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Лабораторная работа №3
по дисциплине
«Методы машинного обучения»
на тему
«Обработка пропусков в данных, кодирование категориальных признаков, масштабирование данных.»

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```python
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
sns.set(style="ticks")
```

```python
data = pd.read_csv('data/restaurant-scores-lives-standard.csv',
sep=",")
```

```python
data.shape
```

```
(53973, 17)
```

```python
data.dtypes
```

```
business_id                int64
business_name             object
business_address          object
business_city             object
business_state            object
business_postal_code      object
business_latitude        float64
business_longitude       float64
business_location         object
business_phone_number    float64
inspection_id             object
inspection_date           object
inspection_score         float64
inspection_type           object
violation_id              object
violation_description     object
risk_category             object
dtype: object
```

```python
data.isnull().sum()
```

```
business_id                  0
business_name                0
business_address             0
business_city                0
```

```
business_state              0
business_postal_code     1083
business_latitude       24095
business_longitude      24095
business_location       24095
business_phone_number   36539
inspection_id               0
inspection_date             0
inspection_score        14114
inspection_type             0
violation_id            13462
violation_description   13462
risk_category           13462
dtype: int64
```

```
data.head()
```

Out[8]:

	business_id	business_name	business_address	business_city	business_state	business_postal_code	business_latitude	business_lon
0	69618	Fancy Wheatfield Bakery	1362 Stockton St	San Francisco	CA	94133	NaN	
1	97975	BREADBELLY	1408 Clement St	San Francisco	CA	94118	NaN	
2	69487	Hakkasan San Francisco	1 Kearny St	San Francisco	CA	94108	NaN	
3	91044	Chopsticks Restaurant	4615 Mission St	San Francisco	CA	94112	NaN	
4	85987	Tselogs	552 Jones St	San Francisco	CA	94102	NaN	

1 Обработка пропусков в данных

```
# Удаление колонок, содержащих пустые значения
data_new_1 = data.dropna(axis=1, how='any')
(data.shape, data_new_1.shape)
print(f'Удалено колонок: {data.shape[1] - data_new_1.shape[1]}')
```

```
Удалено колонок: 9
```

```python
# Удаление строк, содержащих пустые значения
data_new_2 = data.dropna(axis=0, how='any')
(data.shape, data_new_2.shape)
print(f'Удалено строк: {data.shape[0] - data_new_2.shape[0]}')
```

```
Удалено строк: 48262
```

1.1 Обработка пропусков в числовых данных

```python
rows_count = data.shape[0]
num_cols = []
for col in data.columns:
    # Количество пустых значений
    temp_null_count = data[data[col].isnull()].shape[0]
    dt = str(data[col].dtype)
    if temp_null_count > 0 and (dt=='float64' or dt=='int64'):
        num_cols.append(col)
        temp_perc = round((temp_null_count / rows_count) * 100.0, 2)
        print('Колонка {}. Тип данных {}. Количество пустых значений
{}, {}%.'.format(col, dt, temp_null_count, temp_perc))
```

```
Колонка business_latitude. Тип данных float64. Количество пустых
значений 24095, 44.64%.
Колонка business_longitude. Тип данных float64. Количество пустых
значений 24095, 44.64%.
Колонка business_phone_number. Тип данных float64. Количество пустых
значений 36539, 67.7%.
Колонка inspection_score. Тип данных float64. Количество пустых
значений 14114, 26.15%.
```

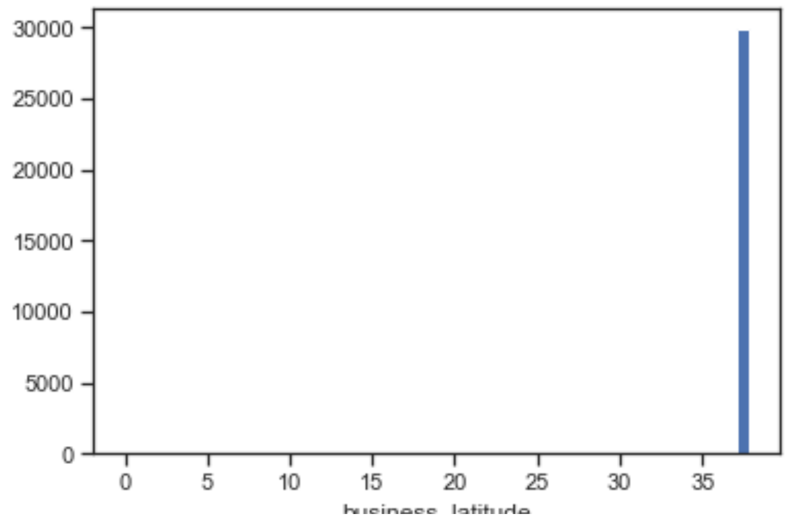
```python
# Фильтр по колонкам с пропущенными значениями
data_num = data[num_cols]
data_num
```

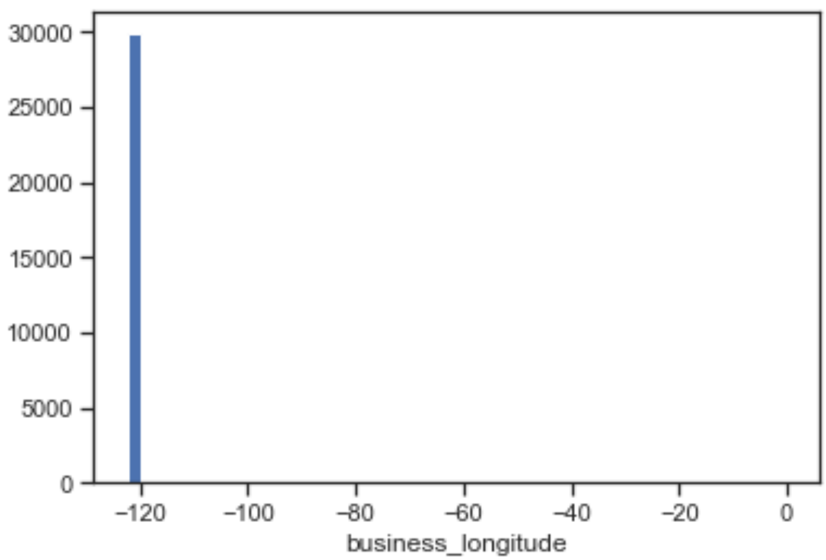
Out[19]:

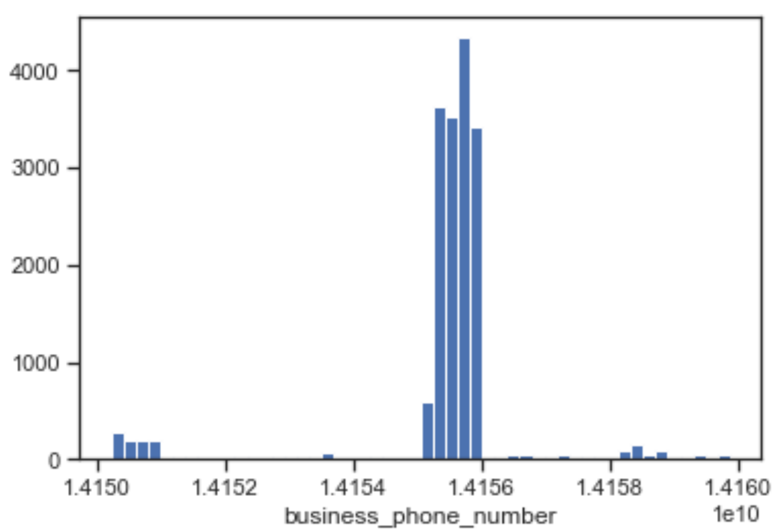
	business_latitude	business_longitude	business_phone_number	inspection_score
0	NaN	NaN	NaN	NaN
1	NaN	NaN	1.415724e+10	96.0
2	NaN	NaN	NaN	88.0
3	NaN	NaN	NaN	NaN
4	NaN	NaN	NaN	94.0
...	...	...	...	...
53968	NaN	NaN	1.415596e+10	94.0
53969	NaN	NaN	NaN	75.0
53970	NaN	NaN	1.415530e+10	84.0
53971	NaN	NaN	1.415544e+10	83.0
53972	NaN	NaN	1.415551e+10	NaN

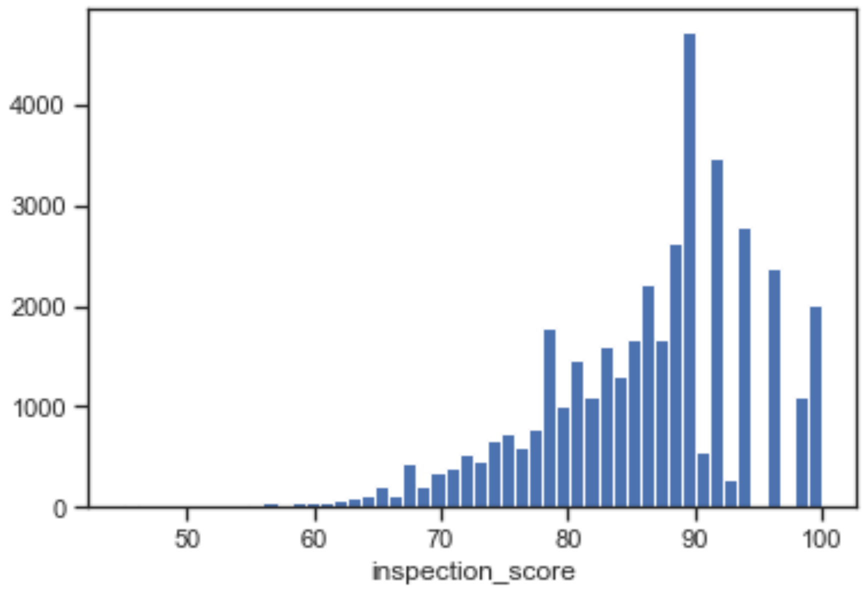
53973 rows × 4 columns

```
# Гистограмма по признакам
for col in data_num:
    plt.hist(data[col], 50)
    plt.xlabel(col)
    plt.show()
```


30000
25000
20000
15000
10000
5000
0
0
5
10
15
20
25
30
35


30000
25000
20000
15000
10000
5000
0
−120
−100
−80
−60
−40
−20
0
business_longitude


4000
3000
2000
1000
0
1.4150
1.4152
1.4154
1.4156
1.4158
1.4160
business_phone_number
1e10




```python
# Фильтр по пустым значениям поля inspection_score
data[data['inspection_score'].isnull()]
```

Out[27]:

	business_id	business_name	business_address	business_city	business_state	business_postal_code	business_latitude	business
0	69618	Fancy Wheatfield Bakery	1362 Stockton St	San Francisco	CA	94133	NaN	
3	91044	Chopsticks Restaurant	4615 Mission St	San Francisco	CA	94112	NaN	
5	96024	Fig & Thistle Market	691 14th St	San Francisco	CA	94114	NaN	
6	97503	Moscone South Main Kitchen	747 Howard St	San Francisco	CA	94103	NaN	
7	97748	FISTFUL OF TACOS	201 Harrison St Unit C-2	San Francisco	CA	94105	NaN	
...	...	...	...	...	...	...	...	
53955	94521	Joe & The Juice Howard	301 Howard St	San Francisco	CA	94105	NaN	
53957	81789	Koja Kitchen Truck	Off The Grid	San Francisco	CA	NaN	NaN	
53958	98279	LITTLE GEM	2184 UNION ST	San Francisco	CA	94123	NaN	
53961	99249	BLACK SANDS BREWERY	701 HAIGHT ST	San Francisco	CA	94117	NaN	
53972	77681	Tart To Tart Inc.	641 Irving St	San Francisco	CA	94122	NaN	

14114 rows × 17 columns

```
# Запоминаем индексы строк с пустыми значениями
flt_index = data[data['inspection_score'].isnull()].index
flt_index
```

```
Int64Index([    0,     3,     5,     6,     7,    10,    11,    13,
14,
               15,
            ...
            53932, 53936, 53941, 53945, 53950, 53955, 53957, 53958,
53961,
            53972],
           dtype='int64', length=14114)
```

```
# Проверяем что выводятся нужные строки
data[data.index.isin(flt_index)]
```

Out[26]:

	business_id	business_name	business_address	business_city	business_state	business_postal_code	business_latitude	business
0	69618	Fancy Wheatfield Bakery	1362 Stockton St	San Francisco	CA	94133	NaN	
3	91044	Chopsticks Restaurant	4615 Mission St	San Francisco	CA	94112	NaN	
5	96024	Fig & Thistle Market	691 14th St	San Francisco	CA	94114	NaN	
6	97503	Moscone South Main Kitchen	747 Howard St	San Francisco	CA	94103	NaN	
7	97748	FISTFUL OF TACOS	201 Harrison St Unit C-2	San Francisco	CA	94105	NaN	
...	...	...	...	...	...	...	...	
53955	94521	Joe & The Juice Howard	301 Howard St	San Francisco	CA	94105	NaN	
53957	81789	Koja Kitchen Truck	Off The Grid	San Francisco	CA	NaN	NaN	
53958	98279	LITTLE GEM	2184 UNION ST	San Francisco	CA	94123	NaN	
53961	99249	BLACK SANDS BREWERY	701 HAIGHT ST	San Francisco	CA	94117	NaN	
53972	77681	Tart To Tart Inc.	641 Irving St	San Francisco	CA	94122	NaN	

14114 rows × 17 columns

```python
# фильтр по колонке
data_num[data_num.index.isin(flt_index)]['inspection_score']
```

```
0        NaN
3        NaN
5        NaN
6        NaN
7        NaN
          ..
53955    NaN
53957    NaN
53958    NaN
53961    NaN
53972    NaN
Name: inspection_score, Length: 14114, dtype: float64
```

```python
data_num_inspection_score = data_num[['inspection_score']]
data_num_inspection_score.head()
```

	inspection_score
0	NaN
1	96.0
2	88.0
3	NaN
4	94.0

```python
from sklearn.impute import SimpleImputer
from sklearn.impute import MissingIndicator
```

```python
# Фильтр для проверки заполнения пустых значений
indicator = MissingIndicator()
mask_missing_values_only =
indicator.fit_transform(data_num_inspection_score)
mask_missing_values_only
```

```
array([[ True],
       [False],
       [False],
       ...,
       [False],
```

```
       [False],
       [ True]])
```

```python
strategies=['mean', 'median','most_frequent']

def test_num_impute_col(dataset, column, strategy_param):
    temp_data = dataset[[column]]

    indicator = MissingIndicator()
    mask_missing_values_only = indicator.fit_transform(temp_data)

    imp_num = SimpleImputer(strategy=strategy_param)
    data_num_imp = imp_num.fit_transform(temp_data)

    filled_data = data_num_imp[mask_missing_values_only]

    return column, strategy_param, filled_data.size, filled_data[0],
filled_data[filled_data.size-1]

data[['inspection_score']].describe()
```

Out[63]:

	inspection_score
count	39859.000000
mean	86.235254
std	8.480003
min	45.000000
25%	81.000000
50%	88.000000
75%	92.000000
max	100.000000

```
for strategy in strategies:
    print(test_num_impute_col(data, 'inspection_score', strategy))
    print(test_num_impute_col(data, 'business_latitude', strategy))
    print(test_num_impute_col(data, 'business_longitude', strategy),
end='\n\n')
```

```
('inspection_score', 'mean', 14114, 86.23525427130636,
86.23525427130636)
('business_latitude', 'mean', 24095, 37.7552651997791,
37.7552651997791)
('business_longitude', 'mean', 24095, -122.37375472595221,
-122.37375472595221)


('inspection_score', 'median', 14114, 88.0, 88.0)
('business_latitude', 'median', 24095, 37.780174, 37.780174)
('business_longitude', 'median', 24095, -122.41913600000001,
-122.41913600000001)


('inspection_score', 'most_frequent', 14114, 90.0, 90.0)
('business_latitude', 'most_frequent', 24095, 37.808240000000005,
37.808240000000005)
('business_longitude', 'most_frequent', 24095, -122.41018899999999,
-122.41018899999999)
```

1.2 Обработка пропусков в категориальных данных

```
cat_cols = []
for col in data.columns:
    # Количество пустых значений
    temp_null_count = data[data[col].isnull()].shape[0]
    dt = str(data[col].dtype)
    if temp_null_count>0 and (dt=='object'):
        cat_cols.append(col)
        temp_perc = round((temp_null_count / rows_count) * 100.0, 2)
        print('Колонка {}. Тип данных {}. Количество пустых значений
{}, {}%.'.format(col, dt, temp_null_count, temp_perc))
```

```
Колонка business_postal_code. Тип данных object. Количество пустых
значений 1083, 2.01%.
Колонка business_location. Тип данных object. Количество пустых
```

```
значений 24095, 44.64%.
Колонка violation_id. Тип данных object. Количество пустых значений
13462, 24.94%.
Колонка violation_description. Тип данных object. Количество пустых
значений 13462, 24.94%.
Колонка risk_category. Тип данных object. Количество пустых значений
13462, 24.94%.
```

```
cat_temp_data = data[['risk_category']]
```

```
cat_temp_data['risk_category'].unique()
```

```
array(['Moderate Risk', nan, 'Low Risk', 'High Risk'], dtype=object)
```

```
cat_temp_data[cat_temp_data['risk_category'].isnull()].shape
```

```
(13462, 1)
```

```
# Импьютация наиболее частыми значениями
imp2 = SimpleImputer(missing_values=np.nan, strategy='most_frequent')
data_imp2 = imp2.fit_transform(cat_temp_data)
data_imp2
```

```
array([['Moderate Risk'],
       ['Moderate Risk'],
       ['Moderate Risk'],
       ...,
       ['Moderate Risk'],
       ['High Risk'],
       ['Low Risk']], dtype=object)
```

```
# Пустые значения отсутствуют
np.unique(data_imp2)
```

```
array(['High Risk', 'Low Risk', 'Moderate Risk'], dtype=object)
```

```
# Импьютация константой
imp3 = SimpleImputer(missing_values=np.nan, strategy='constant',
fill_value='Unknown')
data_imp3 = imp3.fit_transform(cat_temp_data)
data_imp3
```

```
array([['Moderate Risk'],
       ['Moderate Risk'],
```

```
       ['Moderate Risk'],
       ...,
       ['Moderate Risk'],
       ['High Risk'],
       ['Unknown']], dtype=object)
```

```
np.unique(data_imp3)
```

```
array(['High Risk', 'Low Risk', 'Moderate Risk', 'Unknown'],
dtype=object)
```

```
data_imp3[data_imp3=='Unknown'].size
```

```
13462
```

2 Преобразование категориальных признаков в числовые

```
cat_enc = pd.DataFrame({'c1':data_imp2.T[0]})
cat_enc
```

Out[77]:

	c1
0	Moderate Risk
1	Moderate Risk
2	Moderate Risk
3	Low Risk
4	Moderate Risk
...	...
53968	Low Risk
53969	Moderate Risk
53970	Moderate Risk
53971	High Risk
53972	Low Risk

53973 rows × 1 columns

2.1 Кодирование категорий целочисленными значениями

```
from sklearn.preprocessing import LabelEncoder, OneHotEncoder
```

```
le = LabelEncoder()
cat_enc_le = le.fit_transform(cat_enc['c1'])
cat_enc['c1'].unique()
```

```
array(['Moderate Risk', 'Low Risk', 'High Risk'], dtype=object)
```

```
np.unique(cat_enc_le)
```

```
array([0, 1, 2])
```

```
le.inverse_transform([0, 1, 2])
```

```
array(['High Risk', 'Low Risk', 'Moderate Risk'], dtype=object)
```

2.2 Кодирование категорий наборами бинарных значений

```
ohe = OneHotEncoder()
cat_enc_ohe = ohe.fit_transform(cat_enc[['c1']])
cat_enc.shape
```

```
(53973, 1)
```

```
cat_enc_ohe.shape
```

```
(53973, 3)
```

```
cat_enc_ohe
```

```
<53973x3 sparse matrix of type '<class 'numpy.float64'>'
    with 53973 stored elements in Compressed Sparse Row format>
```

```
cat_enc_ohe.todense()[0:10]
```

```
matrix([[0., 0., 1.],
        [0., 0., 1.],
        [0., 0., 1.],
        [0., 1., 0.],
        [0., 0., 1.],
        [0., 1., 0.],
```

```
       [0., 1., 0.],
       [0., 1., 0.],
       [0., 1., 0.],
       [0., 1., 0.]])
```

2.3 Быстрый вариант one-hot кодирования

```
pd.get_dummies(cat_enc).head()
```

Out[88]:

	c1_High Risk	c1_Low Risk	c1_Moderate Risk
0	0	0	1
1	0	0	1
2	0	0	1
3	0	1	0
4	0	0	1

```
pd.get_dummies(cat_temp_data, dummy_na=True).head()
```

Out[89]:

	risk_category_High Risk	risk_category_Low Risk	risk_category_Moderate Risk	risk_category_nan
0	0	0	1	0
1	0	0	1	0
2	0	0	1	0
3	0	0	0	1
4	0	0	1	0

3 Масштабирование данных

Заменяю пропуски в колонке 'inspection_score' исходного датасета, чтобы использовать ее для масштабирования/нормализации

```
def num_impute_col(dataset, column, strategy_param):
    temp_data = dataset[[column]]

    indicator = MissingIndicator()
    mask_missing_values_only = indicator.fit_transform(temp_data)

    imp_num = SimpleImputer(strategy=strategy_param)
    data_num_imp = imp_num.fit_transform(temp_data)
#     data_num_imp = imp_num.fit_transform(dataset[[column]])

    filled_data = data_num_imp[mask_missing_values_only]

    new_data = imp_num.transform(dataset[[column]])

    return new_data
```

```
num_impute_col(data, 'inspection_score', 'mean')
```

```
array([[86.23525427],
       [96.        ],
       [88.        ],
       ...,
       [84.        ],
       [83.        ],
       [86.23525427]])
```

```
data[['inspection_score']] = num_impute_col(data, 'inspection_score',
'mean')
```

```
data[['inspection_score']]
```

Out[116]:

	inspection_score
0	86.235254
1	96.000000
2	88.000000
3	86.235254
4	94.000000
...	...
53968	94.000000
53969	75.000000
53970	84.000000
53971	83.000000
53972	86.235254

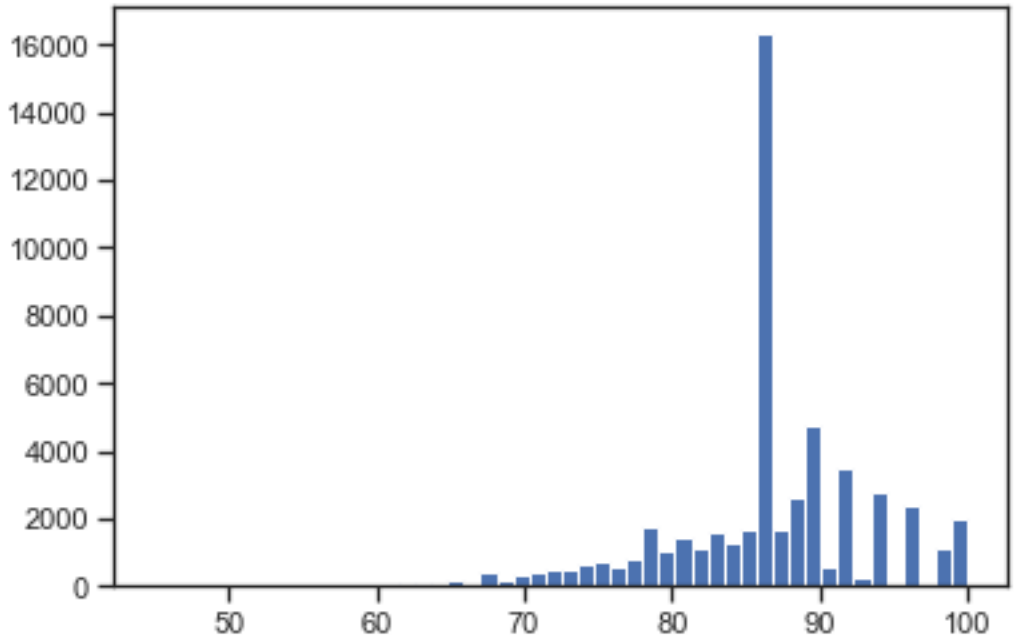
53973 rows × 1 columns

3.1 MinMax масштабирование

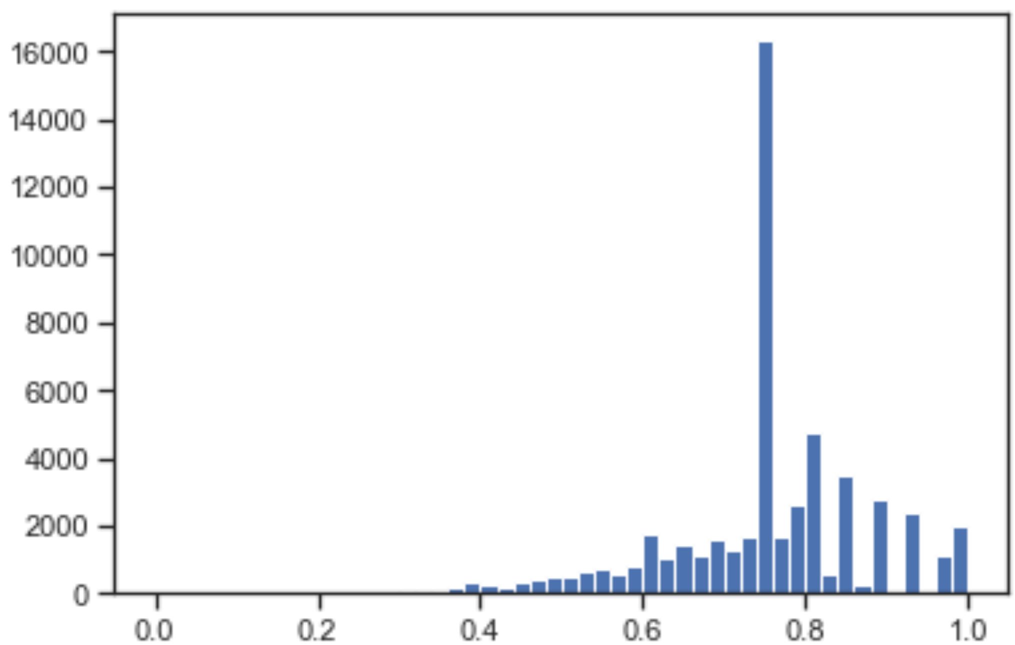
```
from sklearn.preprocessing import MinMaxScaler, StandardScaler,
Normalizer

sc1 = MinMaxScaler()
sc1_data = sc1.fit_transform(data[['inspection_score']])

plt.hist(data['inspection_score'], 50)
plt.show()
```




```
plt.hist(sc1_data, 50)
plt.show()
```

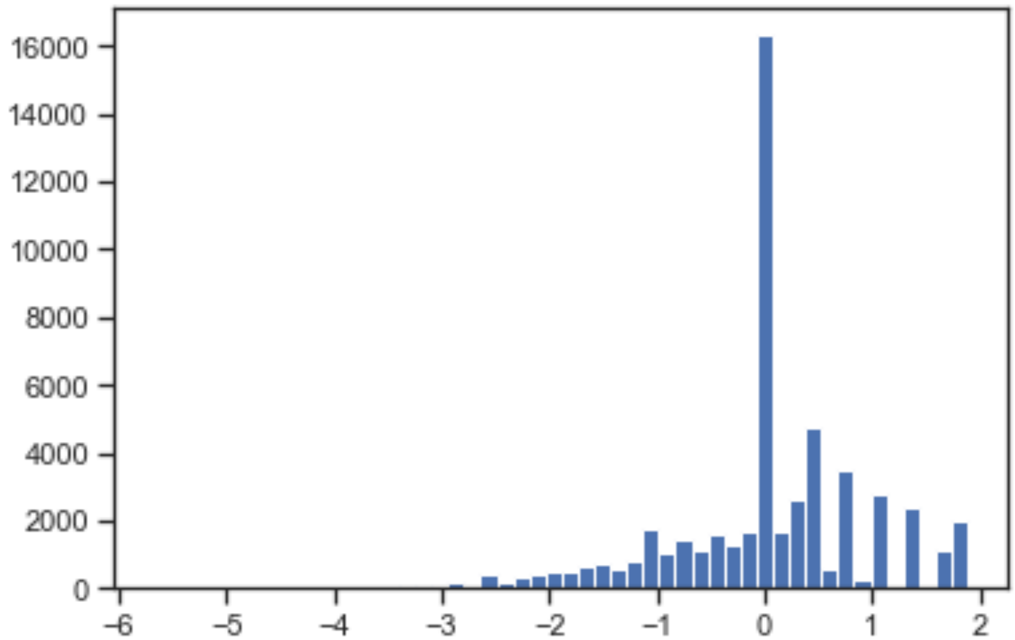


3.2 Масштабирование данных на основе Z-оценки

```
sc2 = StandardScaler()
sc2_data = sc2.fit_transform(data[['inspection_score']])

plt.hist(sc2_data, 50)
plt.show()
```

3.3.



Нормализация данных

```
sc3 = Normalizer()
sc3_data = sc3.fit_transform(data[['inspection_score']])

plt.hist(sc3_data, 50)
plt.show()
```