

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	<a href="https://www.goibibo.com/hotels/woodchime-homes...">https://www.goibibo.com/hotels/woodchime-homes...</a>	87.0	
1	<a href="https://www.goibibo.com/hotels/stepinn-iffco-c...">https://www.goibibo.com/hotels/stepinn-iffco-c...</a>	8.0	
2	<a href="https://www.goibibo.com/hotels/sunrise-beach-r...">https://www.goibibo.com/hotels/sunrise-beach-r...</a>	2.0	
3	<a href="https://www.goibibo.com/hotels/green-cottages-...">https://www.goibibo.com/hotels/green-cottages-...</a>	1.0	
4	<a href="https://www.goibibo.com/hotels/delhi-continent...">https://www.goibibo.com/hotels/delhi-continent...</a>	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    Bevvann 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](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]

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

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

```
[ ]: #
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

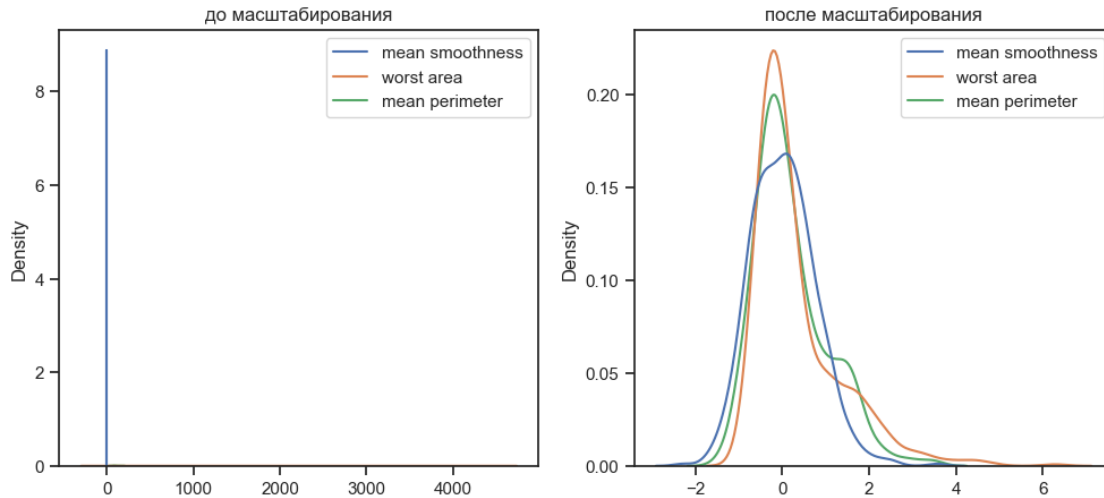
	worst fractal dimension
count	569.000000
mean	0.189419
std	0.875910
min	-1.212415
25%	-0.416101
50%	0.000000
75%	0.583899
max	6.181377

[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)
```

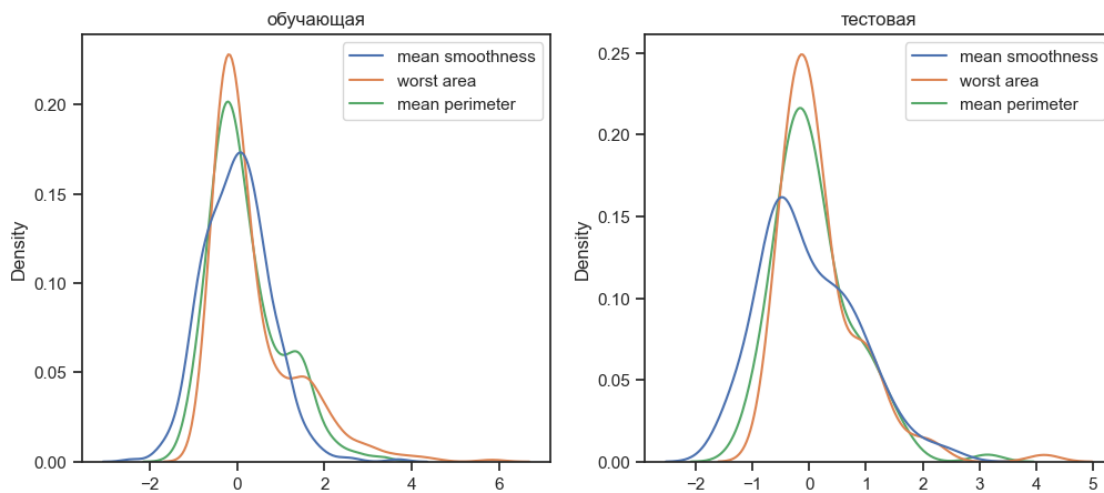
```
[ ]: #
def draw_kde(col_list, df1, df2, label1, label2):
    fig, (ax1, ax2) = plt.subplots(
        ncols=2, figsize=(12, 5))
    #
    ax1.set_title(label1)
    sns.kdeplot(data=df1[col_list], ax=ax1)
    #
    ax2.set_title(label2)
    sns.kdeplot(data=df2[col_list], ax=ax2)
    plt.show()
```

```
[ ]: 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'>

```

