1. Лабороторная работа. Обработка пропусков в данных, кодирование категориальных признаков, масштабирование данных. ## Цель лабораторной работы: изучение способов предварительной обработки данных для дальнейшего формирования моделей.

Требования к отчету:

Отчет по лабораторной работе должен содержать: **1.**титульный лист; **2.**описание задания; **3.**текст программы;

```
4. экранные формы с примерами выполнения программы.
```

Задание:

```
1.Выбрать набор данных (датасет), содержащий категориальные признаки и пропуски в данных. Для выполнения следующих пунктов можно использовать не
сколько различных наборов данных (один для обработки пропусков, другой для категориальных признаков и т.д.)
2.Для выбранного датасета (датасетов) на основе материалов лекции решить следующие задачи:
    2.1 обработку пропусков в данных;
    2.2 кодирование категориальных признаков;
    2.3 масштабирование данных.
```

Ход работы:

In [6]:

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

В качестве датасета будем использовать данные о птицах и их средах обитания с некоторыми пропущенными значениями.

In [7]:

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

In [8]:

```
data.shape
```

Out[8]:

```
(420, 12)
```

In [9]:

```
data.dtypes
```

Out[9]:

```
id         int64
huml     float64
humw     float64
ulnal    float64
ulnaw    float64
feml     float64
femw     float64
tibl     float64
tibw     float64
tarl     float64
tarw      object
type      object
dtype: object
```

Посмотрим датасет на наличие пропусков

In [10]:

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

Out[10]:

```
id       0
huml     1
humw     1
ulnal    3
ulnaw    2
feml     2
femw     1
tibl     2
tibw     1
tarl     1
tarw     1
type     0
dtype: int64
```

Проверим правильность загрузки данных

In [11]:

```
data.head()
```

Out[11]:

	id	huml	humw	ulnal	ulnaw	feml	femw	tibl	tibw	tarl	tarw	type
0	0	80.78	6.68	72.01	4.88	41.81	3.70	5.50	4.03	38.70	'?'	SW

	id	huml	humw	ulnal	ulnaw	feml	femw	tibl	tibw	tarl	tarw	type
1	1	88.91	6.63	80.53	5.59	47.04	4.30	80.22	4.51	41.50	4.01	SW
2	2	79.97	6.37	69.26	5.28	43.07	3.90	75.35	4.04	38.31	3.34	SW
3	3	77.65	5.70	65.76	4.77	40.04	3.52	69.17	3.40	35.78	3.41	SW
4	4	62.80	4.84	52.09	3.73	33.95	2.72	56.27	2.96	31.88	3.13	SW

Обработка пропусков:

1. Удаление колонок с пустыми значениями

In [12]:

```
data_new_1 = data.dropna(axis=1, how='any')
(data.shape, data_new_1.shape)
```

Out[12]:

```
((420, 12), (420, 2))
```

2) Удаление строк, содержащих пустые значения

In [13]:

```
data_new_2 = data.dropna(axis=0, how='any')
(data.shape, data_new_2.shape)
```

Out[13]:

```
((420, 12), (413, 12))
```

3) Заполнение всех пустых значений 0

In [14]:

```
data_new_3 = data.fillna(0)
data_new_3.head()
```

Out[14]:

	id	huml	humw	ulnal	ulnaw	feml	femw	tibl	tibw	tarl	tarw	type
0	0	80.78	6.68	72.01	4.88	41.81	3.70	5.50	4.03	38.70	'?'	SW
1	1	88.91	6.63	80.53	5.59	47.04	4.30	80.22	4.51	41.50	4.01	SW
2	2	79.97	6.37	69.26	5.28	43.07	3.90	75.35	4.04	38.31	3.34	SW
3	3	77.65	5.70	65.76	4.77	40.04	3.52	69.17	3.40	35.78	3.41	SW
4	4	62.80	4.84	52.09	3.73	33.95	2.72	56.27	2.96	31.88	3.13	SW

"Внедрение значений" - импьютация

Обработка пропусков в числовых данных

Выведем информацию по числовым колонкам, содержащим пустые значения:

In [15]:

```
num_cols = []
total_count = 205
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 / total_count) * 100.0, 2)
        print('Колонка {}. Тип данных {}. Количество пустых значений {}, {}%.'.format(col, dt, temp_null_count, temp_perc))
```

```
Колонка huml. Тип данных float64. Количество пустых значений 1, 0.49%.
Колонка humw. Тип данных float64. Количество пустых значений 1, 0.49%.
Колонка ulnal. Тип данных float64. Количество пустых значений 3, 1.46%.
Колонка ulnaw. Тип данных float64. Количество пустых значений 2, 0.98%.
Колонка feml. Тип данных float64. Количество пустых значений 2, 0.98%.
Колонка femw. Тип данных float64. Количество пустых значений 1, 0.49%.
Колонка tibl. Тип данных float64. Количество пустых значений 2, 0.98%.
Колонка tibw. Тип данных float64. Количество пустых значений 1, 0.49%.
Колонка tarl. Тип данных float64. Количество пустых значений 1, 0.49%.
```

In [16]:

```
data_num = data[num_cols]
data_num
```

Out[16]:

	huml	humw	ulnal	ulnaw	feml	femw	tibl	tibw	tarl
0	80.78	6.68	72.01	4.88	41.81	3.70	5.50	4.03	38.70
1	88.91	6.63	80.53	5.59	47.04	4.30	80.22	4.51	41.50
2	79.97	6.37	69.26	5.28	43.07	3.90	75.35	4.04	38.31
3	77.65	5.70	65.76	4.77	40.04	3.52	69.17	3.40	35.78
4	62.80	4.84	52.09	3.73	33.95	2.72	56.27	2.96	31.88
...	...	...	...	...	...	...	...	...	...
415	17.96	1.63	19.25	1.33	18.36	1.54	31.25	1.33	21.99
416	19.21	1.64	20.76	1.49	19.24	1.45	33.21	1.28	23.60
417	18.79	1.63	19.83	1.53	20.96	1.43	34.45	1.41	22.86
418	20.38	1.78	22.53	1.50	21.35	1.48	36.09	1.53	25.98

	huml	humw	ulnal	ulnaw	feml	femw	tibl	tibw	tarl
419	17.89	1.44	19.26	1.10	17.62	1.34	29.81	1.24	21.69

420 rows × 9 columns

Запоминаем индексы строк с пустыми значениями

In [17]:

```
flt_index = data[data['ulnal'].isnull()].index
flt_index
```

Out[17]:

```
Int64Index([204, 342, 378], dtype='int64')
```

Проверяем

In [19]:

```
data[data.index.isin(flt_index)]
```

Out[19]:

	id	huml	humw	ulnal	ulnaw	feml	femw	tibl	tibw	tarl	tarw	type
204	204	63.76	4.74	NaN	NaN	57.33	4.88	75.67	4.33	60.19	3.82	R
342	342	NaN	NaN	NaN	NaN	32.54	2.65	55.06	2.81	38.94	2.25	SO
378	378	20.10	1.86	NaN	1.52	17.21	1.22	NaN	NaN	18.46	0.91	SO

используем импьютацию из библиотеки **scikit-learn:**

In [20]:

```
data_num_price = data_num[['ulnal']]
data_num_price.head()
```

Out[20]:

	ulnal
0	72.01
1	80.53
2	69.26
3	65.76
4	52.09

In [21]:

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

Проверка**:**

In [22]:

```
indicator = MissingIndicator()
mask_missing_values_only = indicator.fit_transform(data_num_price)
mask_missing_values_only
```

Out[22]:

```
array([[False],
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```

Используем различные методы:

In [24]:

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

In [27]:

