In [1]:

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

In [2]:

```
data = pd.read_csv('C:/Users/maxim/OneDrive/Рабочий стол/ТМО/20222703 Causes Of Death Clean Output V2.0.csv', sep=",")
```

In [3]:

```
data.shape
```

Out[3]:

```
(201762, 6)
```

In [4]:

```
data.dtypes
```

Out[4]:

```
Causes name                 object
Causes Full Description     object
Death Numbers              float64
Entity                      object
Code                        object
Year                         int64
dtype: object
```

In [5]:

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

Out[5]:

```
Causes name                    0
Causes Full Description        0
Death Numbers              11187
Entity                         0
Code                        1485
Year                           0
dtype: int64
```

In [6]:

```
data.head()
```

Out[6]:

	Causes name	Causes Full Description	Death Numbers	Entity	Code	Year
0	Meningitis	Deaths - Meningitis - Sex: Both - Age: All Age...	2933.0	Afghanistan	AFG	2007
1	Neoplasms	Deaths - Neoplasms - Sex: Both - Age: All Ages...	15925.0	Afghanistan	AFG	2007
2	Fire, heat, and hot substances	Deaths - Fire, heat, and hot substances - Sex:...	481.0	Afghanistan	AFG	2007
3	Malaria	Deaths - Malaria - Sex: Both - Age: All Ages (...	393.0	Afghanistan	AFG	2007
4	Drowning	Deaths - Drowning - Sex: Both - Age: All Ages ...	2127.0	Afghanistan	AFG	2007

In [7]:

```
total_count = data.shape[0]
print('Всего строк: {}'.format(total_count))
```

```
Всего строк: 201762
```

In [8]:

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

Out[8]:

```
((201762, 6), (201762, 4))
```

In [9]:

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

Out[9]:

```
((201762, 6), (189630, 6))
```

In [10]:

```
data_new_1.head()
```

Out[10]:

	Causes name	Causes Full Description	Entity	Year
0	Meningitis	Deaths - Meningitis - Sex: Both - Age: All Age...	Afghanistan	2007
1	Neoplasms	Deaths - Neoplasms - Sex: Both - Age: All Ages...	Afghanistan	2007
2	Fire, heat, and hot substances	Deaths - Fire, heat, and hot substances - Sex:...	Afghanistan	2007
3	Malaria	Deaths - Malaria - Sex: Both - Age: All Ages (...	Afghanistan	2007
4	Drowning	Deaths - Drowning - Sex: Both - Age: All Ages ...	Afghanistan	2007

In [11]:

```
data_new_2.head()
```

Out[11]:

	Causes name	Causes Full Description	Death Numbers	Entity	Code	Year
0	Meningitis	Deaths - Meningitis - Sex: Both - Age: All Age...	2933.0	Afghanistan	AFG	2007
1	Neoplasms	Deaths - Neoplasms - Sex: Both - Age: All Ages...	15925.0	Afghanistan	AFG	2007
2	Fire, heat, and hot substances	Deaths - Fire, heat, and hot substances - Sex:...	481.0	Afghanistan	AFG	2007
3	Malaria	Deaths - Malaria - Sex: Both - Age: All Ages (...	393.0	Afghanistan	AFG	2007
4	Drowning	Deaths - Drowning - Sex: Both - Age: All Ages ...	2127.0	Afghanistan	AFG	2007

In [12]:

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

Out[12]:

	Causes name	Causes Full Description	Death Numbers	Entity	Code	Year
0	Meningitis	Deaths - Meningitis - Sex: Both - Age: All Age...	2933.0	Afghanistan	AFG	2007
1	Neoplasms	Deaths - Neoplasms - Sex: Both - Age: All Ages...	15925.0	Afghanistan	AFG	2007
2	Fire, heat, and hot substances	Deaths - Fire, heat, and hot substances - Sex:...	481.0	Afghanistan	AFG	2007
3	Malaria	Deaths - Malaria - Sex: Both - Age: All Ages (...	393.0	Afghanistan	AFG	2007
4	Drowning	Deaths - Drowning - Sex: Both - Age: All Ages ...	2127.0	Afghanistan	AFG	2007

In [13]:

```
# Выберем числовые колонки с пропущенными значениями
# Цикл по колонкам датасета
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 / total_count) * 100.0, 2)
        print('Колонка {}. Тип данных {}. Количество пустых значений {}, {}%.'.format(col, dt, temp_null_count, temp_perc))
```

Колонка Death Numbers. Тип данных float64. Количество пустых значений 11187, 5.54%.

In [14]:

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

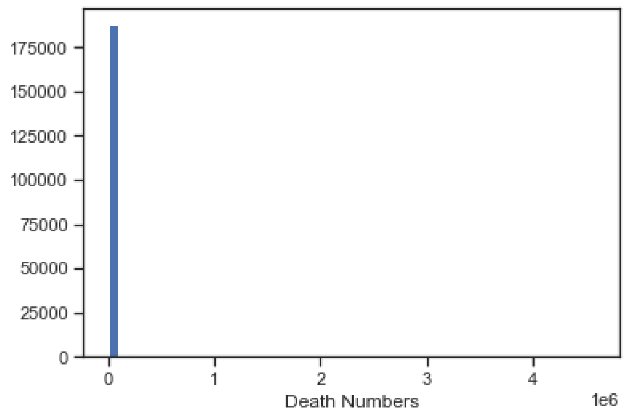
Out[14]:

	Death Numbers
0	2933.0
1	15925.0
2	481.0
3	393.0
4	2127.0
...	...
201757	4437.0
201758	136.0
201759	812.0
201760	232.0
201761	NaN

201762 rows × 1 columns

In [15]:

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



In [16]:

```
data_num_Death = data_num[['Death Numbers']]
data_num_Death.head()
```

Out[16]:

	Death Numbers
0	2933.0
1	15925.0
2	481.0
3	393.0
4	2127.0

In [17]:

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

In [18]:

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

Out[18]:

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

In [19]:

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

In [20]:

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

In [21]:

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

Out[21]:

```
('mean',
 array([8567.73583104, 8567.73583104, 8567.73583104, ..., 8567.73583104,
        8567.73583104, 8567.73583104]))
```

In [22]:

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

Out[22]:

```
('median', array([213., 213., 213., ..., 213., 213., 213.]))
```

In [23]:

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

Out[23]:

```
('most_frequent', array([0., 0., 0., ..., 0., 0., 0.]))
```

In [24]:

```
# Более сложная функция, ко т орая позволяе т задава т ь колонку и вид импью т ации
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 [25]:

```
data[['Death Numbers']].describe()
```

Out[25]:

	Death Numbers
count	1.905750e+05
mean	8.567736e+03
std	7.389484e+04
min	0.000000e+00
25%	1.400000e+01
50%	2.130000e+02
75%	1.919000e+03
max	4.584273e+06

In [26]:

```
test_num_impute_col(data, 'Death Numbers', strategies[0])
```

Out[26]:

```
('Death Numbers', 'mean', 11187, 8567.73583103765, 8567.73583103765)
```

In [27]:

```
test_num_impute_col(data, 'Death Numbers', strategies[1])
```

Out[27]:

```
('Death Numbers', 'median', 11187, 213.0, 213.0)
```

In [28]:

```
test_num_impute_col(data, 'Death Numbers', strategies[2])
```

Out[28]:

('Death Numbers', 'most_frequent', 11187, 0.0, 0.0)

In [29]:

```
# Выберем категориальные колонки с пропущенными значениями
# Цикл по колонкам датасета
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 Code. Тип данных object. Количество пустых значений 1485, 0.74%.

In [30]:

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

Out[30]:

	Code
0	AFG
1	AFG
2	AFG
3	AFG
4	AFG

In [31]:

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

Out[31]:

```
array(['AFG', 'ALB', 'DZA', nan, 'ASM', 'AND', 'AGO', 'ATG', 'ARG', 'ARM',
       'AUS', 'AUT', 'AZE', 'BHS', 'BHR', 'BGD', 'BRB', 'BLR', 'BEL',
       'BLZ', 'BEN', 'BMU', 'BTN', 'BOL', 'BIH', 'BWA', 'BRA', 'BRN',
       'BGR', 'BFA', 'BDI', 'KHM', 'CMR', 'CAN', 'CPV', 'CAF', 'TCD',
       'CHL', 'CHN', 'COL', 'COM', 'COG', 'COK', 'CRI', 'HRV', 'CUB',
       'CYP', 'CZE', 'COD', 'DNK', 'DJI', 'DMA', 'DOM', 'ECU', 'EGY',
       'SLV', 'GNQ', 'ERI', 'EST', 'SWZ', 'ETH', 'FJI', 'FIN', 'FRA',
       'GUF', 'PYF', 'GAB', 'GMB', 'GEO', 'DEU', 'GHA', 'GRC', 'GRL',
       'GRD', 'GLP', 'GUM', 'GTM', 'GIN', 'GNB', 'GUY', 'HTI', 'HND',
       'HKG', 'HUN', 'ISL', 'IND', 'IDN', 'IRN', 'IRQ', 'IRL', 'ISR',
       'ITA', 'JAM', 'JPN', 'JOR', 'KAZ', 'KEN', 'KIR', 'OWID_KOS', 'KWT',
       'KGZ', 'LAO', 'LVA', 'LBN', 'LSO', 'LBR', 'LBY', 'LTU', 'LUX',
       'MDG', 'MWI', 'MYS', 'MDV', 'MLI', 'MLT', 'MHL', 'MTQ', 'MRT',
       'MUS', 'MEX', 'MDA', 'MCO', 'MNG', 'MNE', 'MAR', 'MOZ', 'MMR',
       'NAM', 'NRU', 'NPL', 'NLD', 'NCL', 'NZL', 'NIC', 'NER', 'NGA',
       'NIU', 'PRK', 'MKD', 'MNP', 'NOR', 'OMN', 'PAK', 'PLW', 'PSE',
       'PAN', 'PNG', 'PRY', 'PER', 'PHL', 'POL', 'PRT', 'PRI', 'QAT',
       'ROU', 'RUS', 'RWA', 'KNA', 'LCA', 'VCT', 'WSM', 'SMR', 'STP',
       'SAU', 'SEN', 'SRB', 'SYC', 'SLE', 'SGP', 'SVK', 'SVN', 'SLB',
       'SOM', 'ZAF', 'KOR', 'SSD', 'ESP', 'LKA', 'SDN', 'SUR', 'SWE',
       'CHE', 'SYR', 'TWN', 'TJK', 'TZA', 'THA', 'TGO', 'TKL', 'TON',
       'TTO', 'TUN', 'TUR', 'TKM', 'TUV', 'UGA', 'UKR', 'ARE', 'GBR',
       'USA', 'VIR', 'URY', 'UZB', 'VUT', 'VEN', 'VNM', 'WLF', 'ESH',
       'YEM', 'ZMB', 'ZWE'], dtype=object)
```

In [32]:

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

Out[32]:

(1485, 1)

In [33]:

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

Out[33]:

```
array([['AFG'],
       ['AFG'],
       ['AFG'],
       ...,
       ['ZWE'],
       ['ZWE'],
       ['ZWE']], dtype=object)
```

In [34]:

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

Out[34]:

```
array(['AFG', 'AGO', 'ALB', 'AND', 'ARE', 'ARG', 'ARM', 'ASM', 'ATG',
       'AUS', 'AUT', 'AZE', 'BDI', 'BEL', 'BEN', 'BFA', 'BGD', 'BGR',
       'BHR', 'BHS', 'BIH', 'BLR', 'BLZ', 'BMU', 'BOL', 'BRA', 'BRB',
       'BRN', 'BTN', 'BWA', 'CAF', 'CAN', 'CHE', 'CHL', 'CHN', 'CMR',
       'COD', 'COG', 'COK', 'COL', 'COM', 'CPV', 'CRI', 'CUB', 'CYP',
       'CZE', 'DEU', 'DJI', 'DMA', 'DNK', 'DOM', 'DZA', 'ECU', 'EGY',
       'ERI', 'ESH', 'ESP', 'EST', 'ETH', 'FIN', 'FJI', 'FRA', 'GAB',
       'GBR', 'GEO', 'GHA', 'GIN', 'GLP', 'GMB', 'GNB', 'GNQ', 'GRC',
       'GRD', 'GRL', 'GTM', 'GUF', 'GUM', 'GUY', 'HKG', 'HND', 'HRV',
       'HTI', 'HUN', 'IDN', 'IND', 'IRL', 'IRN', 'IRQ', 'ISL', 'ISR',
       'ITA', 'JAM', 'JOR', 'JPN', 'KAZ', 'KEN', 'KGZ', 'KHM', 'KIR',
       'KNA', 'KOR', 'KWT', 'LAO', 'LBN', 'LBR', 'LBY', 'LCA', 'LKA',
       'LSO', 'LTU', 'LUX', 'LVA', 'MAR', 'MCO', 'MDA', 'MDG', 'MDV',
       'MEX', 'MHL', 'MKD', 'MLI', 'MLT', 'MMR', 'MNE', 'MNG', 'MNP',
       'MOZ', 'MRT', 'MTQ', 'MUS', 'MWI', 'MYS', 'NAM', 'NCL', 'NER',
       'NGA', 'NIC', 'NIU', 'NLD', 'NOR', 'NPL', 'NRU', 'NZL', 'OMN',
       'OWID_KOS', 'PAK', 'PAN', 'PER', 'PHL', 'PLW', 'PNG', 'POL', 'PRI',
       'PRK', 'PRT', 'PRY', 'PSE', 'PYF', 'QAT', 'ROU', 'RUS', 'RWA',
       'SAU', 'SDN', 'SEN', 'SGP', 'SLB', 'SLE', 'SLV', 'SMR', 'SOM',
       'SRB', 'SSD', 'STP', 'SUR', 'SVK', 'SVN', 'SWE', 'SWZ', 'SYC',
       'SYR', 'TCD', 'TGO', 'THA', 'TJK', 'TKL', 'TKM', 'TON', 'TTO',
       'TUN', 'TUR', 'TUV', 'TWN', 'TZA', 'UGA', 'UKR', 'URY', 'USA',
       'UZB', 'VCT', 'VEN', 'VIR', 'VNM', 'VUT', 'WLF', 'WSM', 'YEM',
       'ZAF', 'ZMB', 'ZWE'], dtype=object)
```

