```json
{
  "authors": [
    {
      "name": "Алексеев Андрей Сергеевич"
    }
  ],
  "group": "ИУ5-62Б",
  "kernelspec": {
    "name": "python3",
    "display_name": "Python 3 (ipykernel)",
    "language": "python"
  },
  "language_info": {
    "name": "python",
    "version": "3.9.7",
    "mimetype": "text/x-python",
    "codemirror_mode": {
      "name": "ipython",
      "version": 3
    },
    "pygments_lexer": "ipython3",
    "nbconvert_exporter": "python",
    "file_extension": ".py"
  },
  "title": "Линейные модели, SVM и деревья решений"
}
```


```python
import numpy as np
import pandas as pd
from typing import Dict, Tuple
from scipy import stats
from scipy.optimize import fmin_tnc
from IPython.display import Image
from sklearn.datasets import load_iris, load_boston
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.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
```

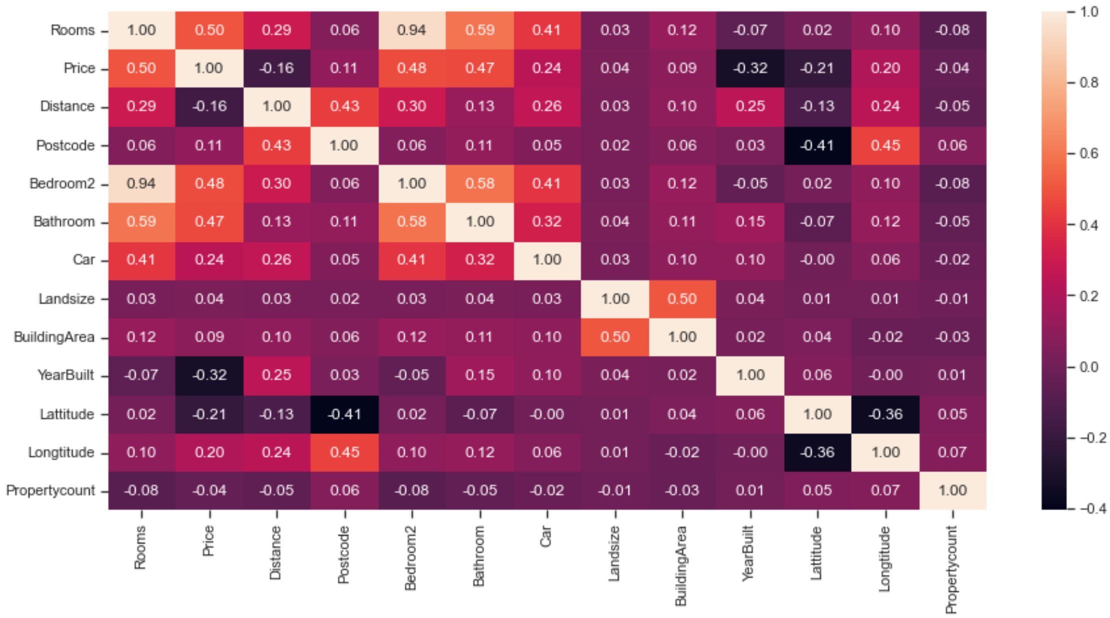
```
%matplotlib inline
sns.set(style="ticks")

data = pd.read_csv('melb_data.csv', sep=",")

data.head()
```

```
       Suburb           Address  Rooms Type      Price Method SellerG  
\
0  Abbotsford      85 Turner St      2    h  1480000.0      S  Biggin   

1  Abbotsford   25 Bloomburg St      2    h  1035000.0      S  Biggin   

2  Abbotsford      5 Charles St      3    h  1465000.0     SP  Biggin   

3  Abbotsford  40 Federation La      3    h   850000.0     PI  Biggin   

4  Abbotsford       55a Park St      4    h  1600000.0     VB  Nelson   


        Date  Distance  Postcode  ...  Bathroom  Car  Landsize 
BuildingArea  \
0  3/12/2016       2.5    3067.0  ...       1.0  1.0     202.0 
NaN   
1  4/02/2016       2.5    3067.0  ...       1.0  0.0     156.0 
79.0   
2  4/03/2017       2.5    3067.0  ...       2.0  0.0     134.0 
150.0   
3  4/03/2017       2.5    3067.0  ...       2.0  1.0      94.0 
NaN   
4  4/06/2016       2.5    3067.0  ...       1.0  2.0     120.0 
142.0   

   YearBuilt  CouncilArea Lattitude  Longtitude             Regionname 
\
0        NaN        Yarra  -37.7996    144.9984  Northern Metropolitan   

1     1900.0        Yarra  -37.8079    144.9934  Northern Metropolitan   

2     1900.0        Yarra  -37.8093    144.9944  Northern Metropolitan   

3        NaN        Yarra  -37.7969    144.9969  Northern Metropolitan   

4     2014.0        Yarra  -37.8072    144.9941  Northern Metropolitan   


  Propertycount  
0        4019.0  
1        4019.0  
2        4019.0  
```

```
3        4019.0
4        4019.0

[5 rows x 21 columns]
```

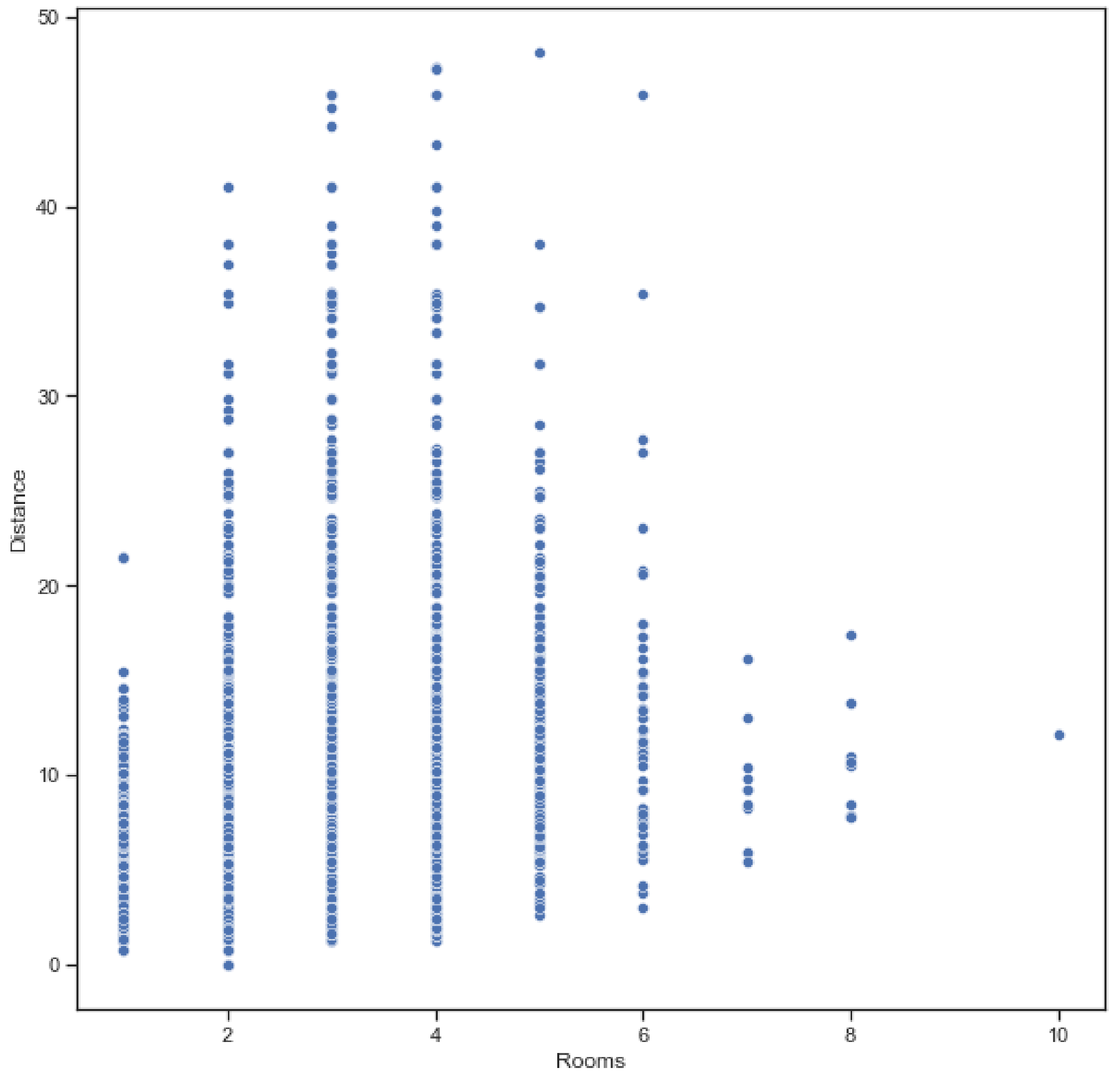
```python
#Построим корреляционную матрицу
fig, ax = plt.subplots(figsize=(15,7))
sns.heatmap(data.corr(method='pearson'), ax=ax, annot=True, fmt='.2f')
```

```
<AxesSubplot:>
```



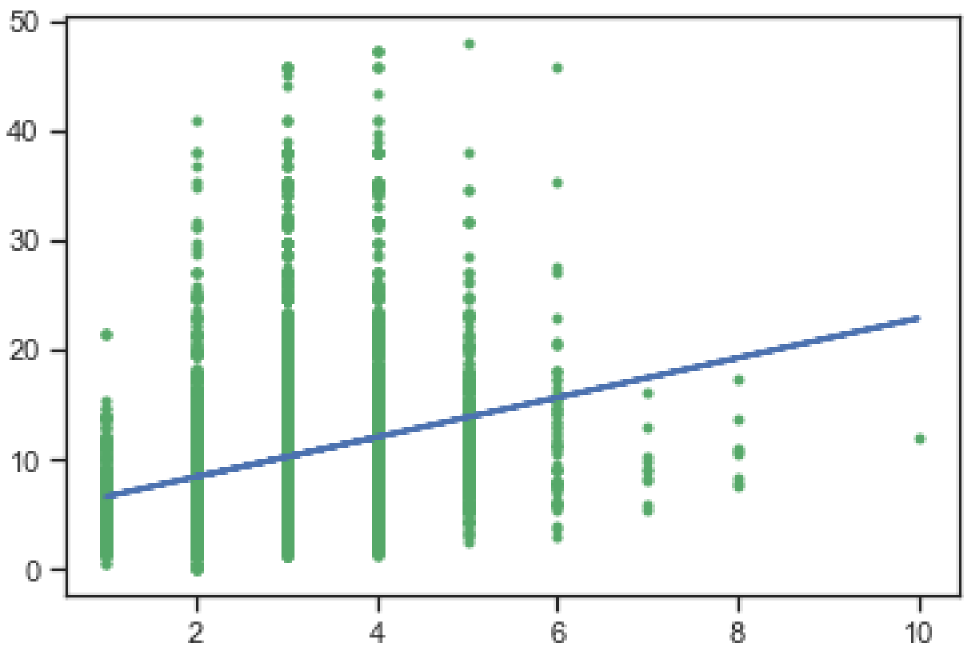

```python
fig, ax = plt.subplots(figsize=(10,10))
sns.scatterplot(ax=ax, x='Rooms', y='Distance', data=data)
```

```
<AxesSubplot:xlabel='Rooms', ylabel='Distance'>
```

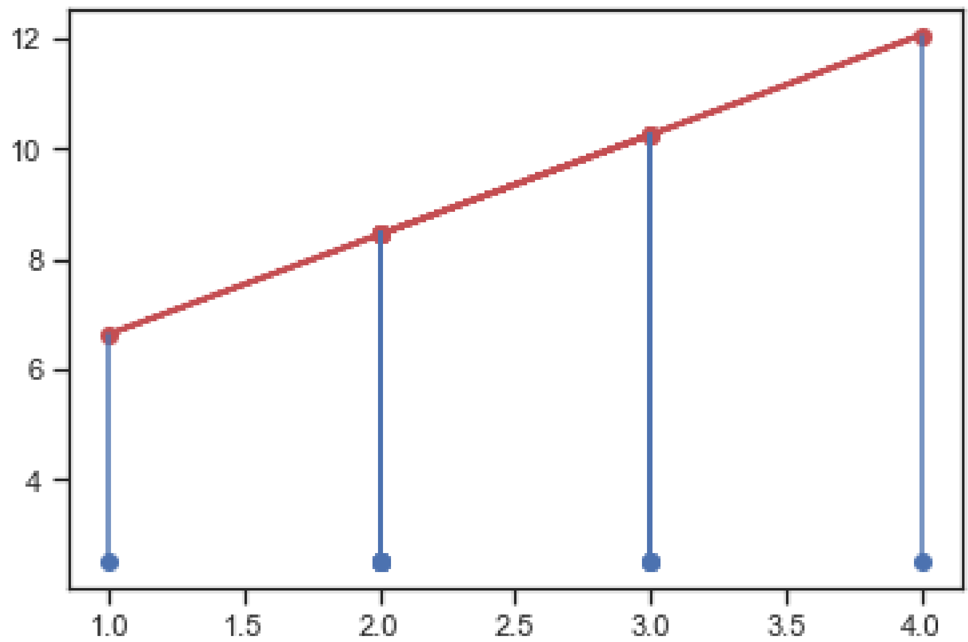



```
# Аналитическое вычисление коэффициентов регрессии
def analytic_regr_coef(x_array : np.ndarray,
                       y_array : np.ndarray) -> Tuple[float, float]:
    x_mean = np.mean(x_array)
    y_mean = np.mean(y_array)
    var1 = np.sum([(x-x_mean)**2 for x in x_array])
    cov1 = np.sum([(x-x_mean)*(y-y_mean)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

x_array = data['Rooms'].values
y_array = data['Distance'].values

b0, b1 = analytic_regr_coef(x_array, y_array)
b0, b1
```

```
(4.83017680419352, 1.8065366434170134)

# Вычисление значений у на основе х 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

y_array_regr = y_regr(x_array, b0, b1)

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



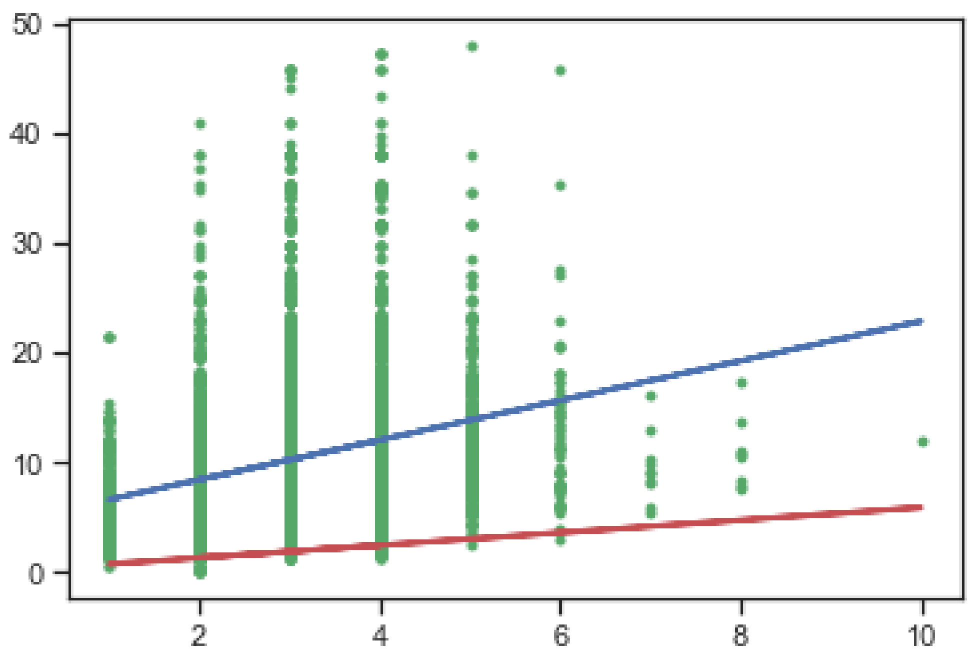

```
# Синими отрезками показаны ошибки между
# истинными и предсказанными значениями
K_mnk=10

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()
```




```
# 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

def show_gradient_descent(epochs, b0_0, b1_0):
    grad_b0, grad_b1, grad_y_pred = gradient_descent(x_array, y_array,
```

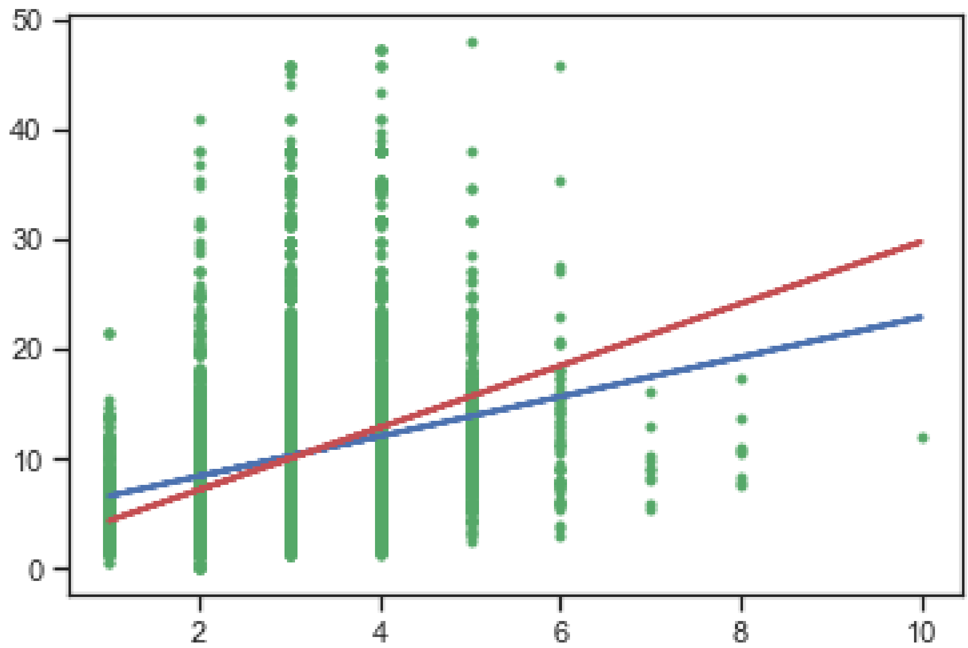
```
b0_0, b1_0, epochs)
    print('b0 = {} - (теоретический), {} - (градиентный
спуск)'.format(b0, grad_b0))
    print('b1 = {} - (теоретический), {} - (градиентный
спуск)'.format(b1, grad_b1))
    print('MSE = {}'.format(mean_squared_error(y_array_regr,
grad_y_pred)))
    plt.plot(x_array, y_array, '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()

# Примеры использования градиентного спуска
show_gradient_descent(10, 0, 0)
```

```
b0 = 4.83017680419352 - (теоретический), 0.1852987147824515 -
(градиентный спуск)
b1 = 1.8065366434170134 - (теоретический), 0.5725191196015689 -
(градиентный спуск)
MSE = 69.79071771536495
```



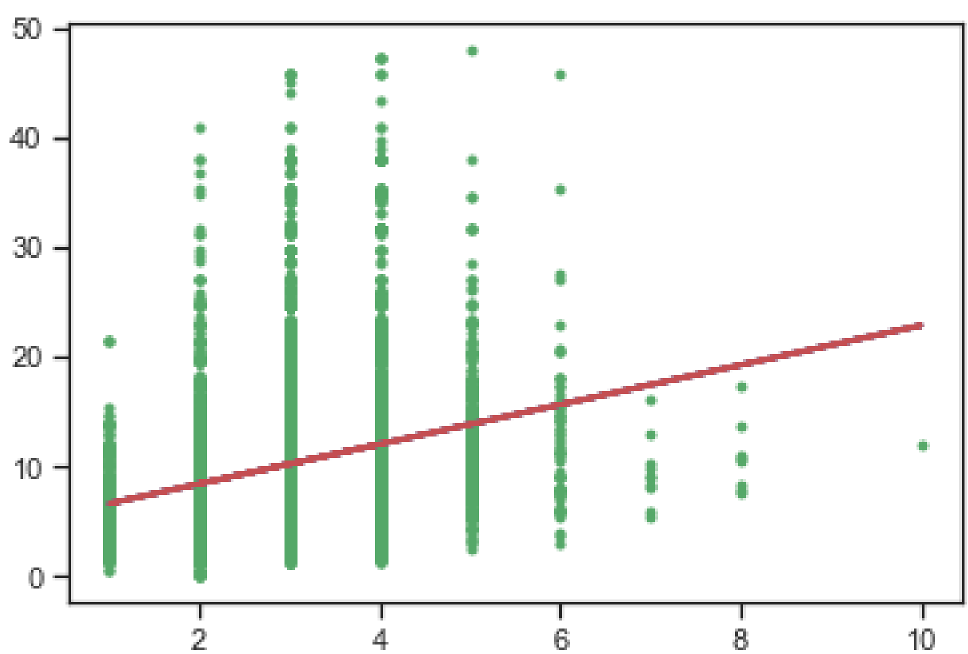

```
show_gradient_descent(1000, 0, 0)
```

```
b0 = 4.83017680419352 - (теоретический), 1.5609200283930669 -
(градиентный спуск)
b1 = 1.8065366434170134 - (теоретический), 2.8220996378843677 -
(градиентный спуск)
MSE = 1.0235687847709871
```




```
%%time
show_gradient_descent(50000, 0, 0)
```

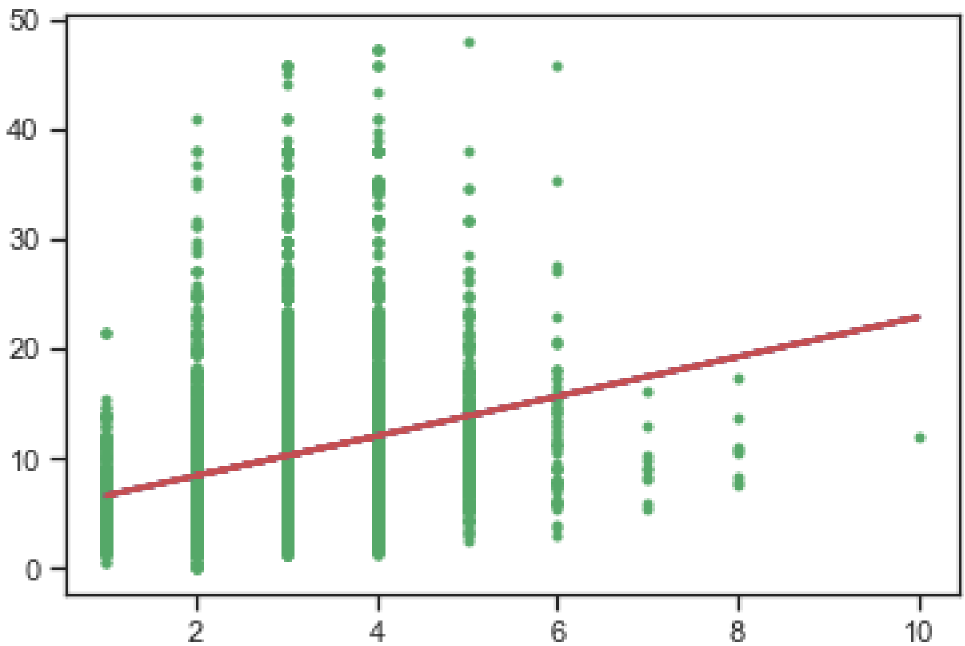
```
b0 = 4.83017680419352 - (теоретический), 4.829550371293804 -
(градиентный спуск)
b1 = 1.8065366434170134 - (теоретический), 1.8067312387383558 -
(градиентный спуск)
MSE = 3.758097860837766e-08
```




```
Wall time: 3.6 s
```

```
%%time
show_gradient_descent(100000, 0, 0)
```

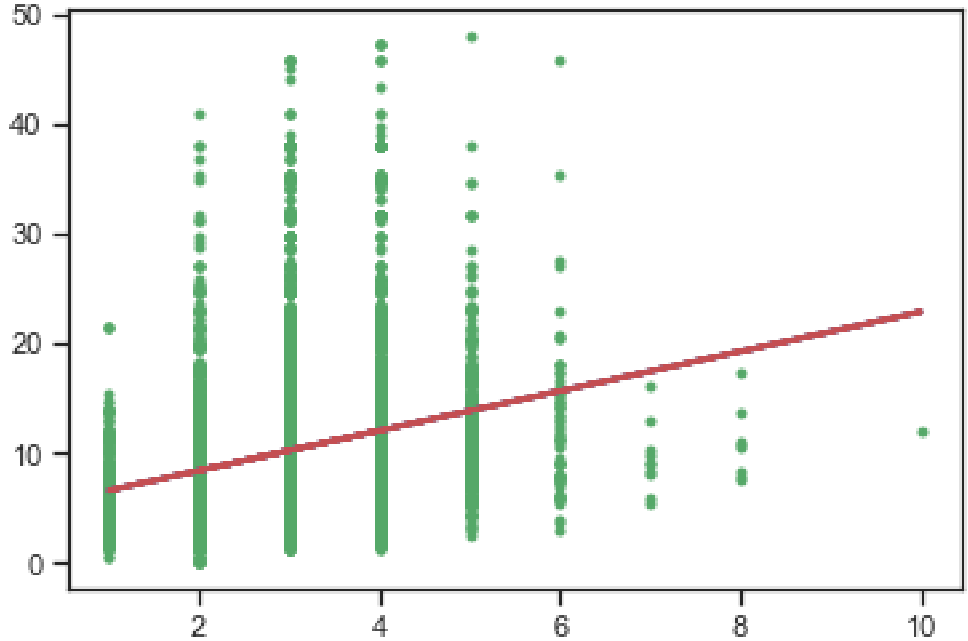
```
b0 = 4.83017680419352 - (теоретический), 4.830176703400344 -
(градиентный спуск)
b1 = 1.8065366434170134 - (теоретический), 1.8065366747274394 -
(градиентный спуск)
MSE = 9.729291730126751e-16
```




```
Wall time: 6.96 s
```

```
%%time
show_gradient_descent(1000000, 0, 0)
```

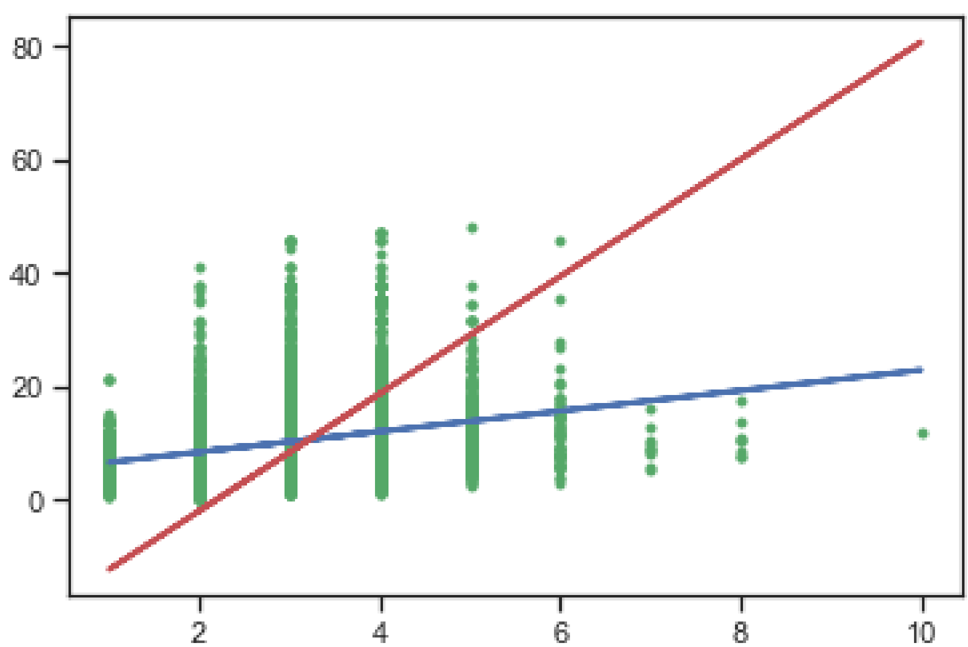
```
b0 = 4.83017680419352 - (теоретический), 4.8301768041910265 -
(градиентный спуск)
b1 = 1.8065366434170134 - (теоретический), 1.8065366434177865 -
(градиентный спуск)
MSE = 5.957213408071935e-25
```




```
Wall time: 1min 8s
```

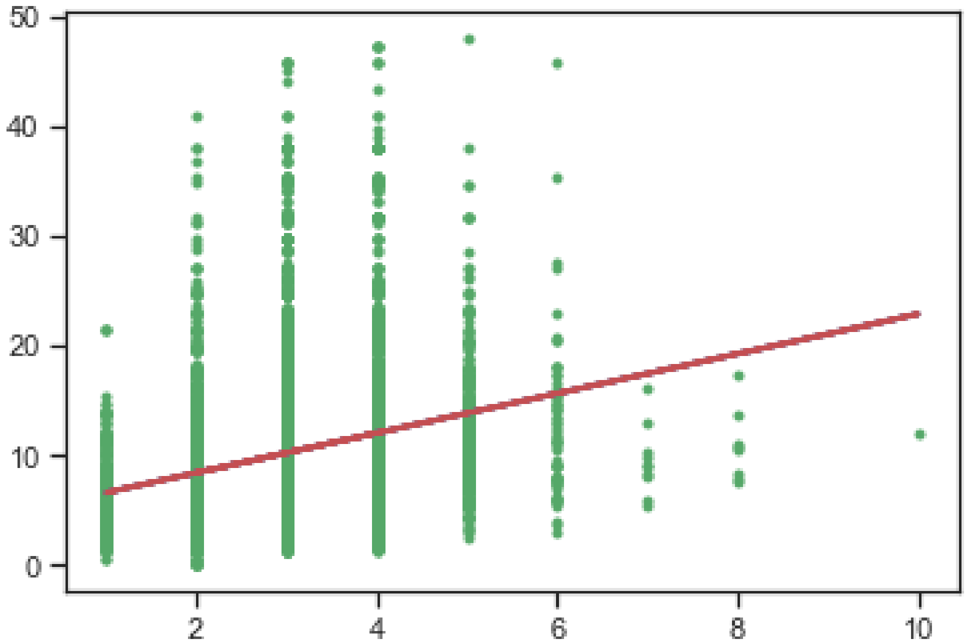
```
# Сходимость алгоритма может сильно зависеть от начальных значений
show_gradient_descent(1000, -30, 5)
```

```
b0 = 4.83017680419352 - (теоретический), -22.60297578385468 -
(градиентный спуск)
b1 = 1.8065366434170134 - (теоретический), 10.328380152221749 -
(градиентный спуск)
MSE = 72.07263599382124
```



```
show_gradient_descent(100000, -30, 5)
```

```
b0 = 4.83017680419352 - (теоретический), 4.830175958412565 -
(градиентный спуск)
b1 = 1.8065366434170134 - (теоретический), 1.8065369061506864 -
(градиентный спуск)
MSE = 6.850697195193023e-14
```



```
# 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_)
```

```
((1.8065366434170134, array([[1.80653664]])),
 (4.83017680419352, array([4.8301768])))
```

```
# 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 - 13580
```

```
((1.8065366434170134, array([1.86537821])),
 (4.83017680419352, array([4.86889697])))
```

```
from sklearn.linear_model import Lasso
```

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

```
((1.8065366434170134, array([0.71171029])),
 (4.83017680419352, 8.046773399101927))
```

```
from sklearn.linear_model import Ridge
```

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

```
((1.8065366434170134, array([1.80639101])),
 (4.83017680419352, 4.830604670995869))
```

```
from sklearn.linear_model import ElasticNet
```

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

```
((1.8065366434170134, array([0.81369571])),
 (4.83017680419352, 7.747140532157479))
```

```
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import PolynomialFeatures
```

```
poly_model = Pipeline([('poly', PolynomialFeatures(degree=3)),
                       ('linear',
LinearRegression(fit_intercept=False))])
```

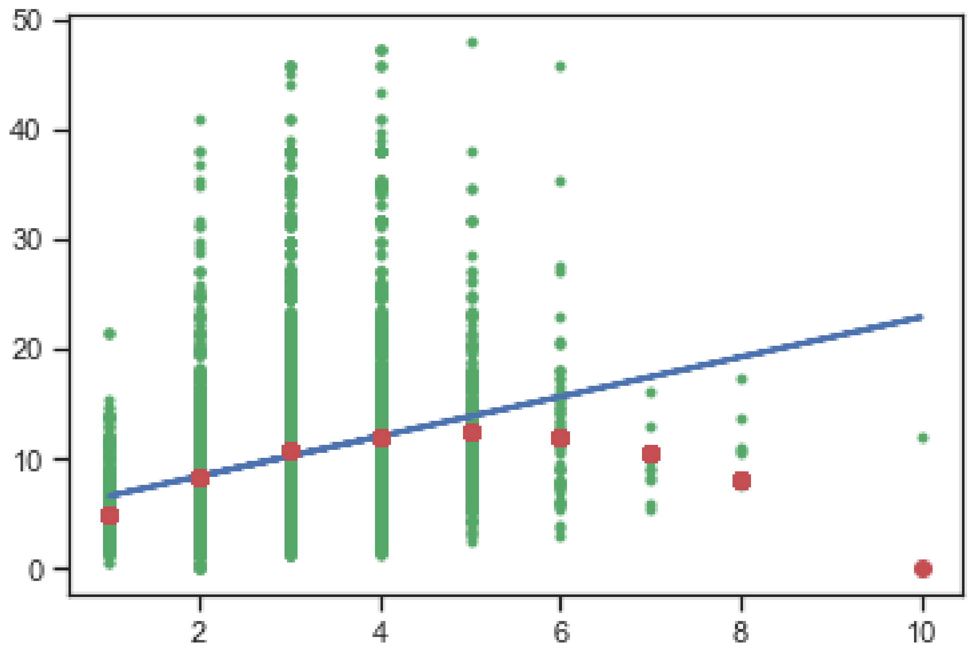
```
poly_model.fit(x_array.reshape(-1, 1), y_array)
```

```
Pipeline(steps=[('poly', PolynomialFeatures(degree=3)),
                ('linear', LinearRegression(fit_intercept=False))])
```

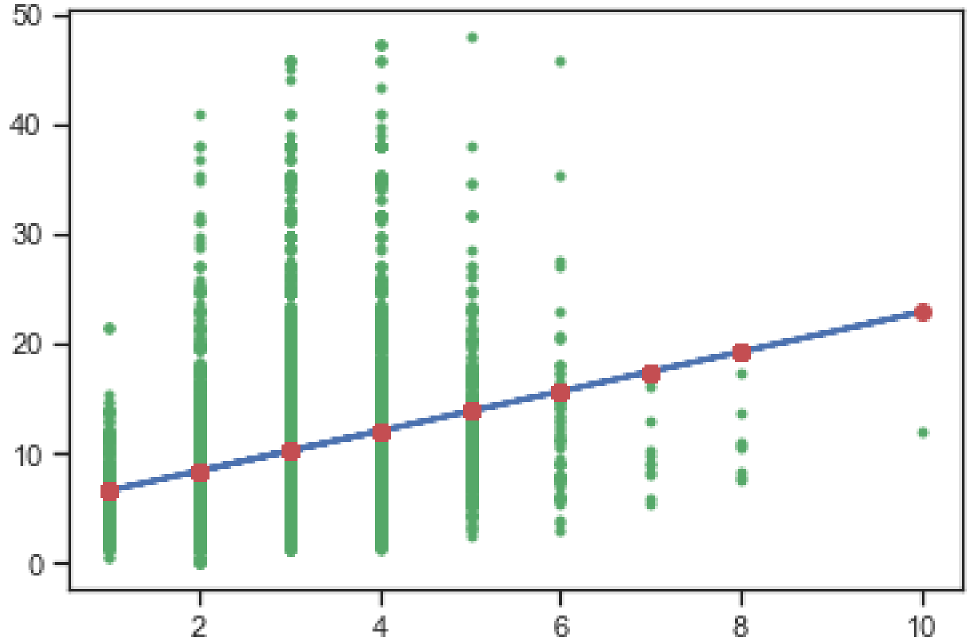
```
poly_model.fit(x_array.reshape(-1, 1), y_array)
```

```
Pipeline(steps=[('poly', PolynomialFeatures(degree=3)),
                ('linear', LinearRegression(fit_intercept=False))])
```

```
poly_y_pred = poly_model.predict(x_array.reshape(-1, 1))
plt.plot(x_array, y_array, 'g.')
plt.plot(x_array, y_array_regr, 'b', linewidth=2.0)
plt.plot(x_array, poly_y_pred, 'ro')
plt.show()
```

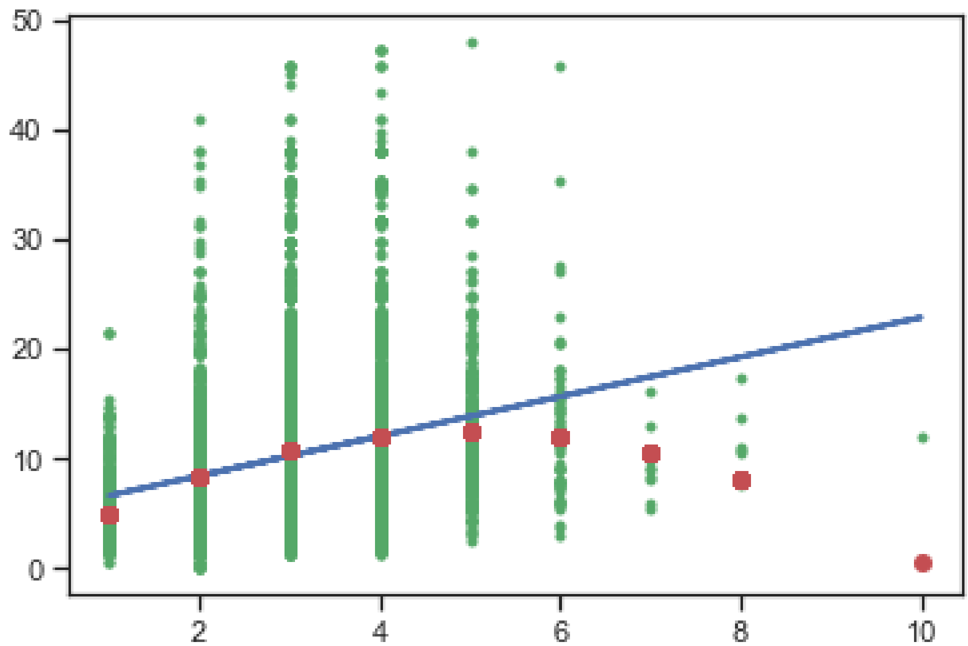



```
# Степени полинома
poly_model.named_steps['linear'].coef_,
poly_model.named_steps['linear'].intercept_

(array([ 6.62627100e-01,  4.74434239e+00, -4.60319777e-01, -
2.07070134e-03]),
 0.0)

def test_poly_model(degree=3):
    poly_model = Pipeline([('poly',
PolynomialFeatures(degree=degree)),
                           ('linear',
LinearRegression(fit_intercept=False))])
    poly_model.fit(x_array.reshape(-1, 1), y_array)
    poly_y_pred = poly_model.predict(x_array.reshape(-1, 1))

    plt.plot(x_array, y_array, 'g.')
    plt.plot(x_array, y_array_regr, 'b', linewidth=2.0)
    plt.plot(x_array, poly_y_pred, 'ro')
    plt.show()

    print('Степени полинома -
{}'.format(poly_model.named_steps['linear'].coef_))

test_poly_model(degree=1)
```



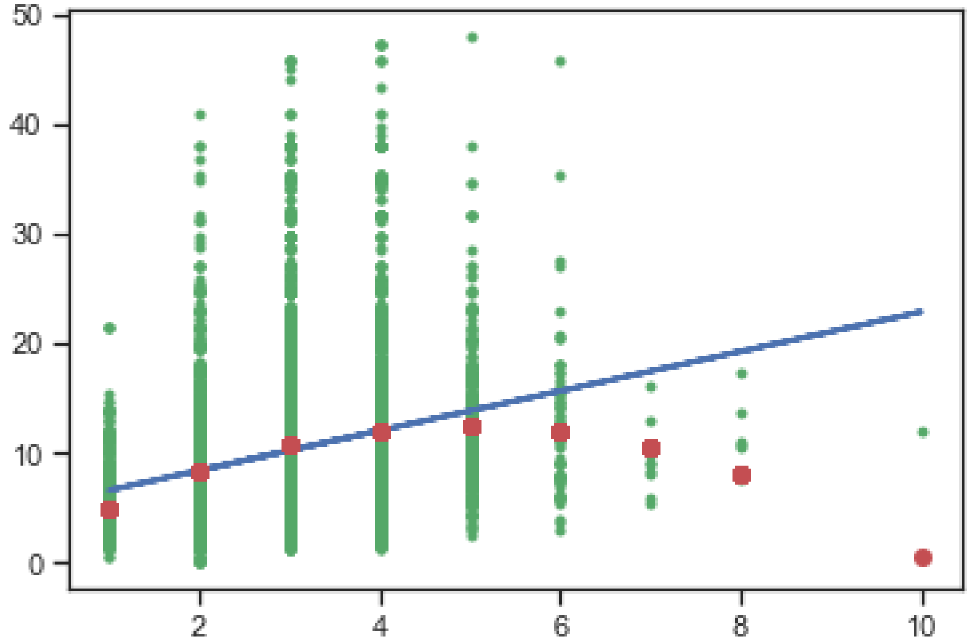
Степени полинома - [4.8301768 1.80653664]

```
test_poly_model(degree=2)
```



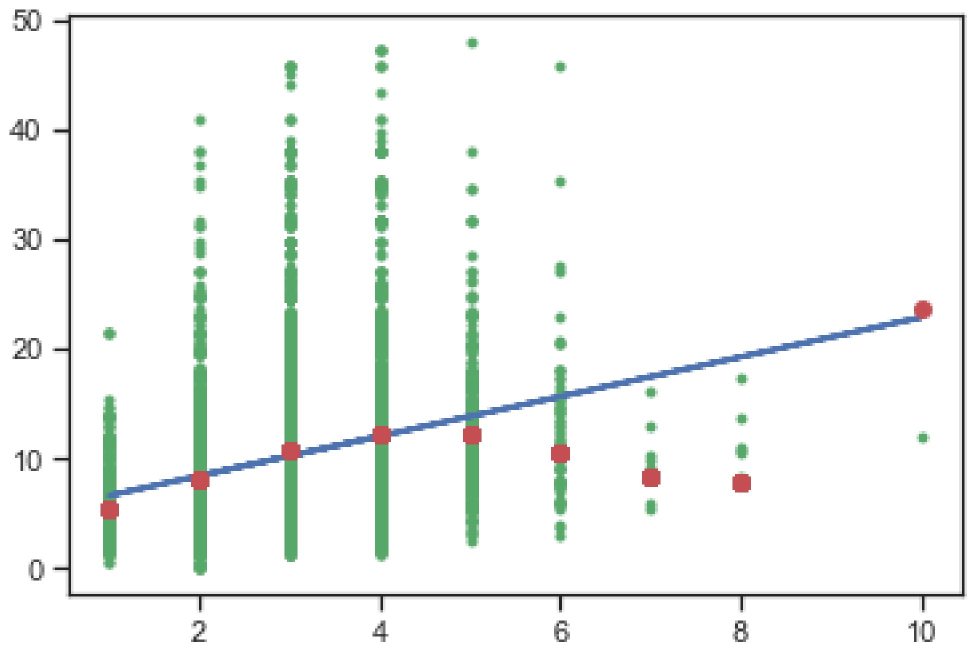
Степени полинома - [0.59525262 4.81584462 -0.48258887]

```
test_poly_model(degree=2)
```



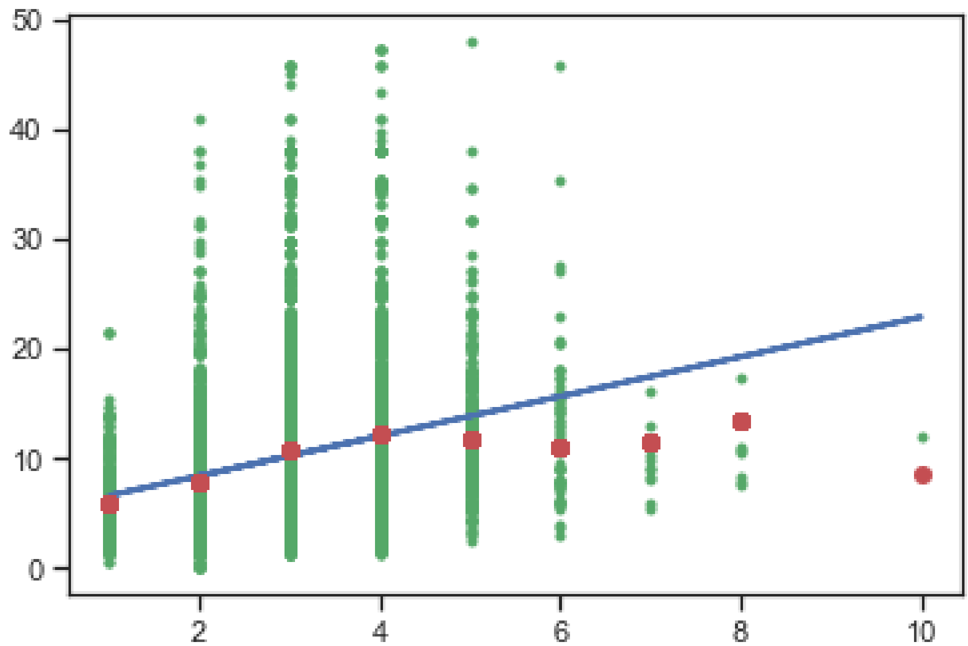
```
Степени полинома - [ 0.59525262  4.81584462 -0.48258887]
```

```
test_poly_model(degree=4)
```



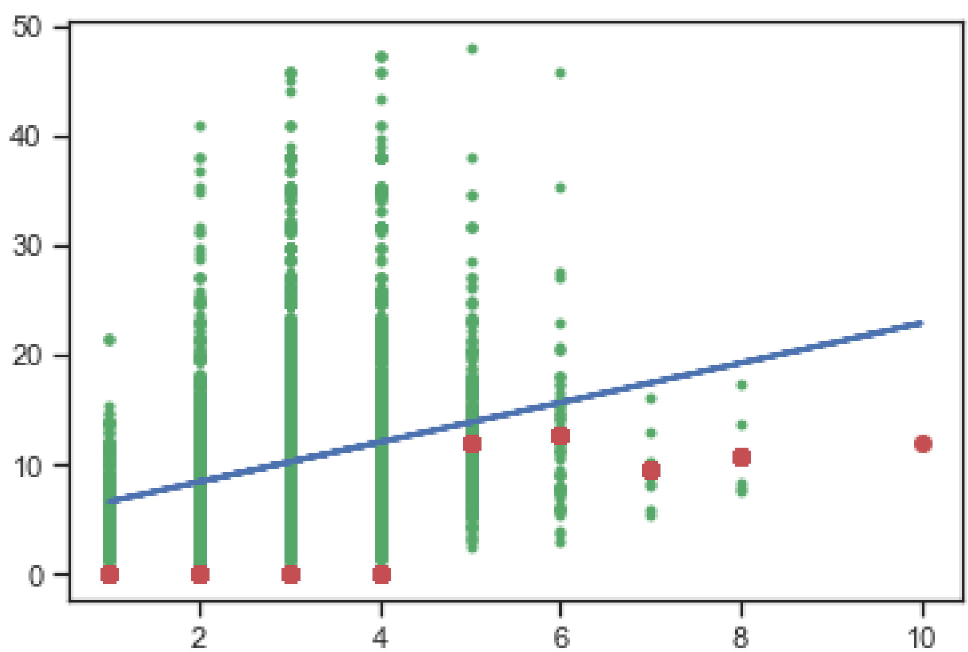
```
Степени полинома - [ 5.668722   -2.39146926  2.83283556 -0.59633531
0.0355107 ]
```

```
test_poly_model(degree=5)
```



Степени полинома - [1.25241705e+01 -1.47843538e+01 1.05762708e+01 -
2.73729652e+00
  3.00633274e-01 -1.18266141e-02]

```
test_poly_model(degree=35)
```



Степени полинома - [5.15135913e-22 -3.58491391e-23 1.21353054e-26
7.17358085e-30
 -4.03429661e-33 4.81489351e-35 2.15947621e-34 8.97789572e-34
  3.84432602e-33 1.68652620e-32 7.54545558e-32 3.42881182e-31

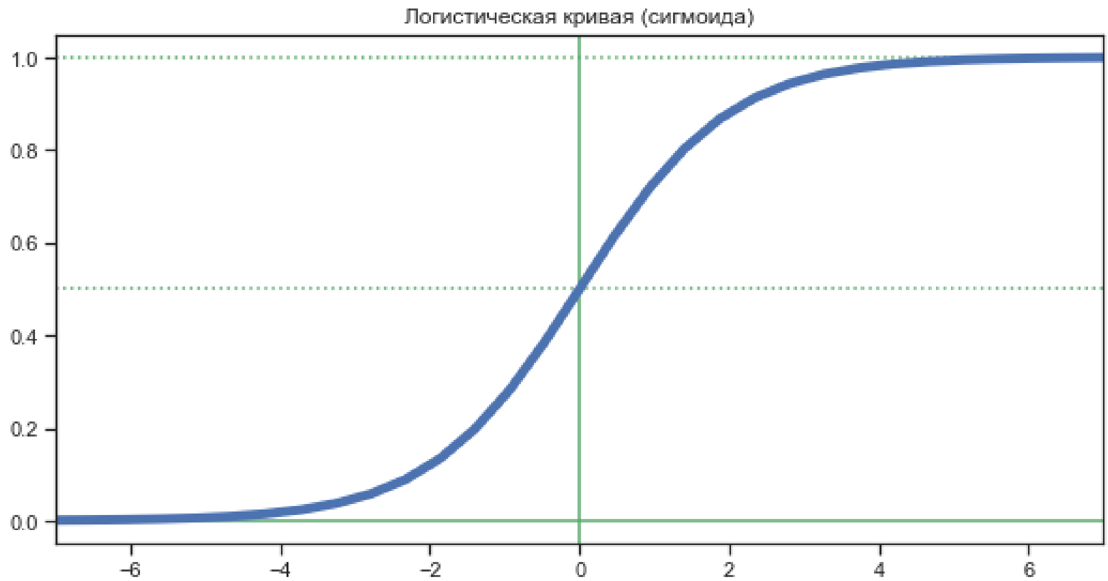
```
  1.57700135e-30  7.31801450e-30  3.41669826e-29  1.60083832e-28
  7.50838930e-28  3.51682219e-27  1.64087558e-26  7.60610119e-26
  3.49230698e-25  1.58276493e-24  7.05096010e-24  3.07127939e-23
  1.29914186e-22  5.28748312e-22  2.04383858e-21  7.35961933e-21
  2.39377335e-20  6.65883009e-20  1.41110934e-19  1.57956363e-19
 -1.13227238e-19  2.44389672e-20 -2.21637950e-21  7.31997130e-23]
```

```
# Определение функции
# f(0)=0.5
x = np.linspace(-7, 7, 31)
y = 1 / (1 + np.exp(-x))
list(zip(x,y))
```

```
[(-7.0, 0.0009110511944006454),
 (-6.533333333333333, 0.0014520391100099122),
 (-6.066666666666666, 0.0023135251651203942),
 (-5.6, 0.003684239899435989),
 (-5.133333333333333, 0.005862302196338335),
 (-4.666666666666666, 0.009315959345066693),
 (-4.2, 0.014774031693273055),
 (-3.7333333333333334, 0.023354516476977092),
 (-3.2666666666666666, 0.03673259067202974),
 (-2.8, 0.057324175898868755),
 (-2.333333333333333, 0.08839967720705845),
 (-1.8666666666666663, 0.1339278883240737),
 (-1.4000000000000004, 0.1978161114414182),
 (-0.9333333333333336, 0.28224894304225995),
 (-0.4666666666666668, 0.3854055017324505),
 (0.0, 0.5),
 (0.4666666666666668, 0.6145944982675495),
 (0.9333333333333336, 0.71775105695774),
 (1.4000000000000004, 0.8021838885585818),
 (1.8666666666666671, 0.8660721116759263),
 (2.333333333333334, 0.9116003227929417),
 (2.8000000000000007, 0.9426758241011313),
 (3.2666666666666675, 0.9632674093279703),
 (3.7333333333333343, 0.9766454835230229),
 (4.199999999999999, 0.9852259683067269),
 (4.666666666666666, 0.9906840406549333),
 (5.133333333333333, 0.9941376978036617),
 (5.6, 0.9963157601005641),
 (6.066666666666666, 0.9976864748348797),
 (6.533333333333333, 0.9985479608899902),
 (7.0, 0.9990889488055994)]
```

```
# Вывод графика и осей
plt.figure(figsize=(10, 5))
plt.plot([-7, 7], [0, 0], "g-")
plt.plot([-7, 7], [0.5, 0.5], "g:")
plt.plot([-7, 7], [1, 1], "g:")
plt.plot([0, 0], [-1.1, 1.1], "g-")
```

```
plt.plot(x, y, "b-", linewidth=5)
plt.axis([-7, 7, -0.05, 1.05])
plt.title('Логистическая кривая (сигмоида)')
plt.show()
```




```
# Подготовка данных
data1 = pd.read_csv('melb_data.csv', sep=",")
iris = load_iris()
iris_x_ds = pd.DataFrame(data=iris['data'],
columns=iris['feature_names'])
iris_x_ds_lr = iris_x_ds[['petal length (cm)', 'sepal length (cm)']]
data1['x0'] = 1
iris_x_ds_lr['target'] = iris.target
data1.head()
```

```
C:\Users\7272~1\AppData\Local\Temp/ipykernel_17792/75802874.py:7:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
  iris_x_ds_lr['target'] = iris.target

       Suburb           Address  Rooms Type      Price Method SellerG
\
0  Abbotsford      85 Turner St      2    h  1480000.0      S  Biggin

1  Abbotsford   25 Bloomburg St      2    h  1035000.0      S  Biggin

2  Abbotsford      5 Charles St      3    h  1465000.0     SP  Biggin
```

```
3  Abbotsford  40 Federation La      3    h   850000.0     PI  Biggin

4  Abbotsford       55a Park St      4    h  1600000.0     VB  Nelson


        Date  Distance  Postcode  ...  Car  Landsize  BuildingArea
YearBuilt  \
0  3/12/2016       2.5    3067.0  ...  1.0     202.0           NaN
NaN
1  4/02/2016       2.5    3067.0  ...  0.0     156.0          79.0
1900.0
2  4/03/2017       2.5    3067.0  ...  0.0     134.0         150.0
1900.0
3  4/03/2017       2.5    3067.0  ...  1.0      94.0           NaN
NaN
4  4/06/2016       2.5    3067.0  ...  2.0     120.0         142.0
2014.0

   CouncilArea  Lattitude Longtitude             Regionname
Propertycount x0
0        Yarra   -37.7996   144.9984  Northern Metropolitan
4019.0  1
1        Yarra   -37.8079   144.9934  Northern Metropolitan
4019.0  1
2        Yarra   -37.8093   144.9944  Northern Metropolitan
4019.0  1
3        Yarra   -37.7969   144.9969  Northern Metropolitan
4019.0  1
4        Yarra   -37.8072   144.9941  Northern Metropolitan
4019.0  1

[5 rows x 22 columns]
```

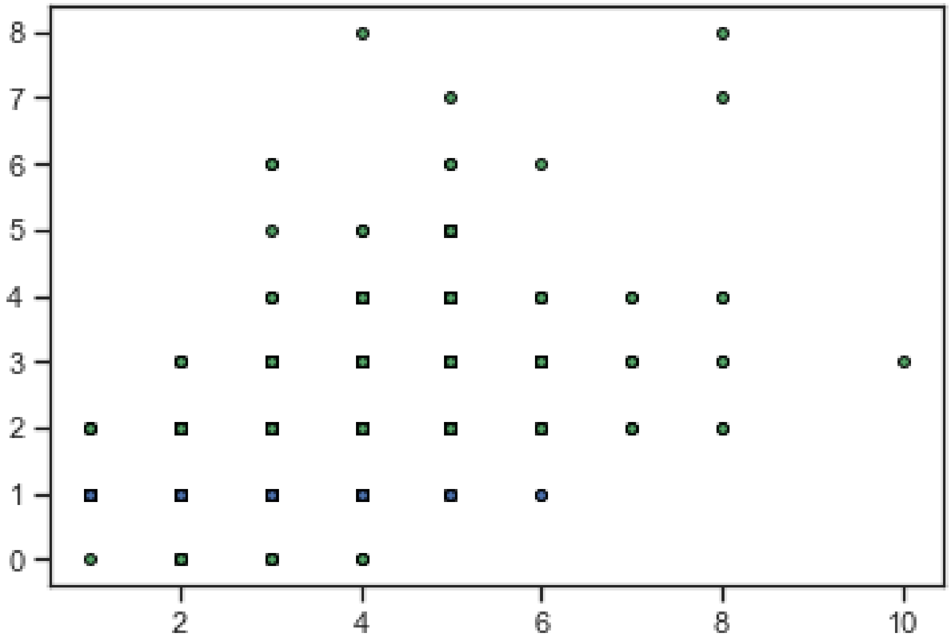
```python
def convert_target_to_binary(array:data1['Car'], Bathroom:int) ->
data1['Car']:
    # Если целевой признак совпадает с указанным, то 1 иначе 0
    res = [1 if x==Bathroom else 0 for x in array]
    return res

bin_iris_y = convert_target_to_binary(data1['Bathroom'], 1)

data1['target_bin'] = bin_iris_y
data1.head()
```

```
       Suburb           Address  Rooms Type      Price Method SellerG
\
0  Abbotsford      85 Turner St      2    h  1480000.0      S  Biggin

1  Abbotsford   25 Bloomburg St      2    h  1035000.0      S  Biggin
```

```
2  Abbotsford      5 Charles St      3    h  1465000.0     SP  Biggin

3  Abbotsford  40 Federation La      3    h   850000.0     PI  Biggin

4  Abbotsford       55a Park St      4    h  1600000.0     VB  Nelson


        Date  Distance  Postcode  ...  Landsize  BuildingArea
YearBuilt  \
0  3/12/2016       2.5    3067.0  ...     202.0           NaN
NaN
1  4/02/2016       2.5    3067.0  ...     156.0          79.0
1900.0
2  4/03/2017       2.5    3067.0  ...     134.0         150.0
1900.0
3  4/03/2017       2.5    3067.0  ...      94.0           NaN
NaN
4  4/06/2016       2.5    3067.0  ...     120.0         142.0
2014.0

   CouncilArea  Lattitude  Longtitude             Regionname
Propertycount  \
0        Yarra   -37.7996    144.9984  Northern Metropolitan
4019.0
1        Yarra   -37.8079    144.9934  Northern Metropolitan
4019.0
2        Yarra   -37.8093    144.9944  Northern Metropolitan
4019.0
3        Yarra   -37.7969    144.9969  Northern Metropolitan
4019.0
4        Yarra   -37.8072    144.9941  Northern Metropolitan
4019.0

   x0 target_bin
0   1          1
1   1          1
2   1          0
3   1          0
4   1          1

[5 rows x 23 columns]
```

```
# Визуализация данных
colors = "gb"
#X_viz = iris.data[:, [1,2]]
X_viz = data1[['Rooms', 'Bathroom']].values
y_viz = data1['target_bin'].values
n_classes = len(np.unique(y_viz))
for i, color in zip(range(n_classes), colors):
```

```
    idx = np.where(y_viz == i)
    plt.scatter(X_viz[idx, 0], X_viz[idx, 1],
                c=color,
                cmap=plt.cm.RdYlBu,
                edgecolor='black', s=15)
plt.show()
```




```
# Реализация градиентного спуска
def sigmoid(x):
    '''
    Функция - сигмоида
    '''
    return 1 / (1 + np.exp(-x))

def proba(b, x):
    '''
    Вероятность единичного класса
    '''
    return sigmoid(np.dot(x,b))

def cost_function(b, x, y):
    '''
    Функция потерь
    '''
    k = x.shape[0]
    res = -(1 / k) * np.sum(
        y * np.log(proba(b, x))
        + (1 - y) * np.log(1 - proba(b, x)))
    return res
```

```python
def gradient(b, x, y):
    '''
    Определение градиента
    '''
    k = x.shape[0]
    res = (1 / k) * np.dot(
        x.T, (proba(b, x) - y))

def optimize_lr(x, y, b):
    '''
    Для оптимизации используется функция
    scipy.optimize.fmin_tnc
    '''
    opt_weights = fmin_tnc(
        func=cost_function,
        x0=b,
        fprime=gradient,
        approx_grad=True,
        args=(x, y))
    return opt_weights[0]
```

```python
opt_x = data1[['x0', 'Rooms', 'Bathroom']].values
opt_x[:5]
```

```
array([[1., 2., 1.],
       [1., 2., 1.],
       [1., 3., 2.],
       [1., 3., 2.],
       [1., 4., 1.]])
```

```python
opt_y = data1['target_bin']
opt_y[:5]
```

```
0    1
1    1
2    0
3    0
4    1
Name: target_bin, dtype: int64
```

```python
b_init = np.zeros(3)
b_init
```

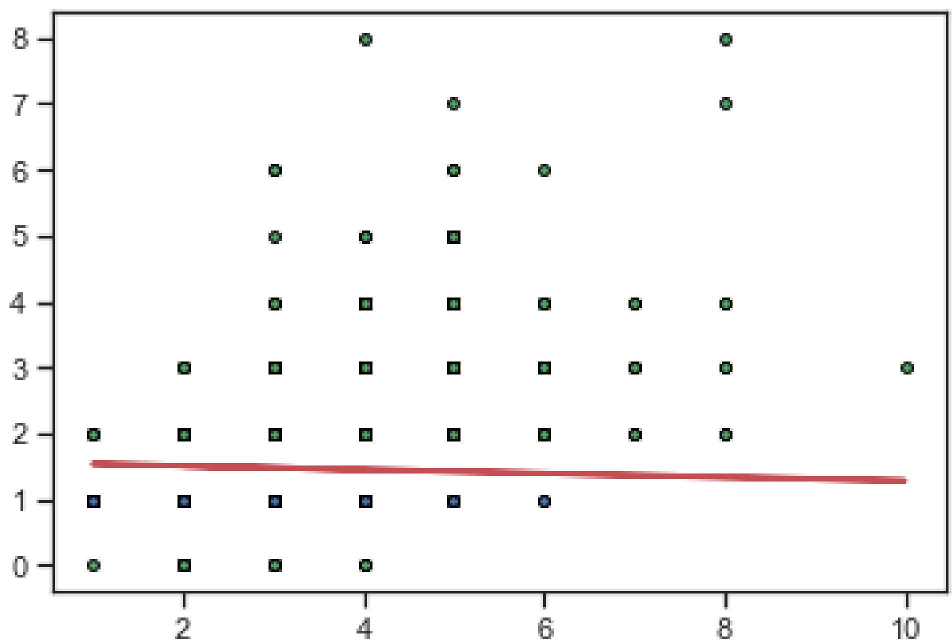
```
array([0., 0., 0.])
```

```python
b_res = optimize_lr(opt_x, opt_y, b_init)
b_res
```

```
array([14.89013702, -0.27069669, -9.50234537])
```

```python
def vis_lr(b):
    '''
```

```
    Визуализация результата
    '''
    colors = "gb"
    X_viz = data1[['Rooms', 'Bathroom']].values
    y_viz = data1['target_bin'].values
    n_classes = len(np.unique(y_viz))
    for i, color in zip(range(n_classes), colors):
        idx = np.where(y_viz == i)
        plt.scatter(X_viz[idx, 0], X_viz[idx, 1],
                    c=color,
                    cmap=plt.cm.RdYlBu,
                    edgecolor='black', s=15)
    t1 = data1['Rooms'].values
    t2 = -((b[0]+np.dot(b[1], t1))/b[2])
    plt.plot(t1, t2, 'r', linewidth=2.0)
    plt.show()

vis_lr(b_res)
```




```
import numpy as np
import pandas as pd
from typing import Dict, Tuple
from scipy import stats
from IPython.display import Image
from sklearn.datasets import load_iris, load_boston
from sklearn.model_selection import train_test_split
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.datasets import make_blobs, make_circles
from sklearn.model_selection import cross_val_score, cross_validate
from sklearn.svm import SVC, NuSVC, LinearSVC, OneClassSVM, SVR,
NuSVR, LinearSVR
import seaborn as sns
from sklearn.neighbors import KNeighborsRegressor,
KNeighborsClassifier
from sklearn.metrics import plot_confusion_matrix
from collections import Counter
import matplotlib.pyplot as plt
from sklearn.linear_model import LogisticRegression
%matplotlib inline
sns.set(style="ticks")
data = pd.read_csv('melb_data.csv', sep=",")
data_2 = data.dropna(axis=0, how='any')
(data.shape, data_2.shape)
```

```
((13580, 21), (6196, 21))
```

```
# формирование второго целевого признака для классификации
data1 = {'a': [], 'b': []}
data2 = {'c': []}
df = pd.DataFrame(data1)
df1 = pd.DataFrame(data2)
iris = load_iris()
df['a'] = data_2['Rooms']
df['b'] = data_2['Bathroom']
df1['c'] = data_2['Car']
df = df.astype({'a': int, 'b': int})
df1 = df1.astype({'c': int})
X = df.to_numpy()
y = df1.to_numpy()
data
```

```
              Suburb           Address  Rooms Type      Price
Method  \
0         Abbotsford      85 Turner St      2    h  1480000.0      S

1         Abbotsford   25 Bloomburg St      2    h  1035000.0      S

2         Abbotsford      5 Charles St      3    h  1465000.0     SP

3         Abbotsford  40 Federation La      3    h   850000.0     PI

4         Abbotsford       55a Park St      4    h  1600000.0     VB
```

```
...              ...                 ...    ...  ...        ...    ...

13575  Wheelers Hill      12 Strada Cr      4    h  1245000.0      S

13576   Williamstown     77 Merrett Dr      3    h  1031000.0     SP

13577   Williamstown       83 Power St      3    h  1170000.0      S

13578   Williamstown      96 Verdon St      4    h  2500000.0     PI

13579     Yarraville        6 Agnes St      4    h  1285000.0     SP


        SellerG        Date  Distance  Postcode  ...  Bathroom  Car
Landsize  \
0        Biggin   3/12/2016       2.5    3067.0  ...       1.0  1.0
202.0
1        Biggin   4/02/2016       2.5    3067.0  ...       1.0  0.0
156.0
2        Biggin   4/03/2017       2.5    3067.0  ...       2.0  0.0
134.0
3        Biggin   4/03/2017       2.5    3067.0  ...       2.0  1.0
94.0
4        Nelson   4/06/2016       2.5    3067.0  ...       1.0  2.0
120.0
...         ...         ...       ...       ...  ...       ...  ...
...
13575     Barry  26/08/2017      16.7    3150.0  ...       2.0  2.0
652.0
13576  Williams  26/08/2017       6.8    3016.0  ...       2.0  2.0
333.0
13577     Raine  26/08/2017       6.8    3016.0  ...       2.0  4.0
436.0
13578   Sweeney  26/08/2017       6.8    3016.0  ...       1.0  5.0
866.0
13579   Village  26/08/2017       6.3    3013.0  ...       1.0  1.0
362.0

       BuildingArea  YearBuilt  CouncilArea Lattitude  Longtitude  \
0               NaN        NaN        Yarra -37.79960   144.99840
1              79.0     1900.0        Yarra -37.80790   144.99340
2             150.0     1900.0        Yarra -37.80930   144.99440
3               NaN        NaN        Yarra -37.79690   144.99690
4             142.0     2014.0        Yarra -37.80720   144.99410
...             ...        ...          ...       ...         ...
13575           NaN     1981.0          NaN -37.90562   145.16761
13576         133.0     1995.0          NaN -37.85927   144.87904
13577           NaN     1997.0          NaN -37.85274   144.88738
13578         157.0     1920.0          NaN -37.85908   144.89299
```

```
13579         112.0     1920.0         NaN -37.81188   144.88449

                       Regionname Propertycount
0           Northern Metropolitan       4019.0
1           Northern Metropolitan       4019.0
2           Northern Metropolitan       4019.0
3           Northern Metropolitan       4019.0
4           Northern Metropolitan       4019.0
...                           ...          ...
13575  South-Eastern Metropolitan       7392.0
13576        Western Metropolitan       6380.0
13577        Western Metropolitan       6380.0
13578        Western Metropolitan       6380.0
13579        Western Metropolitan       6543.0

[13580 rows x 21 columns]
```

```python
# Разделение выборки на обучающую и тестовую
X_train, X_test, y_train, y_test = train_test_split(X, y,
                                                    train_size=0.5,
                                                    random_state=1)
```

```python
cl1 = LogisticRegression()
```

```python
cl1.fit(X_train, y_train)
```

```
C:\Users\Админ\AppData\Local\Programs\Python\Python39\lib\site-packages\sklearn\utils\validation.py:993: DataConversionWarning: A column-vector y was passed when a 1d array was expected. Please change the shape of y to (n_samples, ), for example using ravel().
  y = column_or_1d(y, warn=True)
C:\Users\Админ\AppData\Local\Programs\Python\Python39\lib\site-packages\sklearn\linear_model\_logistic.py:814: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:

https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
```

```
LogisticRegression()
```

```python
pred_test = cl1.predict(X_test)
pred_test
```

```
array([2, 2, 2, ..., 2, 2, 2])
```

```python
pred_test_proba = cl1.predict_proba(X_test)
pred_test_proba[:10]
```

```
array([[1.32013711e-02, 2.96290842e-01, 6.03483202e-01, 3.96693291e-
02,
        3.39316368e-02, 4.11248106e-03, 1.96059893e-03, 6.99851374e-
03,
        3.52025237e-04],
       [2.57712450e-02, 1.55746500e-01, 6.44845065e-01, 8.68156869e-
02,
        7.01437630e-02, 8.18680938e-03, 6.15007736e-03, 1.92599816e-
03,
        4.14855267e-04],
       [4.10886501e-02, 3.84717424e-01, 4.91431234e-01, 4.50435637e-
02,
        2.90271381e-02, 3.32958632e-03, 2.84935269e-03, 1.99862602e-
03,
        5.14425780e-04],
       [4.10886501e-02, 3.84717424e-01, 4.91431234e-01, 4.50435637e-
02,
        2.90271381e-02, 3.32958632e-03, 2.84935269e-03, 1.99862602e-
03,
        5.14425780e-04],
       [2.78185967e-05, 2.31238831e-03, 6.50181267e-01, 4.99576129e-
02,
        1.96945112e-01, 2.96621145e-02, 1.65387858e-03, 6.92445740e-
02,
        1.52346602e-05],
       [1.14282381e-01, 6.91603435e-01, 1.70936890e-01, 1.48735030e-
02,
        5.75952787e-03, 6.14497816e-04, 1.07531917e-03, 3.31971672e-
04,
        5.22475421e-04],
       [2.57712450e-02, 1.55746500e-01, 6.44845065e-01, 8.68156869e-
02,
        7.01437630e-02, 8.18680938e-03, 6.15007736e-03, 1.92599816e-
03,
        4.14855267e-04],
       [2.57712450e-02, 1.55746500e-01, 6.44845065e-01, 8.68156869e-
02,
        7.01437630e-02, 8.18680938e-03, 6.15007736e-03, 1.92599816e-
03,
        4.14855267e-04],
       [1.32013711e-02, 2.96290842e-01, 6.03483202e-01, 3.96693291e-
02,
        3.39316368e-02, 4.11248106e-03, 1.96059893e-03, 6.99851374e-
03,
        3.52025237e-04],
       [2.57712450e-02, 1.55746500e-01, 6.44845065e-01, 8.68156869e-
02,
```

```
        7.01437630e-02, 8.18680938e-03, 6.15007736e-03, 1.92599816e-
03,
        4.14855267e-04]])
```

```
# Вероятность принадлежности к 0 классу
[round(x, 4) for x in pred_test_proba[:10,0]]
```

```
[0.0132, 0.0258, 0.0411, 0.0411, 0.0, 0.1143, 0.0258, 0.0258, 0.0132,
0.0258]
```

```
# Вероятность принадлежности к 1 классу
[round(x, 4) for x in pred_test_proba[:10,1]]
```

```
[0.2963,
 0.1557,
 0.3847,
 0.3847,
 0.0023,
 0.6916,
 0.1557,
 0.1557,
 0.2963,
 0.1557]
```

```
# Сумма вероятностей равна 1
pred_test_proba[:10,0] + pred_test_proba[:10,1]
```

```
array([0.30949221, 0.18151775, 0.42580607, 0.42580607, 0.00234021,
       0.80588582, 0.18151775, 0.18151775, 0.30949221, 0.18151775])
```

```
accuracy_score(y_test, pred_test)
```

```
0.6007101355713363
```

```
def accuracy_score_for_classes(
    y_true: np.ndarray,
    y_pred: np.ndarray) -> Dict[int, float]:
    """
    Вычисление метрики accuracy для каждого класса
    y_true - истинные значения классов
    y_pred - предсказанные значения классов
    Возвращает словарь: ключ - метка класса,
    значение - Accuracy для данного класса
    """
    # Для удобства фильтрации сформируем Pandas DataFrame
    d = {'t': y_true, 'p': y_pred}
    df = pd.DataFrame(data=d)
    # Метки классов
    classes = np.unique(y_true)
    # Результирующий словарь
    res = dict()
    # Перебор меток классов
```

```
    for c in classes:
        # отфильтруем данные, которые соответствуют
        # текущей метке класса в истинных значениях
        temp_data_flt = df[df['t']==c]
        # расчет accuracy для заданной метки класса
        temp_acc = accuracy_score(
            temp_data_flt['t'].values,
            temp_data_flt['p'].values)
        # сохранение результата в словарь
        res[c] = temp_acc
    return res

def print_accuracy_score_for_classes(
    y_true: np.ndarray,
    y_pred: np.ndarray):
    """
    Вывод метрики accuracy для каждого класса
    """
    accs = accuracy_score_for_classes(y_true, y_pred)
    if len(accs)>0:
        print('Метка \t Accuracy')
    for i in accs:
        print('{} \t {}'.format(i, accs[i]))
```