```
def test_num_impute(strategy_param):
    imp_num = SimpleImputer(strategy=strategy_param)
    data_num_imp = imp_num.fit_transform(data_num_price)
    return data_num_imp[mask_missing_values_only]
```

In [28]:

```
strategies[0], test_num_impute(strategies[0])
```

Out[28]:

```
('mean', array([69.1153717, 69.1153717, 69.1153717]))
```

In [29]:

```
strategies[1], test_num_impute(strategies[1])
```

Out[29]:

```
('median', array([43.71, 43.71, 43.71]))
```

In [30]:

```
strategies[2], test_num_impute(strategies[2])
```

Out[30]:

```
('most_frequent', array([142., 142., 142.]))
```

In [32]:

```
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]
```

In [33]:

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

Out[33]:

	ulnal
count	417.000000
mean	69.115372
std	58.784775
min	14.090000
25%	28.050000
50%	43.710000
75%	97.520000
max	422.000000

In [34]:

```
test_num_impute_col(data, 'ulnal', strategies[0])
```

Out[34]:

```
('ulnal', 'mean', 3, 69.1153717026379, 69.1153717026379)
```

In [35]:

```
test_num_impute_col(data, 'ulnal', strategies[1])
```

Out[35]:

```
('ulnal', 'median', 3, 43.71, 43.71)
```

In [36]:

```
test_num_impute_col(data, 'ulnal', strategies[2])
```

Out[36]:

```
('ulnal', 'most_frequent', 3, 142.0, 142.0)
```

Обработка пропусков категориальных данных

In [37]:

```
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 / total_count) * 100.0, 2)
        print('Колонка {}. Тип данных {}. Количество пустых значений {}, {}%.'.format(col, dt, temp_null_count, temp_perc))
```

```
Колонка tarw. Тип данных object. Количество пустых значений 1, 0.49%.
```

In [38]:

```
cat_temp_data = data[['tarw']]
cat_temp_data.head()
```

Out[38]:

	tarw
0	'?'
1	4.01
2	3.34
3	3.41
4	3.13

In [39]:

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

Out[39]:

```
array(["'?'", '4.01', '3.34', '3.41', '3.13', '2.83', '3.64', '3.81',
       '4.37', '6.34', '6.63', '4.59', '5.5', '4.24', '3.36', '3.52',
       '3.53', '3.28', '3.06', '3.35', '2.69', '4.25', '3.84', '1.97',
       '2.28', '10.73', '10.24', '9.45', '13.82', '14.09', '3.65', '6.51',
       '7.16', '6.3', '6.64', '6.41', '7.21', '8.91', '10.05', '4.82',
       '5.07', '6.7', '6.91', '5.1', '4.93', '6.02', '8.79', '8.23',
       '7.97', '8.41', '7.44', '7.87', '1.72', '1.77', '2.03', '7.69',
       '7.04', '8.93', '6.13', '7.55', '1.83', '2.52', '1.31', '2.82',
       '2.76', '1.13', '1.09', '1.2', '1.36', '0.83', '0.88', '1.92',
       '2.99', '3.33', '3.48', '3.22', '1.73', '1.56', '2.14', '2.23',
       '3.82', '4.07', '2.75', '2.94', '3.23', '2.66', '2.38', '2.47',
       '1.9', '1.99', '3.0', '2.89', '2.2', '3.12', '2.95', '2.0', '2.25',
       '1.63', '2.37', '2.05', '2.98', '3.03', '1.91', '2.22', '3.2',
       '2.08', '1.89', '6.77', '7.0', '3.02', '3.79', '4.74', '5.12',
       '4.14', '4.32', '4.57', '1.95', '1.93', '1.57', '1.54', '1.47',
       '4.36', '4.47', '2.19', '2.64', '2.12', '1.45', '1.25', '3.43',
       '3.45', '1.16', '2.84', '1.28', '2.72', '3.94', '3.1', '3.05',
       '4.11', '3.57', '3.25', '3.87', '4.33', '2.58', '3.63', '2.1',
       '2.48', '2.42', '2.53', '2.33', '1.7', '2.7', '1.71', '1.05',
       '1.01', '1.04', '1.26', '1.0', '2.34', '1.55', '2.51', '2.27',
       '2.45', '2.39', '2.49', '2.63', '5.66', '2.67', '7.96', '8.19',
       '2.86', '3.78', '3.86', nan, '3.29', '2.9', '7.11', '7.36', '6.1',
       '6.15', '5.11', '4.56', '5.29', '5.86', '6.8', '7.89', '6.06',
       '5.87', '6.97', '5.47', '5.63', '4.72', '5.99', '2.29', '9.64',
       '8.26', '8.88', '2.78', '2.61', '7.91', '8.25', '6.9', '6.92',
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```

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      dtype=object)
```

In [40]:

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

Out[40]:

```
(1, 1)
```

Импьютация наиболее частыми значениями

In [41]:

```
imp2 = SimpleImputer(missing_values=np.nan, strategy='most_frequent')
data_imp2 = imp2.fit_transform(cat_temp_data)
data_imp2
```

Out[41]:

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       ['1.05']], dtype=object)
```

In [42]:

```
np.unique(data_imp2)
```

Out[42]:

```
array(["'?'", '0.66', '0.69', '0.73', '0.74', '0.75', '0.78', '0.79',
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       '0.94', '0.96', '0.97', '0.98', '1.0', '1.01', '1.02', '1.04',
       '1.05', '1.06', '1.08', '1.09', '1.11', '1.12', '1.13', '1.14',
       '1.15', '1.16', '1.18', '1.2', '1.21', '1.22', '1.23', '1.24',
       '1.25', '1.26', '1.27', '1.28', '1.29', '1.31', '1.32', '1.33',
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       '1.55', '1.56', '1.57', '1.58', '1.6', '1.61', '1.62', '1.63',
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       '8.41', '8.79', '8.88', '8.91', '8.93', '9.45', '9.64'],
      dtype=object)
```

Импьютация константой:

In [43]:

```
imp3 = SimpleImputer(missing_values=np.nan, strategy='constant', fill_value='const')
data_imp3 = imp3.fit_transform(cat_temp_data)
data_imp3
```

Out[43]:

```
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       ['1.26'],
       ['1.14'],
       ['1.57'],
       ['1.43'],
       ['1.39'],
       ['1.47'],
       ['1.08'],
       ['0.88'],
       ['1.02'],
       ['1.04'],
       ['0.98'],
       ['1.18'],
       ['1.15'],
       ['1.27'],
       ['1.39'],
       ['1.23'],
       ['1.34'],
       ['0.81'],
       ['0.81'],
       ['0.74'],
       ['1.08'],
       ['1.32'],
       ['1.27'],
       ['1.24'],
       ['1.25'],
       ['1.02'],
       ['1.01'],
       ['1.15'],
       ['1.15'],
       ['1.21'],
       ['1.24'],
       ['1.05']], dtype=object)
```

Преобразование категориальных признаков в числовые:

In [44]:

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

Out[44]:

	c1
0	'?'
1	4.01
2	3.34
3	3.41
4	3.13
...	...
415	1.15
416	1.15
417	1.21
418	1.24
419	1.05

420 rows × 1 columns

Кодирование категорий целочисленными значениями

In [45]:

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

In [46]:

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

In [47]:

```
cat_enc['c1'].unique()
```

Out[47]:

```
array(["'?'", '4.01', '3.34', '3.41', '3.13', '2.83', '3.64', '3.81',
       '4.37', '6.34', '6.63', '4.59', '5.5', '4.24', '3.36', '3.52',
       '3.53', '3.28', '3.06', '3.35', '2.69', '4.25', '3.84', '1.97',
       '2.28', '10.73', '10.24', '9.45', '13.82', '14.09', '3.65', '6.51',
       '7.16', '6.3', '6.64', '6.41', '7.21', '8.91', '10.05', '4.82',
```

```
       '5.07', '6.7', '6.91', '5.1', '4.93', '6.02', '8.79', '8.23',
       '7.97', '8.41', '7.44', '7.87', '1.72', '1.77', '2.03', '7.69',
       '7.04', '8.93', '6.13', '7.55', '1.83', '2.52', '1.31', '2.82',
       '2.76', '1.13', '1.09', '1.2', '1.36', '0.83', '0.88', '1.92',
       '2.99', '3.33', '3.48', '3.22', '1.73', '1.56', '2.14', '2.23',
       '3.82', '4.07', '2.75', '2.94', '3.23', '2.66', '2.38', '2.47',
       '1.9', '1.99', '3.0', '2.89', '2.2', '3.12', '2.95', '2.0', '2.25',
       '1.63', '2.37', '2.05', '2.98', '3.03', '1.91', '2.22', '3.2',
       '2.08', '1.89', '6.77', '7.0', '3.02', '3.79', '4.74', '5.12',
       '4.14', '4.32', '4.57', '1.95', '1.93', '1.57', '1.54', '1.47',
       '4.36', '4.47', '2.19', '2.64', '2.12', '1.45', '1.25', '3.43',
       '3.45', '1.16', '2.84', '1.28', '2.72', '3.94', '3.1', '3.05',
       '4.11', '3.57', '3.25', '3.87', '4.33', '2.58', '3.63', '2.1',
       '2.48', '2.42', '2.53', '2.33', '1.7', '2.7', '1.71', '1.05',
       '1.01', '1.04', '1.26', '1.0', '2.34', '1.55', '2.51', '2.27',
       '2.45', '2.39', '2.49', '2.63', '5.66', '2.67', '7.96', '8.19',
       '2.86', '3.78', '3.86', '3.29', '2.9', '7.11', '7.36', '6.1',
       '6.15', '5.11', '4.56', '5.29', '5.86', '6.8', '7.89', '6.06',
       '5.87', '6.97', '5.47', '5.63', '4.72', '5.99', '2.29', '9.64',
       '8.26', '8.88', '2.78', '2.61', '7.91', '8.25', '6.9', '6.92',
       '2.43', '4.4', '4.95', '4.29', '4.38', '4.21', '3.15', '1.62',
       '1.88', '2.71', '3.04', '3.09', '2.16', '1.29', '1.52', '1.23',
       '3.6', '1.46', '2.06', '1.67', '1.78', '1.98', '1.53', '1.43',
       '1.64', '1.8', '1.24', '1.69', '1.79', '1.85', '2.41', '2.24',
       '2.54', '2.57', '1.37', '1.14', '1.4', '1.12', '1.51', '1.41',
       '1.48', '1.27', '1.18', '1.11', '1.32', '0.98', '0.92', '0.97',
       '1.6', '1.58', '1.76', '0.86', '0.94', '1.34', '1.81', '0.78',
       '1.22', '1.08', '0.96', '1.61', '0.75', '0.89', '0.8', '0.73',
       '0.69', '0.79', '0.66', '0.91', '1.02', '1.65', '1.06', '2.46',
       '1.39', '1.42', '1.33', '1.15', '0.81', '0.74', '1.21'],
      dtype=object)
```

In [48]:

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

Out[48]:

```
array([  0,   1,   2,   3,   4,   5,   6,   7,   8,   9,  10,  11,  12,
        13,  14,  15,  16,  17,  18,  19,  20,  21,  22,  23,  24,  25,
        26,  27,  28,  29,  30,  31,  32,  33,  34,  35,  36,  37,  38,
        39,  40,  41,  42,  43,  44,  45,  46,  47,  48,  49,  50,  51,
        52,  53,  54,  55,  56,  57,  58,  59,  60,  61,  62,  63,  64,
        65,  66,  67,  68,  69,  70,  71,  72,  73,  74,  75,  76,  77,
        78,  79,  80,  81,  82,  83,  84,  85,  86,  87,  88,  89,  90,
        91,  92,  93,  94,  95,  96,  97,  98,  99, 100, 101, 102, 103,
       104, 105, 106, 107, 108, 109, 110, 111, 112, 113, 114, 115, 116,
       117, 118, 119, 120, 121, 122, 123, 124, 125, 126, 127, 128, 129,
       130, 131, 132, 133, 134, 135, 136, 137, 138, 139, 140, 141, 142,
       143, 144, 145, 146, 147, 148, 149, 150, 151, 152, 153, 154, 155,
       156, 157, 158, 159, 160, 161, 162, 163, 164, 165, 166, 167, 168,
       169, 170, 171, 172, 173, 174, 175, 176, 177, 178, 179, 180, 181,
       182, 183, 184, 185, 186, 187, 188, 189, 190, 191, 192, 193, 194,
       195, 196, 197, 198, 199, 200, 201, 202, 203, 204, 205, 206, 207,
       208, 209, 210, 211, 212, 213, 214, 215, 216, 217, 218, 219, 220,
       221, 222, 223, 224, 225, 226, 227, 228, 229, 230, 231, 232, 233,
       234, 235, 236, 237, 238, 239, 240, 241, 242, 243, 244, 245, 246,
       247, 248, 249, 250, 251, 252, 253, 254, 255, 256, 257, 258, 259,
       260, 261, 262, 263, 264, 265, 266, 267, 268, 269, 270, 271, 272,
       273, 274, 275, 276, 277, 278, 279])
```

In [49]:

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

Out[49]:

```
array(["'?'", '0.66'], dtype=object)
```

Кодирование категорий наборами бинарных значений:

In [50]:

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

In [51]:

```
cat_enc.shape
```

Out[51]:

```
(420, 1)
```

In [52]:

```
cat_enc_ohe.shape
```

Out[52]:

```
(420, 280)
```

In [53]:

```
cat_enc_ohe
```

Out[53]:

```
<420x280 sparse matrix of type '<class 'numpy.float64'>'
 with 420 stored elements in Compressed Sparse Row format>
```

In [54]:

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

Out[54]:

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

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

In [55]:

```
cat_enc.head(10)
```

Out[55]:

	c1
0	'?'
1	4.01
2	3.34
3	3.41
4	3.13
5	2.83
6	3.64
7	3.81
8	4.37
9	6.34

Масштабирование данных

In [56]:

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

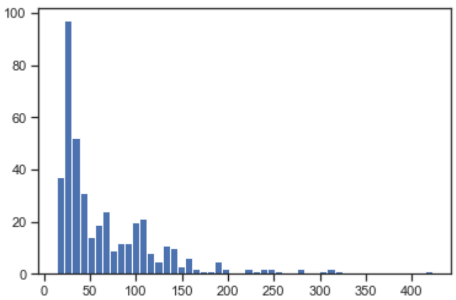
MinMax масштабирование

In [57]:

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

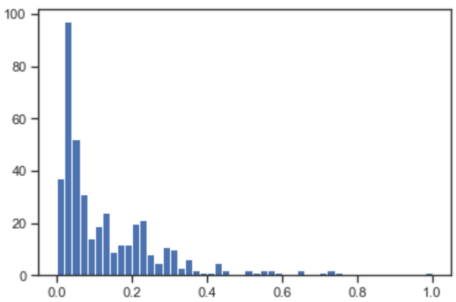
In [58]:

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



In [59]:

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



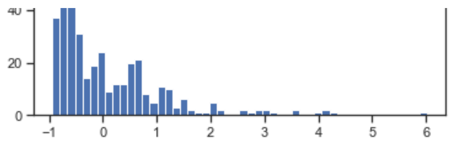
Масштабирование данных на основе Z-оценки

In [60]:

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

In [61]:

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



In [ ]: