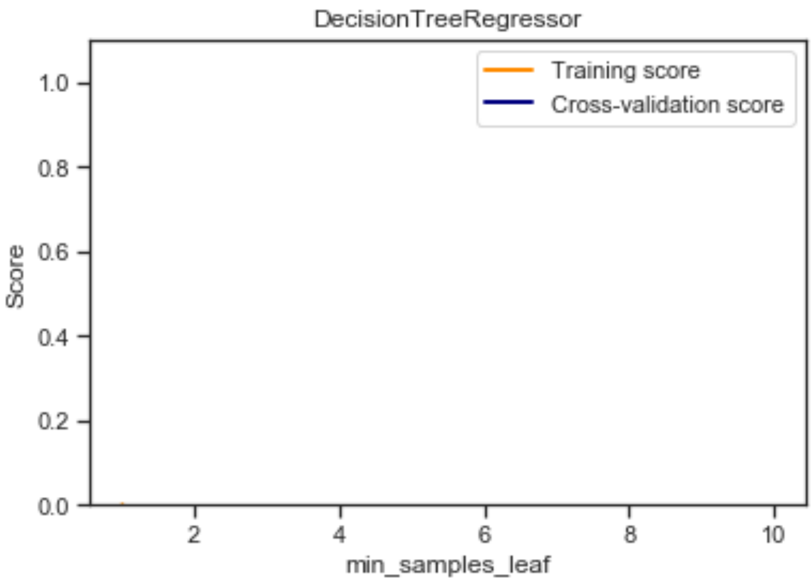
In [436]:
```
plot_validation_curve(DecisionTreeRegressor(random_state=state), 'DecisionTreeRegressor',
                      X, y.values.ravel(),
                      param_name='min_samples_split', param_range=range(2, 11),
                      cv=KFold(n_splits=10), scoring="neg_median_absolute_error")
```

Out[436]:
```
<module 'matplotlib.pyplot' from '/Users/artyom.andreev/Study/.venv/lib/python3.7/site-packages/matplotlib/pyplot.py'>
```



In [438]:
```
plot_validation_curve(DecisionTreeRegressor(random_state=state), 'DecisionTreeRegressor',
                      X, y.values.ravel(),
                      param_name='min_samples_leaf', param_range=range(1, 11),
                      cv=KFold(n_splits=10), scoring="neg_median_absolute_error")
```

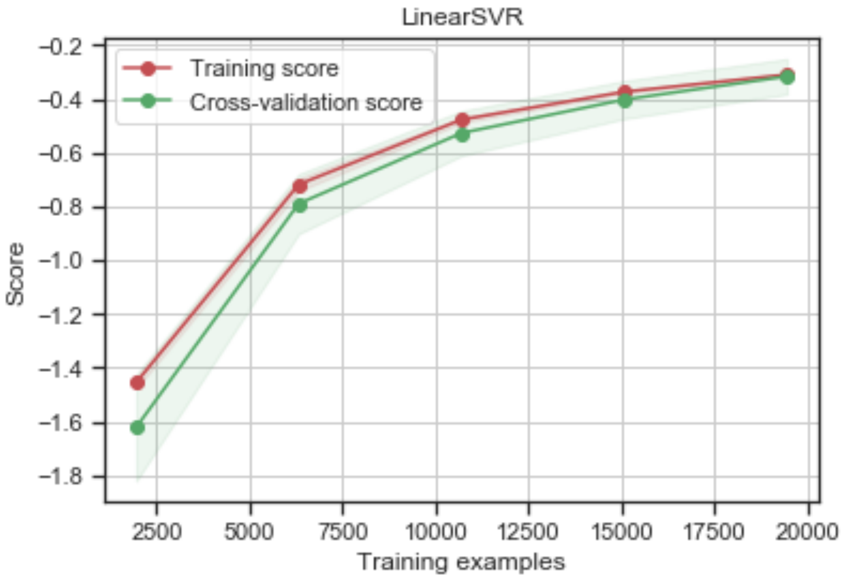
Out[438]:
```
<module 'matplotlib.pyplot' from '/Users/artyom.andreev/Study/.venv/lib/python3.7/site-packages/matplotlib/pyplot.py'>
```