In [35]:

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

Out[35]:

```
array([['AFG'],
       ['AFG'],
       ['AFG'],
       ...,
       ['ZWE'],
       ['ZWE'],
       ['ZWE']], dtype=object)
```

In [36]:

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

Out[36]:

```
array(['AFG', 'AGO', 'ALB', 'AND', 'ARE', 'ARG', 'ARM', 'ASM', 'ATG',
       'AUS', 'AUT', 'AZE', 'BDI', 'BEL', 'BEN', 'BFA', 'BGD', 'BGR',
       'BHR', 'BHS', 'BIH', 'BLR', 'BLZ', 'BMU', 'BOL', 'BRA', 'BRB',
       'BRN', 'BTN', 'BWA', 'CAF', 'CAN', 'CHE', 'CHL', 'CHN', 'CMR',
       'COD', 'COG', 'COK', 'COL', 'COM', 'CPV', 'CRI', 'CUB', 'CYP',
       'CZE', 'DEU', 'DJI', 'DMA', 'DNK', 'DOM', 'DZA', 'ECU', 'EGY',
       'ERI', 'ESH', 'ESP', 'EST', 'ETH', 'FIN', 'FJI', 'FRA', 'GAB',
       'GBR', 'GEO', 'GHA', 'GIN', 'GLP', 'GMB', 'GNB', 'GNQ', 'GRC',
       'GRD', 'GRL', 'GTM', 'GUF', 'GUM', 'GUY', 'HKG', 'HND', 'HRV',
       'HTI', 'HUN', 'IDN', 'IND', 'IRL', 'IRN', 'IRQ', 'ISL', 'ISR',
       'ITA', 'JAM', 'JOR', 'JPN', 'KAZ', 'KEN', 'KGZ', 'KHM', 'KIR',
       'KNA', 'KOR', 'KWT', 'LAO', 'LBN', 'LBR', 'LBY', 'LCA', 'LKA',
       'LSO', 'LTU', 'LUX', 'LVA', 'MAR', 'MCO', 'MDA', 'MDG', 'MDV',
       'MEX', 'MHL', 'MKD', 'MLI', 'MLT', 'MMR', 'MNE', 'MNG', 'MNP',
       'MOZ', 'MRT', 'MTQ', 'MUS', 'MWI', 'MYS', 'NA', 'NAM', 'NCL',
       'NER', 'NGA', 'NIC', 'NIU', 'NLD', 'NOR', 'NPL', 'NRU', 'NZL',
       'OMN', 'OWID_KOS', 'PAK', 'PAN', 'PER', 'PHL', 'PLW', 'PNG', 'POL',
       'PRI', 'PRK', 'PRT', 'PRY', 'PSE', 'PYF', 'QAT', 'ROU', 'RUS',
       'RWA', 'SAU', 'SDN', 'SEN', 'SGP', 'SLB', 'SLE', 'SLV', 'SMR',
       'SOM', 'SRB', 'SSD', 'STP', 'SUR', 'SVK', 'SVN', 'SWE', 'SWZ',
       'SYC', 'SYR', 'TCD', 'TGO', 'THA', 'TJK', 'TKL', 'TKM', 'TON',
       'TTO', 'TUN', 'TUR', 'TUV', 'TWN', 'TZA', 'UGA', 'UKR', 'URY',
       'USA', 'UZB', 'VCT', 'VEN', 'VIR', 'VNM', 'VUT', 'WLF', 'WSM',
       'YEM', 'ZAF', 'ZMB', 'ZWE'], dtype=object)
```

In [37]:

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

Out[37]:

```
1485
```

In [38]:

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

Out[38]:

	c1
0	AFG
1	AFG
2	AFG
3	AFG
4	AFG
...	...
201757	ZWE
201758	ZWE
201759	ZWE
201760	ZWE
201761	ZWE

201762 rows × 1 columns

In [39]:

```
from sklearn.preprocessing import LabelEncoder
```

In [40]:

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

Out[40]:

```
array(['AFG', 'ALB', 'DZA', 'ASM', 'AND', 'AGO', 'ATG', 'ARG', 'ARM',
       'AUS', 'AUT', 'AZE', 'BHS', 'BHR', 'BGD', 'BRB', 'BLR', 'BEL',
       'BLZ', 'BEN', 'BMU', 'BTN', 'BOL', 'BIH', 'BWA', 'BRA', 'BRN',
       'BGR', 'BFA', 'BDI', 'KHM', 'CMR', 'CAN', 'CPV', 'CAF', 'TCD',
       'CHL', 'CHN', 'COL', 'COM', 'COG', 'COK', 'CRI', 'HRV', 'CUB',
       'CYP', 'CZE', 'COD', 'DNK', 'DJI', 'DMA', 'DOM', 'ECU', 'EGY',
       'SLV', 'GNQ', 'ERI', 'EST', 'SWZ', 'ETH', 'FJI', 'FIN', 'FRA',
       'GUF', 'PYF', 'GAB', 'GMB', 'GEO', 'DEU', 'GHA', 'GRC', 'GRL',
       'GRD', 'GLP', 'GUM', 'GTM', 'GIN', 'GNB', 'GUY', 'HTI', 'HND',
       'HKG', 'HUN', 'ISL', 'IND', 'IDN', 'IRN', 'IRQ', 'IRL', 'ISR',
       'ITA', 'JAM', 'JPN', 'JOR', 'KAZ', 'KEN', 'KIR', 'OWID_KOS', 'KWT',
       'KGZ', 'LAO', 'LVA', 'LBN', 'LSO', 'LBR', 'LBY', 'LTU', 'LUX',
       'MDG', 'MWI', 'MYS', 'MDV', 'MLI', 'MLT', 'MHL', 'MTQ', 'MRT',
       'MUS', 'MEX', 'MDA', 'MCO', 'MNG', 'MNE', 'MAR', 'MOZ', 'MMR',
       'NAM', 'NRU', 'NPL', 'NLD', 'NCL', 'NZL', 'NIC', 'NER', 'NGA',
       'NIU', 'PRK', 'MKD', 'MNP', 'NOR', 'OMN', 'PAK', 'PLW', 'PSE',
       'PAN', 'PNG', 'PRY', 'PER', 'PHL', 'POL', 'PRT', 'PRI', 'QAT',
       'ROU', 'RUS', 'RWA', 'KNA', 'LCA', 'VCT', 'WSM', 'SMR', 'STP',
       'SAU', 'SEN', 'SRB', 'SYC', 'SLE', 'SGP', 'SVK', 'SVN', 'SLB',
       'SOM', 'ZAF', 'KOR', 'SSD', 'ESP', 'LKA', 'SDN', 'SUR', 'SWE',
       'CHE', 'SYR', 'TWN', 'TJK', 'TZA', 'THA', 'TGO', 'TKL', 'TON',
       'TTO', 'TUN', 'TUR', 'TKM', 'TUV', 'UGA', 'UKR', 'ARE', 'GBR',
       'USA', 'VIR', 'URY', 'UZB', 'VUT', 'VEN', 'VNM', 'WLF', 'ESH',
       'YEM', 'ZMB', 'ZWE'], dtype=object)
```

In [41]:

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

In [42]:

```
# Наименования категорий в соответствии с порядковыми номерами
# Свойство называется classes, потому что предполагается что мы решаем
# задачу классификации и каждое значение категории соответствует
# какому-либо классу целевого признака
le.classes_
```

Out[42]:

```
array(['AFG', 'AGO', 'ALB', 'AND', 'ARE', 'ARG', 'ARM', 'ASM', 'ATG',
       'AUS', 'AUT', 'AZE', 'BDI', 'BEL', 'BEN', 'BFA', 'BGD', 'BGR',
       'BHR', 'BHS', 'BIH', 'BLR', 'BLZ', 'BMU', 'BOL', 'BRA', 'BRB',
       'BRN', 'BTN', 'BWA', 'CAF', 'CAN', 'CHE', 'CHL', 'CHN', 'CMR',
       'COD', 'COG', 'COK', 'COL', 'COM', 'CPV', 'CRI', 'CUB', 'CYP',
       'CZE', 'DEU', 'DJI', 'DMA', 'DNK', 'DOM', 'DZA', 'ECU', 'EGY',
       'ERI', 'ESH', 'ESP', 'EST', 'ETH', 'FIN', 'FJI', 'FRA', 'GAB',
       'GBR', 'GEO', 'GHA', 'GIN', 'GLP', 'GMB', 'GNB', 'GNQ', 'GRC',
       'GRD', 'GRL', 'GTM', 'GUF', 'GUM', 'GUY', 'HKG', 'HND', 'HRV',
       'HTI', 'HUN', 'IDN', 'IND', 'IRL', 'IRN', 'IRQ', 'ISL', 'ISR',
       'ITA', 'JAM', 'JOR', 'JPN', 'KAZ', 'KEN', 'KGZ', 'KHM', 'KIR',
       'KNA', 'KOR', 'KWT', 'LAO', 'LBN', 'LBR', 'LBY', 'LCA', 'LKA',
       'LSO', 'LTU', 'LUX', 'LVA', 'MAR', 'MCO', 'MDA', 'MDG', 'MDV',
       'MEX', 'MHL', 'MKD', 'MLI', 'MLT', 'MMR', 'MNE', 'MNG', 'MNP',
       'MOZ', 'MRT', 'MTQ', 'MUS', 'MWI', 'MYS', 'NAM', 'NCL', 'NER',
       'NGA', 'NIC', 'NIU', 'NLD', 'NOR', 'NPL', 'NRU', 'NZL', 'OMN',
       'OWID_KOS', 'PAK', 'PAN', 'PER', 'PHL', 'PLW', 'PNG', 'POL', 'PRI',
       'PRK', 'PRT', 'PRY', 'PSE', 'PYF', 'QAT', 'ROU', 'RUS', 'RWA',
       'SAU', 'SDN', 'SEN', 'SGP', 'SLB', 'SLE', 'SLV', 'SMR', 'SOM',
       'SRB', 'SSD', 'STP', 'SUR', 'SVK', 'SVN', 'SWE', 'SWZ', 'SYC',
       'SYR', 'TCD', 'TGO', 'THA', 'TJK', 'TKL', 'TKM', 'TON', 'TTO',
       'TUN', 'TUR', 'TUV', 'TWN', 'TZA', 'UGA', 'UKR', 'URY', 'USA',
       'UZB', 'VCT', 'VEN', 'VIR', 'VNM', 'VUT', 'WLF', 'WSM', 'YEM',
       'ZAF', 'ZMB', 'ZWE'], dtype=object)
```

In [43]:

```
cat_enc_le
```

Out[43]:

```
array([  0,   0,   0, ..., 209, 209, 209])
```

In [44]:

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

Out[44]:

```
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])
```

In [45]:

```
# В этом примере видно, что перед кодированием
# уникальные значения признака сортируются в лексикографиеском порядке
le.inverse_transform([0, 1, 2, 3])
```

Out[45]:

```
array(['AFG', 'AGO', 'ALB', 'AND'], dtype=object)
```

In [46]:

```
from sklearn.preprocessing import OrdinalEncoder
```

In [47]:

```
data_oe = data[['Code']]
data_oe.head()
```

Out[47]:

	Code
0	AFG
1	AFG
2	AFG
3	AFG
4	AFG

In [48]:

```
imp4 = SimpleImputer(missing_values=np.nan, strategy='constant', fill_value='NA')
data_oe_filled = imp4.fit_transform(data_oe)
data_oe_filled
```

Out[48]:

```
array([['AFG'],
       ['AFG'],
       ['AFG'],
       ...,
       ['ZWE'],
       ['ZWE'],
       ['ZWE']], dtype=object)
```

In [49]:

```
oe = OrdinalEncoder()
cat_enc_oe = oe.fit_transform(data_oe_filled)
cat_enc_oe
```

Out[49]:

```
array([[  0.],
       [  0.],
       [  0.],
       ...,
       [210.],
       [210.],
       [210.]])
```

In [50]:

```
# Уникальные значения 1 признака
np.unique(cat_enc_oe[:, 0])
```

Out[50]:

```
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.])
```

In [51]:

```
# Наименования категорий в соответствии с порядковыми номерами
oe.categories_
```

Out[51]:

```
[array(['AFG', 'AGO', 'ALB', 'AND', 'ARE', 'ARG', 'ARM', 'ASM', 'ATG',
       'AUS', 'AUT', 'AZE', 'BDI', 'BEL', 'BEN', 'BFA', 'BGD', 'BGR',
       'BHR', 'BHS', 'BIH', 'BLR', 'BLZ', 'BMU', 'BOL', 'BRA', 'BRB',
       'BRN', 'BTN', 'BWA', 'CAF', 'CAN', 'CHE', 'CHL', 'CHN', 'CMR',
       'COD', 'COG', 'COK', 'COL', 'COM', 'CPV', 'CRI', 'CUB', 'CYP',
       'CZE', 'DEU', 'DJI', 'DMA', 'DNK', 'DOM', 'DZA', 'ECU', 'EGY',
       'ERI', 'ESH', 'ESP', 'EST', 'ETH', 'FIN', 'FJI', 'FRA', 'GAB',
       'GBR', 'GEO', 'GHA', 'GIN', 'GLP', 'GMB', 'GNB', 'GNQ', 'GRC',
       'GRD', 'GRL', 'GTM', 'GUF', 'GUM', 'GUY', 'HKG', 'HND', 'HRV',
       'HTI', 'HUN', 'IDN', 'IND', 'IRL', 'IRN', 'IRQ', 'ISL', 'ISR',
       'ITA', 'JAM', 'JOR', 'JPN', 'KAZ', 'KEN', 'KGZ', 'KHM', 'KIR',
       'KNA', 'KOR', 'KWT', 'LAO', 'LBN', 'LBR', 'LBY', 'LCA', 'LKA',
       'LSO', 'LTU', 'LUX', 'LVA', 'MAR', 'MCO', 'MDA', 'MDG', 'MDV',
       'MEX', 'MHL', 'MKD', 'MLI', 'MLT', 'MMR', 'MNE', 'MNG', 'MNP',
       'MOZ', 'MRT', 'MTQ', 'MUS', 'MWI', 'MYS', 'NA', 'NAM', 'NCL',
       'NER', 'NGA', 'NIC', 'NIU', 'NLD', 'NOR', 'NPL', 'NRU', 'NZL',
       'OMN', 'OWID_KOS', 'PAK', 'PAN', 'PER', 'PHL', 'PLW', 'PNG', 'POL',
       'PRI', 'PRK', 'PRT', 'PRY', 'PSE', 'PYF', 'QAT', 'ROU', 'RUS',
       'RWA', 'SAU', 'SDN', 'SEN', 'SGP', 'SLB', 'SLE', 'SLV', 'SMR',
       'SOM', 'SRB', 'SSD', 'STP', 'SUR', 'SVK', 'SVN', 'SWE', 'SWZ',
       'SYC', 'SYR', 'TCD', 'TGO', 'THA', 'TJK', 'TKL', 'TKM', 'TON',
       'TTO', 'TUN', 'TUR', 'TUV', 'TWN', 'TZA', 'UGA', 'UKR', 'URY',
       'USA', 'UZB', 'VCT', 'VEN', 'VIR', 'VNM', 'VUT', 'WLF', 'WSM',
       'YEM', 'ZAF', 'ZMB', 'ZWE'], dtype=object)]
```

In [52]:

```
# Обратное преобразование
oe.inverse_transform(cat_enc_oe)
```

Out[52]:

```
array([['AFG'],
      ['AFG'],
      ['AFG'],
      ...,
      ['ZWE'],
      ['ZWE'],
      ['ZWE']], dtype=object)
```

In [53]:

```
# пример шкалы порядка 'small' < 'medium' < 'large'
sizes = ['small', 'medium', 'large', 'small', 'medium', 'large', 'small', 'medium', 'large']
```

In [54]:

```
pd_sizes = pd.DataFrame(data={'sizes':sizes})
pd_sizes
```

Out[54]:

	sizes
0	small
1	medium
2	large
3	small
4	medium
5	large
6	small
7	medium
8	large

In [55]:

```
pd_sizes['sizes_codes'] = pd_sizes['sizes'].map({'small':1, 'medium':2, 'large':3})
pd_sizes
```

Out[55]:

	sizes	sizes_codes
0	small	1
1	medium	2
2	large	3
3	small	1
4	medium	2
5	large	3
6	small	1
7	medium	2
8	large	3

In [56]:

```
pd_sizes['sizes_decoded'] = pd_sizes['sizes_codes'].map({1:'small', 2:'medium', 3:'large'})
pd_sizes
```

Out[56]:

	sizes	sizes_codes	sizes_decoded
0	small	1	small
1	medium	2	medium
2	large	3	large
3	small	1	small
4	medium	2	medium
5	large	3	large
6	small	1	small
7	medium	2	medium
8	large	3	large

In [57]:

```
from sklearn.preprocessing import OneHotEncoder
```

In [58]:

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

In [59]:

```
cat_enc.shape
```

Out[59]:

```
(201762, 1)
```

In [60]:

```
cat_enc_ohe.shape
```

Out[60]:

```
(201762, 210)
```

In [61]:

```
cat_enc_ohe
```

Out[61]:

```
<201762x210 sparse matrix of type '<class 'numpy.float64'>'
 with 201762 stored elements in Compressed Sparse Row format>
```

In [62]:

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

Out[62]:

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

In [63]:

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

Out[63]:

	c1
0	AFG
1	AFG
2	AFG
3	AFG
4	AFG
5	AFG
6	AFG
7	AFG
8	AFG
9	AFG

In [64]:

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

Out[64]:

	c1_AFG	c1_AGO	c1_ALB	c1_AND	c1_ARE	c1_ARG	c1_ARM	c1_ASM	c1_ATG	c1_AUS	...	c1_VEN	c1_VIR	c1_VNM	c1_VUT	c1_WLF	c1_WSM	c
0	1	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	
1	1	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	
2	1	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	
3	1	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	
4	1	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	

5 rows × 210 columns

In [65]:

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

Out[65]:

	Code_AFG	Code_AGO	Code_ALB	Code_AND	Code_ARE	Code_ARG	Code_ARM	Code_ASM	Code_ATG	Code_AUS	...	Code_VIR	Code_VNM	Code_'
0	1	0	0	0	0	0	0	0	0	0	...	0	0	
1	1	0	0	0	0	0	0	0	0	0	...	0	0	
2	1	0	0	0	0	0	0	0	0	0	...	0	0	
3	1	0	0	0	0	0	0	0	0	0	...	0	0	
4	1	0	0	0	0	0	0	0	0	0	...	0	0	

5 rows × 211 columns

In [66]:

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

In [67]:

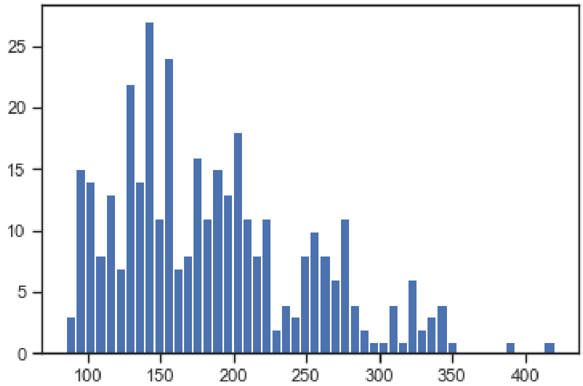
```
data = pd.read_csv('C:/Users/maxim/OneDrive/Рабочий стол/TMO/rice_wheat_corn_prices.csv', sep=",")
```

In [68]:

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

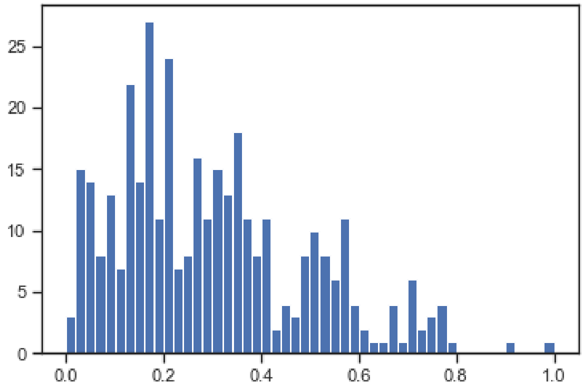
In [69]:

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



In [70]:

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

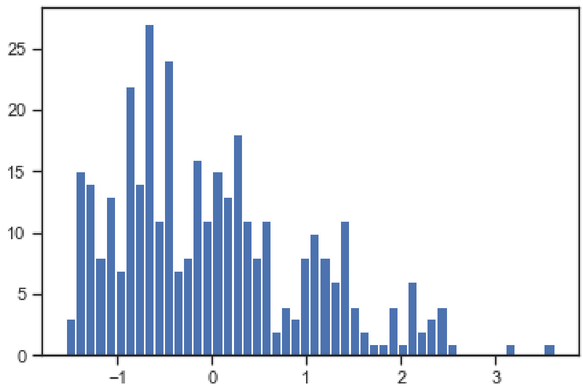


In [71]:

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

In [72]:

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



In [ ]: