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Кафедра «Системы обработки информации и управления»

Лабораторная работа №5
по дисциплине
«Методы машинного обучения»
на тему
«Линейные модели, SVM и деревья решений»

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1. Линейные модели, SVM и деревья решений

2. Задание:

Выберите набор данных (датасет) для решения задачи классификации или регрессии.
В случае необходимости проведите удаление или заполнение пропусков и кодирование категориальных признаков.
С использованием метода train_test_split разделите выборку на обучающую и тестовую.
Обучите следующие модели:
одну из линейных моделей;
SVM;
дерево решений.
Оцените качество моделей с помощью трех подходящих для задачи метрик. Сравните качество полученных моделей.
Произведите для каждой модели подбор одного гиперпараметра с использованием GridSearchCV и кросс-валидации.
Повторите пункт 4 для найденных оптимальных значений гиперпараметров. Сравните качество полученных моделей с качеством моделей, полученных в пункте 4.
Дополнительные задания:
Проведите эксперименты с важностью признаков в дереве решений.
Визуализируйте дерево решений.

[1]:
```
import numpy as np
import pandas as pd
from typing import Dict, Tuple
from scipy import stats
from IPython.display import Image
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsRegressor, KNeighborsClassifier
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 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.preprocessing import MinMaxScaler
from sklearn.model_selection import cross_val_score, cross_validate
from sklearn.svm import SVC, NuSVC, LinearSVC, OneClassSVM, SVR, NuSVR,
  ↪LinearSVR
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import SGDRegressor
from sklearn.linear_model import SGDClassifier
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
sns.set(style="ticks")
def make_dataframe(ds_function):
    ds = ds_function()
    df = pd.DataFrame(data= np.c_[ds['data'], ds['target']],
```

```
                      columns= list(ds['feature_names']) + ['target'])
    return df
from sklearn.datasets import fetch_california_housing
from sklearn.externals.six import StringIO
import graphviz
import pydotplus
from sklearn.tree import DecisionTreeClassifier, DecisionTreeRegressor,
 ↪export_graphviz
from sklearn.model_selection import GridSearchCV
```

```
/usr/local/lib/python3.6/dist-packages/statsmodels/tools/_testing.py:19:
FutureWarning: pandas.util.testing is deprecated. Use the functions in
 ↪the
public API at pandas.testing instead.
  import pandas.util.testing as tm
/usr/local/lib/python3.6/dist-packages/sklearn/externals/six.py:31:
FutureWarning: The module is deprecated in version 0.21 and will be
 ↪removed in
version 0.23 since we've dropped support for Python 2.7. Please rely on
 ↪the
official version of six (https://pypi.org/project/six/).
  "(https://pypi.org/project/six/).", FutureWarning)
```

[0]:
```
data = fetch_california_housing()
```

3. Датасет данных о жилье в Калифорнии(пропуски отсутствуют, нет категориальных признаков для кодирования):

4. Разбиение выборки:

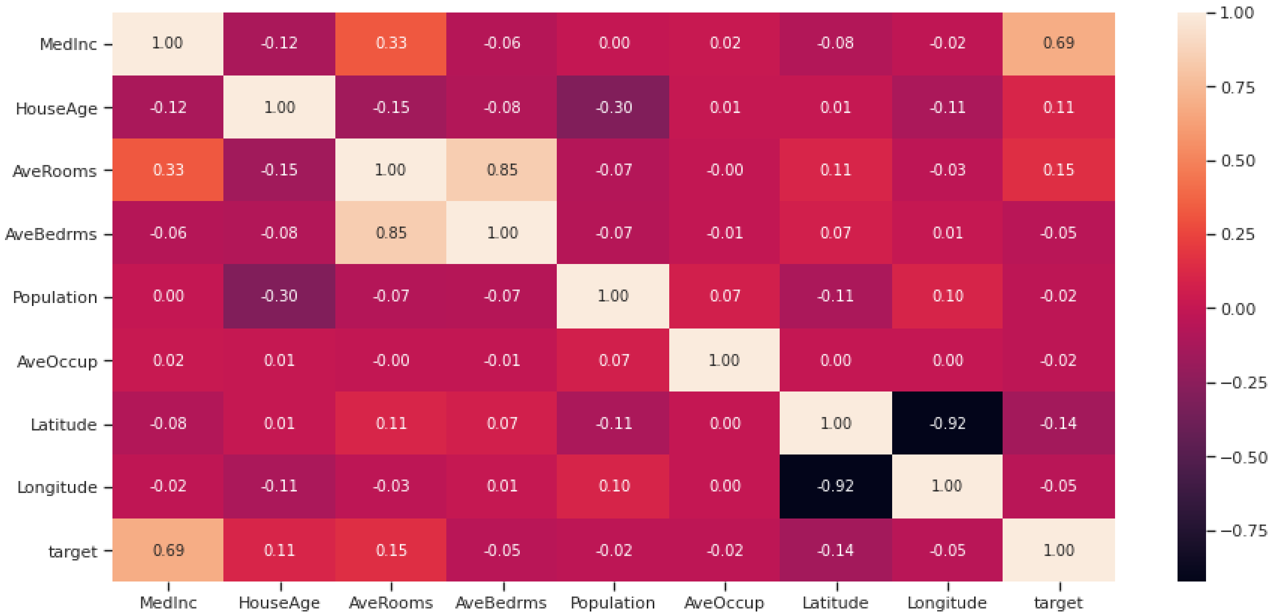
[3]:
```
df_california = pd.DataFrame(data.data,columns=data.feature_names)
df_california['target'] = pd.Series(data.target)
df_california.head()
```

[3]:
```
   MedInc  HouseAge  AveRooms  AveBedrms  …  AveOccup  Latitude 
 ↪Longitude
target
0  8.3252      41.0  6.984127   1.023810  …  2.555556     37.88    -122.
 ↪23
4.526
1  8.3014      21.0  6.238137   0.971880  …  2.109842     37.86    -122.
 ↪22
3.585
2  7.2574      52.0  8.288136   1.073446  …  2.802260     37.85    -122.
 ↪24
3.521
```

```
3  5.6431       52.0  5.817352   1.073059  …  2.547945     37.85    -122.
  ↪25
3.413
4  3.8462       52.0  6.281853   1.081081  …  2.181467     37.85    -122.
  ↪25
3.422

[5 rows x 9 columns]
```

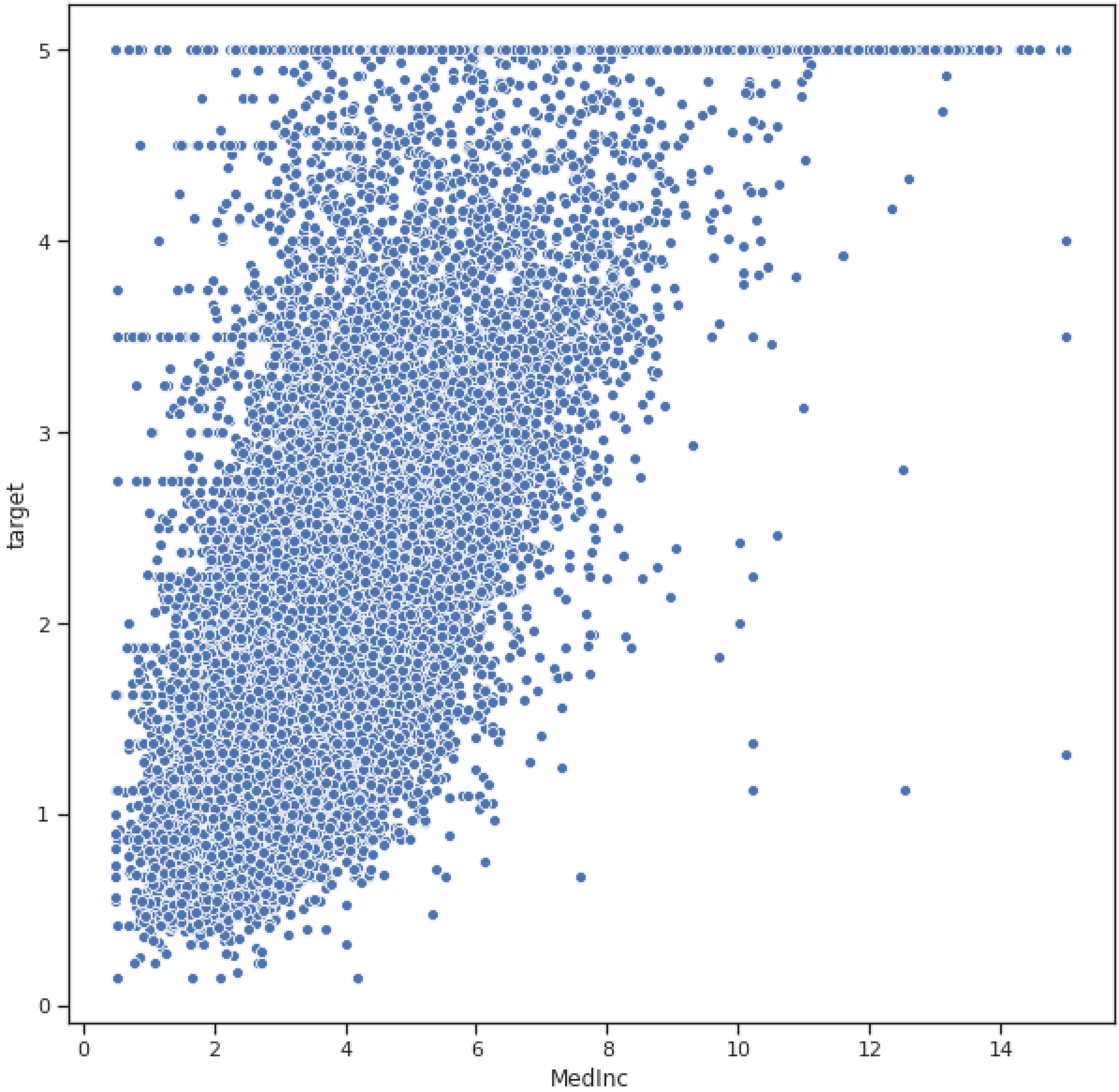
[4]:
```
fig, ax = plt.subplots(figsize=(15,7))
sns.heatmap(df_california.corr(method='pearson'), ax=ax, annot=True,
  ↪fmt='.2f')
```

[4]: <matplotlib.axes._subplots.AxesSubplot at 0x7f5cef4d8668>



[5]:
```
fig, ax = plt.subplots(figsize=(10,10))
sns.scatterplot(ax=ax, x='MedInc', y='target', data=df_california)
```

[5]: <matplotlib.axes._subplots.AxesSubplot at 0x7f5cff5e0ac8>



Между признаком “MedInc” и целевым признаком “target” существует зависимость, близкая к линейной, коэффициент корреляции = 0,69

Попробуем восстановить данную линейную зависимость.

аналитическое вычисление коэффициентов:

```
[0]: def analytic_regr_coef(x_array : np.ndarray,
                          y_array : np.ndarray) -> Tuple[float, float]:
         x_mean = np.mean(x_array)
         y_mean = np.mean(y_array)
         var1 = np.sum([(x-x_mean)**2 for x in x_array])
         cov1 = np.sum([(x-x_mean)*(y-x_mean) for x, y in zip(x_array,
      ↪y_array)])
         b1 = cov1 / var1
         b0 = y_mean - b1*x_mean
         return b0, b1
```

[0]:
```
x_array = df_california['MedInc'].values
y_array = df_california['target'].values
```

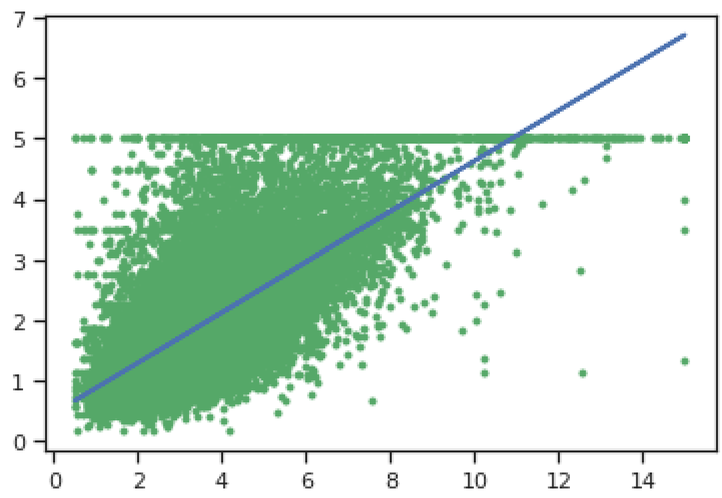
[8]:
```
b0, b1 = analytic_regr_coef(x_array, y_array)
b0, b1
```

[8]:
```
(0.45085576703268027, 0.41793849201896244)
```

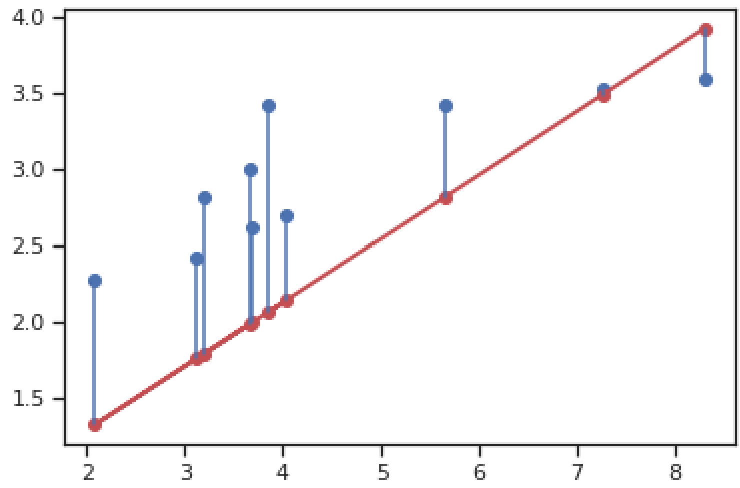
[0]:
```
# Вычисление значений y на основе x для регрессии
def y_regr(x_array : np.ndarray, b0: float, b1: float) -> np.ndarray:
    res = [b1*x+b0 for x in x_array]
    return res
```

[0]:
```
y_array_regr = y_regr(x_array, b0, b1)
```

[11]:
```
plt.plot(x_array, y_array, 'g.')
plt.plot(x_array, y_array_regr, 'b', linewidth=2.0)
plt.show()
```



[12]:
```
# Синими отрезками показаны ошибки между
# истинными и предсказанными значениями
K_mnk=10

plt.plot(x_array[1:K_mnk+1], y_array[1:K_mnk+1], 'bo')
plt.plot(x_array[1:K_mnk+1], y_array_regr[1:K_mnk+1], '-ro',
  ↪linewidth=2.0)

for i in range(len(x_array[1:K_mnk+1])):
    x1 = x_array[1:K_mnk+1][i]
    y1 = y_array[1:K_mnk+1][i]
    y2 = y_array_regr[1:K_mnk+1][i]
    plt.plot([x1,x1],[y1,y2],'b-')

plt.show()
```



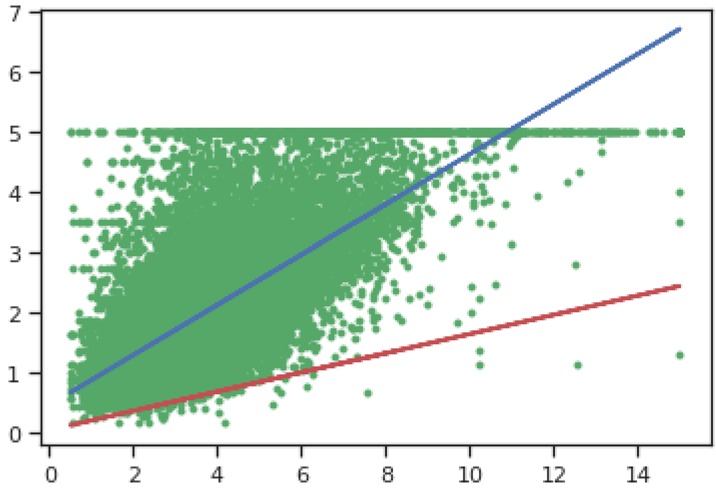
[0]:
```
# Простейшая реализация градиентного спуска
def gradient_descent(x_array : np.ndarray,
                     y_array : np.ndarray,
                     b0_0 : float,
                     b1_0 : float,
                     epochs : int,
                     learning_rate : float = 0.001
                    ) -> Tuple[float, float]:
    # Значения для коэффициентов по умолчанию
    b0, b1 = b0_0, b1_0
    k = float(len(x_array))
    for i in range(epochs):
        # Вычисление новых предсказанных значений
        # используется векторизованное умножение и сложение для вектора␣
 ↪и константы
        y_pred = b1 * x_array + b0
        # Расчет градиентов
        # np.multiply - поэлементное умножение векторов
        dL_db1 = (-2/k) * np.sum(np.multiply(x_array, (y_array -␣
 ↪y_pred)))
        dL_db0 = (-2/k) * np.sum(y_array - y_pred)
        # Изменение значений коэффициентов:
        b1 = b1 - learning_rate * dL_db1
        b0 = b0 - learning_rate * dL_db0
    # Результирующие значения
    y_pred = b1 * x_array + b0
    return b0, b1, y_pred
```

[0]:
```
def show_gradient_descent(epochs, b0_0, b1_0):
    grad_b0, grad_b1, grad_y_pred = gradient_descent(x_array, y_array,␣
 ↪b0_0, b1_0, epochs)
    print('b0 = {} - (теоретический), {} - (градиентный спуск)'.
 ↪format(b0, grad_b0))
```

```
    print('b1 = {} - (теоретический), {} - (градиентный спуск)'.
 ↪format(b1, grad_b1))
    print('MSE = {}'.format(mean_squared_error(y_array_regr,␣
 ↪grad_y_pred)))
    plt.plot(x_array, y_array, 'g.')
    plt.plot(x_array, y_array_regr, 'b', linewidth=2.0)
    plt.plot(x_array, grad_y_pred, 'r', linewidth=2.0)
    plt.show()
```

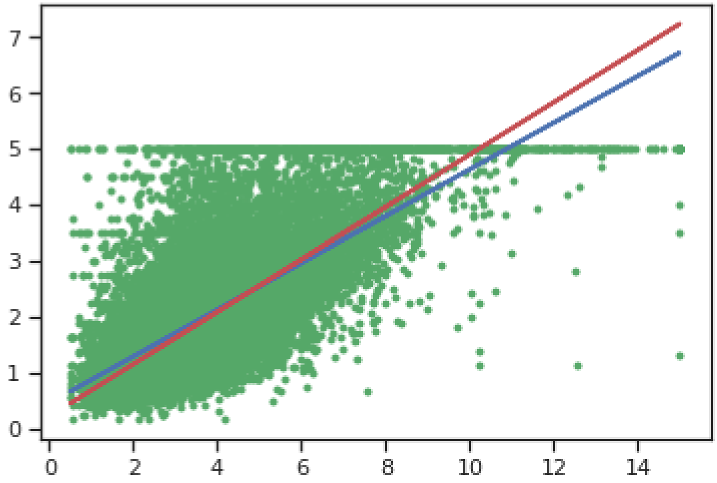
[15]:
```
# Примеры использования градиентного спуска
show_gradient_descent(10, 0, 0)
```

```
b0 = 0.45085576703268027 - (теоретический), 0.035046884360901316 -␣
 ↪(градиентный
спуск)
b1 = 0.41793849201896244 - (теоретический), 0.16024063837885774 -␣
 ↪(градиентный
спуск)
MSE = 2.237016080434203
```



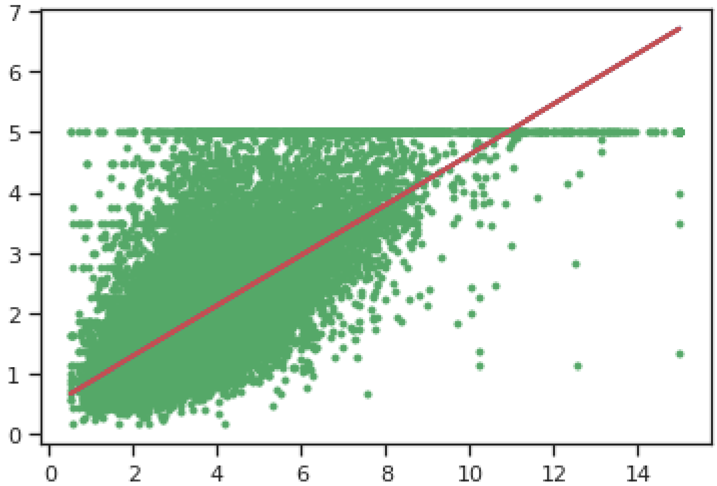
[16]:
```
show_gradient_descent(1000, 0, 0)
```

```
b0 = 0.45085576703268027 - (теоретический), 0.21125447583768953 -␣
 ↪(градиентный
спуск)
b1 = 0.41793849201896244 - (теоретический), 0.46832724481210447 -␣
 ↪(градиентный
спуск)
MSE = 0.011149582877403865
```



[17]:
```
show_gradient_descent(50000, 0, 0)
```

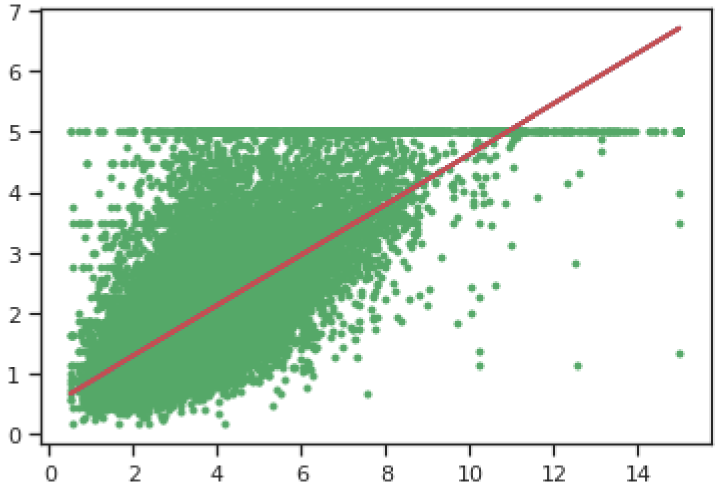
```
b0 = 0.45085576703268027 - (теоретический), 0.4508557641340037 -
  ↪(градиентный
спуск)
b1 = 0.41793849201896244 - (теоретический), 0.4179384926285615 -
  ↪(градиентный
спуск)
MSE = 1.6318485911138797e-18
```



[18]:
```
show_gradient_descent(100000, 0, 0)
```

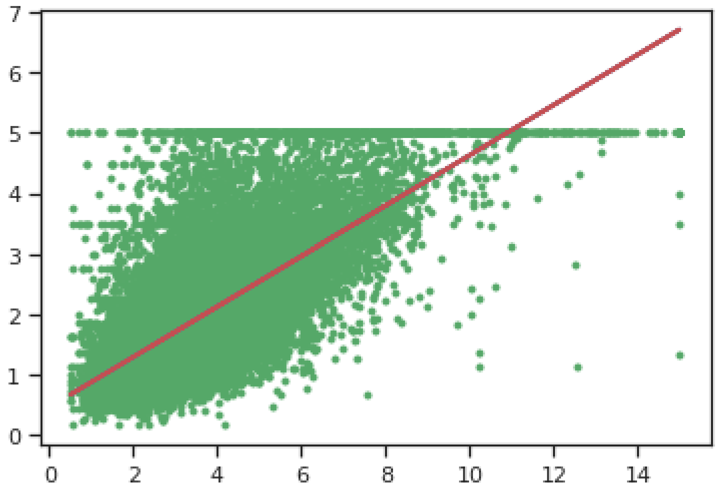
```
b0 = 0.45085576703268027 - (теоретический), 0.45085576703259417 -
  ↪(градиентный
спуск)
b1 = 0.41793849201896244 - (теоретический), 0.41793849201898114 -
  ↪(градиентный
```

спуск)
MSE = 1.4521197259897182e-27



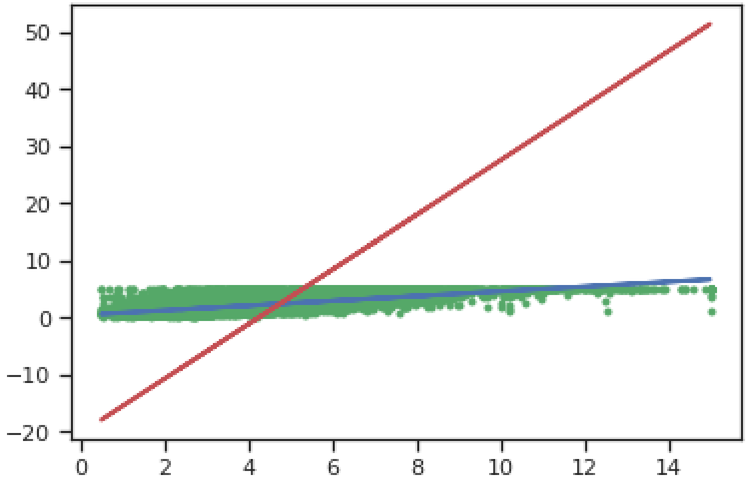
[19]:
```
show_gradient_descent(1000000, 0, 0)
```

b0 = 0.45085576703268027 - (теоретический), 0.45085576703259417 -
↪(градиентный
спуск)
b1 = 0.41793849201896244 - (теоретический), 0.41793849201898114 -
↪(градиентный
спуск)
MSE = 1.4521197259897182e-27



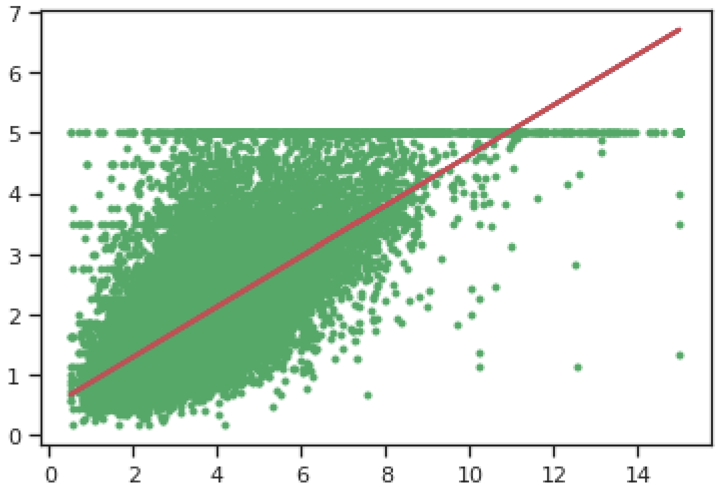
[20]:
```
show_gradient_descent(1000, -30, 5)
```

```
b0 = 0.45085576703268027 - (теоретический), -20.286696565576065 -
↪(градиентный
спуск)
b1 = 0.41793849201896244 - (теоретический), 4.779097786324618 -
↪(градиентный
спуск)
MSE = 83.52092622146682
```



[21]:
```
show_gradient_descent(100000, -30, 5)
```

```
b0 = 0.45085576703268027 - (теоретический), 0.45085576703259417 -
↪(градиентный
спуск)
b1 = 0.41793849201896244 - (теоретический), 0.41793849201898114 -
↪(градиентный
спуск)
MSE = 1.4521197259897182e-27
```



5. Линейная регрессия при помощи библиотеки scikit-learn

[0]:
```
california_x_columns = ['MedInc',
 'HouseAge',
 'AveRooms',
 'AveBedrms',
 'Population',
 'AveOccup',
 'Latitude',
 'Longitude']
```

[23]:
```
# Обучим линейную регрессию и сравним коэффициенты с рассчитанными ранее
reg1 = LinearRegression().fit(x_array.reshape(-1, 1), y_array.
 ↪reshape(-1, 1))
(b1, reg1.coef_), (b0, reg1.intercept_)
```

[23]:
```
((0.41793849201896244, array([[0.41793849]])),
 (0.45085576703268027, array([0.45085577])))
```

[0]:
```
sc1 = MinMaxScaler()
sc1_data = sc1.fit_transform(df_california[california_x_columns])
```

[0]:
```
scoring = {'MAE': 'neg_mean_absolute_error',
           'MSE': 'neg_mean_squared_error',
           'R2': 'r2'}
```

[26]:
```
scores_3 = cross_validate(LinearRegression(),
                        sc1_data, df_california['target'],
 ↪scoring=scoring,
                        cv=3, return_train_score=True)
scores_3
```

[26]:
```
{'fit_time': array([0.00827169, 0.00720763, 0.00623298]),
 'score_time': array([0.00176811, 0.00223017, 0.00171518]),
 'test_MAE': array([-0.57887213, -0.50877351, -0.56305949]),
 'test_MSE': array([-0.59988822, -0.49188049, -0.59155481]),
 'test_R2': array([0.55502126, 0.58837838, 0.58544641]),
 'train_MAE': array([-0.51394065, -0.54832542, -0.52079949]),
 'train_MSE': array([-0.49933994, -0.54483711, -0.50929041]),
 'train_R2': array([0.62059396, 0.61067588, 0.59991471])}
```

6. Данные метрик линейной регрессии для сравнения с другими моделями

[27]:
```
-np.mean(scores_3['train_MAE']), -np.mean(scores_3['test_MAE']), \
-np.mean(scores_3['train_MSE']), -np.mean(scores_3['test_MSE']), \
np.mean(scores_3['train_R2']), np.mean(scores_3['test_R2'])
```

[27]: (0.5276885217738251,
 0.5502350422781422,
 0.5178224843539592,
 0.561107836816535,
 0.6103948517000314,
 0.5762820158960761)

```
[28]: # Для небольшой выборки качество обучения сильно уступает
      ↪нестохастическому градиентному спуску.
      print('Размер выборки - {}'.format(x_array.shape[0]))
      reg2 = SGDRegressor().fit(x_array.reshape(-1, 1), y_array)
      (b1, reg2.coef_), (b0, reg2.intercept_)
```

Размер выборки - 20640

[28]: ((0.41793849201896244, array([0.42488581])),
 (0.45085576703268027, array([0.45235938])))

```
[0]: from sklearn.linear_model import Lasso
```

```
[30]: reg3 = Lasso().fit(x_array.reshape(-1, 1), y_array)
      (b1, reg3.coef_), (b0, reg3.intercept_)
```

[30]: ((0.41793849201896244, array([0.14086477])),
 (0.45085576703268027, 1.5233170059994505))

```
[0]: from sklearn.linear_model import Ridge
```

```
[32]: reg4 = Ridge().fit(x_array.reshape(-1, 1), y_array)
      (b1, reg4.coef_), (b0, reg4.intercept_)
```

[32]: ((0.41793849201896244, array([0.41793288])),
 (0.45085576703268027, 0.4508774829636899))

```
[0]: from sklearn.linear_model import ElasticNet
```

```
[34]: reg5 = ElasticNet().fit(x_array.reshape(-1, 1), y_array)
      (b1, reg5.coef_), (b0, reg5.intercept_)
```

[34]: ((0.41793849201896244, array([0.24540411])),
 (0.45085576703268027, 1.1186795859141516))

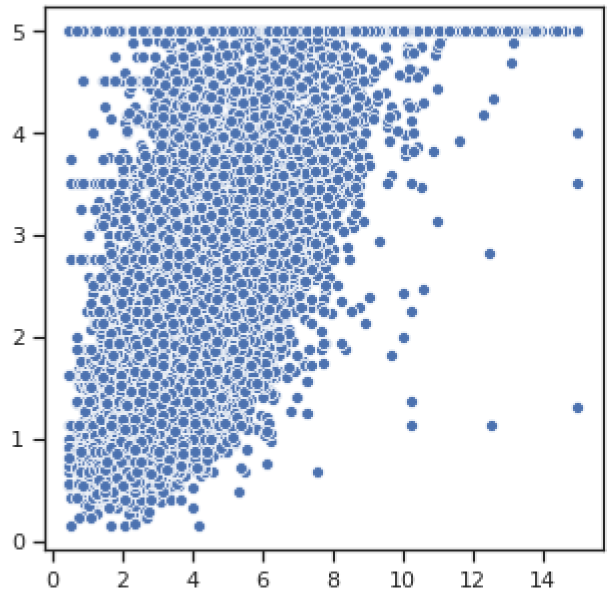
7. Машина опорных векторов

8. Реализация в коде

[0]:
```
california_x = df_california['MedInc'].values
california_y = df_california['target'].values
```

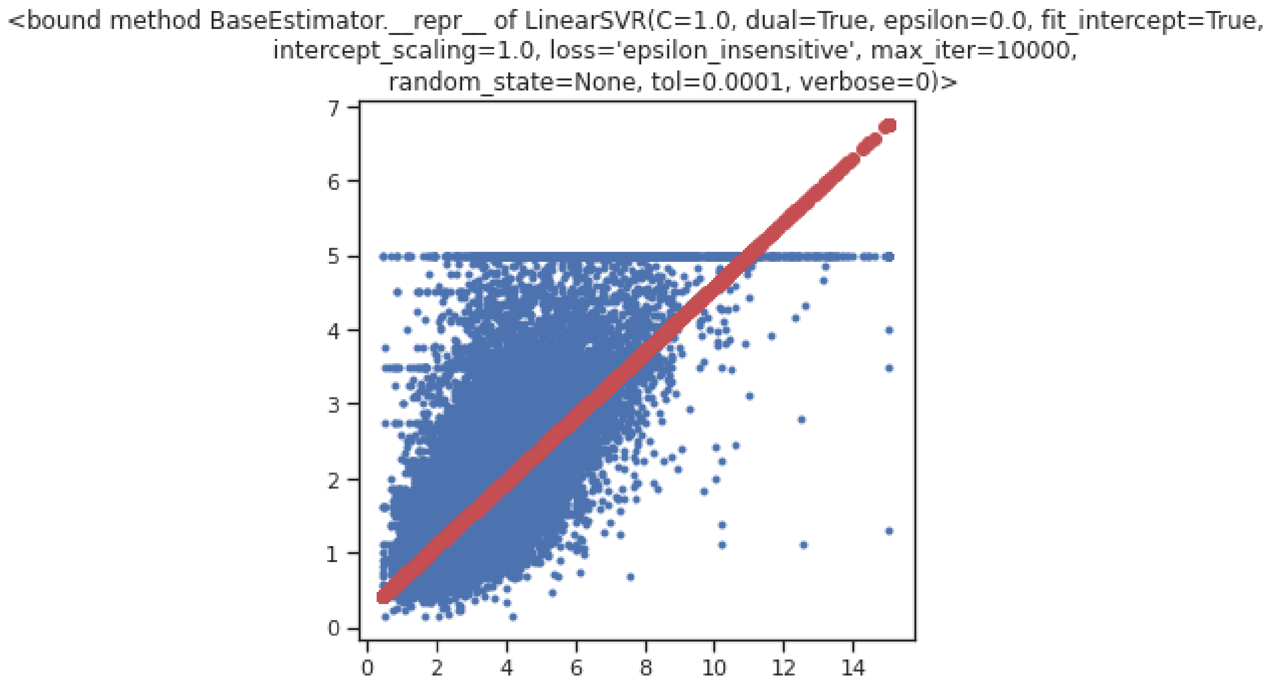
[36]:
```
fig, ax = plt.subplots(figsize=(5,5))
sns.scatterplot(ax=ax, x=california_x, y=california_y)
```

[36]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f5ceaf35438>
```



[0]:
```
def plot_regr(clf):
    title = clf.__repr__
    clf.fit(california_x.reshape(-1, 1), california_y)
    california_y_pred = clf.predict(california_x.reshape(-1, 1))
    fig, ax = plt.subplots(figsize=(5,5))
    ax.set_title(title)
    ax.plot(california_x, california_y, 'b.')
    ax.plot(california_x, california_y_pred, 'ro')
    plt.show()
```

[38]:
```
plot_regr(LinearSVR(C=1.0, max_iter=10000))
```



[0]:
```
#plot_regr(LinearSVR(C=1.0, loss='squared_epsilon_insensitive',␣
 ↪max_iter=10000))
```

[0]:
```
#plot_regr(SVR(kernel='linear', C=1.0))
```

[0]:
```
#plot_regr(SVR(kernel='rbf', gamma=0.2, C=1.0))
```

[0]:
```
#plot_regr(SVR(kernel='rbf', gamma=0.8, C=1.0))
```

[0]:
```
#plot_regr(NuSVR(kernel='rbf', gamma=0.8, nu=0.1, C=1.0))
```

[0]:
```
#plot_regr(NuSVR(kernel='rbf', gamma=0.8, nu=0.9, C=1.0))
```

[0]:
```
#plot_regr(SVR(kernel='poly', degree=2, gamma='auto', C=1.0))
```

[0]:
```
#plot_regr(SVR(kernel='poly', degree=3, gamma=0.2, C=1.0))
```

[0]:
```
#plot_regr(SVR(kernel='poly', degree=4, gamma=0.2, C=1.0))
```

[48]:
```
df_california.head()
```

[48]:
```
   MedInc  HouseAge  AveRooms  AveBedrms  …  AveOccup  Latitude ␣
 ↪Longitude
target
0  8.3252      41.0  6.984127   1.023810  …  2.555556     37.88    -122.
 ↪23
4.526
1  8.3014      21.0  6.238137   0.971880  …  2.109842     37.86    -122.
 ↪22
3.585
```

```
2  7.2574       52.0  8.288136   1.073446  …  2.802260      37.85    -122.
  ↪24
3.521
3  5.6431       52.0  5.817352   1.073059  …  2.547945      37.85    -122.
  ↪25
3.413
4  3.8462       52.0  6.281853   1.081081  …  2.181467      37.85    -122.
  ↪25
3.422

[5 rows x 9 columns]
```

[0]:
```
california_x_columns = ['MedInc',
 'HouseAge',
 'AveRooms',
 'AveBedrms',
 'Population',
 'AveOccup',
 'Latitude',
 'Longitude']
```

[50]:
```
# Диапазоны значений достаточно сильно различаются
df_california[california_x_columns].describe()
```

[50]:
```
             MedInc      HouseAge  …      Latitude     Longitude
count  20640.000000  20640.000000  …  20640.000000  20640.000000
mean       3.870671     28.639486  …     35.631861   -119.569704
std        1.899822     12.585558  …      2.135952      2.003532
min        0.499900      1.000000  …     32.540000   -124.350000
25%        2.563400     18.000000  …     33.930000   -121.800000
50%        3.534800     29.000000  …     34.260000   -118.490000
75%        4.743250     37.000000  …     37.710000   -118.010000
max       15.000100     52.000000  …     41.950000   -114.310000

[8 rows x 8 columns]
```

Модель без масштабирования данных

[51]:
```
california_X_train_1, california_X_test_1, california_y_train_1,
 ↪california_y_test_1 = train_test_split(
    df_california[california_x_columns], df_california['target'],
 ↪test_size=0.2, random_state=1)

california_X_train_1.shape, california_X_test_1.shape
```

[51]:
```
((16512, 8), (4128, 8))
```

[52]:
```
svr_1 = SVR()
svr_1.fit(california_X_train_1, california_y_train_1)
```

[52]:
```
SVR(C=1.0, cache_size=200, coef0=0.0, degree=3, epsilon=0.1,
 ↪gamma='scale',
```

```
    kernel='rbf', max_iter=-1, shrinking=True, tol=0.001, verbose=False)
```

```
[0]: california_y_pred_1 = svr_1.predict(california_X_test_1)
```

```
[54]: mean_absolute_error(california_y_test_1, california_y_pred_1),
      ↪mean_squared_error(california_y_test_1, california_y_pred_1)
```

```
[54]: (0.8591093473587432, 1.320732383526986)
```

Модель с масштабированием данных

```
[0]: # Масштабирование данных в диапазоне от 0 до 1
     sc1 = MinMaxScaler()
     sc1_data = sc1.fit_transform(df_california[california_x_columns])
```

```
[56]: sc1_data[:2]
```

```
[56]: array([[0.53966842, 0.78431373, 0.0435123 , 0.02046866, 0.00894083,
              0.00149943, 0.5674814 , 0.21115538],
             [0.53802706, 0.39215686, 0.03822395, 0.01892926, 0.0672104 ,
              0.00114074, 0.565356  , 0.21215139]])
```

```
[57]: california_X_train_2, california_X_test_2, california_y_train_2,
      ↪california_y_test_2 = train_test_split(
          sc1_data, df_california['target'], test_size=0.2, random_state=1)

      california_X_train_2.shape, california_X_test_2.shape
```

```
[57]: ((16512, 8), (4128, 8))
```

```
[58]: svr_2 = SVR()
      svr_2.fit(california_X_train_2, california_y_train_2)
```

```
[58]: SVR(C=1.0, cache_size=200, coef0=0.0, degree=3, epsilon=0.1,
      ↪gamma='scale',
          kernel='rbf', max_iter=-1, shrinking=True, tol=0.001, verbose=False)
```

```
[0]: california_y_pred_2 = svr_2.predict(california_X_test_2)
```

```
[60]: mean_absolute_error(california_y_test_2, california_y_pred_2),
      ↪mean_squared_error(california_y_test_2, california_y_pred_2)
```

```
[60]: (0.4505817514262831, 0.45299763645897284)
```

Эксперимент на основе кросс-валидации:

```
[0]: scoring = {'MAE': 'neg_mean_absolute_error',
                'MSE': 'neg_mean_squared_error',
                'R2': 'r2'}
```

```
[62]: scores_1 = cross_validate(SVR(),
                                df_california[california_x_columns],
      ↪df_california['target'], scoring=scoring,
                                cv=3, return_train_score=True)
```

```
scores_1
```

```
[62]: {'fit_time': array([12.11082315, 12.1236763 , 12.2641027 ]),
 'score_time': array([2.76550102, 2.76244593, 2.79872417]),
 'test_MAE': array([-0.88547721, -0.81302601, -0.95274753]),
 'test_MSE': array([-1.33180311, -1.2491849 , -1.59989289]),
 'test_R2': array([ 0.01210917, -0.04535864, -0.12118326]),
 'train_MAE': array([-0.86838827, -0.90060707, -0.83393092]),
 'train_MSE': array([-1.35236242, -1.40856087, -1.31120754]),
 'train_R2': array([-0.02754543, -0.00651499, -0.03005051])}
```

```
[63]: # Без масштабирования
-np.mean(scores_1['train_MAE']), -np.mean(scores_1['test_MAE']), \
-np.mean(scores_1['train_MSE']), -np.mean(scores_1['test_MSE'])
```

```
[63]: (0.8676420830790912, 0.8837502471655386, 1.3573769428582043, 1.
 ↪393626970258224)
```

```
[64]: scores_2 = cross_validate(SVR(),
                        sc1_data, df_california['target'],
 ↪scoring=scoring,
                        cv=3, return_train_score=True)
scores_2
```

```
[64]: {'fit_time': array([11.35171986, 11.65829659, 11.28841114]),
 'score_time': array([2.4718802 , 2.4750576 , 2.41563725]),
 'test_MAE': array([-0.51033856, -0.45036369, -0.56060072]),
 'test_MSE': array([-0.54870328, -0.433136  , -0.61684615]),
 'test_R2': array([0.59298868, 0.63753767, 0.56772258]),
 'train_MAE': array([-0.44006452, -0.46199119, -0.43109582]),
 'train_MSE': array([-0.43456878, -0.46134241, -0.42690641]),
 'train_R2': array([0.66980806, 0.67033867, 0.66463343])}
```

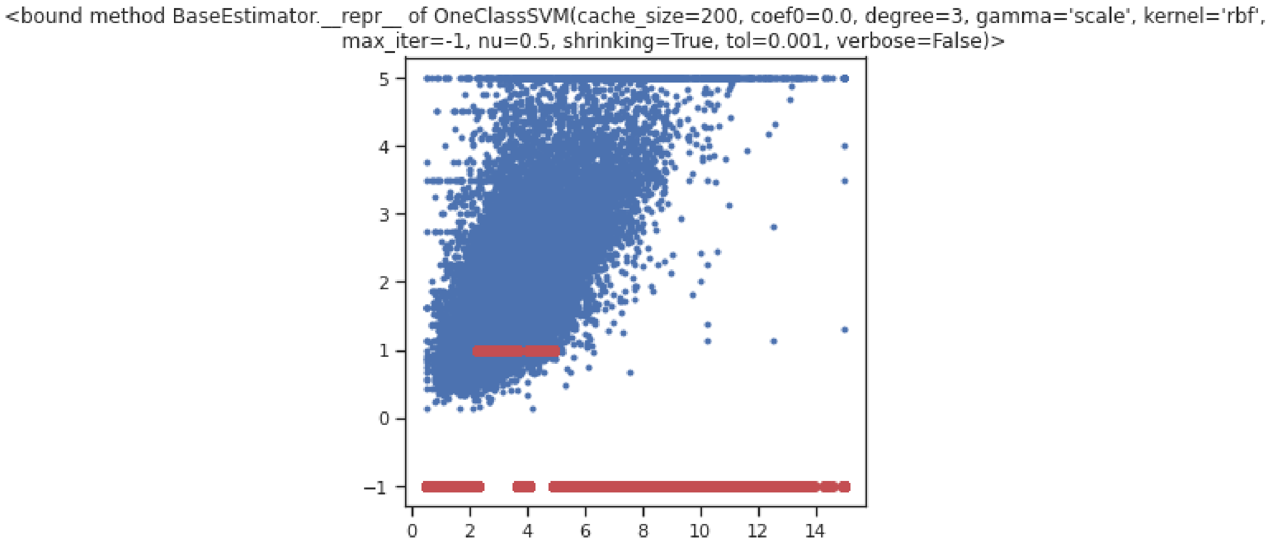
9. Данные метрик машины опорных векторов для сравнения с другими моделями

```
[65]: # С масштабированием
-np.mean(scores_2['train_MAE']), -np.mean(scores_2['test_MAE']), \
-np.mean(scores_2['train_MSE']), -np.mean(scores_2['test_MSE']), \
np.mean(scores_2['train_R2']), np.mean(scores_2['test_R2'])
```

```
[65]: (0.4443838432807796,
 0.507100989083478,
 0.4409392026959420 6,
 0.5328951447989484,
 0.6682600547769003,
 0.599416311806581)
```

Аномалии

```
[66]: anom_cl = OneClassSVM()
      anom_cl.fit(california_x.reshape(-1, 1))
      np.unique(anom_cl.predict(california_x.reshape(-1, 1)))

[66]: array([-1,  1])

[67]: plot_regr(OneClassSVM())
```

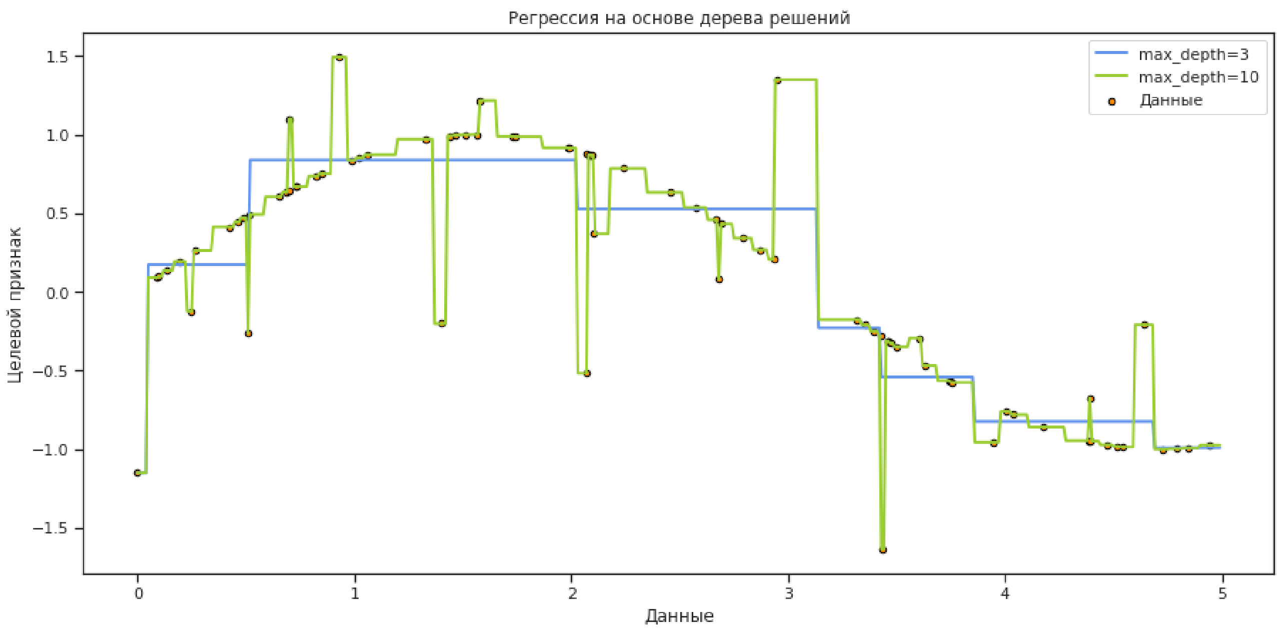


Дерево решений для регрессии

```
[0]: def random_dataset_for_regression():
         """
         Создание случайного набора данных для регрессии
         """
         rng = np.random.RandomState(1)
         X_train = np.sort(5 * rng.rand(80, 1), axis=0)
         y_train = np.sin(X_train).ravel()
         y_train[::5] += 3 * (0.5 - rng.rand(16))
         X_test = np.arange(0.0, 5.0, 0.01)[:, np.newaxis]
         return X_train, y_train, X_test

[0]: def plot_tree_regression(X_train, y_train, X_test):
         """
         Построение деревьев и вывод графиков для заданного датасета
         """

         # Обучение регрессионной модели
         regr_1 = DecisionTreeRegressor(max_depth=3)
         regr_2 = DecisionTreeRegressor(max_depth=10)
         regr_1.fit(X_train, y_train)
         regr_2.fit(X_train, y_train)

         # Предсказание
```

```
    y_1 = regr_1.predict(X_test)
    y_2 = regr_2.predict(X_test)

    # Вывод графика
    fig, ax = plt.subplots(figsize=(15,7))
    plt.scatter(X_train, y_train, s=20, edgecolor="black",
 ↪c="darkorange", label="Данные")
    plt.plot(X_test, y_1, color="cornflowerblue", label="max_depth=3",
 ↪linewidth=2)
    plt.plot(X_test, y_2, color="yellowgreen", label="max_depth=10",
 ↪linewidth=2)
    plt.xlabel("Данные")
    plt.ylabel("Целевой признак")
    plt.title("Регрессия на основе дерева решений")
    plt.legend()
    plt.show()
```

[70]:
```
X_train, y_train, X_test = random_dataset_for_regression()
plot_tree_regression(X_train, y_train, X_test)
```



10. Дерево решений

[71]:
```
california_tree_regr = DecisionTreeRegressor(random_state=1)
california_tree_regr.fit(df_california, data.target)
california_tree_regr
```

[71]:
```
DecisionTreeRegressor(ccp_alpha=0.0, criterion='mse', max_depth=None,
                      max_features=None, max_leaf_nodes=None,
```

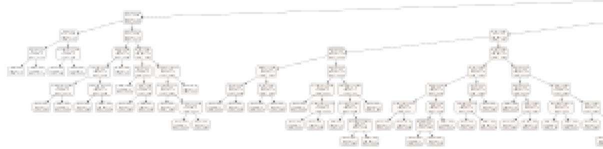
```
                         min_impurity_decrease=0.0,
 ↪min_impurity_split=None,
                         min_samples_leaf=1, min_samples_split=2,
                         min_weight_fraction_leaf=0.0,
 ↪presort='deprecated',
                         random_state=1, splitter='best')
```

[0]:
```
# Визуализация дерева
def get_png_tree(tree_model_param, feature_names_param):
    dot_data = StringIO()
    export_graphviz(tree_model_param, out_file=dot_data,
 ↪feature_names=feature_names_param,
                    filled=True, rounded=True, special_characters=True)
    graph = pydotplus.graph_from_dot_data(dot_data.getvalue())
    return graph.create_png()
```

[73]:
```
Image(get_png_tree(california_tree_regr, df_california.columns),
 ↪height="500")
```

```
dot: graph is too large for cairo-renderer bitmaps. Scaling by 0.0643085
 ↪to fit
```

[73]:

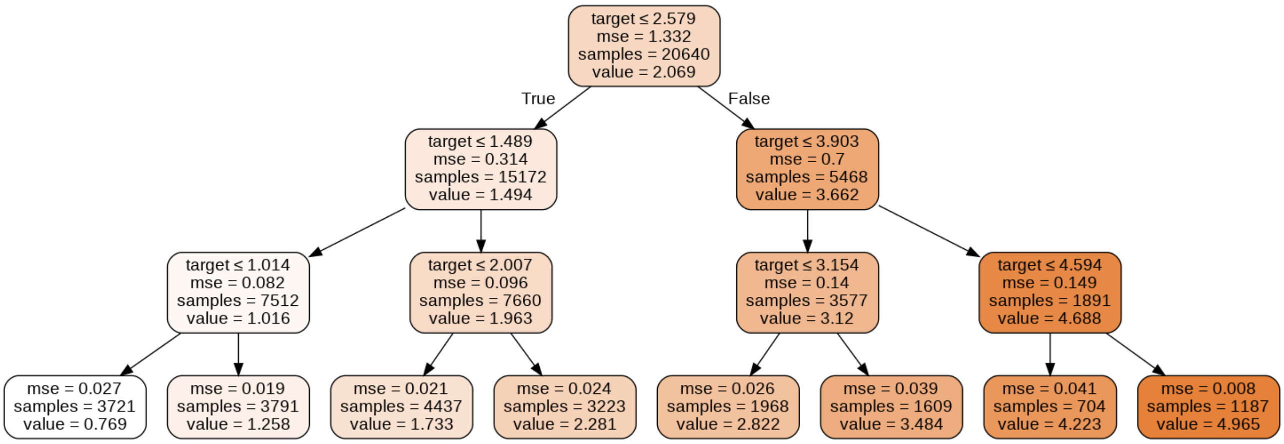


[74]:
```
california_tree_regr_prun = DecisionTreeRegressor(random_state=1,
 ↪max_depth=3)
california_tree_regr_prun.fit(df_california, data.target)
california_tree_regr_prun
```

[74]:
```
DecisionTreeRegressor(ccp_alpha=0.0, criterion='mse', max_depth=3,
                         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=1, splitter='best')
```

[75]:
```
Image(get_png_tree(california_tree_regr_prun, df_california.columns),
 ↪height="500")
```

[75]:



[76]:
```
scores_4 = cross_validate(DecisionTreeRegressor(random_state=1,
 ↪max_depth=3),
                        sc1_data, df_california['target'],
 ↪scoring=scoring,
                        cv=3, return_train_score=True)
scores_4
```

[76]:
```
{'fit_time': array([0.05726457, 0.04353571, 0.03309608]),
 'score_time': array([0.00187492, 0.00159335, 0.00155783]),
 'test_MAE': array([-0.60197332, -0.5610655 , -0.65599163]),
 'test_MSE': array([-0.63497084, -0.5636626 , -0.78360926]),
 'test_R2': array([0.52899805, 0.52830877, 0.45085724]),
 'train_MAE': array([-0.59865069, -0.60456721, -0.55194598]),
 'train_MSE': array([-0.61718838, -0.64270341, -0.56133664]),
 'train_R2': array([0.53105093, 0.54074358, 0.55902855])}
```

11. Данные метрик дерева решений для сравнения с другими моделями

[77]:
```
-np.mean(scores_4['train_MAE']), -np.mean(scores_4['test_MAE']), \
-np.mean(scores_4['train_MSE']), -np.mean(scores_4['test_MSE']), \
np.mean(scores_4['train_R2']), np.mean(scores_4['test_R2'])
```

[77]:
```
(0.5850546241714393,
 0.6063434807383564,
 0.6070761448129344,
 0.6607475666049402,
 0.5436076857580303,
 0.5027213535306057)
```

12. Все методы показали примерно одинаковые результаты, однако в целом наилучший результат дала машина опорных векторов

[99]:
```
-np.mean(scores_3['train_MAE']), -np.mean(scores_3['test_MAE']), \
-np.mean(scores_3['train_MSE']), -np.mean(scores_3['test_MSE']), \
np.mean(scores_3['train_R2']), np.mean(scores_3['test_R2'])
```

[99]:
```
(0.5276885217738251,
 0.550235042278142２,
 0.5178224843539592,
 0.5611078368165351,
 0.6103948517000314,
 0.5762820158960761)
```

[79]:
```
-np.mean(scores_2['train_MAE']), -np.mean(scores_2['test_MAE']), \
-np.mean(scores_2['train_MSE']), -np.mean(scores_2['test_MSE']), \
np.mean(scores_2['train_R2']), np.mean(scores_2['test_R2'])
```

[79]:
```
(0.4443838432807796,
 0.507100989083478,
 0.44093920269594206,
 0.5328951447989484,
 0.6682600547769003,
 0.599416311806581)
```

[80]:
```
-np.mean(scores_4['train_MAE']), -np.mean(scores_4['test_MAE']), \
-np.mean(scores_4['train_MSE']), -np.mean(scores_4['test_MSE']), \
np.mean(scores_4['train_R2']), np.mean(scores_4['test_R2'])
```

[80]:
```
(0.5850546241714393,
 0.6063434807383564,
 0.6070761448129344,
 0.6607475666049402,
 0.5436076857580303,
 0.5027213535306057)
```

13. Подбор одного гиперпараметра

Линейная регрессия

[121]:
```
n_range = np.array(range(0,100,5))
tuned_parameters = [{'n_jobs': n_range}]
tuned_parameters
```

[121]:
```
[{'n_jobs': array([ 0,  5, 10, 15, 20, 25, 30, 35, 40, 45, 50, 55, 60,
 ↪65, 70,
75, 80,
        85, 90, 95])}]
```

[0]:
```
from sklearn.model_selection import GridSearchCV, RandomizedSearchCV
from sklearn.model_selection import learning_curve, validation_curve
```

[122]:
```
from sklearn.model_selection import KFold, RepeatedKFold, LeaveOneOut,
 ↪LeavePOut, ShuffleSplit, StratifiedKFold
reg_gs = GridSearchCV(LinearRegression(), tuned_parameters,
 ↪cv=ShuffleSplit(), scoring='neg_mean_absolute_error')
reg_gs.fit(data.data, data.target)
```

[122]:
```
GridSearchCV(cv=ShuffleSplit(n_splits=10, random_state=None,
 ↪test_size=None,
train_size=None),
             error_score=nan,
             estimator=LinearRegression(copy_X=True, fit_intercept=True,
                                        n_jobs=None, normalize=False),
             iid='deprecated', n_jobs=None,
             param_grid=[{'n_jobs': array([ 0,  5, 10, 15, 20, 25, 30,
 ↪35, 40,
45, 50, 55, 60, 65, 70, 75, 80,
       85, 90, 95])}],
             pre_dispatch='2*n_jobs', refit=True,
 ↪return_train_score=False,
             scoring='neg_mean_absolute_error', verbose=0)
```

[96]:
```
reg_gs.best_estimator_
```

[96]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=0,
 ↪normalize=False)
```

[89]:
```
LinearRegression().get_params().keys()
```

[89]:
```
dict_keys(['copy_X', 'fit_intercept', 'n_jobs', 'normalize'])
```

[98]:
```
scores_lin_improved = cross_validate(reg_gs.best_estimator_,
                            sc1_data, df_california['target'],
 ↪scoring=scoring,
                            cv=3, return_train_score=True)
scores_lin_improved
```

[98]:
```
{'fit_time': array([0.01382542, 0.00902247, 0.00635958]),
 'score_time': array([0.00205398, 0.00235367, 0.0018456 ]),
 'test_MAE': array([-0.57887213, -0.50877351, -0.56305949]),
 'test_MSE': array([-0.59988822, -0.49188049, -0.59155481]),
 'test_R2': array([0.55502126, 0.58837838, 0.58544641]),
 'train_MAE': array([-0.51394065, -0.54832542, -0.52079949]),
 'train_MSE': array([-0.49933994, -0.54483711, -0.50929041]),
 'train_R2': array([0.62059396, 0.61067588, 0.59991471])}
```

[101]:

```
-np.mean(scores_lin_improved['train_MAE']), -np.
 ↪mean(scores_lin_improved['test_MAE']), \
-np.mean(scores_lin_improved['train_MSE']), -np.
 ↪mean(scores_lin_improved['test_MSE']), \
np.mean(scores_lin_improved['train_R2']), np.
 ↪mean(scores_lin_improved['test_R2'])
```

[101]:
```
(0.5276885217738251,
 0.5502350422781422,
 0.5178224843539592,
 0.5611078368165351,
 0.6103948517000314,
 0.5762820158960761)
```

Вспоминаем метрики при случайно подобранном гиперпараметре:

[100]:
```
-np.mean(scores_3['train_MAE']), -np.mean(scores_3['test_MAE']), \
-np.mean(scores_3['train_MSE']), -np.mean(scores_3['test_MSE']), \
np.mean(scores_3['train_R2']), np.mean(scores_3['test_R2'])
```

[100]:
```
(0.5276885217738251,
 0.5502350422781422,
 0.5178224843539592,
 0.5611078368165351,
 0.6103948517000314,
 0.5762820158960761)
```

Для линейной регрессии отличий нет

Машина опорных векторов

[102]:
```
SVR().get_params().keys()
```

[102]:
```
dict_keys(['C', 'cache_size', 'coef0', 'degree', 'epsilon', 'gamma',
 ↪'kernel',
'max_iter', 'shrinking', 'tol', 'verbose'])
```

[103]:
```
n_range = np.array(range(1,20,1))
tuned_parameters = [{'C': n_range}]
tuned_parameters
```

[103]:
```
[{'C': array([ 1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14,
 ↪15, 16,
17,
         18, 19])}]
```

[105]:
```
reg_gs_svr = GridSearchCV(SVR(), tuned_parameters, cv=3,
                      scoring='neg_mean_absolute_error')
reg_gs_svr.fit(data.data, data.target)
```

[105]:
```
GridSearchCV(cv=3, error_score=nan,
             estimator=SVR(C=1.0, cache_size=200, coef0=0.0, degree=3,
                           epsilon=0.1, gamma='scale', kernel='rbf',
                           max_iter=-1, shrinking=True, tol=0.001,
```

```
                        verbose=False),
             iid='deprecated', n_jobs=None,
             param_grid=[{'C': array([ 1,  2,  3,  4,  5,  6,  7,  8, ␣
 ↪9, 10,
11, 12, 13, 14, 15, 16, 17,
       18, 19])}],
             pre_dispatch='2*n_jobs', refit=True,␣
 ↪return_train_score=False,
             scoring='neg_mean_absolute_error', verbose=0)
```

[106]:
```
reg_gs_svr.best_estimator_
```

[106]:
```
SVR(C=19, cache_size=200, coef0=0.0, degree=3, epsilon=0.1,␣
 ↪gamma='scale',
    kernel='rbf', max_iter=-1, shrinking=True, tol=0.001, verbose=False)
```

[107]:
```
scores_svr_improved = cross_validate(reg_gs_svr.best_estimator_,
                        sc1_data, df_california['target'],␣
 ↪scoring=scoring,
                        cv=3, return_train_score=True)
scores_svr_improved
```

[107]:
```
{'fit_time': array([15.53939581, 16.61715221, 15.49336576]),
 'score_time': array([2.32830477, 2.38654304, 2.32462382]),
 'test_MAE': array([-0.49278758, -0.4468058 , -0.541635  ]),
 'test_MSE': array([-0.52777176, -0.40829368, -0.63635923]),
 'test_R2': array([0.60851505, 0.65832654, 0.55404807]),
 'train_MAE': array([-0.41046405, -0.42600974, -0.40093578]),
 'train_MSE': array([-0.39641595, -0.41509394, -0.38038344]),
 'train_R2': array([0.69879716, 0.70338643, 0.70118067])}
```

[108]:
```
-np.mean(scores_svr_improved['train_MAE']), -np.
 ↪mean(scores_svr_improved['test_MAE']), \
-np.mean(scores_svr_improved['train_MSE']), -np.
 ↪mean(scores_svr_improved['test_MSE']), \
np.mean(scores_svr_improved['train_R2']), np.
 ↪mean(scores_svr_improved['test_R2'])
```

[108]:
```
(0.4124698590661901,
 0.49374279450566805,
 0.3972977772757442,
 0.5241415550388026,
 0.7011214195108509,
 0.6069632218804634)
```

Данные с произвольным параметром

[109]:
```
-np.mean(scores_2['train_MAE']), -np.mean(scores_2['test_MAE']), \
-np.mean(scores_2['train_MSE']), -np.mean(scores_2['test_MSE']), \
np.mean(scores_2['train_R2']), np.mean(scores_2['test_R2'])
```

```
[109]: (0.4443838432807796,
 0.507100989083478,
 0.4409392026959420 6,
 0.5328951447989484,
 0.6682600547769003,
 0.599416311806581)
```

В целом результат стал лучше для машины опорных векторов

Решающее дерево

```
[110]: DecisionTreeRegressor().get_params().keys()
```

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

```
[111]: n_range = np.array(range(1,7,1))
tuned_parameters = [{'max_depth': n_range}]
tuned_parameters
```

```
[111]: [{'max_depth': array([1, 2, 3, 4, 5, 6])}]
```

```
[118]: reg_gs_dt = GridSearchCV(DecisionTreeRegressor(random_state=1),
  ↪tuned_parameters,
                          cv=3, scoring='neg_mean_absolute_error')
reg_gs_dt.fit(data.data, data.target)
```

```
[118]: GridSearchCV(cv=3, error_score=nan,
             estimator=DecisionTreeRegressor(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=1,
  ↪splitter='best'),
             iid='deprecated', n_jobs=None,
             param_grid=[{'max_depth': array([1, 2, 3, 4, 5, 6])}],
             pre_dispatch='2*n_jobs', refit=True,
  ↪return_train_score=False,
             scoring='neg_mean_absolute_error', verbose=0)
```

```
[120]: reg_gs_dt.best_estimator_
```

```
[120]: DecisionTreeRegressor(ccp_alpha=0.0, criterion='mse', max_depth=6,
                             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=1, splitter='best')
```

```
[123]: scores_dt_improved = cross_validate(reg_gs_dt.best_estimator_,
                               sc1_data, df_california['target'],
         ↪scoring=scoring,
                               cv=3, return_train_score=True)
       scores_dt_improved
```

```
[123]: {'fit_time': array([0.07014084, 0.06682444, 0.06235528]),
        'score_time': array([0.00182557, 0.00171566, 0.00167012]),
        'test_MAE': array([-0.61119449, -0.49988436, -0.59795421]),
        'test_MSE': array([-0.69455089, -0.47155863, -0.70879242]),
        'test_R2': array([0.48480339, 0.60538437, 0.50328787]),
        'train_MAE': array([-0.45610619, -0.48600847, -0.40178872]),
        'train_MSE': array([-0.40015903, -0.44928409, -0.32800898]),
        'train_R2': array([0.69595312, 0.67895518, 0.74232468])}
```

```
[124]: -np.mean(scores_dt_improved['train_MAE']), -np.
         ↪mean(scores_dt_improved['test_MAE']), \
       -np.mean(scores_dt_improved['train_MSE']), -np.
         ↪mean(scores_dt_improved['test_MSE']), \
       np.mean(scores_dt_improved['train_R2']), np.
         ↪mean(scores_dt_improved['test_R2'])
```

```
[124]: (0.4479677942838462,
        0.5696776857508322,
        0.39248403231981016,
        0.624967314819766,
        0.7057443261913532,
        0.5311585429990194)
```

Метрики для произвольного параметра:

```
[125]: -np.mean(scores_4['train_MAE']), -np.mean(scores_4['test_MAE']), \
       -np.mean(scores_4['train_MSE']), -np.mean(scores_4['test_MSE']), \
       np.mean(scores_4['train_R2']), np.mean(scores_4['test_R2'])
```

```
[125]: (0.5850546241714393,
        0.6063434807383564,
        0.6070761448129344,
        0.6607475666049402,
        0.5436076857580303,
        0.5027213535306057)
```

В целом результаты для дерева решений стали лучше

14. Итого:

[126]:
```
-np.mean(scores_lin_improved['train_MAE']), -np.
 ↪mean(scores_lin_improved['test_MAE']), \
-np.mean(scores_lin_improved['train_MSE']), -np.
 ↪mean(scores_lin_improved['test_MSE']), \
np.mean(scores_lin_improved['train_R2']), np.
 ↪mean(scores_lin_improved['test_R2'])
```

[126]:
```
(0.5276885217738251,
 0.5502350422781422,
 0.5178224843539592,
 0.5611078368165351,
 0.6103948517000314,
 0.5762820158960761)
```

[127]:
```
-np.mean(scores_svr_improved['train_MAE']), -np.
 ↪mean(scores_svr_improved['test_MAE']), \
-np.mean(scores_svr_improved['train_MSE']), -np.
 ↪mean(scores_svr_improved['test_MSE']), \
np.mean(scores_svr_improved['train_R2']), np.
 ↪mean(scores_svr_improved['test_R2'])
```

[127]:
```
(0.4124698590661901,
 0.49374279450566805,
 0.3972977772757442,
 0.5241415550388026,
 0.7011214195108509,
 0.6069632218804634)
```

[128]:
```
-np.mean(scores_dt_improved['train_MAE']), -np.
 ↪mean(scores_dt_improved['test_MAE']), \
-np.mean(scores_dt_improved['train_MSE']), -np.
 ↪mean(scores_dt_improved['test_MSE']), \
np.mean(scores_dt_improved['train_R2']), np.
 ↪mean(scores_dt_improved['test_R2'])
```

[128]:
```
(0.4479677942838462,
 0.5696776857508322,
 0.39248403231981016,
 0.624967314819766,
 0.7057443261913532,
 0.5311585429990194)
```

#Вывод: #Машина опорных векторов показывает наилучшие результаты, на втором месте решающее дерево, на третьем - линейная регрессия.