LinearSVR

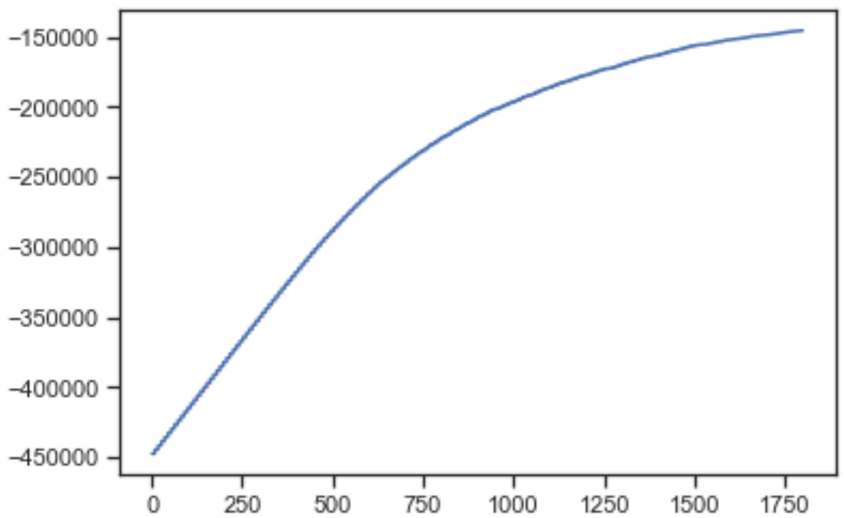
In [442]:
```
plot_learning_curve(lin_svr_grid.best_estimator_, 'LinearSVR',
                    X_n, y.values.ravel(), cv=KFold(n_splits=10))
```

Out[442]:
```
<module 'matplotlib.pyplot' from '/Users/artyom.andreev/Study/.ven
v/lib/python3.7/site-packages/matplotlib/pyplot.py'>
```



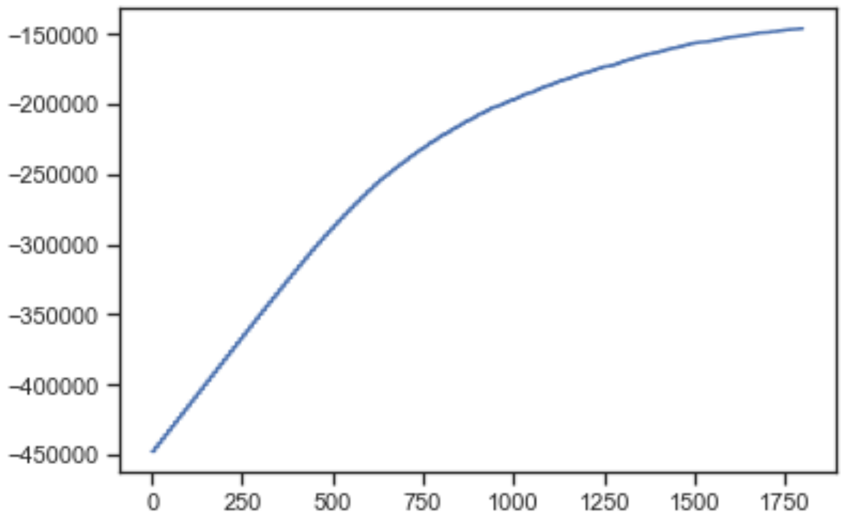
In [459]:
```
plt.plot(range(1800), lin_svr_grid.cv_results_['mean_train_score'])
```

Out[459]:
```
[<matplotlib.lines.Line2D at 0x170abe7f0>]
```



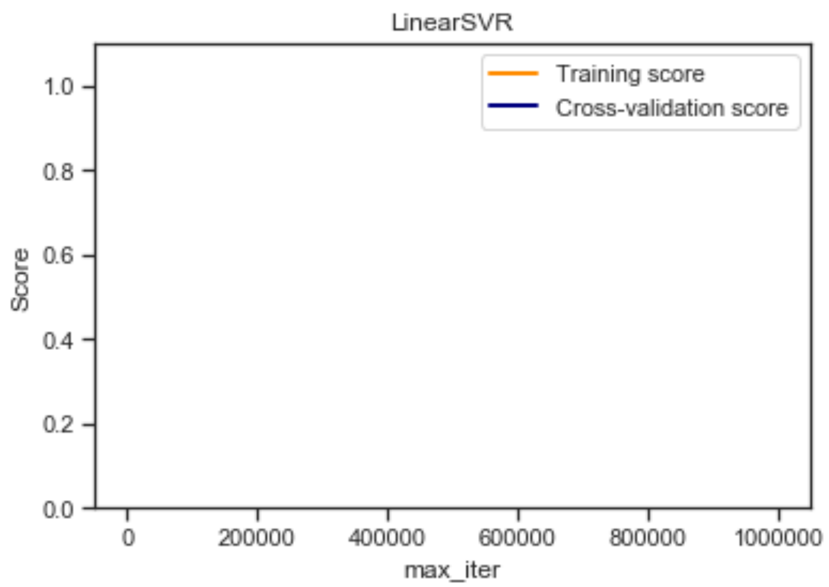
```
In [460]: plt.plot(range(1800), lin_svr_grid.cv_results_['mean_test_score'])
```

```
Out[460]: [<matplotlib.lines.Line2D at 0x16f538080>]
```




```
In [443]: parameters_lin_svr = {'max_iter': np.array([1000, 5000, 10000, 2500
          0, 50000, 100000, 250000, 500000, 1000000])}
          plot_validation_curve(LinearSVR(), 'LinearSVR',
                                X, y.values.ravel(),
                                param_name='max_iter', param_range=[1000, 500
          0, 10000, 25000, 50000, 100000, 250000, 500000, 1000000],
                                cv=KFold(n_splits=10), scoring="neg_median_ab
          solute_error")
```

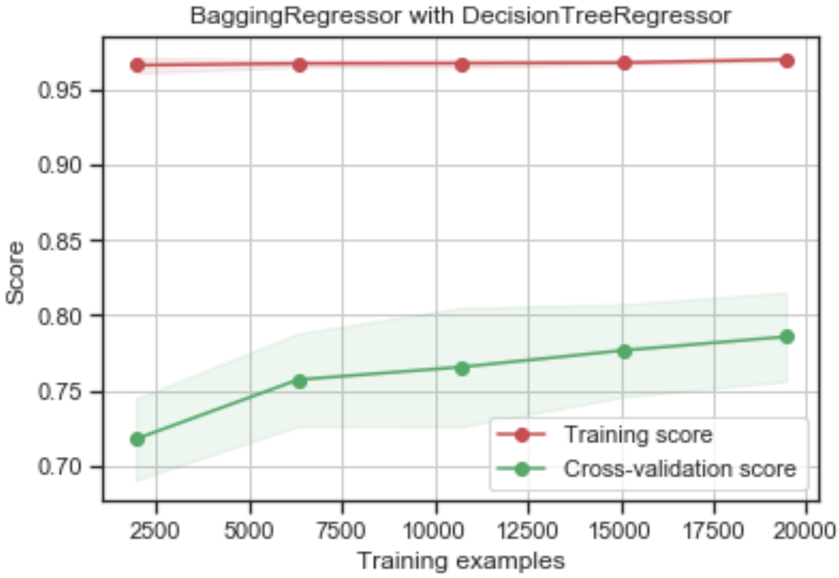
```
Out[443]: <module 'matplotlib.pyplot' from '/Users/artyom.andreev/Study/.ven
          v/lib/python3.7/site-packages/matplotlib/pyplot.py'>
```



Ensemble: BaggingRegressor with DecisionTreeRegressor

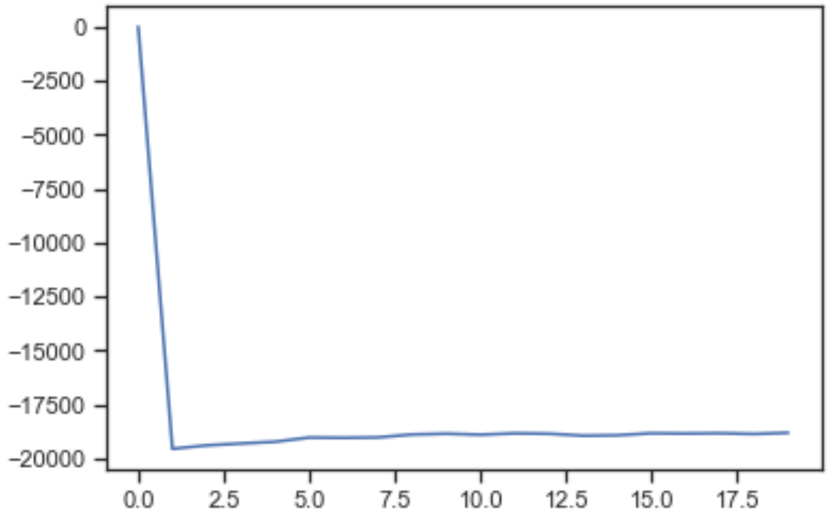
In [445]:
```
plot_learning_curve(bagreg_grid.best_estimator_, 'BaggingRegressor with DecisionTreeRegressor',
                    X, y.values.ravel(), cv=KFold(n_splits=10))
```

Out[445]:
```
<module 'matplotlib.pyplot' from '/Users/artyom.andreev/Study/.venv/lib/python3.7/site-packages/matplotlib/pyplot.py'>
```

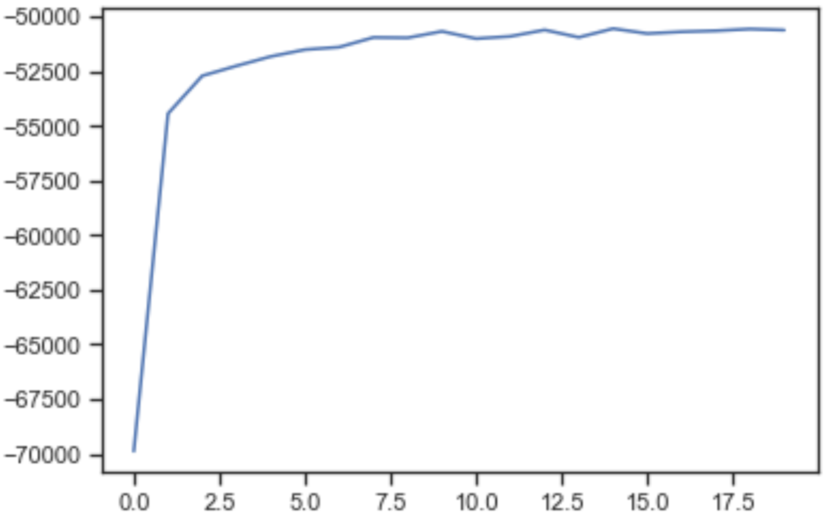


In [462]:
```
plt.plot(range(20), bagreg_grid.cv_results_['mean_train_score'])
```

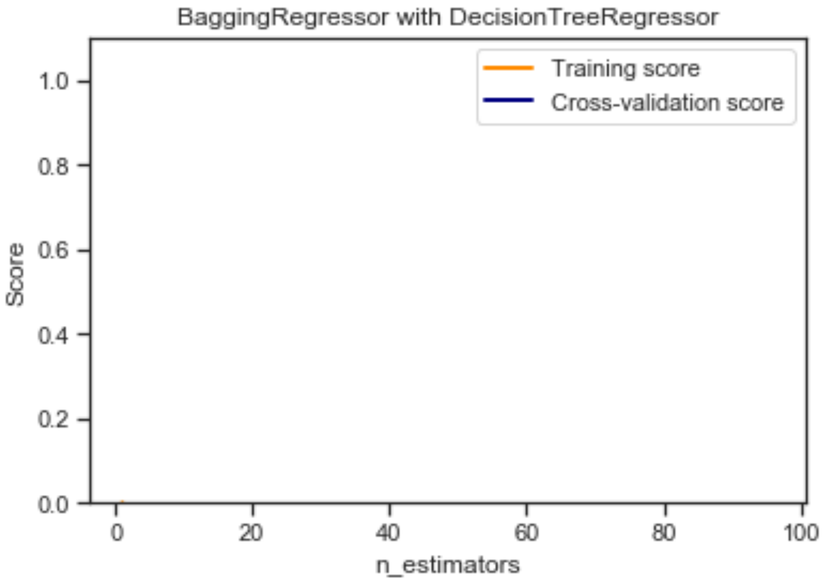
Out[462]:
```
[<matplotlib.lines.Line2D at 0x170ccd240>]
```



In [463]:
```
plt.plot(range(20), bagreg_grid.cv_results_['mean_test_score'])
```
Out[463]: [<matplotlib.lines.Line2D at 0x170204400>]



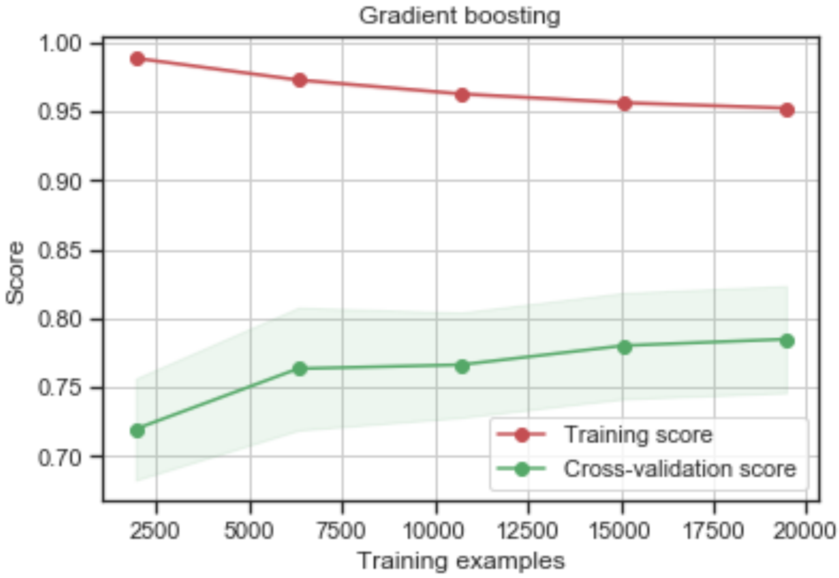
In [469]:
```
parameters_bagging = [{'n_estimators': np.array(range(1, 101, 5))}]


plot_validation_curve(BaggingRegressor(DecisionTreeRegressor(random
_state=state)), 'BaggingRegressor with DecisionTreeRegressor',
                      X, y.values.ravel(),
                      param_name='n_estimators', param_range=np.arr
ay(range(1, 101, 5)),
                      cv=KFold(n_splits=10), scoring="neg_median_ab
solute_error")
```
Out[469]: <module 'matplotlib.pyplot' from '/Users/artyom.andreev/Study/.ven v/lib/python3.7/site-packages/matplotlib/pyplot.py'>



Ensemble: Gradient boosting (XGBRegressor from xgboost library)

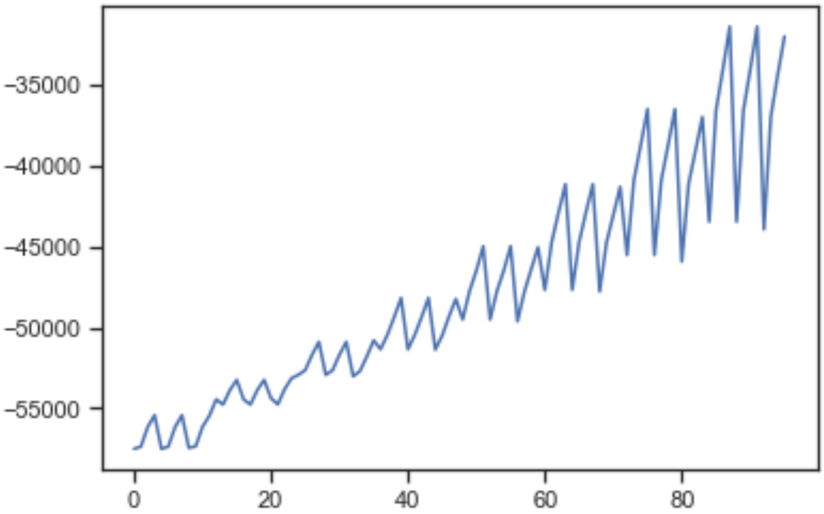
In [449]:
```
plot_learning_curve(xgbreg_grid.best_estimator_, 'Gradient boosting
',
                    X, y.values.ravel(), cv=KFold(n_splits=10))
```

Out[449]:
```
<module 'matplotlib.pyplot' from '/Users/artyom.andreev/Study/.ven
v/lib/python3.7/site-packages/matplotlib/pyplot.py'>
```



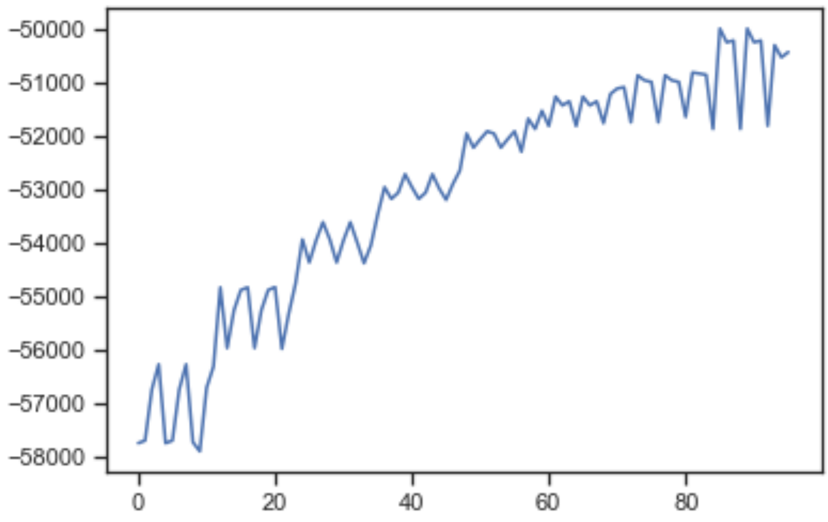
In [467]:
```
plt.plot(range(96), xgbreg_grid.cv_results_['mean_train_score'])
```

Out[467]:
```
[<matplotlib.lines.Line2D at 0x171193748>]
```



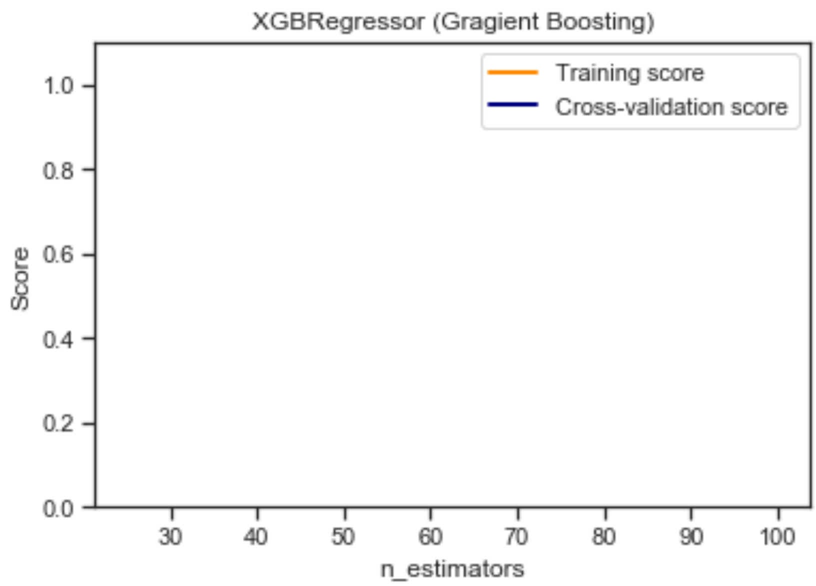
In [468]:
```
plt.plot(range(96), xgbreg_grid.cv_results_['mean_test_score'])
```

Out[468]: [<matplotlib.lines.Line2D at 0x16015d080>]



In [450]:
```
parameters_xgb = [{"colsample_bytree": [1.0], "min_child_weight": [
0.8, 1.0, 1.2],
                   'max_depth': range(3, 11), 'n_estimators': [25, 50,
75, 100]}]

plot_validation_curve(XGBRegressor(), 'XGBRegressor (Gragient Boost
ing)',
                      X, y.values.ravel(),
                      param_name='n_estimators', param_range=[25, 5
0, 75, 100],
                      cv=KFold(n_splits=10), scoring="neg_median_ab
solute_error")
```

Out[450]: <module 'matplotlib.pyplot' from '/Users/artyom.andreev/Study/.ven
v/lib/python3.7/site-packages/matplotlib/pyplot.py'>



In [ ]:

Заключение

Таким образом, внедрение технологий машинного обучения может помочь решении задач, которые возникают во всех сферах жизни человека, в предсказании стоимости различных объектов в зависимости от их свойств, времени, географического положения итд. На этом датасете самые хорошие результаты по всем метрикам качества показали методы ансамбль градиентного бустинга на базе XGBoost, Бэггинг на базе дерева решений для регрессии и само дерево решений для регрессии.

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