Text classification on real data.

This notebook based on my laboratory work. Only minor adjustments have been made.

Getting data

The reviews were taken from the marketplace https://www.wildberries.ru. A parser was developed that uses the `requests` and `pydantic` libraries. The data on the site page is loaded dynamically using requests to the API (for example, to server with reviews, to server with product catalogs, etc.). Using the `requests` library functions, requests are made to wildberries, then the response is parsed according to the specified data models and their attributes based on the `pydantic` class.

- `models.py` stores data models;
- `parser.py` implements the parser class;

The algorithm of the parser:

- Initializes the parser class with links to different product from the marketplace
- The product ID is parsed from the link using the `re` regular expression library
- A request is made to wildberries, with the parameter obtained in the previous step, and the ID of the seller is extracted from the request, whose goods will then be parsed in the cycle
- A csv file is created with the columns `name`, `brand`, `price`, `sale`, `price_with_sale`, `number of photos in the card - pics`, `pros`, `cons`, `availability of photos in the review - hasPhoto`, `useful`, `useless`, `text`, `rating - target`
- As long as the server returns a non-empty json response, we make a request to it, receiving a list of the seller's products page by page, with the fields above
- Receiving a list of products, we make a request to the server with feedback - reviews for one product from the list, process the received data and put them in a csv file

As links to products, I randomly selected products from the site from different categories of different sellers to make the sample representative.

Import necessary libraries

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

import nltk
nltk.download("stopwords")
from nltk.corpus import stopwords
from wordcloud import WordCloud, STOPWORDS
from pymorphy3 import MorphAnalyzer

from sklearn.preprocessing import StandardScaler
from sklearn.feature_extraction.text import TfidfVectorizer

from sklearn.neural_network import MLPClassifier
from sklearn.ensemble import AdaBoostClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier

from sklearn.model_selection import train_test_split
from imblearn.under_sampling import RandomUnderSampler
from sklearn.metrics import classification_report, accuracy_score


%matplotlib inline
```

```
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\ibasl\AppData\Roaming\nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
```

Cleaning data and descriptive statistics

Read data, rename columns from Russian to English

In [2]:
```
df = pd.read_csv("../../data/dataset.csv")
df.rename(columns={
    "название": "name",
    "бренд": "brand",
    "цена": "price",
    "скидка в %": "sale",
    "цена со скидкой": "price_with_sale",
    "кол-во фото в карточке": "pics",
    "плюсы": "pros",
    "минусы": "cons",
    "наличие фото в отзыве": "hasPhoto",
    "полезно": "useful",
    "неполезно": "useless",
    "текст отзыва": "text",
    'рейтинг': 'target',},
    inplace=True)
df.head()
```

```
C:\Users\ibasl\AppData\Local\Temp\ipykernel_17344\2546511965.py:1: DtypeWarning: Co
lumns (8) have mixed types. Specify dtype option on import or set low_memory=False.
  df = pd.read_csv("../../data/dataset.csv")
```

Out[2]:

	name	brand	price	sale	price_with_sale	pics	pros	cons	hasPhoto	useful	use
0	Клиппер маникюрный, кусачки для ногтей	Zebo Professional	499.0	59	204.0	5	NaN	NaN	False	0	
1	Клиппер маникюрный, кусачки для ногтей	Zebo Professional	499.0	59	204.0	5	NaN	NaN	False	0	
2	Клиппер маникюрный, кусачки для ногтей	Zebo Professional	499.0	59	204.0	5	NaN	NaN	False	0	
3	Клиппер маникюрный, кусачки для ногтей	Zebo Professional	499.0	59	204.0	5	NaN	NaN	False	0	
4	Клиппер маникюрный, кусачки для ногтей	Zebo Professional	499.0	59	204.0	5	NaN	NaN	False	0	

Drop duplicates and view shape

In [3]:
```
df.drop_duplicates(inplace=True)
df.shape
```

Out[3]:
```
(381859, 13)
```

Main information about dataset

In [4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 381859 entries, 0 to 461663
Data columns (total 13 columns):
 #   Column          Non-Null Count   Dtype  
---  ------          --------------   -----  
 0   name            381859 non-null  object 
 1   brand           381857 non-null  object 
 2   price           381859 non-null  float64
 3   sale            381859 non-null  int64  
 4   price_with_sale 381859 non-null  float64
 5   pics            381859 non-null  int64  
 6   pros            0 non-null       float64
 7   cons            0 non-null       float64
 8   hasPhoto        381033 non-null  object 
 9   useful          381859 non-null  int64  
 10  useless         381859 non-null  int64  
 11  text            380199 non-null  object 
 12  target          381859 non-null  int64  
dtypes: float64(4), int64(5), object(4)
memory usage: 40.8+ MB
```

Change type of `hasPhoto` column

In [5]:
```
df['hasPhoto'] = df['hasPhoto'].astype(bool)
```

Descriptive statistics

In [6]:
```
df.describe()
```

Out[6]:

	price	sale	price_with_sale	pics	pros	cons	useful	
count	381859.000000	381859.000000	381859.000000	381859.000000	0.0	0.0	381859.000000	3ٳ
mean	8620.201093	58.793353	3335.807565	6.952530	NaN	NaN	1.337533	
std	17832.819749	20.181132	6753.828420	4.154662	NaN	NaN	4.079684	
min	99.000000	0.000000	85.000000	1.000000	NaN	NaN	0.000000	
25%	1500.000000	59.000000	465.000000	4.000000	NaN	NaN	0.000000	
50%	3200.000000	66.000000	1288.000000	6.000000	NaN	NaN	0.000000	
75%	7030.000000	70.000000	3146.000000	9.000000	NaN	NaN	1.000000	
max	629990.000000	93.000000	239396.000000	26.000000	NaN	NaN	332.000000	

Descriptive statistics of object columns

In [7]:
```
df.describe(include=['O'])
```

Out[7]:

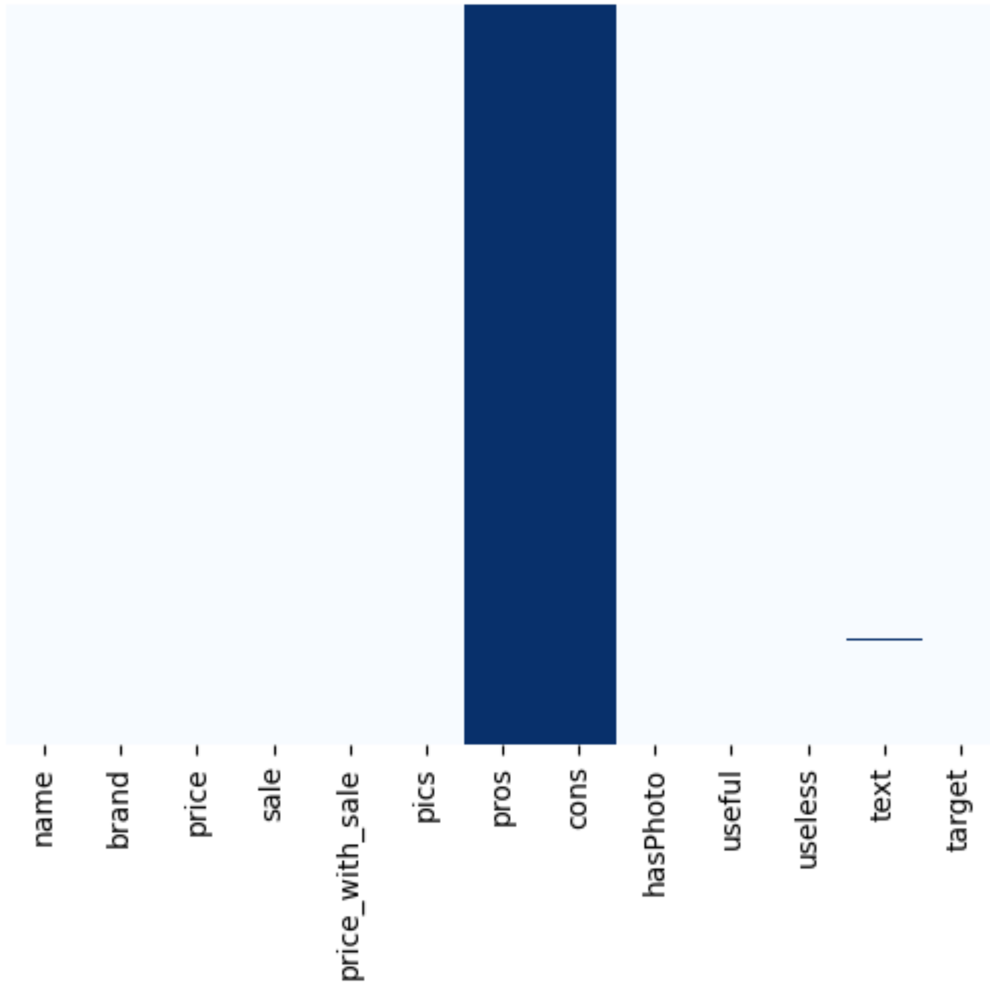
	name	brand	text
count	381859	381857	380199
unique	2012	102	201389
top	Ювелирные серьги женские из серебра 925	SOKOLOV	все отлично
freq	9322	178255	716

Amount of missed values

In [8]:
```
df.isna().sum()
```

Out[8]:
```
name                   0
brand                  2
price                  0
sale                   0
price_with_sale        0
pics                   0
pros              381859
cons              381859
hasPhoto               0
useful                 0
useless                0
text                1660
target                 0
dtype: int64
```

In [9]:
```
sns.heatmap(df.isna(), yticklabels=False, cbar=False, cmap='Blues');
```



`pros` and `cons` columns contain only empty values, remove them. Also we delete all the remaining missed values because we have a lot of data

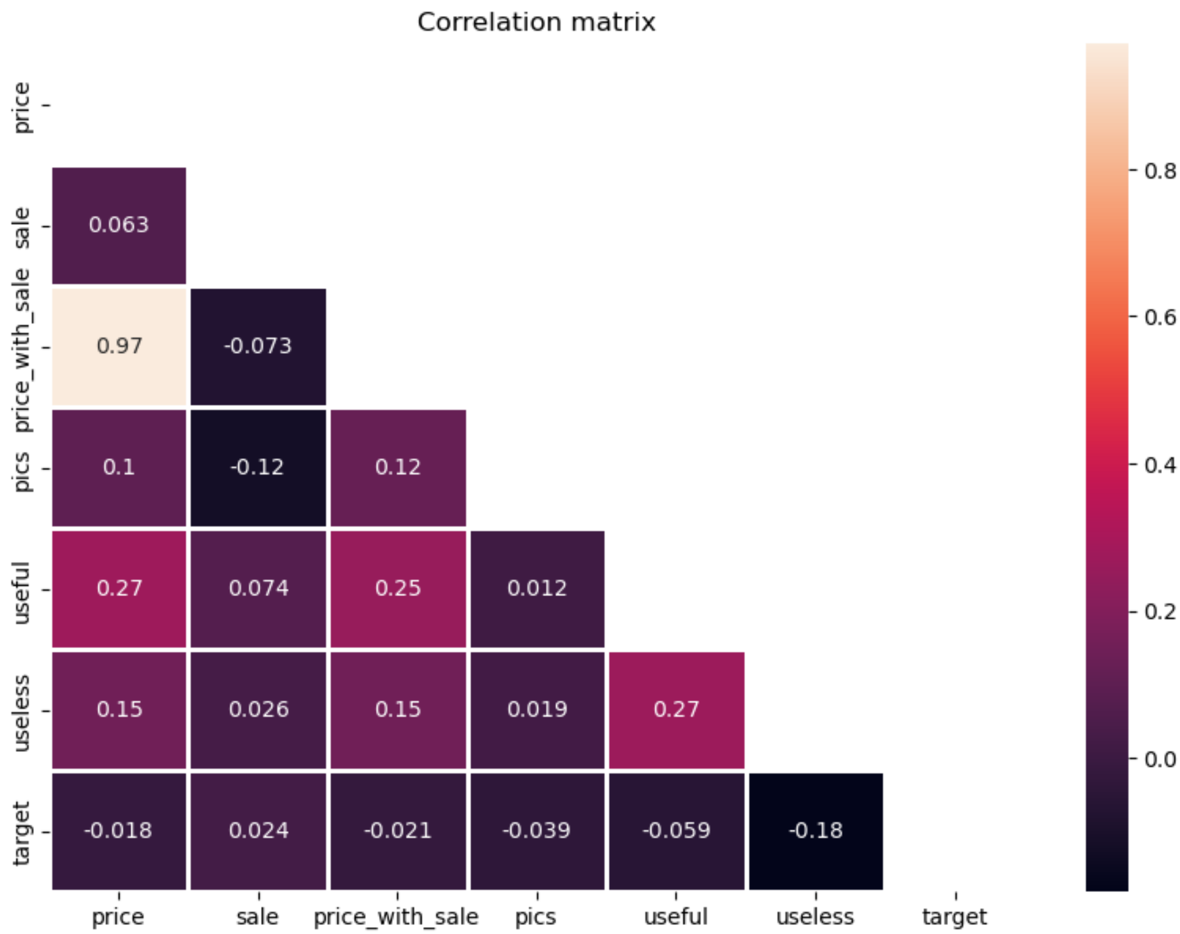
In [10]:
```
df.drop(columns=['pros', 'cons'], inplace=True)
df.dropna(inplace=True)
df.drop_duplicates(subset=['text'], inplace=True)
df.shape
```

Out[10]:
```
(201388, 11)
```

Correlation matrix

In [11]:
```
numeric_cols = df.select_dtypes(include=[np.number]).columns
df_ = df[numeric_cols]
corr = df_.corr()
mask = np.zeros_like(corr, dtype=np.bool_)
mask[np.triu_indices_from(mask)] = True

plt.figure(figsize = (10,7))
plt.title('Correlation matrix')
sns.heatmap(corr,
            mask=mask,
            annot=True,
            fmt='.2g',
            linewidths=2);
```

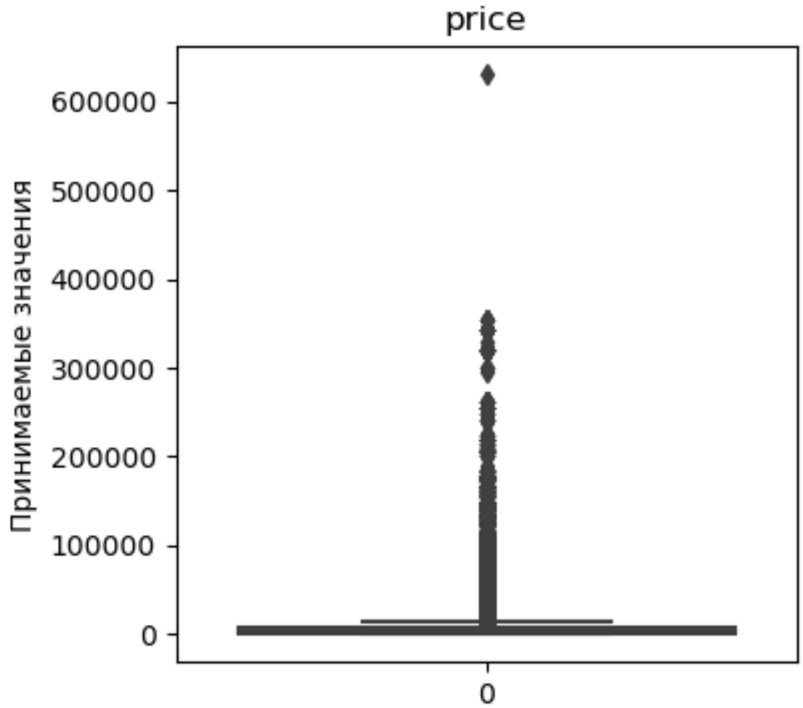


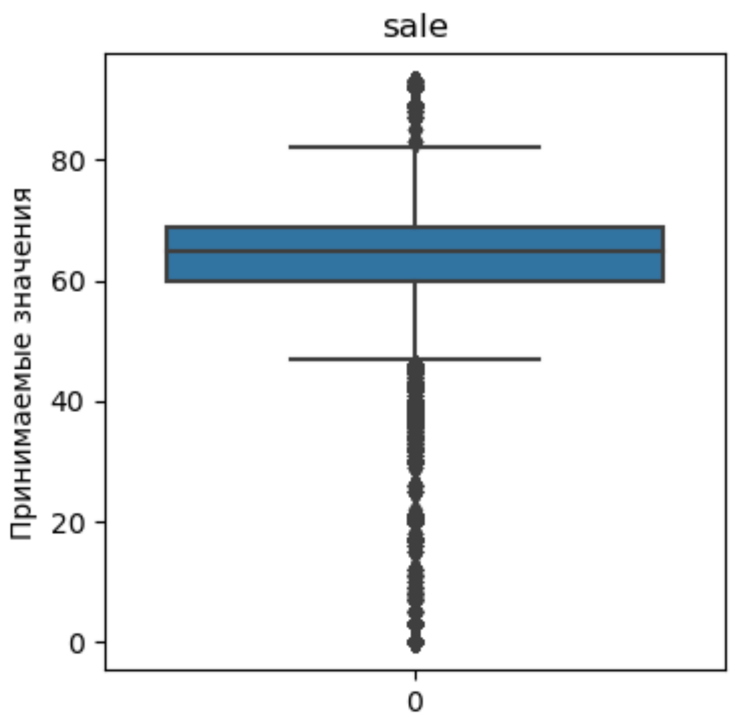
`price_with_sale` and `price` correlate with the value 0.97. Delete `price_with_sale`

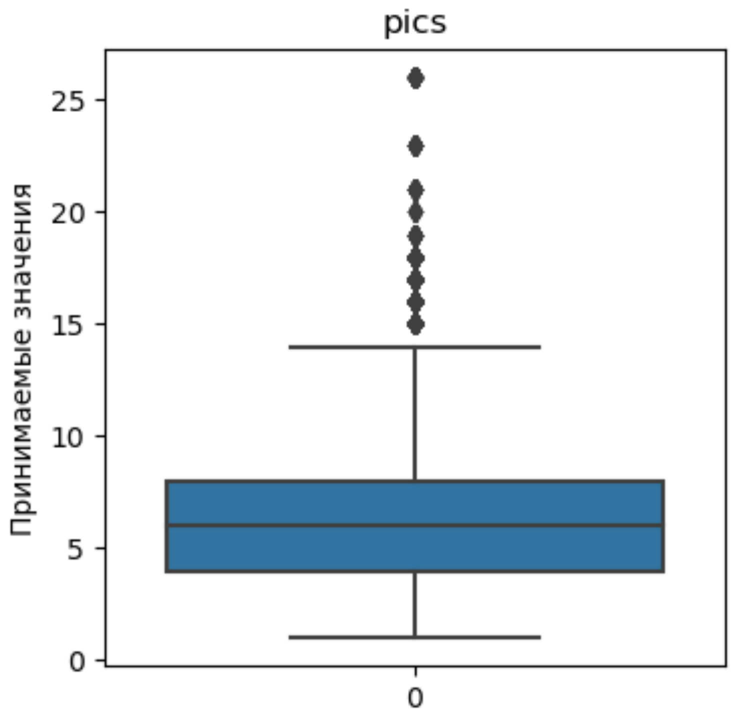
In [12]:
```
df.drop(columns=['price_with_sale'], inplace=True)
```

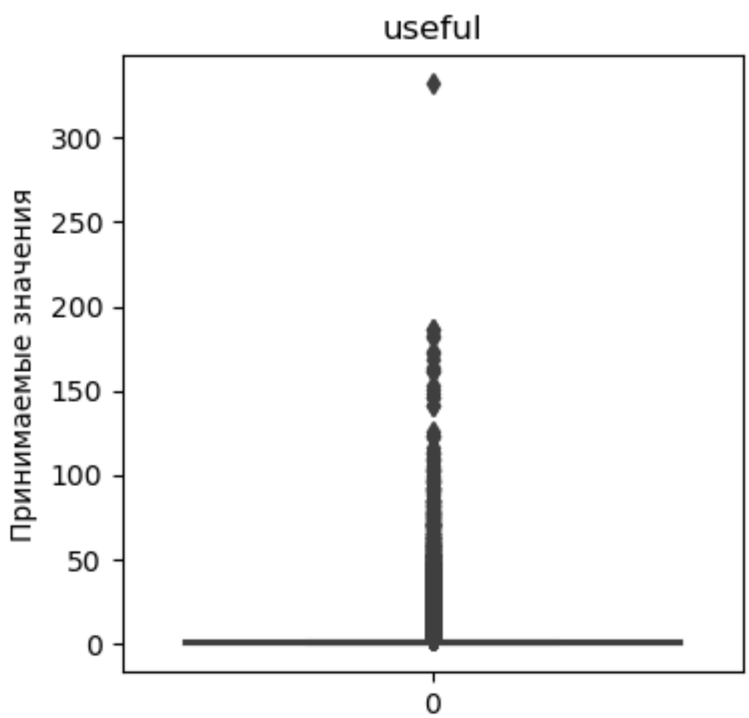
Look at the outliers in numerical data using the boxplot

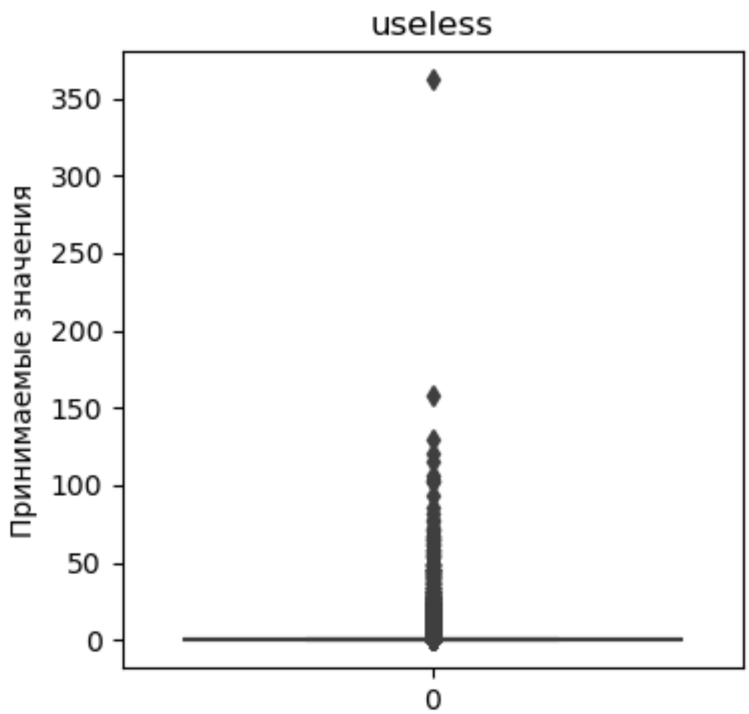
In [13]:
```
numeric_columns = df.select_dtypes(include=np.number).columns.tolist()
for col in numeric_columns:
    plt.figure(figsize=(4,4))
    sns.boxplot(data=df[col])
    plt.title(f'{col}')
    plt.ylabel('Принимаемые значения');
```

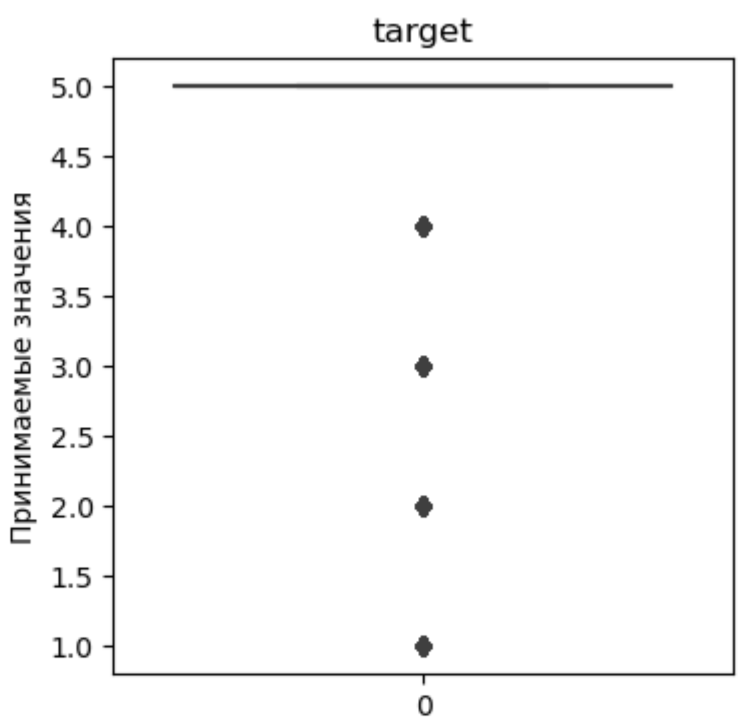

price
Принимаемые значения
600000
500000
400000
300000
200000
100000
0
0


sale
Принимаемые значения
80
60
40
20
0
0


pics
Принимаемые значения
25
20
15
10
5
0
0


useful
Принимаемые значения
300
250
200
150
100
50
0
0





In my opinion, we can remove a little bit of outliers in the `useful` and `useless` columns,

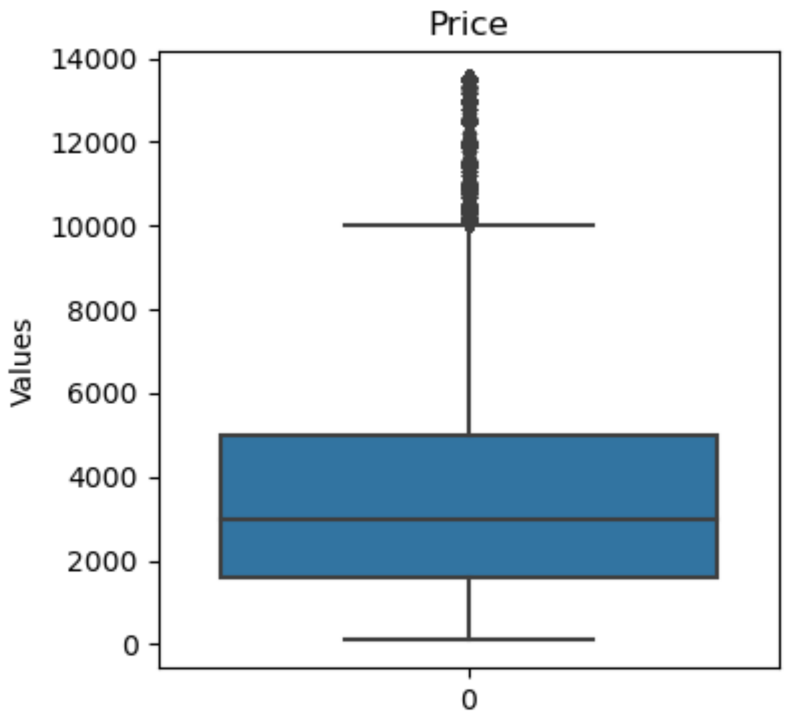
In [14]:
```
Q1 = df['price'].quantile(0.25)
Q3 = df['price'].quantile(0.75)
IQR = Q3 - Q1

lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR

df[(df['price'] >= lower_bound) & (df['price'] <= upper_bound)].shape
```

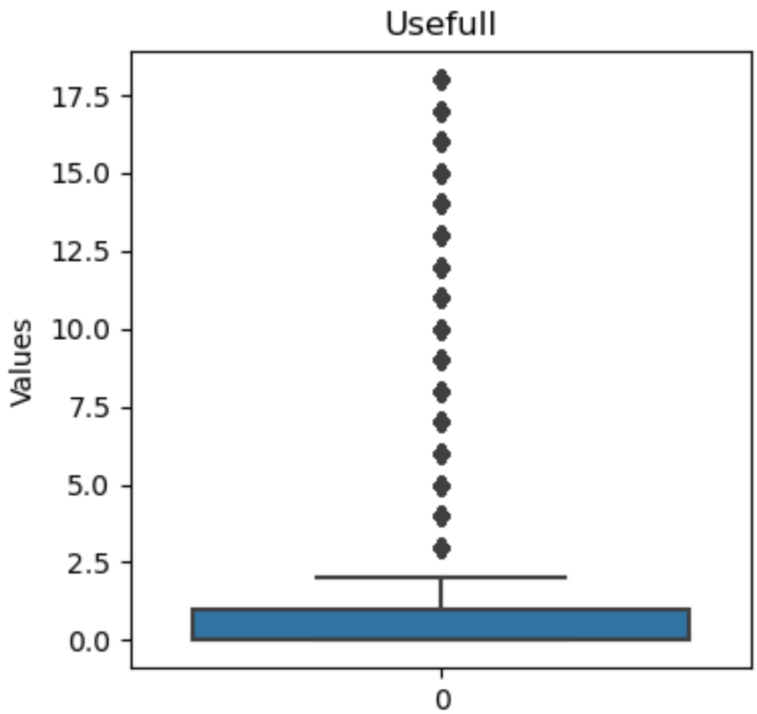
Out[14]: (174487, 10)

In [15]:
```
plt.figure(figsize=(4,4))
sns.boxplot(data=df[(df['price'] >= lower_bound) & (df['price'] <= upper_bound)]['p
plt.title(f'Price')
plt.ylabel('Values');
```



We will remove ~15% of the emissions from the `price` column. There is a lot of data, it is not critical.

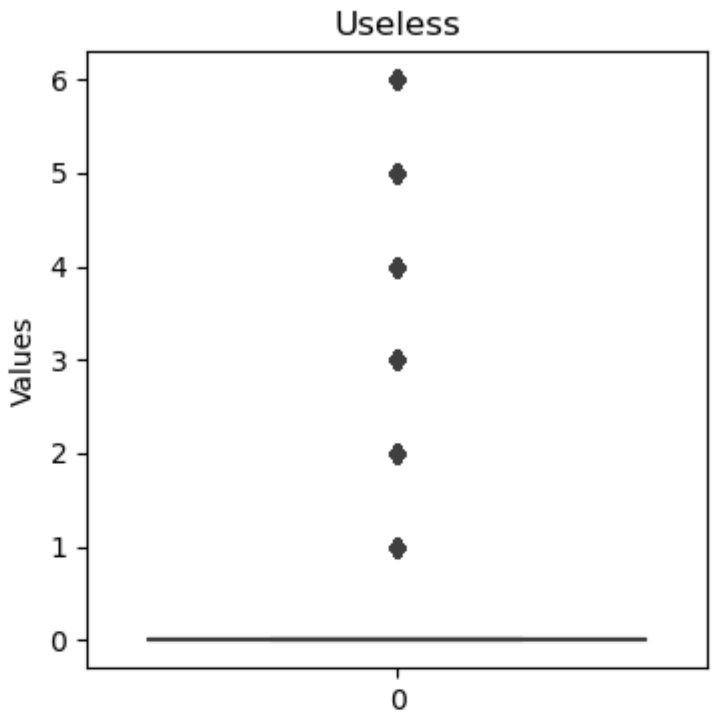
In [16]:
```
plt.figure(figsize=(4,4))
sns.boxplot(data=df['useful'][df['useful'] < df['useful'].quantile(0.99)])
plt.title(f'Usefull')
plt.ylabel('Values');
```



In [17]:
```
df['useful'].value_counts()
```

Out[17]:
```
useful
0      112014
1       40038
2       17313
3        8874
4        5513
        ...
65          1
108         1
110         1
114         1
90          1
Name: count, Length: 127, dtype: int64
```

In [18]:
```
plt.figure(figsize=(4,4))
sns.boxplot(data=df['useless'][df['useless'] < df['useless'].quantile(0.99)])
plt.title(f'Useless')
plt.ylabel('Values');
```



In [19]:
```
df['useless'].value_counts()
```

Out[19]:
```
useless
0      160961
1       24610
2        7409
3        3169
4        1610
        ...  
103         1
63          1
82          1
47          1
72          1
Name: count, Length: 82, dtype: int64
```

Delete 1% of `useless` and `useful`.

In [20]:
```
df = df[df['price'] < df['price'].quantile(0.85)]
df = df[df['useless'] < df['useless'].quantile(0.99)]
df = df[df['useful'] < df['useful'].quantile(0.99)]
df.shape
```

Out[20]:
```
(166779, 10)
```

Look at the basic information of the cleaned dataset

In [21]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 166779 entries, 0 to 461608
Data columns (total 10 columns):
 #   Column    Non-Null Count   Dtype  
---  ------    --------------   -----  
 0   name      166779 non-null  object 
 1   brand     166779 non-null  object 
 2   price     166779 non-null  float64
 3   sale      166779 non-null  int64  
 4   pics      166779 non-null  int64  
 5   hasPhoto  166779 non-null  bool   
 6   useful    166779 non-null  int64  
 7   useless   166779 non-null  int64  
 8   text      166779 non-null  object 
 9   target    166779 non-null  int64  
dtypes: bool(1), float64(1), int64(5), object(3)
memory usage: 12.9+ MB
```

EDA

In [22]:
```
df.head()
```

Out[22]:

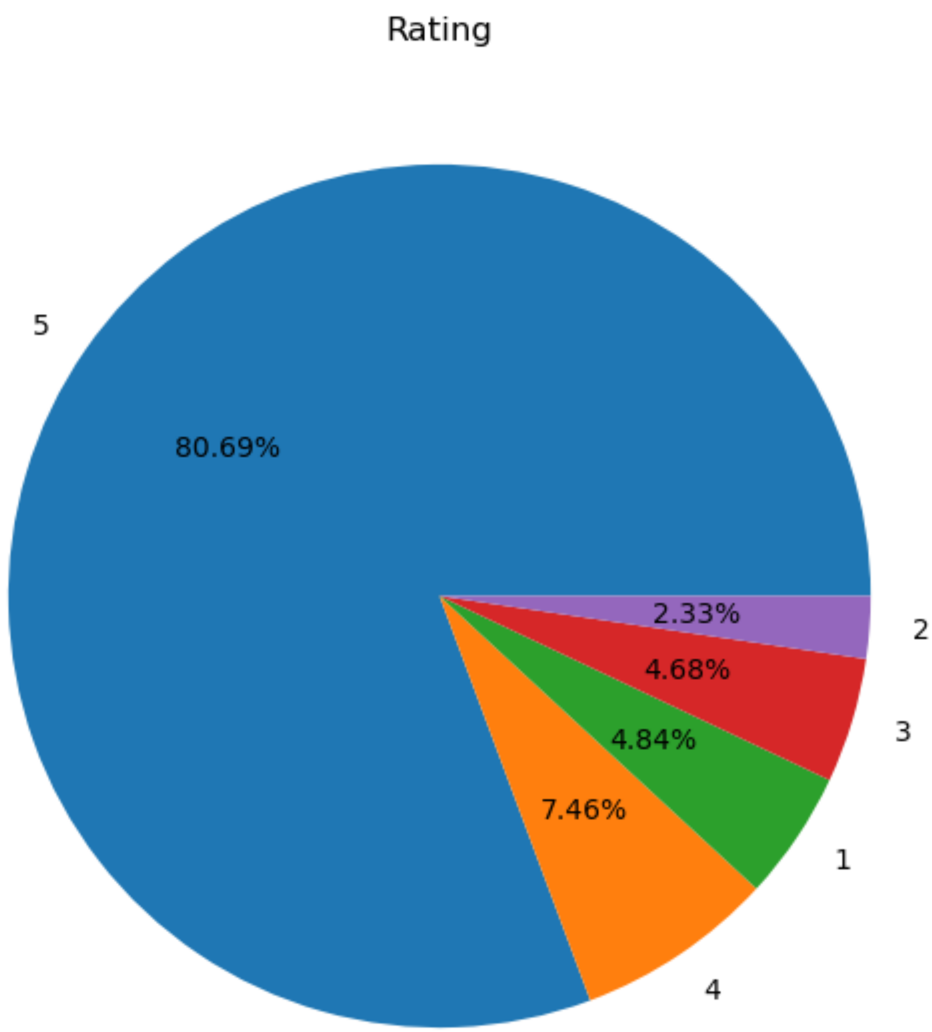
	name	brand	price	sale	pics	hasPhoto	useful	useless	text	target
0	Клиппер маникюрный, кусачки для ногтей	Zebo Professional	499.0	59	5	False	0	1	отличные кусачки заточены хорошо со своей зада...	5
1	Клиппер маникюрный, кусачки для ногтей	Zebo Professional	499.0	59	5	False	0	1	спасибо за качественный товар буду рекомендова...	5
2	Клиппер маникюрный, кусачки для ногтей	Zebo Professional	499.0	59	5	False	0	0	щипчики хорошо стригут ногти все отлично	5
3	Клиппер маникюрный, кусачки для ногтей	Zebo Professional	499.0	59	5	False	0	0	хороший набор пришло все целое	5
4	Клиппер маникюрный, кусачки для ногтей	Zebo Professional	499.0	59	5	False	0	0	получили кусочки пришли быстро и хорошо упаков...	5

Target rating

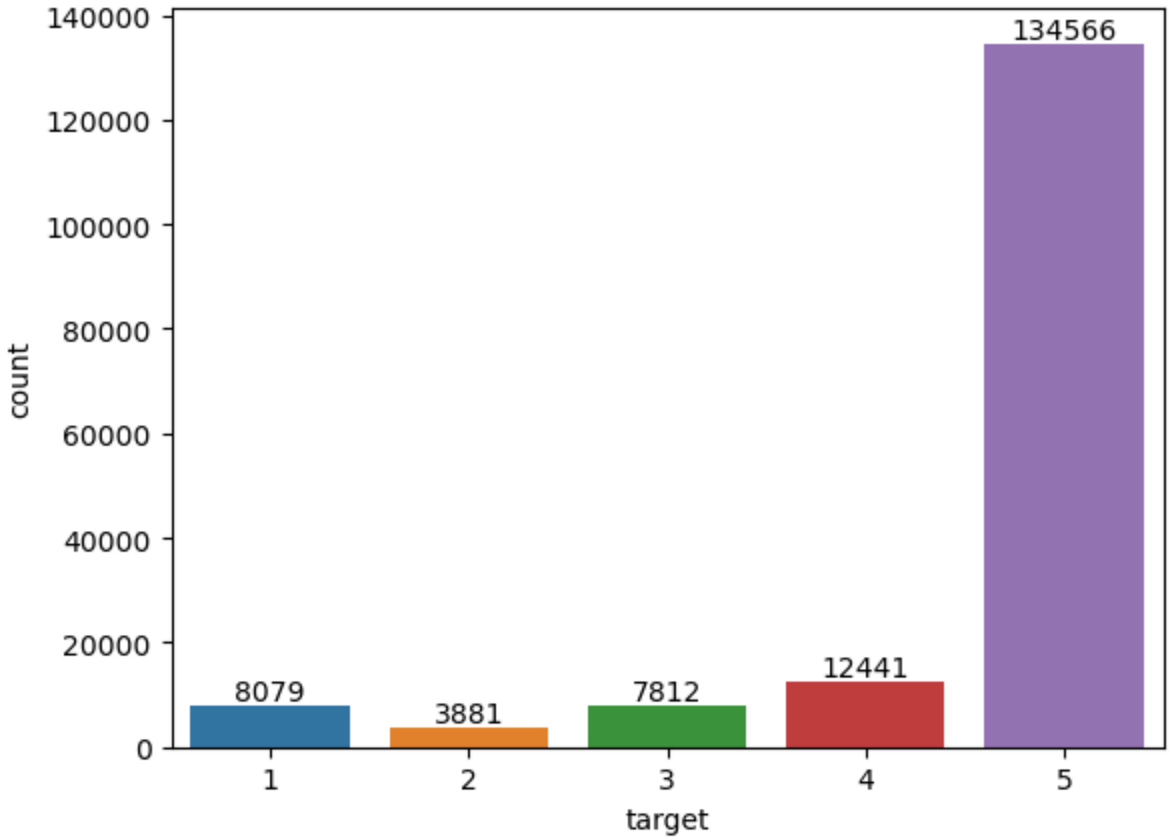
In [23]:
```
df['target'].value_counts()
```

Out[23]:
```
target
5    134566
4     12441
1      8079
3      7812
2      3881
Name: count, dtype: int64
```

In [24]:
```
df["target"].value_counts().plot(
                                kind='pie',
                                title='Rating',
                                figsize=(7, 7),
                                autopct='%.2f%%')
plt.ylabel('');
```



In [25]:
```
ax = sns.countplot(x='target', data=df)
ax.bar_label(ax.containers[0]);
```

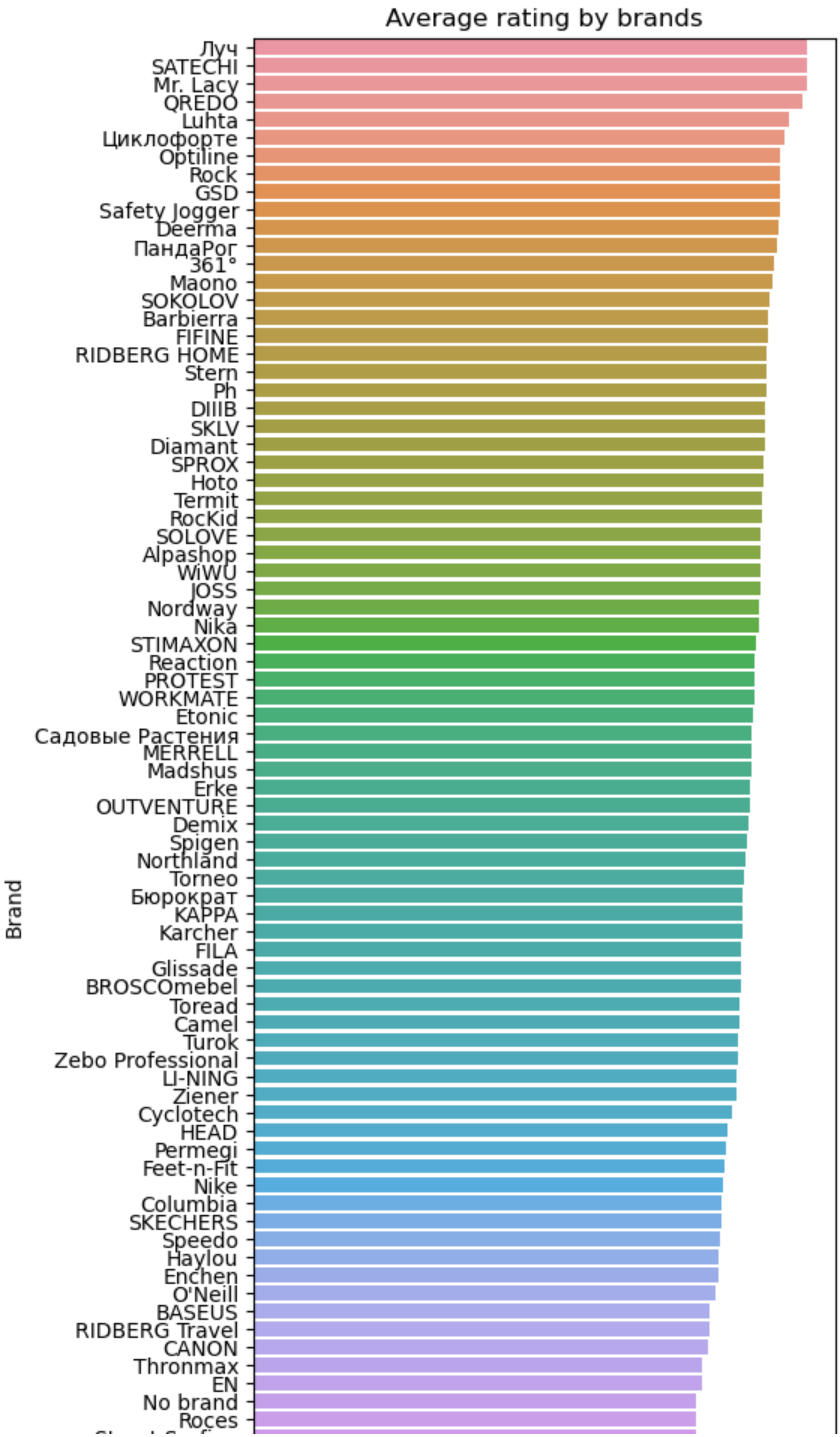


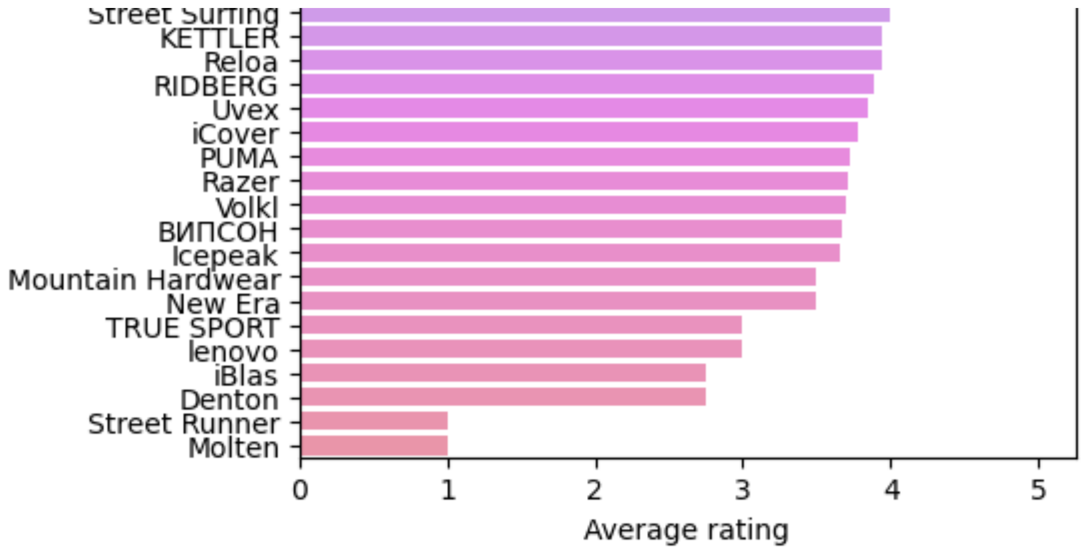
Classes are not balanced - there are too many "5" and too few other grades, they are 4 times less. Since there is a lot of data, we will do undersampling. Each class will have 3800 - this is enough for our model to have good generalization capability.

In addition, it can be concluded that in 4 out of 5 cases, the buyer is satisfied with the purchased product, which is a good indicator.

In [26]:
```
avg_rate_by_brand = pd.DataFrame(df.groupby('brand')['target'].mean())\
                                    .reset_index()\
                                    .sort_values(by='target', ascending=False)

plt.figure(figsize=(5, 15))
sns.barplot(x='target', y='brand', data=avg_rate_by_brand, orient='h')
plt.xlabel('Average rating')
plt.ylabel('Brand')
plt.title('Average rating by brands')
plt.show()
```

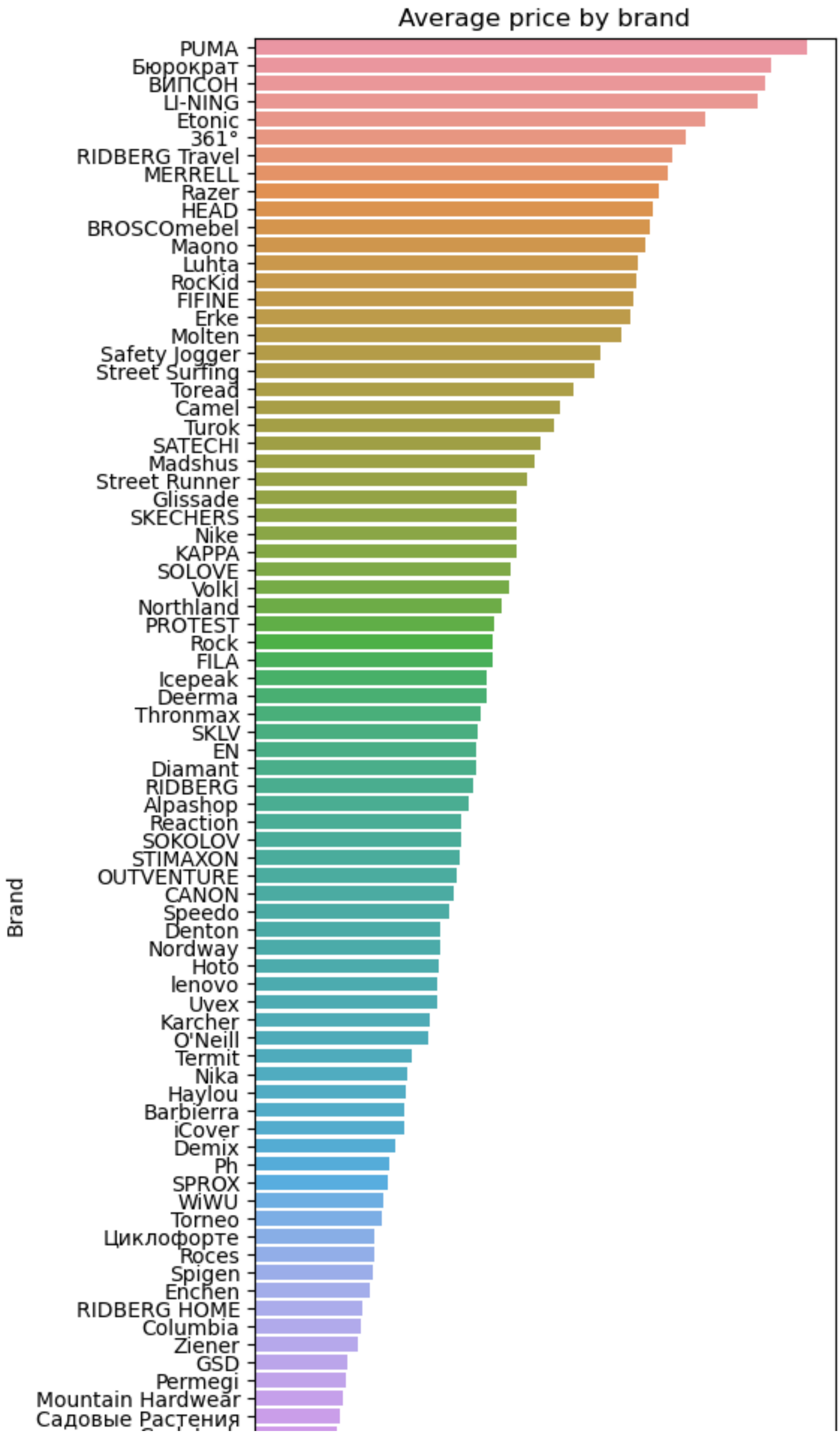

Average rating by brands
Brand
Луч
SATECHI
Mr. Lacy
QREDO
Luhta
Циклофорте
Optiline
Rock
GSD
Safety Jogger
Deerma
ПандаРог
361°
Maono
SOKOLOV
Barbierra
FIFINE
RIDBERG HOME
Stern
Ph
DIIIB
SKLV
Diamant
SPROX
Hoto
Termit
RocKid
SOLOVE
Alpashop
WiWU
JOSS
Nordway
Nika
STIMAXON
Reaction
PROTEST
WORKMATE
Etonic
Садовые Растения
MERRELL
Madshus
Erke
OUTVENTURE
Demix
Spigen
Northland
Torneo
Бюрократ
KAPPA
Karcher
FILA
Glissade
BROSCOmebel
Toread
Camel
Turok
Zebo Professional
LI-NING
Ziener
Cyclotech
HEAD
Permegi
Feet-n-Fit
Nike
Columbia
SKECHERS
Speedo
Haylou
Enchen
O'Neill
BASEUS
RIDBERG Travel
CANON
Thronmax
EN
No brand
Roces

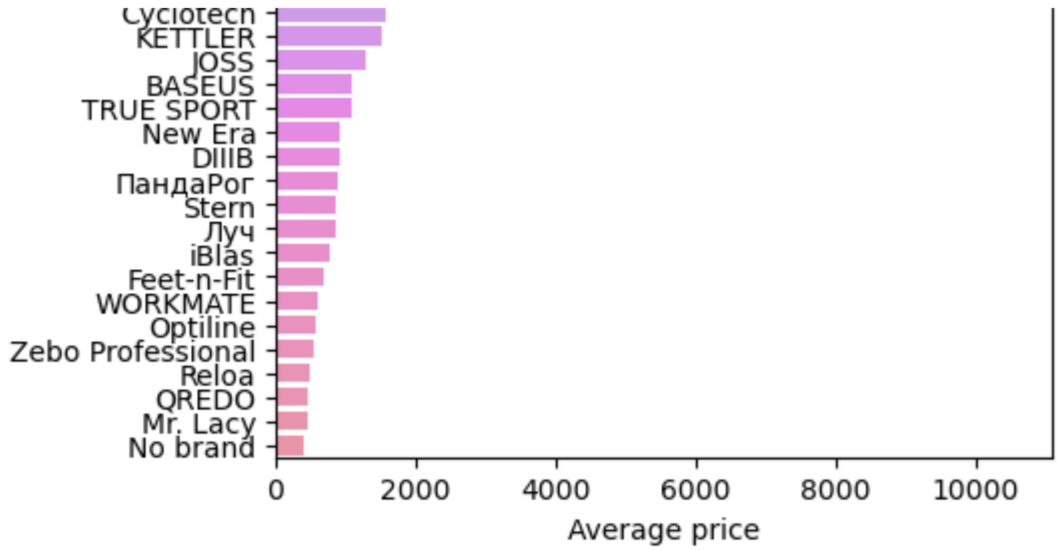


Most brands keep the quality - the average rating is 4 or higher, but there are also unscrupulous ones who sell goods of poor quality, which have a rating of 3 or lower, but there are only 6 such manufacturers.

In [27]:
```
avg_price_by_brand = pd.DataFrame(df.groupby('brand')['price'].mean())\
                                    .reset_index()\
                                    .sort_values(by='price', ascending=False)

plt.figure(figsize=(5, 15))
sns.barplot(x='price', y='brand', data=avg_price_by_brand, orient='h')
plt.xlabel('Average price')
plt.ylabel('Brand')
plt.title('Average price by brand')
plt.show()
```


Average price by brand
Brand
PUMA
Бюрократ
ВИПСОН
LI-NING
Etonic
361°
RIDBERG Travel
MERRELL
Razer
HEAD
BROSCOmebel
Maono
Luhta
RocKid
FIFINE
Erke
Molten
Safety Jogger
Street Surfing
Toread
Camel
Turok
SATECHI
Madshus
Street Runner
Glissade
SKECHERS
Nike
KAPPA
SOLOVE
Volkl
Northland
PROTEST
Rock
FILA
Icepeak
Deerma
Thronmax
SKLV
EN
Diamant
RIDBERG
Alpashop
Reaction
SOKOLOV
STIMAXON
OUTVENTURE
CANON
Speedo
Denton
Nordway
Hoto
lenovo
Uvex
Karcher
O'Neill
Termit
Nika
Haylou
Barbierra
iCover
Demix
Ph
SPROX
WiWU
Torneo
Циклофорте
Roces
Spigen
Enchen
RIDBERG HOME
Columbia
Ziener
GSD
Permegi
Mountain Hardwear
Садовые Растения

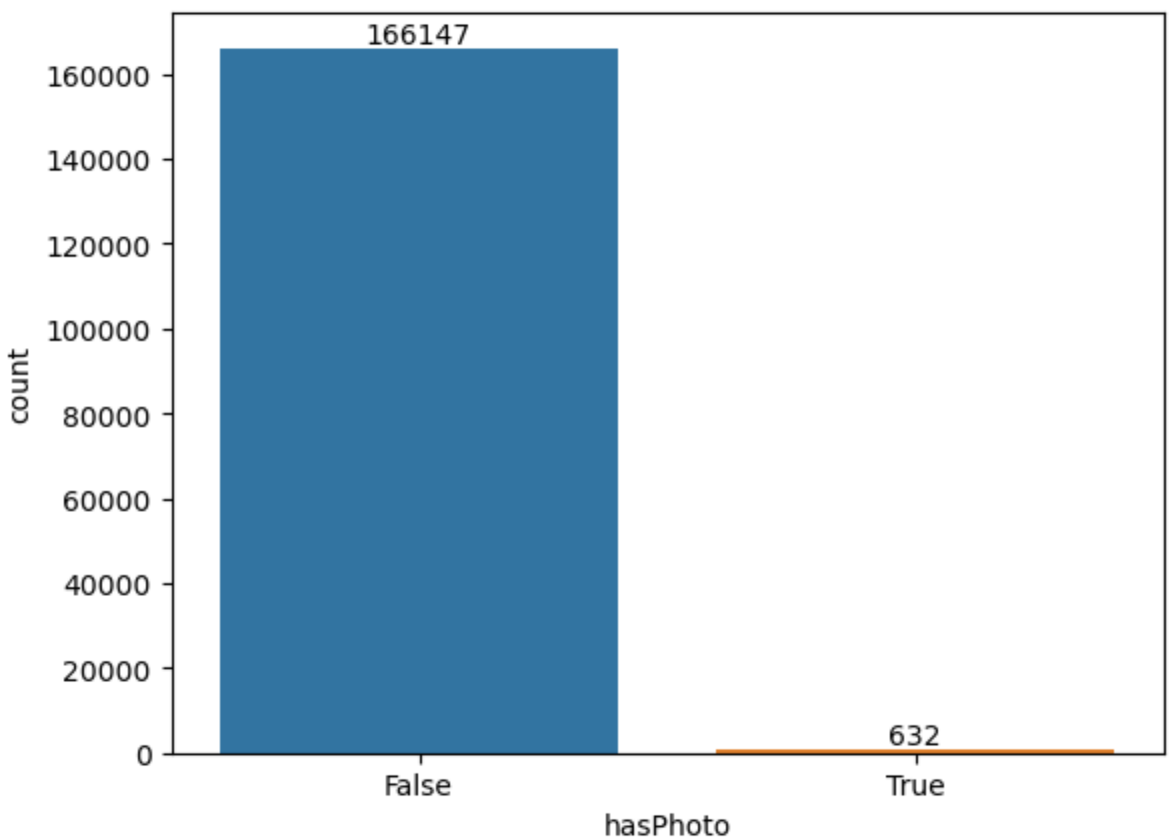


Most of the products of various brands are sold at an average price of up to ~5000 rubles.

It can also be noted that the closing three brands according to the average rating have a price for goods of 4-6 thousand rubles, i.e. for relatively big money, buyers receive a terrible product.

Column hasPhoto

In [28]:
```
ax = sns.countplot(x='hasPhoto', data=df)
ax.bar_label(ax.containers[0]);
```

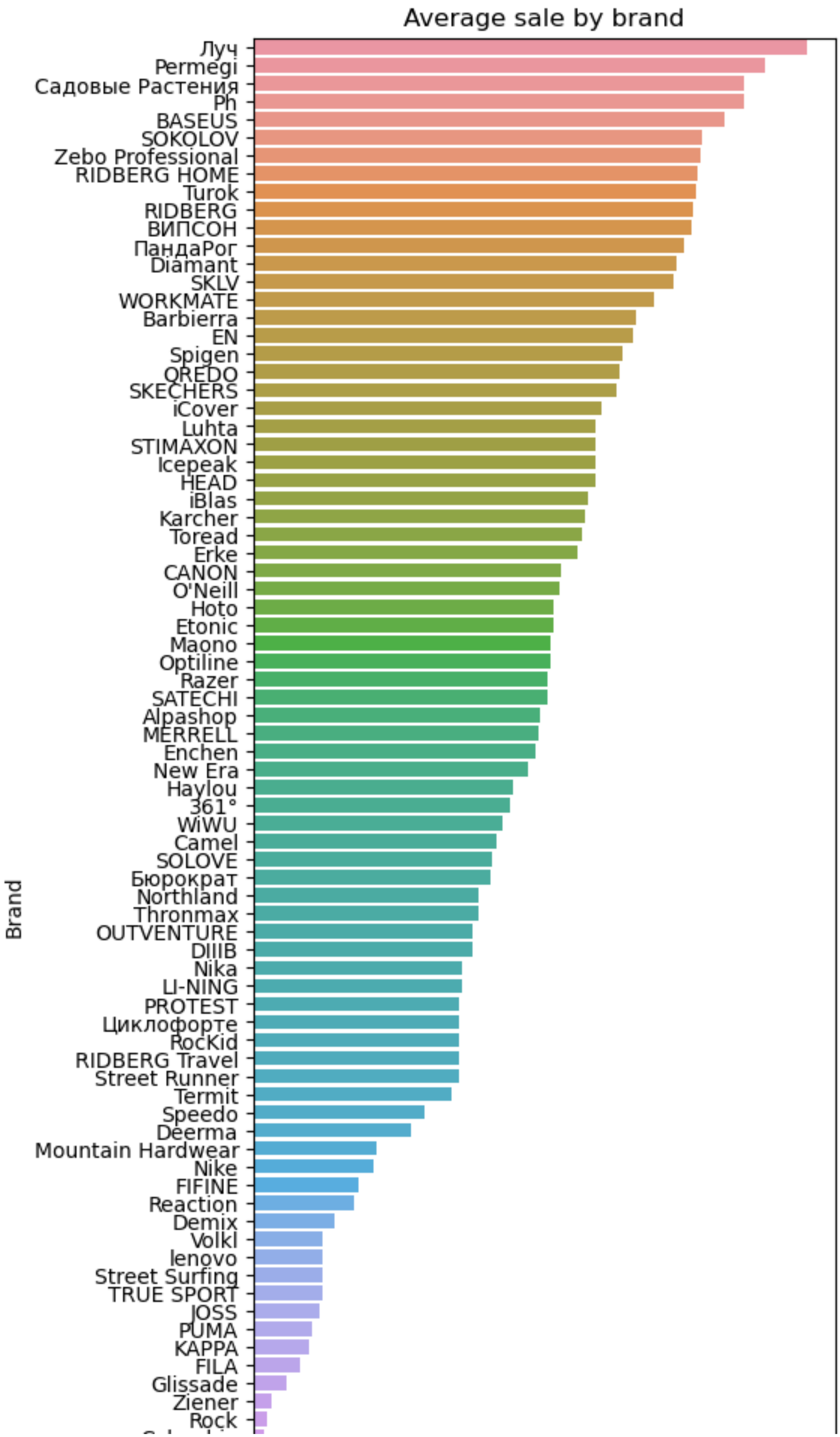


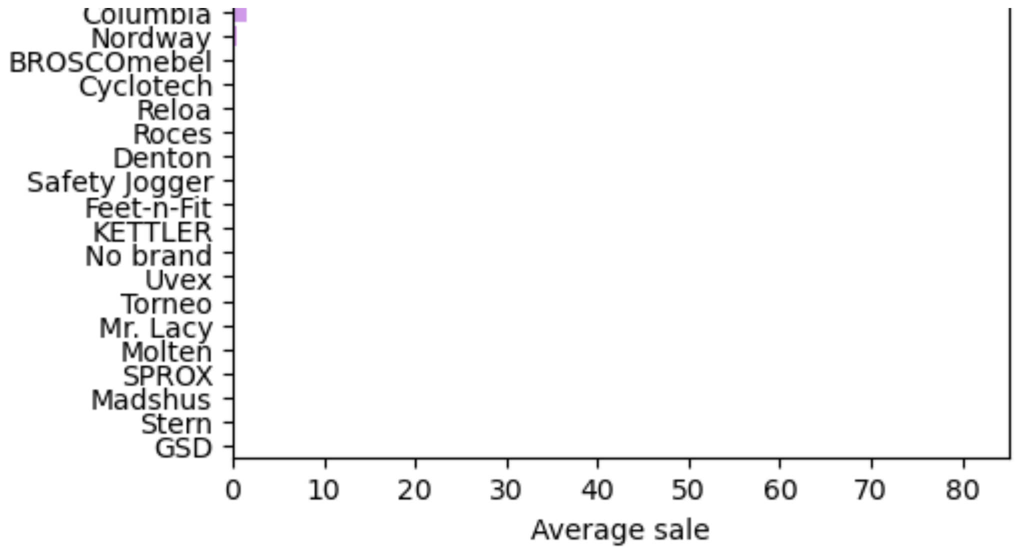
Conclusion: the vast majority of users prefer to leave reviews without photos.

Column `sale`

In [29]:
```
avg_sale_by_brand = pd.DataFrame(df.groupby('brand')['sale'].mean())\
                                    .reset_index()\
                                    .sort_values(by='sale', ascending=False)

plt.figure(figsize=(5, 15))
sns.barplot(x='sale', y='brand', data=avg_sale_by_brand, orient='h')
plt.xlabel('Average sale')
plt.ylabel('Brand')
plt.title('Average sale by brand')
plt.show()
```

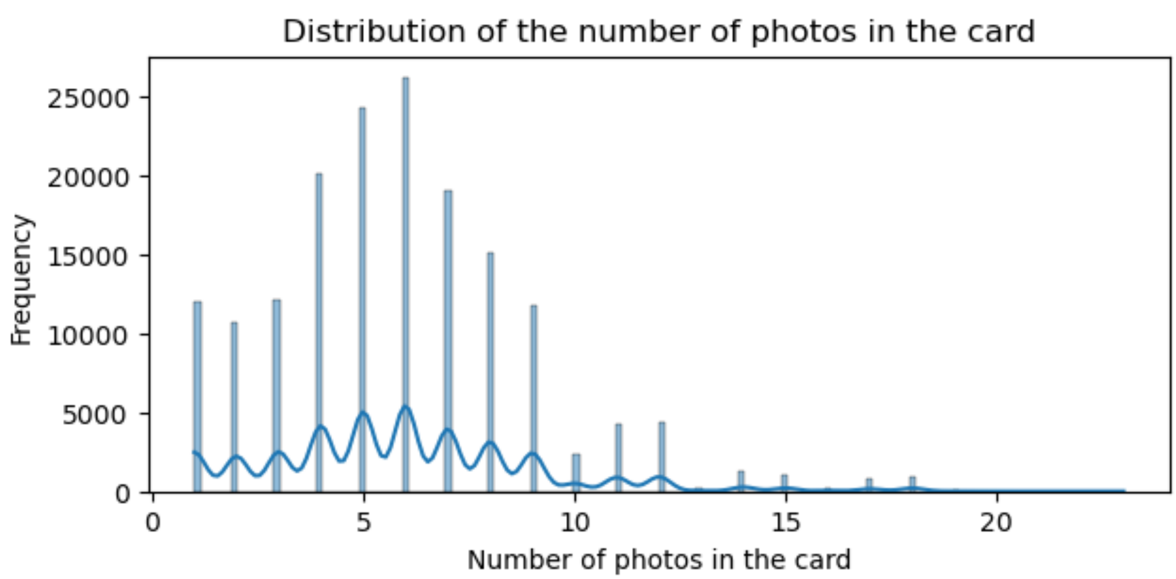

Average sale by brand
Brand
Луч
Permegi
Садовые Растения
Ph
BASEUS
SOKOLOV
Zebo Professional
RIDBERG HOME
Turok
RIDBERG
ВИПСОН
ПандаРог
Diamant
SKLV
WORKMATE
Barbierra
EN
Spigen
QREDO
SKECHERS
iCover
Luhta
STIMAXON
Icepeak
HEAD
iBlas
Karcher
Toread
Erke
CANON
O'Neill
Hoto
Etonic
Maono
Optiline
Razer
SATECHI
Alpashop
MERRELL
Enchen
New Era
Haylou
361°
WiWU
Camel
SOLOVE
Бюрократ
Northland
Thronmax
OUTVENTURE
DIIIB
Nika
LI-NING
PROTEST
Циклофорте
RocKid
RIDBERG Travel
Street Runner
Termit
Speedo
Deerma
Mountain Hardwear
Nike
FIFINE
Reaction
Demix
Volkl
lenovo
Street Surfing
TRUE SPORT
JOSS
PUMA
KAPPA
FILA
Glissade
Ziener
Rock



About half of the brands have a discount of more than 40%, which is undoubtedly a cheat, since this is done to promote product cards to the top of the list and create the effect of acquiring benefits for the buyer. About 20% of brands do not have a discount.

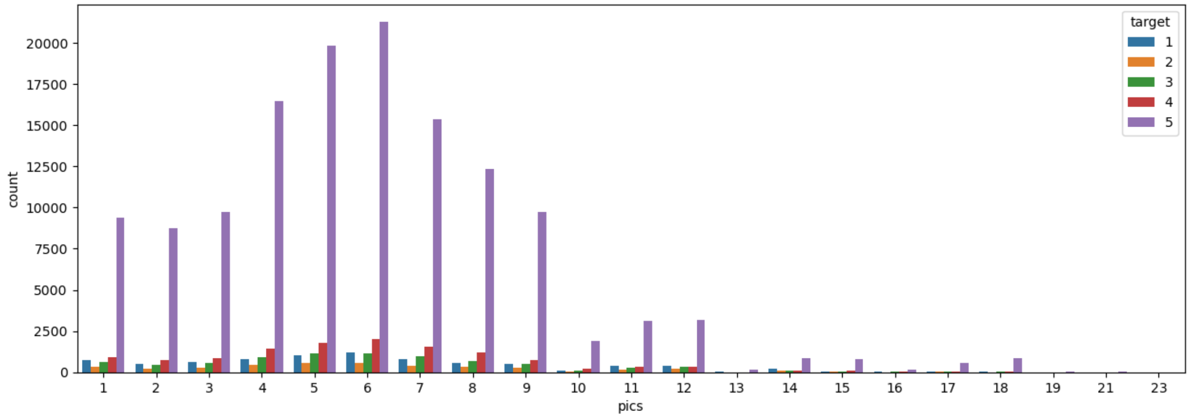
Column `pics` - number of images in product card

In [30]:
```
plt.figure(figsize=(7,3))
sns.histplot(x=df['pics'], kde=True)
plt.title('Distribution of the number of photos in the card')
plt.xlabel('Number of photos in the card')
plt.ylabel('Frequency');
```



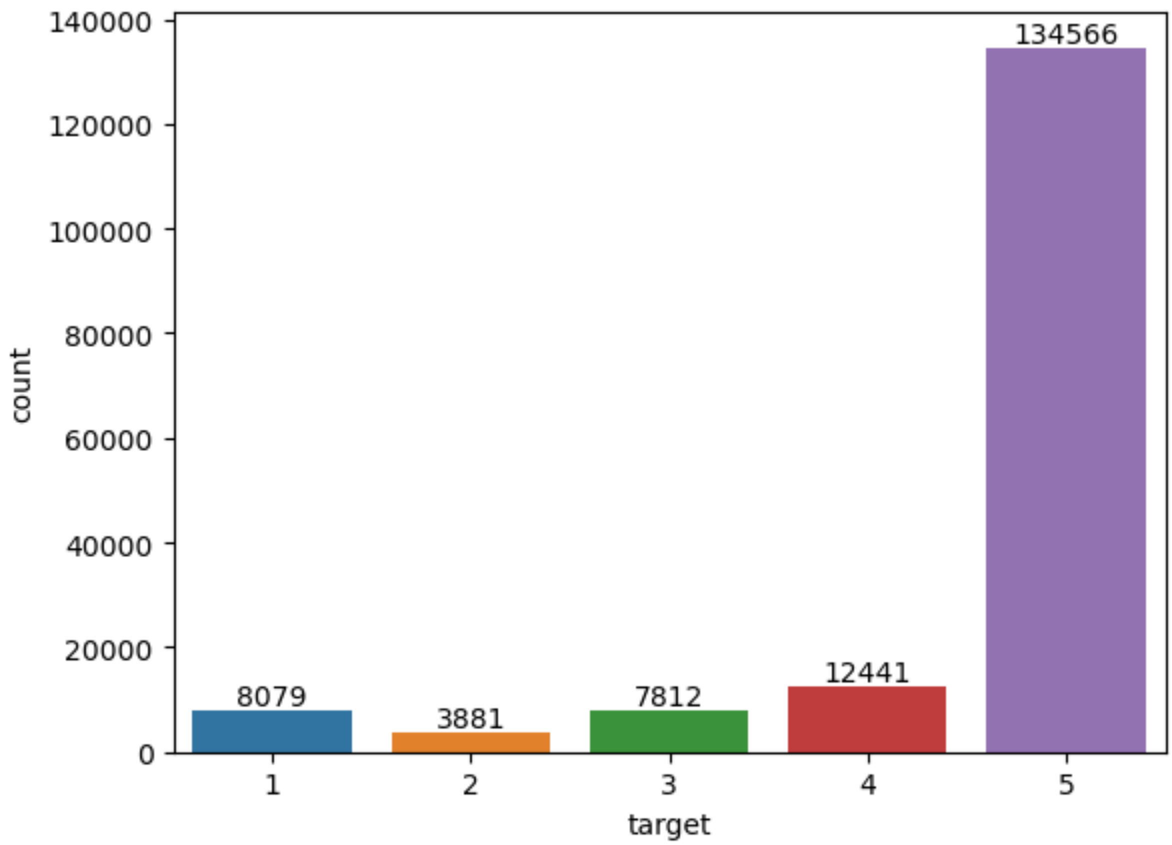
Most often, sellers take from 1 to 9 photos in the card. Let's look at the product rating depending on the number of photos in the product card

In [31]:
```
plt.figure(figsize=(15,5))
ax = sns.countplot(x='pics', data=df, hue='target');
```



There is no special dependence

In [32]:
```
ax = sns.countplot(x='target', data=df)
ax.bar_label(ax.containers[0]);
```



As I said earlier, the classes are unbalanced, and due to the fact that there is a lot of data, we will do undersampling

Text processing

Word cloud

In [33]:
```
# get list of words from string
def str_corpus(corpus):
    str_corpus = ''
    for i in corpus:
        str_corpus += ' ' + i
    str_corpus = str_corpus.strip()
    return str_corpus


# get all words in corpus
def get_corpus(data):
    corpus = []
    for phrase in data:
        for word in phrase.split():
            corpus.append(word)
    return corpus


# getting word clord
def get_wordCloud(corpus):
    wordCloud = WordCloud(background_color='white',
                          stopwords=STOPWORDS,
                          width=3000,
                          height=2500,
                          max_words=200,
                          random_state=42
                          ).generate(str_corpus(corpus))
    return wordCloud


corpus = get_corpus(df['text'].values)
procWordCloud = get_wordCloud(corpus)

fig = plt.figure(figsize=(20, 8))
plt.subplot(1, 2, 1)
plt.imshow(procWordCloud)
plt.axis('off')
plt.subplot(1, 2, 1);
```

Drop stopwords and look again

In [34]:
```
russian_stopwords = stopwords.words("russian")

df['text'] = df['text'].map(lambda x: x.split(' '))
df['text'] = df['text'].map(lambda x: [token for token in x if token not in russian
                                                                    and token != " "]
df['text'] = df['text'].map(lambda x: ' '.join(x))
```

In [35]:
```
corpus = get_corpus(df['text'].values)
procWordCloud = get_wordCloud(corpus)

fig = plt.figure(figsize=(20, 8))
plt.subplot(1, 2, 1)
plt.imshow(procWordCloud)
plt.axis('off')
plt.subplot(1, 2, 1);
```

A lot of positive russian words because 80% of our dataset has an excellent rating. Let's rebalance and look at the word cloud again.

In [36]:
```
X = df.drop('target', axis=1)
y = df['target']

rus = RandomUnderSampler(sampling_strategy='auto', random_state=42)

X_resampled, y_resampled = rus.fit_resample(X, y)
```

In [37]:
```
y_resampled.value_counts()
```

Out[37]:
```
target
1    3881
2    3881
3    3881
4    3881
5    3881
Name: count, dtype: int64
```

In [38]:
```
X_resampled.reset_index(drop=True, inplace=True)
y_resampled.reset_index(drop=True, inplace=True)

df = pd.concat([X_resampled, y_resampled], axis=1)
```

Now we have 5 balanced classes. Look at word cloud

In [39]:
```
corpus = get_corpus(df['text'].values)
procWordCloud = get_wordCloud(corpus)

fig = plt.figure(figsize=(20, 8))
plt.subplot(1, 2, 1)
plt.imshow(procWordCloud)
plt.axis('off')
plt.subplot(1, 2, 1);
```

Due to the fact that more than half of the dataset consists of reviews of Sokolov(jewelery company) products, there are many words related to the subject of jewelry (for example, silver, earrings, ring, etc.)

Processing of numerical and categorical features

Standardize numerical features, encode categorical features

In [40]:
```
numeric_columns
```

Out[40]:
```
['price', 'sale', 'pics', 'useful', 'useless', 'target']
```

In [41]:
```
scaler = StandardScaler()
df[numeric_columns[:-1]] = scaler.fit_transform(df[numeric_columns[:-1]])
```

```
The history saving thread hit an unexpected error (OperationalError('database is lo
cked')).History will not be written to the database.
```

In [42]:
```
df
```

Out[42]:

	name	brand	price	sale	pics	hasPhoto	useful	useless
0	Шлепанцы Mono	FILA	-0.144880	-2.472030	-0.618441	False	-0.030635	0.600217
1	Кольцо из серебра	SOKOLOV	0.178815	0.401142	-0.925706	False	0.518779	-0.542338
2	Ювелирный каучуковый шнурок с замком из серебр...	SOKOLOV	0.015126	0.575274	-0.925706	False	1.617607	0.600217
3	Ювелирные серьги кольца серебро 925	SOKOLOV	-0.230407	0.314076	-0.618441	False	-0.580049	-0.542338
4	Женские серьги пусеты гвоздики из золота 585 п...	SOKOLOV	2.715995	0.357609	0.610619	False	-0.580049	1.742772
...	...	...	...	...	...	...	...	...
19400	Астильба Арендса Mix	Садовые Растения	-0.962916	0.749406	-1.540236	False	-0.030635	-0.542338
19401	Кольцо из серебра с фианитом	SOKOLOV	-0.312252	0.314076	-0.311176	False	-0.580049	-0.542338
19402	Женское кольцо на помолвку из серебра 925	SOKOLOV	0.015126	0.314076	0.917884	False	-0.580049	-0.542338
19403	Ювелирная подвеска кулон на шею серебро 925	SOKOLOV	-0.475941	0.314076	0.610619	False	2.167021	0.600217

	name	brand	price	sale	pics	hasPhoto	useful	useless
19404	Шлепанцы	FILA	-0.144880	-2.472030	-0.618441	False	-0.580049	-0.542338

19405 rows × 10 columns

Encode categorical features

In [43]:
```
df['brand'].value_counts()
```

Out[43]:
```
brand
SOKOLOV                 9423
Zebo Professional       2060
Садовые Растения        1413
Demix                    911
Permegi                  650
                        ...
Mountain Hardwear          1
HEAD                       1
Denton                     1
Street Surfing             1
QREDO                      1
Name: count, Length: 86, dtype: int64
```

In [44]:
```
df['name'].value_counts()
```

Out[44]:
```
name
Ювелирные серьги женские из серебра 925           711
Кольцо из серебра с фианитами                     667
Цепочка на шею из серебра 925                     423
Ювелирные серьги пусеты-гвоздики из серебра 925   394
Ювелирная цепочка на шею серебро 925              391
                                                 ...
Куртка софтшелл женская                             1
Ролики JUNIOR GIRL                                  1
Перчатки сноубордические KAILA                      1
Виноград девичий Yellow Wall                        1
Куртка утепленная для девочек                       1
Name: count, Length: 988, dtype: int64
```

Encode `brand` by OneHotEncoder and remove its column

In [45]:
```
brand = pd.get_dummies(df["brand"], drop_first=True, dtype=int)
df.drop(columns=["name", "brand"], inplace=True)
df = pd.concat([df, brand], axis=1)
df.head()
```

Out[45]:

	price	sale	pics	hasPhoto	useful	useless	text	target	Alpashop
0	-0.144880	-2.472030	-0.618441	False	-0.030635	0.600217	пришли абсолютно схожи оригиналом фото китайск...	1	0
1	0.178815	0.401142	-0.925706	False	0.518779	-0.542338	кольцо пришло согнутое думаю продавцу нужно пе...	1	0
2	0.015126	0.575274	-0.925706	False	1.617607	0.600217	шнурок вместо сильно разочаровал ваш товар хот...	1	0
3	-0.230407	0.314076	-0.618441	False	-0.580049	-0.542338	серьги еле надела это кошмар	1	0
4	2.715995	0.357609	0.610619	False	-0.580049	1.742772	понравилась застежка	1	0

5 rows × 93 columns

Encode `hasPhoto` by OneHotEncoder

In [46]:
```
has_photo = pd.get_dummies(df["hasPhoto"], drop_first=True, dtype=int)
df.drop(columns=["hasPhoto"], inplace=True)
df = pd.concat([df, has_photo], axis=1)
df.head()
```

Out[46]:

	price	sale	pics	useful	useless	text	target	Alpashop	BASEUS
0	-0.144880	-2.472030	-0.618441	-0.030635	0.600217	пришли абсолютно схожи оригиналом фото китайск...	1	0	0
1	0.178815	0.401142	-0.925706	0.518779	-0.542338	кольцо пришло согнутое думаю продавцу нужно пе...	1	0	0
2	0.015126	0.575274	-0.925706	1.617607	0.600217	шнурок вместо сильно разочаровал ваш товар хот...	1	0	0
3	-0.230407	0.314076	-0.618441	-0.580049	-0.542338	серьги еле надела это кошмар	1	0	0
4	2.715995	0.357609	0.610619	-0.580049	1.742772	понравилась застежка	1	0	0

5 rows × 93 columns

Text processing

In [47]:

```
morph = MorphAnalyzer()
def lemmatize(doc):
    tokens = []
    for token in doc.split():
        if token:
            token = token.strip()
            token = morph.normal_forms(token)[0]
            tokens.append(token)
    if len(tokens) > 0:
        return " ".join(tokens)
    return None

df["text"] = df["text"].apply(lemmatize)
df.head()
```

Out[47]:

	price	sale	pics	useful	useless	text	target	Alpashop	BASEUS
0	-0.144880	-2.472030	-0.618441	-0.030635	0.600217	прислать абсолютно схожий оригинал фото китайс...	1	0	0
1	0.178815	0.401142	-0.925706	0.518779	-0.542338	кольцо прийти согнутый думать продавец нужно п...	1	0	0
2	0.015126	0.575274	-0.925706	1.617607	0.600217	шнурок вместо сильно разочаровать ваш товар хо...	1	0	0
3	-0.230407	0.314076	-0.618441	-0.580049	-0.542338	серьга еле надеть это кошмар	1	0	0
4	2.715995	0.357609	0.610619	-0.580049	1.742772	понравиться застёжка	1	0	0

5 rows × 93 columns

In [48]:
```
df["text"].isna().sum()
```

Out[48]: 6

In [49]:
```
df.dropna(inplace=True)
```

In [50]:
```
df.head()
```

Out[50]:

	price	sale	pics	useful	useless	text	target	Alpashop	BASEUS
0	-0.144880	-2.472030	-0.618441	-0.030635	0.600217	прислать абсолютно схожий оригинал фото китайс...	1	0	0
1	0.178815	0.401142	-0.925706	0.518779	-0.542338	кольцо прийти согнутый думать продавец нужно п...	1	0	0
2	0.015126	0.575274	-0.925706	1.617607	0.600217	шнурок вместо сильно разочаровать ваш товар хо...	1	0	0
3	-0.230407	0.314076	-0.618441	-0.580049	-0.542338	серьга еле надеть это кошмар	1	0	0
4	2.715995	0.357609	0.610619	-0.580049	1.742772	понравиться застёжка	1	0	0

5 rows × 93 columns

In [51]:
```
corpus = df["text"].to_list()

vectorizer = TfidfVectorizer()

X_tf_idf = vectorizer.fit_transform(corpus)

X_tf_idf
```

Out[51]:
```
<19399x12312 sparse matrix of type '<class 'numpy.float64'>'
	with 189726 stored elements in Compressed Sparse Row format>
```

In [52]:
```
tfidf_df = pd.DataFrame(X_tf_idf.toarray(), columns=vectorizer.get_feature_names_ou
```

In [53]:
```
df.reset_index(drop=True, inplace=True)
tfidf_df.reset_index(drop=True, inplace=True)

df = pd.concat([df, tfidf_df], axis=1)
```

In [54]:
```
df.drop(columns=["text"], inplace=True)
```

In [55]:
```
df.columns = df.columns.astype(str)
```

In [56]:
```
X = df.drop(columns=["target"])
y = df["target"]
```

In [57]:
```
y.shape, X.shape, df.shape
```
Out[57]:
```
((19399,), (19399, 12403), (19399, 12404))
```

Trainig model

In [58]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta
```

KNN

In [59]:
```
knnclf = KNeighborsClassifier()
```

Train

In [60]:
```
%%time
knnclf.fit(X_train, y_train)
```
```
CPU times: total: 2.02 s
Wall time: 7.08 s
```
Out[60]:
```
▾ KNeighborsClassifier
KNeighborsClassifier()
```

Test

In [61]:
```
%%time
y_pred = knnclf.predict(X_test)
print(f'accuracy {accuracy_score(y_pred, y_test):.2}')
print(classification_report(y_test, y_pred))
```
```
accuracy 0.33
              precision    recall  f1-score   support

           1       0.34      0.46      0.39       767
           2       0.26      0.27      0.26       773
           3       0.24      0.19      0.21       792
           4       0.30      0.25      0.27       785
           5       0.48      0.47      0.47       763

    accuracy                           0.33      3880
   macro avg       0.32      0.33      0.32      3880
weighted avg       0.32      0.33      0.32      3880

CPU times: total: 1min 46s
Wall time: 11.7 s
```

Random Forest

In [62]:
```
rfc = RandomForestClassifier()
```

Train

In [63]:
```
%%time
rfc.fit(X_train, y_train)
```

```
CPU times: total: 1min 11s
Wall time: 1min 31s
```

Out[63]:
```
▾ RandomForestClassifier

RandomForestClassifier()
```

Test

In [64]:
```
%%time
y_pred = rfc.predict(X_test)
print(f'accuracy {accuracy_score(y_pred, y_test):.2}')
print(classification_report(y_test, y_pred))
```

```
accuracy 0.45
              precision    recall  f1-score   support

           1       0.44      0.63      0.52       767
           2       0.32      0.26      0.29       773
           3       0.31      0.21      0.25       792
           4       0.42      0.36      0.39       785
           5       0.65      0.79      0.71       763

    accuracy                           0.45      3880
   macro avg       0.43      0.45      0.43      3880
weighted avg       0.43      0.45      0.43      3880

CPU times: total: 422 ms
Wall time: 640 ms
```

AdaBoost

In [65]:
```
abc = AdaBoostClassifier()
```

Train

In [66]:
```
%%time
abc.fit(X_train, y_train)
```

```
CPU times: total: 56 s
Wall time: 1min 15s
```

Out[66]:
```
▾ AdaBoostClassifier

AdaBoostClassifier()
```

Test

In [67]:
```
%%time
y_pred = abc.predict(X_test)
print(f'accuracy {accuracy_score(y_pred, y_test):.2}')
print(classification_report(y_test, y_pred))
```

```
accuracy 0.4
              precision    recall  f1-score   support

           1       0.43      0.55      0.49       767
           2       0.28      0.15      0.19       773
           3       0.28      0.30      0.29       792
           4       0.35      0.38      0.36       785
           5       0.62      0.64      0.63       763

    accuracy                           0.40      3880
   macro avg       0.39      0.40      0.39      3880
weighted avg       0.39      0.40      0.39      3880

CPU times: total: 4.5 s
Wall time: 6.32 s
```

MLP

In [68]:
```
mlpc = MLPClassifier()
```

Train

In [69]:
```
%%time
mlpc.fit(X_train, y_train)
```

```
CPU times: total: 3h 57min 30s
Wall time: 49min 5s
C:\Users\ibasl\anaconda3\Lib\site-packages\sklearn\neural_network\_multilayer_perceptron.py:686: ConvergenceWarning: Stochastic Optimizer: Maximum iterations (200) reached and the optimization hasn't converged yet.
  warnings.warn(
```

Out[69]:
```
▾ MLPClassifier
MLPClassifier()
```

Test

In [70]:
```
%%time
y_pred = mlpc.predict(X_test)
print(f'accuracy {accuracy_score(y_pred, y_test):.2}')
print(classification_report(y_test, y_pred))
```

```
accuracy 0.41
              precision    recall  f1-score   support

           1       0.45      0.47      0.46       767
           2       0.32      0.32      0.32       773
           3       0.26      0.26      0.26       792
           4       0.38      0.35      0.36       785
           5       0.66      0.69      0.68       763

    accuracy                           0.41      3880
   macro avg       0.41      0.42      0.41      3880
weighted avg       0.41      0.41      0.41      3880

CPU times: total: 1.44 s
Wall time: 570 ms
```

In [71]:

```
column0 = ['KNN', 'Random Forest','AdaBoost','MLP']
column1 = ["8.49 s", '1min 23s', '1 min 10s', '36 min 18s']
column2 = ["658 ms", '1min 22s', '1min 5s', '36min 17s']
column3 = ['7.82 s', '605 ms', '5.12 s', '406 ms']
column4 = [0.33, 0.45, 0.4, 0.42]


data = {'Model': column0,
        'Run time': column1,
        'Traing time': column2,
        'Test time': column3,
        'Accuracy': column4}
table = pd.DataFrame(data)
table.set_index('Model', inplace=True)
table
```

Out[71]:

Model	Run time	Traing time	Test time	Accuracy
KNN	8.49 s	658 ms	7.82 s	0.33
Random Forest	1min 23s	1min 22s	605 ms	0.45
AdaBoost	1 min 10s	1min 5s	5.12 s	0.40
MLP	36 min 18s	36min 17s	406 ms	0.42

Conclusion

The overall quality of the models is average - each of them is very close to random guessing the rating, with the exception of reviews with a rating of "5". The random forest and multilayer perceptron models distinguish five stars texts much better than the other - with 0.63 and 0.7 f1-score. In my opinion, this is due to four factors - the comments are not long enough for the model to extract the desired message; you need to use word embeddings instead of tf-idf vectorization; you need to use more complex algorithms, for example, deep learning with rnn or with attention layers; the authors' comments are biased and vary;

I said average quality because even modern BERT models do not give an accuracy of more than 0.6 due to the article

Table 2: SST-5 Results

Model	Training Time (per epoch)	Best Test Acc.
$BERT_{BASE}$	5:38	0.549
$BERT_{LARGE}$	12:38	0.562
$ALBERT_{BASE}$	3:16	0.490
$DistilBERT_{BASE}$	2:54	0.532
$RoBERTa_{LARGE}$	N/A	0.602

Table 3: Experiment results for classification task on SST-5 root nodes

In [ ]: