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Факультет «Информатика и системы управления»
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Рубежный контроль №1
по дисциплине «Методы машинного обучения»
«Методы обработки данных»

ИСПОЛНИТЕЛЬ:

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Задание

- Для набора данных проведите кодирование одного (произвольного) категориального признака с использованием метода "count (frequency) encoding".
- Для набора данных проведите масштабирование данных для одного (произвольного) числового признака с использованием масштабирования по медиане.

rk1

April 2, 2023

1 1

1.1

[ ]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from category_encoders.count import CountEncoder as ce_CountEncoder
from sklearn.datasets import load_breast_cancer
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import RobustScaler
%matplotlib inline
sns.set(style="ticks")
```

1.2 №1

( ) “count (frequency) encoding”.

1.2.1

[ ]:
```
#
data_loaded = pd.read_csv('data/hotel.csv', sep=",")
data_loaded.shape
```

[ ]:
```
(4000, 36)
```

[ ]:
```
data_loaded.head()
```

[ ]:
```
                                     additional_info  \
0  Room Service|Internet Access|Restaurant|Free I…
1                                  Room Service|Gym/Spa
2                             Restaurant|Swimming Pool
3                                                   NaN
4                           Internet Access|Restaurant

                                            address           area      city  \
0  15th Mile, N.H.21,Manali, District Kullu,Himac…          Others    Manali
```

```
1  A-585, Sushant Lok-1 ,Near Iffco Chowk Metro S…     Sushant Lok  Gurgaon
2  Cobra Vaddo,Calungate Baga Road, Bardez, Calan…  Calangute Area      Goa
3                                              Simsa   Village Simsa   Manali
4         8180 Street No.-6,Arakashan Road,Paharganj       Paharganj    Delhi

  country  crawl_date  guest_recommendation hotel_brand hotel_category  \
0   India  2016-07-24                  85.0         NaN        gostays
1   India  2016-07-24                  87.0         NaN        regular
2   India  2016-07-24                  50.0         NaN        regular
3   India  2016-07-24                 100.0         NaN        regular
4   India  2016-07-24                  63.0         NaN        regular

                                  hotel_description  … room_count  \
0  The standard check-in time is 12:00 PM and the…  …         17
1  The standard check-in time is 12:00 PM and the…  …         18
2  The standard check-in time is 12:00 PM and the…  …         15
3  The standard check-in time is 12:00 PM and the…  …         24
4  The standard check-in time is 12:00 PM and the…  …         20

                                    room_facilities  \
0  Room Service |Basic Bathroom Amenities|Cable /…
1  Room Service |Air Conditioning |Basic Bathroom…
2  Room Service |Air Conditioning |Cable / Satell…
3  Basic Bathroom Amenities|Cable / Satellite / P…
4  Basic Bathroom Amenities|Cable / Satellite / P…

                    room_type  \
0                 Deluxe Room
1  Deluxe Room With Free WIFI
2               Standard Room
3                 Deluxe Room
4        Standard Room Non AC

                                      similar_hotel site_review_count  \
0  https://www.goibibo.com/hotels/woodchime-homes…              87.0
1  https://www.goibibo.com/hotels/stepinn-iffco-c…               8.0
2  https://www.goibibo.com/hotels/sunrise-beach-r…               2.0
3  https://www.goibibo.com/hotels/green-cottages-…               1.0
4  https://www.goibibo.com/hotels/delhi-continent…             121.0

   site_review_rating                            site_stay_review_rating  \
0                 4.0  Service Quality::3.9|Amenities::3.7|Food and D…
1                 4.5  Service Quality::4.7|Amenities::4.7|Food and D…
2                 2.5  Service Quality::2.5|Amenities::2.5|Food and D…
3                 5.0  Service Quality::5.0|Amenities::5.0|Food and D…
4                 2.8  Service Quality::2.7|Amenities::2.6|Food and D…
```

```
  sitename             state                            uniq_id
0  goibibo  Himachal Pradesh  2c8db027d43a9452a43e88eb30d9f983
1  goibibo           Haryana  e98f69f889c0235e6dc480e7df6de0de
2  goibibo               Goa  9b59d00eaffc273d83000ed7dcda0e83
3  goibibo  Himachal Pradesh  df0971f9c5501af112485ee28b468ce5
4  goibibo             Delhi  0c3514344c9cda8718f558e84bdb44ef

[5 rows x 36 columns]
```

[ ]:
```
data_features = list(zip(
#
[i for i in data_loaded.columns],
zip(
    #
    [str(i) for i in data_loaded.dtypes],
    #
    [i for i in data_loaded.isnull().sum()]
)))
#
data_features
```

[ ]:
```
[('additional_info', ('object', 808)),
 ('address', ('object', 0)),
 ('area', ('object', 35)),
 ('city', ('object', 0)),
 ('country', ('object', 0)),
 ('crawl_date', ('object', 0)),
 ('guest_recommendation', ('float64', 1584)),
 ('hotel_brand', ('object', 3611)),
 ('hotel_category', ('object', 0)),
 ('hotel_description', ('object', 17)),
 ('hotel_facilities', ('object', 194)),
 ('hotel_star_rating', ('int64', 0)),
 ('image_count', ('int64', 0)),
 ('latitude', ('float64', 0)),
 ('locality', ('object', 35)),
 ('longitude', ('float64', 0)),
 ('pageurl', ('object', 0)),
 ('point_of_interest', ('object', 240)),
 ('property_id', ('object', 0)),
 ('property_name', ('object', 0)),
 ('property_type', ('object', 0)),
 ('province', ('object', 0)),
 ('qts', ('object', 1284)),
 ('query_time_stamp', ('object', 0)),
 ('review_count_by_category', ('object', 1585)),
 ('room_area', ('object', 2872)),
```

```
 ('room_count', ('int64', 0)),
 ('room_facilities', ('object', 270)),
 ('room_type', ('object', 0)),
 ('similar_hotel', ('object', 83)),
 ('site_review_count', ('float64', 1584)),
 ('site_review_rating', ('float64', 1584)),
 ('site_stay_review_rating', ('object', 0)),
 ('sitename', ('object', 0)),
 ('state', ('object', 0)),
 ('uniq_id', ('object', 0))]
```

[ ]:
```
#
cols_filter = ['uniq_id', 'property_name', 'property_type', 'city',␣
↪'crawl_date',
        'guest_recommendation', 'sitename']
data = data_loaded[cols_filter]
data.head()
```

[ ]:
```
                            uniq_id        property_name property_type  \
0  2c8db027d43a9452a43e88eb30d9f983     Baragarh Regency        Resort
1  e98f69f889c0235e6dc480e7df6de0de  Asian Suites A- 585   Guest House
2  9b59d00eaffc273d83000ed7dcda0e83        Bevvan Resort        Resort
3  df0971f9c5501af112485ee28b468ce5     Apple Inn Cottage       Cottage
4  0c3514344c9cda8718f558e84bdb44ef  Anmol Hotel Pvt.Ltd         Hotel

      city  crawl_date  guest_recommendation sitename
0   Manali  2016-07-24                  85.0  goibibo
1  Gurgaon  2016-07-24                  87.0  goibibo
2      Goa  2016-07-24                  50.0  goibibo
3   Manali  2016-07-24                 100.0  goibibo
4    Delhi  2016-07-24                  63.0  goibibo
```

[ ]:
```
#
def impute_na(df, variable, value):
    df[variable].fillna(value, inplace=True)

impute_na(data, 'guest_recommendation', data['guest_recommendation'].mean())
```

```
/var/folders/fs/5xh23h99763f_blp7m50x23h0000gq/T/ipykernel_3775/3897478908.py:3:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df[variable].fillna(value, inplace=True)
```

[ ]:
```
#
data.isnull().sum()
```

```
[ ]: uniq_id                 0
     property_name           0
     property_type           0
     city                    0
     crawl_date              0
     guest_recommendation    0
     sitename                0
     dtype: int64
```

1.2.2 "count (frequence) encoding"

```
[ ]: ce_CountEncoder1 = ce_CountEncoder()
     data_COUNT_ENC = ce_CountEncoder1.fit_transform(data[data.columns.
      ↪difference(['uniq_id'])])
```

```
[ ]: data_COUNT_ENC
```

```
[ ]:       city  crawl_date  guest_recommendation  property_name  property_type  \
     0       70         976             85.000000              1            516
     1      101         976             87.000000              1            243
     2      220         976             50.000000              1            516
     3       70         976            100.000000              1             75
     4      137         976             63.000000              1           2314
     …     …           …                     …                    …             …
     3995    16         799             75.537666              1           2314
     3996    62         799             75.537666              2           2314
     3997    65         799             83.000000              1           2314
     3998     3         799             75.537666              2           2314
     3999     1         799             50.000000              1           2314

           sitename
     0         4000
     1         4000
     2         4000
     3         4000
     4         4000
     …          …
     3995      4000
     3996      4000
     3997      4000
     3998      4000
     3999      4000

     [4000 rows x 6 columns]
```

```
[ ]: data['property_type'].unique()
```

```
[ ]: array(['Resort', 'Guest House', 'Cottage', 'Hotel', 'Homestay', 'Villa',
            'Palace', 'Lodge', 'Houseboat', 'Service Apartment', 'BnB',
            'Hostel', 'Bungalow', 'Tent', 'Luxury Yacht', 'Motel', 'Beach Hut',
            'Farm Stay'], dtype=object)
```

```
[ ]: data_COUNT_ENC['property_type'].unique()
```

```
[ ]: array([ 516,  243,   75, 2314,  231,   49,   11,  117,   78,  183,   10,
              46,   57,    3,    9,    2,    7])
```

```
[ ]: ce_CountEncoder2 = ce_CountEncoder(normalize=True)
     data_FREQ_ENC = ce_CountEncoder2.fit_transform(data[data.columns.
      ↪difference(['uniq_id'])])
```

```
[ ]: data_FREQ_ENC
```

```
[ ]:          city  crawl_date  guest_recommendation  property_name  property_type  \
     0     0.01750     0.24400             85.000000        0.00025        0.12900
     1     0.02525     0.24400             87.000000        0.00025        0.06075
     2     0.05500     0.24400             50.000000        0.00025        0.12900
     3     0.01750     0.24400            100.000000        0.00025        0.01875
     4     0.03425     0.24400             63.000000        0.00025        0.57850
     …         …         …                    …              …              …
     3995  0.00400     0.19975             75.537666        0.00025        0.57850
     3996  0.01550     0.19975             75.537666        0.00050        0.57850
     3997  0.01625     0.19975             83.000000        0.00025        0.57850
     3998  0.00075     0.19975             75.537666        0.00050        0.57850
     3999  0.00025     0.19975             50.000000        0.00025        0.57850

           sitename
     0          1.0
     1          1.0
     2          1.0
     3          1.0
     4          1.0
     …          …
     3995       1.0
     3996       1.0
     3997       1.0
     3998       1.0
     3999       1.0

     [4000 rows x 6 columns]
```

```
[ ]: data_FREQ_ENC['property_type'].unique()
```

[ ]:
```
array([1.290e-01, 6.075e-02, 1.875e-02, 5.785e-01, 5.775e-02, 1.225e-02,
       2.750e-03, 2.925e-02, 1.950e-02, 4.575e-02, 2.500e-03, 1.150e-02,
       1.425e-02, 7.500e-04, 2.250e-03, 5.000e-04, 1.750e-03])
```

1.3 №21

( ) .

1.4

[ ]:
```
boston_dataset = load_breast_cancer()
data = pd.DataFrame(boston_dataset.data,
                    columns=boston_dataset.feature_names)
data['Y'] = boston_dataset.target
data.shape
```

[ ]:
```
(569, 31)
```

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

[ ]:
```
   mean radius  mean texture  mean perimeter  mean area  mean smoothness  \
0        17.99         10.38          122.80     1001.0          0.11840
1        20.57         17.77          132.90     1326.0          0.08474
2        19.69         21.25          130.00     1203.0          0.10960
3        11.42         20.38           77.58      386.1          0.14250
4        20.29         14.34          135.10     1297.0          0.10030

   mean compactness  mean concavity  mean concave points  mean symmetry  \
0           0.27760          0.3001              0.14710         0.2419
1           0.07864          0.0869              0.07017         0.1812
2           0.15990          0.1974              0.12790         0.2069
3           0.28390          0.2414              0.10520         0.2597
4           0.13280          0.1980              0.10430         0.1809

   mean fractal dimension  …  worst texture  worst perimeter  worst area  \
0                 0.07871  …          17.33           184.60      2019.0
1                 0.05667  …          23.41           158.80      1956.0
2                 0.05999  …          25.53           152.50      1709.0
3                 0.09744  …          26.50            98.87       567.7
4                 0.05883  …          16.67           152.20      1575.0

   worst smoothness  worst compactness  worst concavity  worst concave points  \
0            0.1622             0.6656           0.7119                0.2654
1            0.1238             0.1866           0.2416                0.1860
2            0.1444             0.4245           0.4504                0.2430
3            0.2098             0.8663           0.6869                0.2575
4            0.1374             0.2050           0.4000                0.1625
```

```
   worst symmetry  worst fractal dimension  Y
0          0.4601                  0.11890  0
1          0.2750                  0.08902  0
2          0.3613                  0.08758  0
3          0.6638                  0.17300  0
4          0.2364                  0.07678  0

[5 rows x 31 columns]
```

```
[ ]: #
     data.describe()
```

```
[ ]:        mean radius  mean texture  mean perimeter    mean area  \
count   569.000000    569.000000      569.000000   569.000000
mean     14.127292     19.289649       91.969033   654.889104
std       3.524049      4.301036       24.298981   351.914129
min       6.981000      9.710000       43.790000   143.500000
25%      11.700000     16.170000       75.170000   420.300000
50%      13.370000     18.840000       86.240000   551.100000
75%      15.780000     21.800000      104.100000   782.700000
max      28.110000     39.280000      188.500000  2501.000000

       mean smoothness  mean compactness  mean concavity  mean concave points  \
count       569.000000        569.000000      569.000000           569.000000
mean          0.096360          0.104341        0.088799             0.048919
std           0.014064          0.052813        0.079720             0.038803
min           0.052630          0.019380        0.000000             0.000000
25%           0.086370          0.064920        0.029560             0.020310
50%           0.095870          0.092630        0.061540             0.033500
75%           0.105300          0.130400        0.130700             0.074000
max           0.163400          0.345400        0.426800             0.201200

       mean symmetry  mean fractal dimension  …  worst texture  \
count     569.000000              569.000000  …     569.000000
mean        0.181162                0.062798  …      25.677223
std         0.027414                0.007060  …       6.146258
min         0.106000                0.049960  …      12.020000
25%         0.161900                0.057700  …      21.080000
50%         0.179200                0.061540  …      25.410000
75%         0.195700                0.066120  …      29.720000
max         0.304000                0.097440  …      49.540000

       worst perimeter  worst area  worst smoothness  worst compactness  \
count       569.000000  569.000000        569.000000         569.000000
mean        107.261213  880.583128          0.132369           0.254265
std          33.602542  569.356993          0.022832           0.157336
min          50.410000  185.200000          0.071170           0.027290
```

```
25%         84.110000   515.300000          0.116600            0.147200
50%         97.660000   686.500000          0.131300            0.211900
75%        125.400000  1084.000000          0.146000            0.339100
max        251.200000  4254.000000          0.222600            1.058000

       worst concavity  worst concave points  worst symmetry  \
count       569.000000            569.000000      569.000000
mean          0.272188              0.114606        0.290076
std           0.208624              0.065732        0.061867
min           0.000000              0.000000        0.156500
25%           0.114500              0.064930        0.250400
50%           0.226700              0.099930        0.282200
75%           0.382900              0.161400        0.317900
max           1.252000              0.291000        0.663800

       worst fractal dimension           Y
count               569.000000  569.000000
mean                  0.083946    0.627417
std                   0.018061    0.483918
min                   0.055040    0.000000
25%                   0.071460    0.000000
50%                   0.080040    1.000000
75%                   0.092080    1.000000
max                   0.207500    1.000000

[8 rows x 31 columns]
```

[ ]:
```python
# DataFrame
X_ALL = data.drop('Y', axis=1)
```

[ ]:
```python
#
#
def arr_to_df(arr_scaled):
    res = pd.DataFrame(arr_scaled, columns=X_ALL.columns)
    return res
```

[ ]:
```python
#
X_train, X_test, y_train, y_test = train_test_split(X_ALL, data['Y'],
                                                    test_size=0.2,
                                                    random_state=1)
#              DataFrame
X_train_df = arr_to_df(X_train)
X_test_df = arr_to_df(X_test)

X_train_df.shape, X_test_df.shape
```

[ ]: ((455, 30), (114, 30))

1.5

[ ]:
```
cs41 = RobustScaler()
data_cs41_scaled_temp = cs41.fit_transform(X_ALL)
#       DataFrame
data_cs41_scaled = arr_to_df(data_cs41_scaled_temp)
data_cs41_scaled.describe()
```

[ ]:

	mean radius	mean texture	mean perimeter	mean area	mean smoothness	\
count	569.000000	569.000000	569.000000	569.000000	569.000000	
mean	0.185611	0.079867	0.198031	0.286394	0.025900	
std	0.863737	0.763950	0.839923	0.971065	0.742954	
min	-1.565931	-1.621670	-1.467335	-1.124724	-2.284205	
25%	-0.409314	-0.474245	-0.382648	-0.360927	-0.501849	
50%	0.000000	0.000000	0.000000	0.000000	0.000000	
75%	0.590686	0.525755	0.617352	0.639073	0.498151	
max	3.612745	3.630551	3.534739	5.380519	3.567353	

	mean compactness	mean concavity	mean concave points	mean symmetry	\
count	569.000000	569.000000	569.000000	569.000000	
mean	0.178848	0.269521	0.287188	0.058043	
std	0.806548	0.788212	0.722720	0.811073	
min	-1.118662	-0.608464	-0.623952	-2.165680	
25%	-0.423183	-0.316195	-0.245670	-0.511834	
50%	0.000000	0.000000	0.000000	0.000000	
75%	0.576817	0.683805	0.754330	0.488166	
max	3.860263	3.611430	3.123487	3.692308	

	mean fractal dimension	…	worst radius	worst texture	\
count	569.000000	…	569.000000	569.000000	
mean	0.149360	…	0.224773	0.030929	
std	0.838523	…	0.836201	0.711372	
min	-1.375297	…	-1.217993	-1.549769	
25%	-0.456057	…	-0.339100	-0.501157	
50%	0.000000	…	0.000000	0.000000	
75%	0.543943	…	0.660900	0.498843	
max	4.263658	…	3.645329	2.792824	

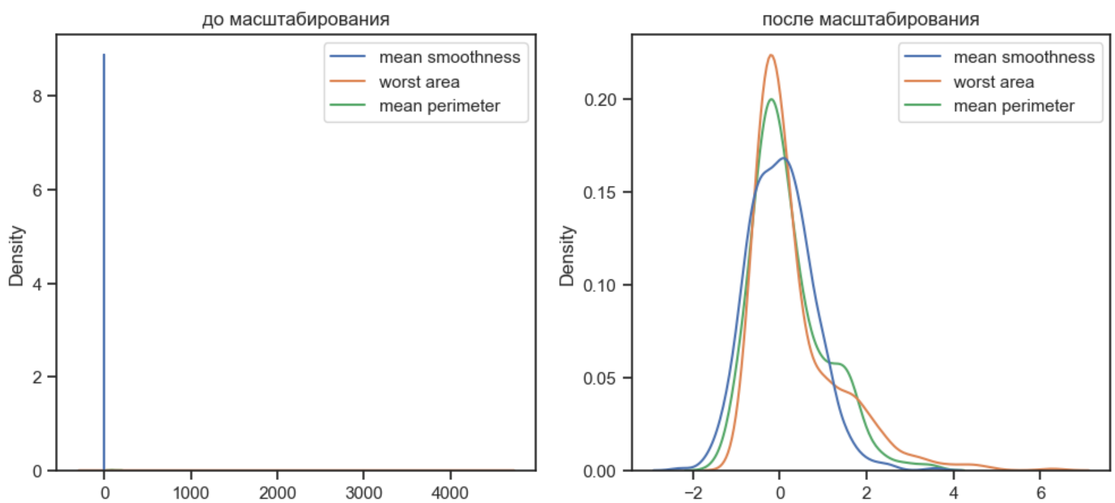
	worst perimeter	worst area	worst smoothness	worst compactness	\
count	569.000000	569.000000	569.000000	569.000000	
mean	0.232531	0.341275	0.036347	0.220766	
std	0.813818	1.001155	0.776613	0.819888	
min	-1.144345	-0.881484	-2.045238	-0.962011	
25%	-0.328167	-0.301037	-0.500000	-0.337155	
50%	0.000000	0.000000	0.000000	0.000000	
75%	0.671833	0.698963	0.500000	0.662845	
max	3.718576	6.273079	3.105442	4.409067	

```
       worst concavity  worst concave points  worst symmetry  \
count       569.000000            569.000000      569.000000
mean          0.169480              0.152133        0.116675
std           0.777289              0.681376        0.916555
min          -0.844635             -1.035866       -1.862222
25%          -0.418033             -0.362807       -0.471111
50%           0.000000              0.000000        0.000000
75%           0.581967              0.637193        0.528889
max           3.820045              1.980616        5.653333

       worst fractal dimension
count               569.000000
mean                  0.189419
std                   0.875910
min                  -1.212415
25%                  -0.416101
50%                   0.000000
75%                   0.583899
max                   6.181377

[8 rows x 30 columns]
```

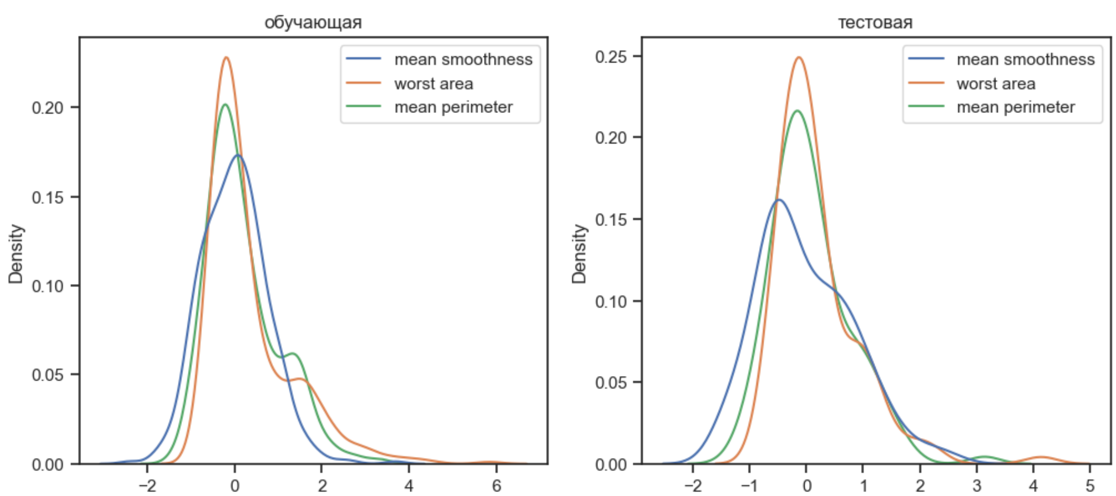
[ ]:
```
cs42 = RobustScaler()
cs42.fit(X_train)
data_cs42_scaled_train_temp = cs42.transform(X_train)
data_cs42_scaled_test_temp = cs42.transform(X_test)
#       DataFrame
data_cs42_scaled_train = arr_to_df(data_cs42_scaled_train_temp)
data_cs42_scaled_test = arr_to_df(data_cs42_scaled_test_temp)
```

[ ]:
```
#
def draw_kde(col_list, df1, df2, label1, label2):
    fig, (ax1, ax2) = plt.subplots(
        ncols=2, figsize=(12, 5))
    #
    ax1.set_title(label1)
    sns.kdeplot(data=df1[col_list], ax=ax1)
    #
    ax2.set_title(label2)
    sns.kdeplot(data=df2[col_list], ax=ax2)
    plt.show()
```

[ ]:
```
draw_kde(['mean smoothness', 'worst area', 'mean perimeter'], data,␣
 ↪data_cs41_scaled, '           ', '            ')
```




```
[ ]: draw_kde(['mean smoothness', 'worst area', 'mean perimeter'],␣
     ↪data_cs42_scaled_train, data_cs42_scaled_test, '      ', '      ')
```

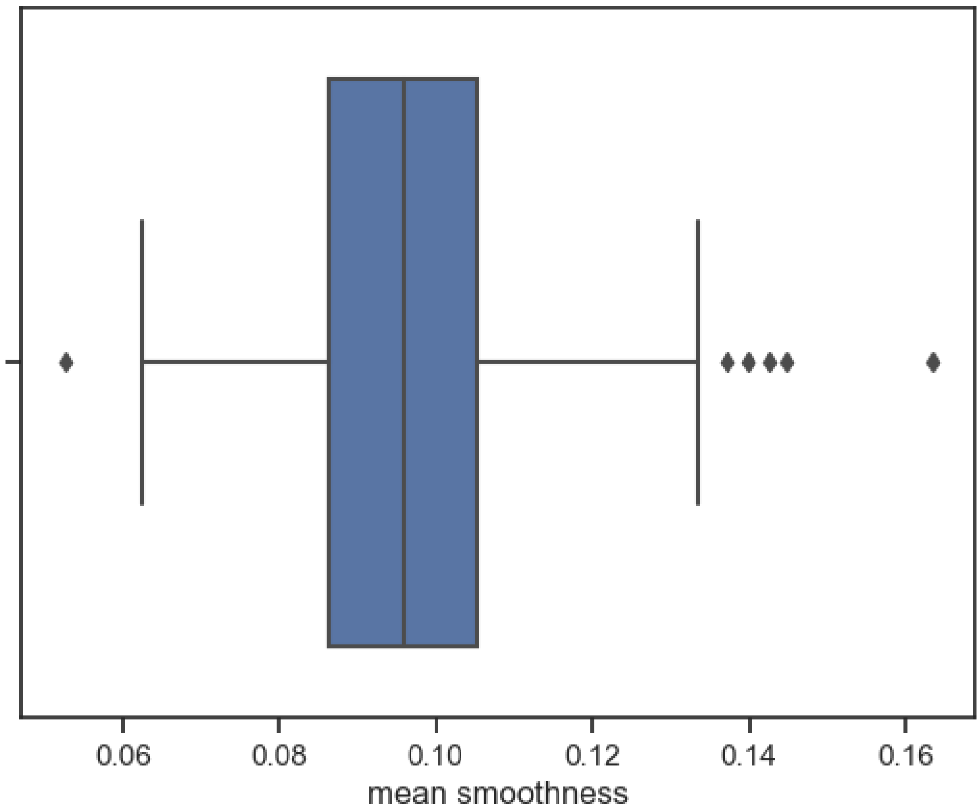


1.6

5-23 ,   5 -23 -   “   (boxplot)”.

```
[ ]: sns.boxplot(data=data, x="mean smoothness")
```

```
[ ]: <Axes: xlabel='mean smoothness'>
```


0.06
0.08
0.10
0.12
0.14
0.16
mean smoothness

rk1

June 22, 2023

1 1

1.1

[ ]:
```python
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from category_encoders.count import CountEncoder as ce_CountEncoder
from sklearn.datasets import load_breast_cancer
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import RobustScaler
%matplotlib inline
sns.set(style="ticks")
```

1.2 №1

( ) "count (frequency) encoding".

1.2.1

[ ]:
```python
#
data_loaded = pd.read_csv('datasets/hotel.csv', sep=",")
data_loaded.shape
```

[ ]:
```
(4000, 36)
```

[ ]:
```python
data_loaded.head()
```

[ ]:
```
                                     additional_info  \
0  Room Service|Internet Access|Restaurant|Free I…
1                                 Room Service|Gym/Spa
2                             Restaurant|Swimming Pool
3                                                  NaN
4                           Internet Access|Restaurant

                                             address          area      city  \
0  15th Mile, N.H.21,Manali, District Kullu,Himac…          Others    Manali
```

```
1  A-585, Sushant Lok-1 ,Near Iffco Chowk Metro S…     Sushant Lok  Gurgaon
2  Cobra Vaddo,Calungate Baga Road, Bardez, Calan…  Calangute Area      Goa
3                                               Simsa   Village Simsa   Manali
4         8180 Street No.-6,Arakashan Road,Paharganj       Paharganj    Delhi

  country  crawl_date  guest_recommendation hotel_brand hotel_category  \
0   India  2016-07-24                  85.0         NaN        gostays
1   India  2016-07-24                  87.0         NaN        regular
2   India  2016-07-24                  50.0         NaN        regular
3   India  2016-07-24                 100.0         NaN        regular
4   India  2016-07-24                  63.0         NaN        regular

                                  hotel_description  … room_count  \
0  The standard check-in time is 12:00 PM and the…  …         17
1  The standard check-in time is 12:00 PM and the…  …         18
2  The standard check-in time is 12:00 PM and the…  …         15
3  The standard check-in time is 12:00 PM and the…  …         24
4  The standard check-in time is 12:00 PM and the…  …         20

                                    room_facilities  \
0  Room Service |Basic Bathroom Amenities|Cable /…
1  Room Service |Air Conditioning |Basic Bathroom…
2  Room Service |Air Conditioning |Cable / Satell…
3  Basic Bathroom Amenities|Cable / Satellite / P…
4  Basic Bathroom Amenities|Cable / Satellite / P…

                    room_type  \
0                 Deluxe Room
1  Deluxe Room With Free WIFI
2               Standard Room
3                 Deluxe Room
4        Standard Room Non AC

                                      similar_hotel site_review_count  \
0  https://www.goibibo.com/hotels/woodchime-homes…              87.0
1  https://www.goibibo.com/hotels/stepinn-iffco-c…               8.0
2  https://www.goibibo.com/hotels/sunrise-beach-r…               2.0
3  https://www.goibibo.com/hotels/green-cottages-…               1.0
4  https://www.goibibo.com/hotels/delhi-continent…             121.0

  site_review_rating                            site_stay_review_rating  \
0                4.0  Service Quality::3.9|Amenities::3.7|Food and D…
1                4.5  Service Quality::4.7|Amenities::4.7|Food and D…
2                2.5  Service Quality::2.5|Amenities::2.5|Food and D…
3                5.0  Service Quality::5.0|Amenities::5.0|Food and D…
4                2.8  Service Quality::2.7|Amenities::2.6|Food and D…
```

```
  sitename             state                            uniq_id
0  goibibo  Himachal Pradesh  2c8db027d43a9452a43e88eb30d9f983
1  goibibo           Haryana  e98f69f889c0235e6dc480e7df6de0de
2  goibibo               Goa  9b59d00eaffc273d83000ed7dcda0e83
3  goibibo  Himachal Pradesh  df0971f9c5501af112485ee28b468ce5
4  goibibo             Delhi  0c3514344c9cda8718f558e84bdb44ef

[5 rows x 36 columns]
```

[ ]:
```
data_features = list(zip(
#
[i for i in data_loaded.columns],
zip(
    #
    [str(i) for i in data_loaded.dtypes],
    #
    [i for i in data_loaded.isnull().sum()]
)))
#
data_features
```

[ ]:
```
[('additional_info', ('object', 808)),
 ('address', ('object', 0)),
 ('area', ('object', 35)),
 ('city', ('object', 0)),
 ('country', ('object', 0)),
 ('crawl_date', ('object', 0)),
 ('guest_recommendation', ('float64', 1584)),
 ('hotel_brand', ('object', 3611)),
 ('hotel_category', ('object', 0)),
 ('hotel_description', ('object', 17)),
 ('hotel_facilities', ('object', 194)),
 ('hotel_star_rating', ('int64', 0)),
 ('image_count', ('int64', 0)),
 ('latitude', ('float64', 0)),
 ('locality', ('object', 35)),
 ('longitude', ('float64', 0)),
 ('pageurl', ('object', 0)),
 ('point_of_interest', ('object', 240)),
 ('property_id', ('object', 0)),
 ('property_name', ('object', 0)),
 ('property_type', ('object', 0)),
 ('province', ('object', 0)),
 ('qts', ('object', 1284)),
 ('query_time_stamp', ('object', 0)),
 ('review_count_by_category', ('object', 1585)),
 ('room_area', ('object', 2872)),
```

```
 ('room_count', ('int64', 0)),
 ('room_facilities', ('object', 270)),
 ('room_type', ('object', 0)),
 ('similar_hotel', ('object', 83)),
 ('site_review_count', ('float64', 1584)),
 ('site_review_rating', ('float64', 1584)),
 ('site_stay_review_rating', ('object', 0)),
 ('sitename', ('object', 0)),
 ('state', ('object', 0)),
 ('uniq_id', ('object', 0))]
```

[ ]:
```
#
cols_filter = ['uniq_id', 'property_name', 'property_type', 'city',␣
 ↪'crawl_date',
        'guest_recommendation', 'sitename']
data = data_loaded[cols_filter]
data.head()
```

[ ]:
```
                            uniq_id        property_name property_type  \
0  2c8db027d43a9452a43e88eb30d9f983     Baragarh Regency        Resort
1  e98f69f889c0235e6dc480e7df6de0de  Asian Suites A- 585   Guest House
2  9b59d00eaffc273d83000ed7dcda0e83        Bevvan Resort        Resort
3  df0971f9c5501af112485ee28b468ce5    Apple Inn Cottage       Cottage
4  0c3514344c9cda8718f558e84bdb44ef  Anmol Hotel Pvt.Ltd         Hotel

      city  crawl_date  guest_recommendation sitename
0   Manali  2016-07-24                  85.0  goibibo
1  Gurgaon  2016-07-24                  87.0  goibibo
2      Goa  2016-07-24                  50.0  goibibo
3   Manali  2016-07-24                 100.0  goibibo
4    Delhi  2016-07-24                  63.0  goibibo
```

[ ]:
```
#
def impute_na(df, variable, value):
    df[variable].fillna(value, inplace=True)

impute_na(data, 'guest_recommendation', data['guest_recommendation'].mean())
```

```
/var/folders/fs/5xh23h99763f_blp7m50x23h0000gq/T/ipykernel_3775/3897478908.py:3:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df[variable].fillna(value, inplace=True)
```

[ ]:
```
#
data.isnull().sum()
```

[ ]:
```
uniq_id                  0
property_name            0
property_type            0
city                     0
crawl_date               0
guest_recommendation     0
sitename                 0
dtype: int64
```

1.2.2 "count (frequence) encoding"

[ ]:
```
ce_CountEncoder1 = ce_CountEncoder()
data_COUNT_ENC = ce_CountEncoder1.fit_transform(data[data.columns.
 ↪difference(['uniq_id'])])
```

[ ]:
```
data_COUNT_ENC
```

[ ]:
```
      city  crawl_date  guest_recommendation  property_name  property_type  \
0       70         976             85.000000              1            516
1      101         976             87.000000              1            243
2      220         976             50.000000              1            516
3       70         976            100.000000              1             75
4      137         976             63.000000              1           2314
…     …          …                     …               …             …
3995    16         799             75.537666              1           2314
3996    62         799             75.537666              2           2314
3997    65         799             83.000000              1           2314
3998     3         799             75.537666              2           2314
3999     1         799             50.000000              1           2314

      sitename
0         4000
1         4000
2         4000
3         4000
4         4000
…          …
3995      4000
3996      4000
3997      4000
3998      4000
3999      4000

[4000 rows x 6 columns]
```

[ ]:
```
data['property_type'].unique()
```

```
[ ]: array(['Resort', 'Guest House', 'Cottage', 'Hotel', 'Homestay', 'Villa',
            'Palace', 'Lodge', 'Houseboat', 'Service Apartment', 'BnB',
            'Hostel', 'Bungalow', 'Tent', 'Luxury Yacht', 'Motel', 'Beach Hut',
            'Farm Stay'], dtype=object)
```

```
[ ]: data_COUNT_ENC['property_type'].unique()
```

```
[ ]: array([ 516,  243,   75, 2314,  231,   49,   11,  117,   78,  183,   10,
              46,   57,    3,    9,    2,    7])
```

```
[ ]: ce_CountEncoder2 = ce_CountEncoder(normalize=True)
     data_FREQ_ENC = ce_CountEncoder2.fit_transform(data[data.columns.
      ↪difference(['uniq_id'])])
```

```
[ ]: data_FREQ_ENC
```

```
[ ]:          city  crawl_date  guest_recommendation  property_name  property_type  \
     0     0.01750     0.24400             85.000000        0.00025        0.12900
     1     0.02525     0.24400             87.000000        0.00025        0.06075
     2     0.05500     0.24400             50.000000        0.00025        0.12900
     3     0.01750     0.24400            100.000000        0.00025        0.01875
     4     0.03425     0.24400             63.000000        0.00025        0.57850
     …         …          …                    …              …              …
     3995  0.00400     0.19975             75.537666        0.00025        0.57850
     3996  0.01550     0.19975             75.537666        0.00050        0.57850
     3997  0.01625     0.19975             83.000000        0.00025        0.57850
     3998  0.00075     0.19975             75.537666        0.00050        0.57850
     3999  0.00025     0.19975             50.000000        0.00025        0.57850

           sitename
     0          1.0
     1          1.0
     2          1.0
     3          1.0
     4          1.0
     …          …
     3995       1.0
     3996       1.0
     3997       1.0
     3998       1.0
     3999       1.0

     [4000 rows x 6 columns]
```

```
[ ]: data_FREQ_ENC['property_type'].unique()
```

```
[ ]: array([1.290e-01, 6.075e-02, 1.875e-02, 5.785e-01, 5.775e-02, 1.225e-02,
            2.750e-03, 2.925e-02, 1.950e-02, 4.575e-02, 2.500e-03, 1.150e-02,
            1.425e-02, 7.500e-04, 2.250e-03, 5.000e-04, 1.750e-03])
```

1.3 №21

( ) .

1.4

```
[ ]: boston_dataset = load_breast_cancer()
     data = pd.DataFrame(boston_dataset.data,
                         columns=boston_dataset.feature_names)
     data['Y'] = boston_dataset.target
     data.shape
```

```
[ ]: (569, 31)
```

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

```
[ ]:    mean radius  mean texture  mean perimeter  mean area  mean smoothness  \
     0        17.99         10.38          122.80     1001.0          0.11840
     1        20.57         17.77          132.90     1326.0          0.08474
     2        19.69         21.25          130.00     1203.0          0.10960
     3        11.42         20.38           77.58      386.1          0.14250
     4        20.29         14.34          135.10     1297.0          0.10030

        mean compactness  mean concavity  mean concave points  mean symmetry  \
     0           0.27760          0.3001              0.14710         0.2419
     1           0.07864          0.0869              0.07017         0.1812
     2           0.15990          0.1974              0.12790         0.2069
     3           0.28390          0.2414              0.10520         0.2597
     4           0.13280          0.1980              0.10430         0.1809

        mean fractal dimension  …  worst texture  worst perimeter  worst area  \
     0                 0.07871  …          17.33           184.60      2019.0
     1                 0.05667  …          23.41           158.80      1956.0
     2                 0.05999  …          25.53           152.50      1709.0
     3                 0.09744  …          26.50            98.87       567.7
     4                 0.05883  …          16.67           152.20      1575.0

        worst smoothness  worst compactness  worst concavity  worst concave points  \
     0            0.1622             0.6656           0.7119                0.2654
     1            0.1238             0.1866           0.2416                0.1860
     2            0.1444             0.4245           0.4504                0.2430
     3            0.2098             0.8663           0.6869                0.2575
     4            0.1374             0.2050           0.4000                0.1625
```

```
   worst symmetry  worst fractal dimension  Y
0          0.4601                  0.11890  0
1          0.2750                  0.08902  0
2          0.3613                  0.08758  0
3          0.6638                  0.17300  0
4          0.2364                  0.07678  0

[5 rows x 31 columns]
```

[ ]:
```
#
data.describe()
```

[ ]:
```
       mean radius  mean texture  mean perimeter    mean area  \
count   569.000000    569.000000      569.000000   569.000000
mean     14.127292     19.289649       91.969033   654.889104
std       3.524049      4.301036       24.298981   351.914129
min       6.981000      9.710000       43.790000   143.500000
25%      11.700000     16.170000       75.170000   420.300000
50%      13.370000     18.840000       86.240000   551.100000
75%      15.780000     21.800000      104.100000   782.700000
max      28.110000     39.280000      188.500000  2501.000000

       mean smoothness  mean compactness  mean concavity  mean concave points  \
count       569.000000        569.000000      569.000000           569.000000
mean          0.096360          0.104341        0.088799             0.048919
std           0.014064          0.052813        0.079720             0.038803
min           0.052630          0.019380        0.000000             0.000000
25%           0.086370          0.064920        0.029560             0.020310
50%           0.095870          0.092630        0.061540             0.033500
75%           0.105300          0.130400        0.130700             0.074000
max           0.163400          0.345400        0.426800             0.201200

       mean symmetry  mean fractal dimension  …  worst texture  \
count     569.000000              569.000000  …     569.000000
mean        0.181162                0.062798  …      25.677223
std         0.027414                0.007060  …       6.146258
min         0.106000                0.049960  …      12.020000
25%         0.161900                0.057700  …      21.080000
50%         0.179200                0.061540  …      25.410000
75%         0.195700                0.066120  …      29.720000
max         0.304000                0.097440  …      49.540000

       worst perimeter   worst area  worst smoothness  worst compactness  \
count       569.000000   569.000000        569.000000         569.000000
mean        107.261213   880.583128          0.132369           0.254265
std          33.602542   569.356993          0.022832           0.157336
min          50.410000   185.200000          0.071170           0.027290
```

```
25%         84.110000   515.300000          0.116600            0.147200
50%         97.660000   686.500000          0.131300            0.211900
75%        125.400000  1084.000000          0.146000            0.339100
max        251.200000  4254.000000          0.222600            1.058000

       worst concavity  worst concave points  worst symmetry  \
count       569.000000            569.000000      569.000000
mean          0.272188              0.114606        0.290076
std           0.208624              0.065732        0.061867
min           0.000000              0.000000        0.156500
25%           0.114500              0.064930        0.250400
50%           0.226700              0.099930        0.282200
75%           0.382900              0.161400        0.317900
max           1.252000              0.291000        0.663800

       worst fractal dimension           Y
count               569.000000  569.000000
mean                  0.083946    0.627417
std                   0.018061    0.483918
min                   0.055040    0.000000
25%                   0.071460    0.000000
50%                   0.080040    1.000000
75%                   0.092080    1.000000
max                   0.207500    1.000000

[8 rows x 31 columns]
```

[ ]:
```python
# DataFrame
X_ALL = data.drop('Y', axis=1)
```

[ ]:
```python
#
#
def arr_to_df(arr_scaled):
    res = pd.DataFrame(arr_scaled, columns=X_ALL.columns)
    return res
```

[ ]:
```python
#
X_train, X_test, y_train, y_test = train_test_split(X_ALL, data['Y'],
                                                    test_size=0.2,
                                                    random_state=1)
#              DataFrame
X_train_df = arr_to_df(X_train)
X_test_df = arr_to_df(X_test)

X_train_df.shape, X_test_df.shape
```

[ ]: ((455, 30), (114, 30))

1.5

[ ]:
```
cs41 = RobustScaler()
data_cs41_scaled_temp = cs41.fit_transform(X_ALL)
#       DataFrame
data_cs41_scaled = arr_to_df(data_cs41_scaled_temp)
data_cs41_scaled.describe()
```

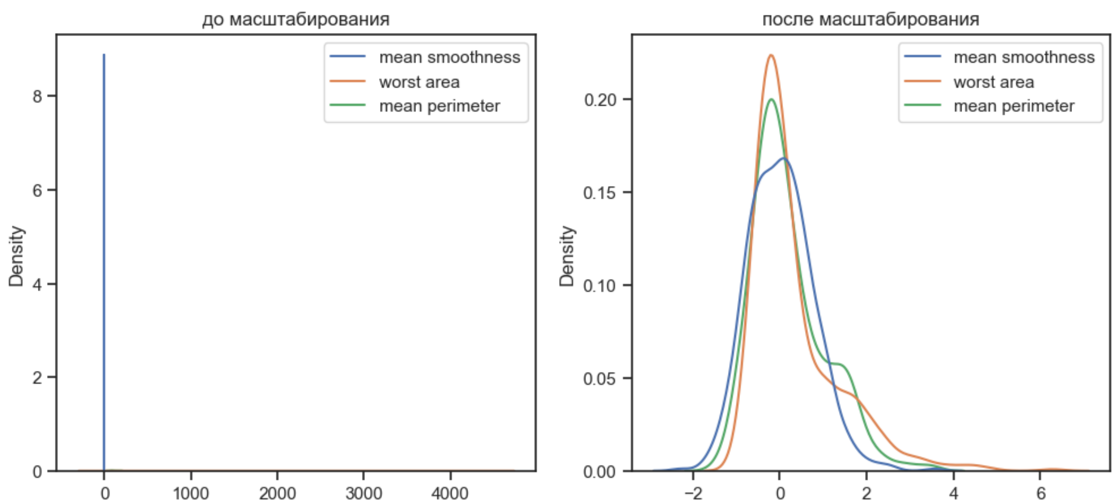
[ ]:
```
       mean radius  mean texture  mean perimeter   mean area  mean smoothness  \
count   569.000000    569.000000      569.000000  569.000000       569.000000
mean      0.185611      0.079867        0.198031    0.286394         0.025900
std       0.863737      0.763950        0.839923    0.971065         0.742954
min      -1.565931     -1.621670       -1.467335   -1.124724        -2.284205
25%      -0.409314     -0.474245       -0.382648   -0.360927        -0.501849
50%       0.000000      0.000000        0.000000    0.000000         0.000000
75%       0.590686      0.525755        0.617352    0.639073         0.498151
max       3.612745      3.630551        3.534739    5.380519         3.567353

       mean compactness  mean concavity  mean concave points  mean symmetry  \
count        569.000000      569.000000           569.000000     569.000000
mean           0.178848        0.269521             0.287188       0.058043
std            0.806548        0.788212             0.722720       0.811073
min           -1.118662       -0.608464            -0.623952      -2.165680
25%           -0.423183       -0.316195            -0.245670      -0.511834
50%            0.000000        0.000000             0.000000       0.000000
75%            0.576817        0.683805             0.754330       0.488166
max            3.860263        3.611430             3.123487       3.692308

       mean fractal dimension  …  worst radius  worst texture  \
count              569.000000  …    569.000000     569.000000
mean                 0.149360  …      0.224773       0.030929
std                  0.838523  …      0.836201       0.711372
min                 -1.375297  …     -1.217993      -1.549769
25%                 -0.456057  …     -0.339100      -0.501157
50%                  0.000000  …      0.000000       0.000000
75%                  0.543943  …      0.660900       0.498843
max                  4.263658  …      3.645329       2.792824

       worst perimeter  worst area  worst smoothness  worst compactness  \
count       569.000000  569.000000        569.000000         569.000000
mean          0.232531    0.341275          0.036347           0.220766
std           0.813818    1.001155          0.776613           0.819888
min          -1.144345   -0.881484         -2.045238          -0.962011
25%          -0.328167   -0.301037         -0.500000          -0.337155
50%           0.000000    0.000000          0.000000           0.000000
75%           0.671833    0.698963          0.500000           0.662845
max           3.718576    6.273079          3.105442           4.409067
```

```
       worst concavity  worst concave points  worst symmetry  \
count       569.000000            569.000000      569.000000
mean          0.169480              0.152133        0.116675
std           0.777289              0.681376        0.916555
min          -0.844635             -1.035866       -1.862222
25%          -0.418033             -0.362807       -0.471111
50%           0.000000              0.000000        0.000000
75%           0.581967              0.637193        0.528889
max           3.820045              1.980616        5.653333

       worst fractal dimension
count               569.000000
mean                  0.189419
std                   0.875910
min                  -1.212415
25%                  -0.416101
50%                   0.000000
75%                   0.583899
max                   6.181377

[8 rows x 30 columns]
```

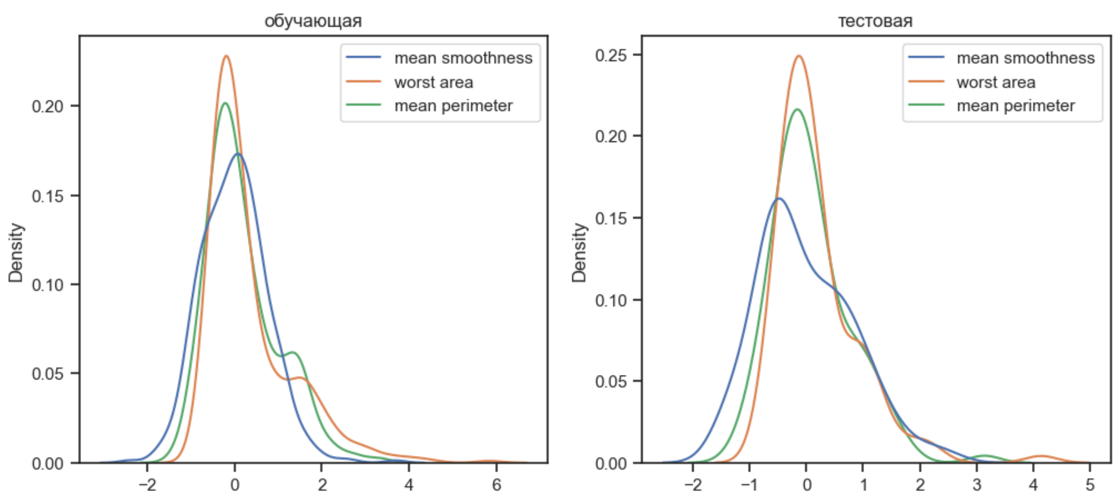
[ ]:
```
cs42 = RobustScaler()
cs42.fit(X_train)
data_cs42_scaled_train_temp = cs42.transform(X_train)
data_cs42_scaled_test_temp = cs42.transform(X_test)
#       DataFrame
data_cs42_scaled_train = arr_to_df(data_cs42_scaled_train_temp)
data_cs42_scaled_test = arr_to_df(data_cs42_scaled_test_temp)
```

[ ]:
```
#
def draw_kde(col_list, df1, df2, label1, label2):
    fig, (ax1, ax2) = plt.subplots(
        ncols=2, figsize=(12, 5))
    #
    ax1.set_title(label1)
    sns.kdeplot(data=df1[col_list], ax=ax1)
    #
    ax2.set_title(label2)
    sns.kdeplot(data=df2[col_list], ax=ax2)
    plt.show()
```

[ ]:
```
draw_kde(['mean smoothness', 'worst area', 'mean perimeter'], data,␣
 ↪data_cs41_scaled, '           ', '            ')
```




```
[ ]: draw_kde(['mean smoothness', 'worst area', 'mean perimeter'],␣
      ↪data_cs42_scaled_train, data_cs42_scaled_test, '      ', '      ')
```

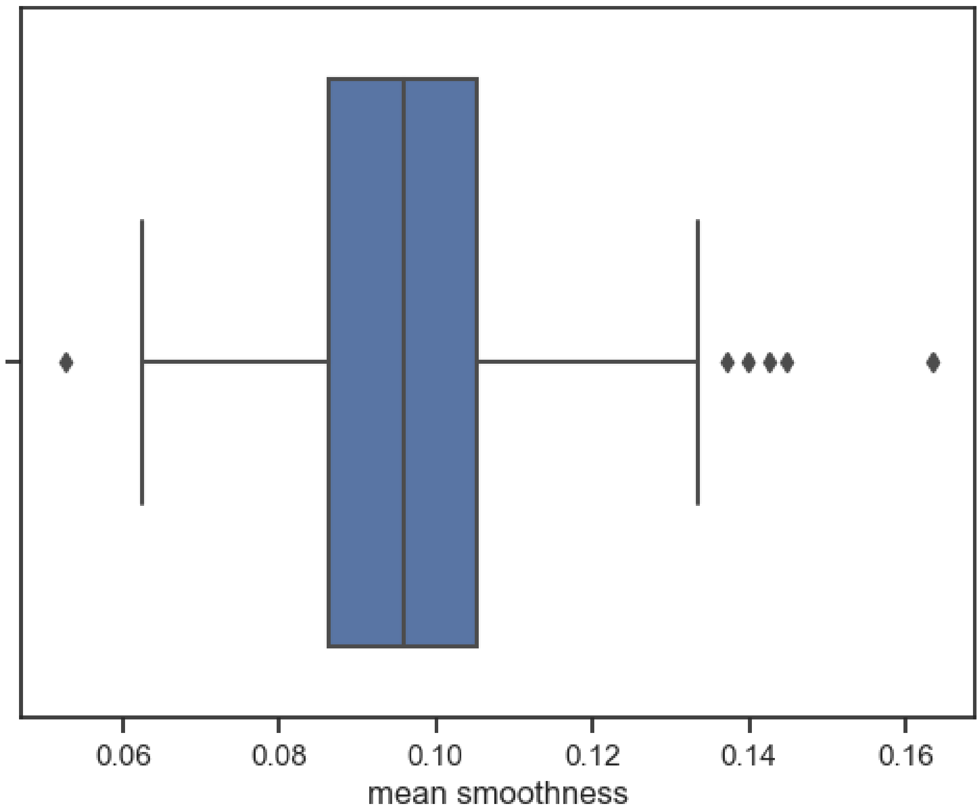


1.6

5-23 ,   5 -23 -   “   (boxplot)”.

```
[ ]: sns.boxplot(data=data, x="mean smoothness")
```

```
[ ]: <Axes: xlabel='mean smoothness'>
```


0.06
0.08
0.10
0.12
0.14
0.16
mean smoothness