Обработка пропусков в данных, кодирование категориальных признаков, масштабирование данных.

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")
```

Загрузка и первичный анализ данных

- Будем работать с датасетом, содержащим информацию о выданных визах **H1B**

In [17]:

```
data = pd.read_csv('C:\\MGTU\\6 semestr\\TMO\\h1b_kaggle.csv', sep=",")
```

In [21]:

```
data.shape
```

Out[21]:

```
(3002458, 11)
```

In [22]:

```
data.dtypes
```

Out[22]:

```
Unnamed: 0               int64
CASE_STATUS             object
EMPLOYER_NAME           object
SOC_NAME                object
JOB_TITLE               object
FULL_TIME_POSITION      object
PREVAILING_WAGE        float64
YEAR                   float64
WORKSITE                object
lon                    float64
lat                    float64
dtype: object
```

In [23]:

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

Out[23]:

```
Unnamed: 0                 0
CASE_STATUS               13
EMPLOYER_NAME             59
SOC_NAME               17734
JOB_TITLE                 43
FULL_TIME_POSITION        15
PREVAILING_WAGE           85
YEAR                      13
WORKSITE                   0
lon                   107242
lat                   107242
dtype: int64
```

data.head()

In [25]:

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

```
Всего строк: 3002458
```

Обработка пропусков в данных

- Удаление или заполнение нулями

In [26]:

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

Out[26]:

```
((3002458, 11), (3002458, 2))
```

In [27]:

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

Out[27]:

```
((3002458, 11), (2877765, 11))
```

In [111]:

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

Out[111]:

	Unnamed: 0	CASE_STATUS	EMPLOYER_NAME	SOC_NAME	JOB_TITLE	FULL_TIME_POSITION	PREVAILING_WA(
0	1	CERTIFIED-WITHDRAWN	UNIVERSITY OF MICHIGAN	BIOCHEMISTS AND BIOPHYSICISTS	POSTDOCTORAL RESEARCH FELLOW	N	36067
1	2	CERTIFIED-WITHDRAWN	GOODMAN NETWORKS, INC.	CHIEF EXECUTIVES	CHIEF OPERATING OFFICER	Y	242674
2	3	CERTIFIED-WITHDRAWN	PORTS AMERICA GROUP, INC.	CHIEF EXECUTIVES	CHIEF PROCESS OFFICER	Y	193066
3	4	CERTIFIED-WITHDRAWN	GATES CORPORATION, A WHOLLY-OWNED SUBSIDIARY O...	CHIEF EXECUTIVES	REGIONAL PRESIDEN, AMERICAS	Y	220314
4	5	WITHDRAWN	PEABODY INVESTMENTS CORP.	CHIEF EXECUTIVES	PRESIDENT MONGOLIA AND INDIA	Y	157518

"Внедрение значений" - импьютация (imputation)

- Обработка пропусков в числовых данных

In [29]:

```
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(co
l, dt, temp_null_count, temp_perc))
```

```
Колонка PREVAILING_WAGE. Тип данных float64. Количество пустых значений 85, 0.0%.
Колонка YEAR. Тип данных float64. Количество пустых значений 13, 0.0%.
Колонка lon. Тип данных float64. Количество пустых значений 107242, 3.57%.
Колонка lat. Тип данных float64. Количество пустых значений 107242, 3.57%.
```

In [30]:

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

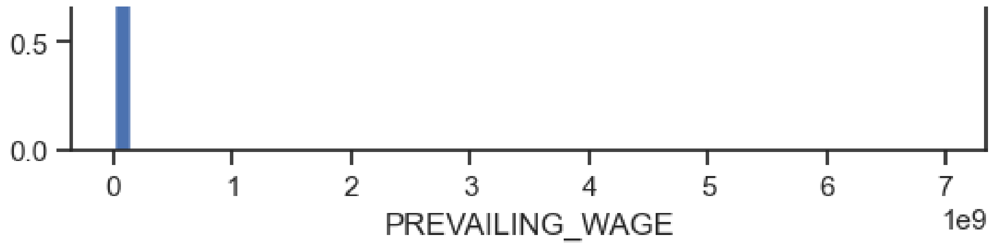
Out[30]:

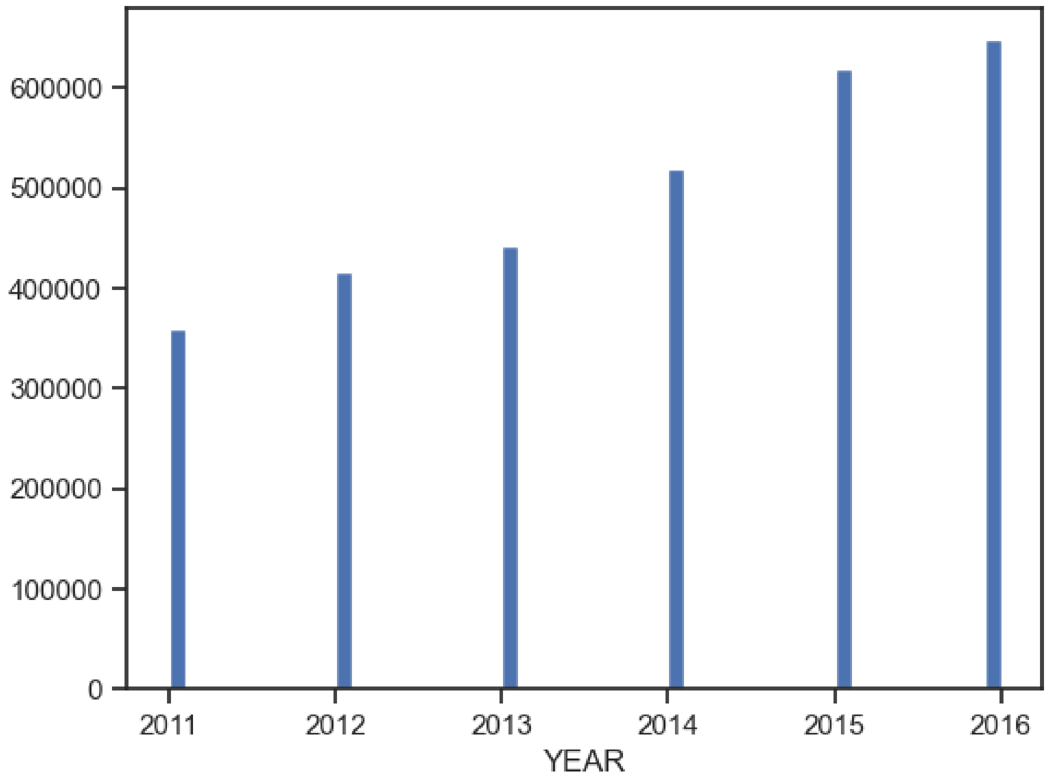
	PREVAILING_WAGE	YEAR	lon	lat
0	36067.0	2016.0	-83.743038	42.280826
1	242674.0	2016.0	-96.698886	33.019843
2	193066.0	2016.0	-74.077642	40.728158
3	220314.0	2016.0	-104.990251	39.739236
4	157518.4	2016.0	-90.199404	38.627003
...	...	...	...	...
3002453	NaN	NaN	-74.005941	40.712784
3002454	NaN	NaN	-97.134178	32.941236
3002455	NaN	NaN	-74.909890	40.636768
3002456	NaN	NaN	-76.780253	39.419550
3002457	NaN	NaN	-84.387982	33.748995

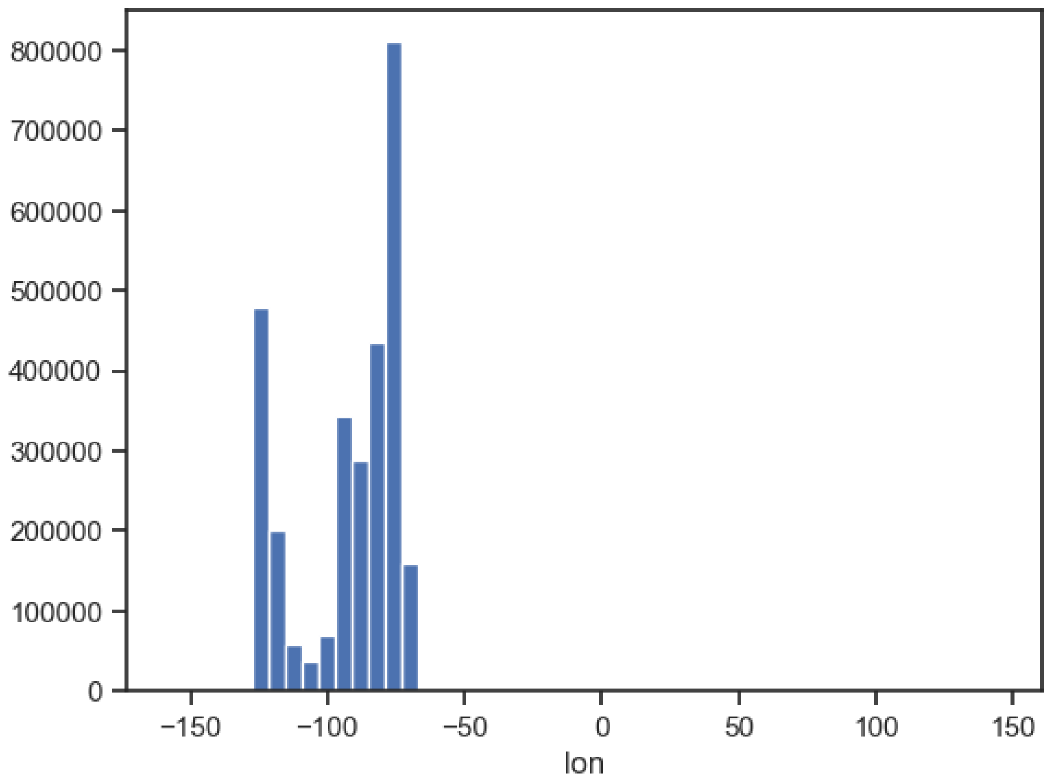
3002458 rows × 4 columns

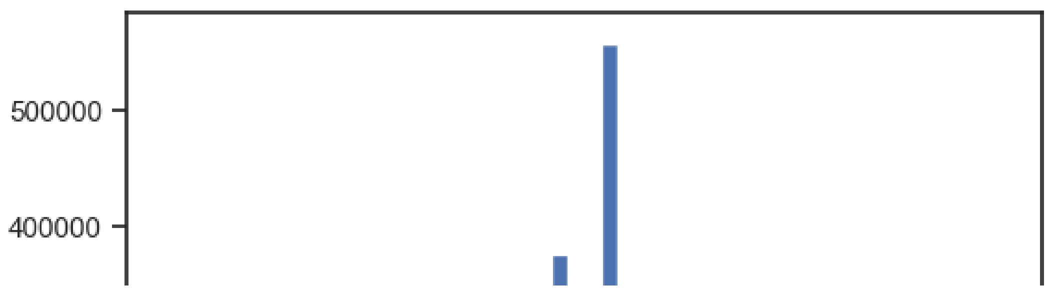
In [31]:

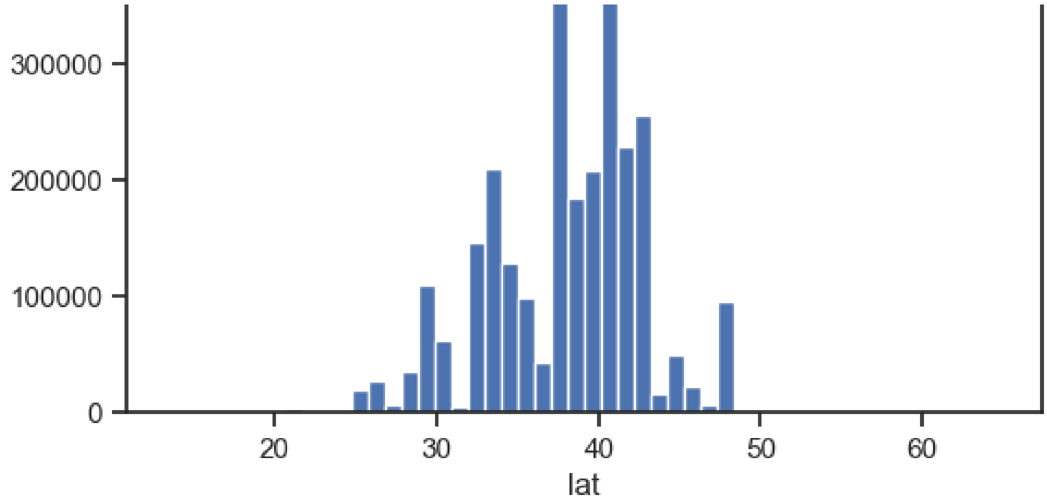
```
for col in data_num:
    plt.hist(data[col], 50)
    plt.xlabel(col)
    plt.show()
```


0.5
0.0
0
1
2
3
4
5
6
7
1e9
PREVAILING_WAGE


600000
500000
400000
300000
200000
100000
0
2011
2012
2013
2014
2015
2016
YEAR


800000
700000
600000
500000
400000
300000
200000
100000
0
−150
−100
−50
0
50
100
150
lon


500000
400000



In [42]:

```
data_num_MasVnrArea = data_num[['lat']]
data_num_MasVnrArea.head()
```

Out[42]:

	lat
0	42.280826
1	33.019843
2	40.728158
3	39.739236
4	38.627003

In [43]:

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

In [44]:

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

Out[44]:

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

In [45]:

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

In [46]:

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

In [47]:

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

Out[47]:

```
('mean',
 array([38.16053785, 38.16053785, 38.16053785, ..., 38.16053785,
        38.16053785, 38.16053785]))
```

In [48]:

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

Out[48]:

```
('median',
 array([39.1031182, 39.1031182, 39.1031182, ..., 39.1031182, 39.1031182,
        39.1031182]))
```

In [49]:

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

Out[49]:

```
('most_frequent',
 array([40.7127837, 40.7127837, 40.7127837, ..., 40.7127837, 40.7127837,
        40.7127837]))
```

In [50]:

```
# Более сложная функция, которая позволяет задавать колонку и вид импьютации
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 [51]:

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

Out[51]:

	lon
count	2.895216e+06
mean	-9.213441e+01
std	1.965591e+01
min	-1.578583e+02
25%	-1.119261e+02
50%	-8.615862e+01
75%	-7.551381e+01
max	1.457298e+02

In [52]:

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

Out[52]:

```
('lon', 'mean', 107242, -92.13440680240892, -92.13440680240892)
```

In [53]:

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

Out[53]:

```
('lon', 'median', 107242, -86.1586156, -86.1586156)
```

In [54]:

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

Out[54]:

```
('lon', 'most_frequent', 107242, -74.0059413, -74.0059413)
```

- Обработка пропусков в категориальных данных

In [55]:

```
# 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(co
l, dt, temp_null_count, temp_perc))
```

```
Колонка CASE_STATUS. Тип данных object. Количество пустых значений 13, 0.0%.
Колонка EMPLOYER_NAME. Тип данных object. Количество пустых значений 59, 0.0%.
Колонка SOC_NAME. Тип данных object. Количество пустых значений 17734, 0.59%.
Колонка JOB_TITLE. Тип данных object. Количество пустых значений 43, 0.0%.
Колонка FULL_TIME_POSITION. Тип данных object. Количество пустых значений 15, 0.0%.
```

In [59]:

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

Out[59]:

	CASE_STATUS
0	CERTIFIED-WITHDRAWN
1	CERTIFIED-WITHDRAWN
2	CERTIFIED-WITHDRAWN
3	CERTIFIED-WITHDRAWN
4	WITHDRAWN

In [60]:

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

Out[60]:

```
array(['CERTIFIED-WITHDRAWN', 'WITHDRAWN', 'CERTIFIED', 'DENIED',
       'REJECTED', 'INVALIDATED',
       'PENDING QUALITY AND COMPLIANCE REVIEW - UNASSIGNED', nan],
      dtype=object)
```

In [62]:

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

Out[62]:

(13, 1)

In [63]:

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

Out[63]:

```
array([['CERTIFIED-WITHDRAWN'],
       ['CERTIFIED-WITHDRAWN'],
       ['CERTIFIED-WITHDRAWN'],
       ...,
       ['CERTIFIED'],
       ['CERTIFIED'],
       ['CERTIFIED']], dtype=object)
```

In [64]:

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

Out[64]:

```
array(['CERTIFIED', 'CERTIFIED-WITHDRAWN', 'DENIED', 'INVALIDATED',
       'PENDING QUALITY AND COMPLIANCE REVIEW - UNASSIGNED', 'REJECTED',
       'WITHDRAWN'], dtype=object)
```

In [65]:

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

Out[65]:

```
array([['CERTIFIED-WITHDRAWN'],
       ['CERTIFIED-WITHDRAWN'],
       ['CERTIFIED-WITHDRAWN'],
       ...,
       ['NA'],
       ['NA'],
       ['NA']], dtype=object)
```

In [66]:

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

Out[66]:

```
array(['CERTIFIED', 'CERTIFIED-WITHDRAWN', 'DENIED', 'INVALIDATED', 'NA',
       'PENDING QUALITY AND COMPLIANCE REVIEW - UNASSIGNED', 'REJECTED',
       'WITHDRAWN'], dtype=object)
```

In [67]:

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

Out[67]:

13

- Преобразование категориальных признаков в числовые

In [68]:

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

Out[68]:

	c1
0	CERTIFIED-WITHDRAWN
1	CERTIFIED-WITHDRAWN
2	CERTIFIED-WITHDRAWN
3	CERTIFIED-WITHDRAWN
4	WITHDRAWN
...	...
3002453	CERTIFIED
3002454	CERTIFIED
3002455	CERTIFIED
3002456	CERTIFIED
3002457	CERTIFIED

3002458 rows × 1 columns

Кодирование категорий целочисленными значениями (label encoding)

- Использование **LabelEncoder**

In [69]:

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

In [70]:

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

Out[70]:

```
array(['CERTIFIED-WITHDRAWN', 'WITHDRAWN', 'CERTIFIED', 'DENIED',
       'REJECTED', 'INVALIDATED',
       'PENDING QUALITY AND COMPLIANCE REVIEW - UNASSIGNED'], dtype=object)
```

In [71]:

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

In [72]:

```
# 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[72]:

```
array(['CERTIFIED', 'CERTIFIED-WITHDRAWN', 'DENIED', 'INVALIDATED',
       'PENDING QUALITY AND COMPLIANCE REVIEW - UNASSIGNED', 'REJECTED',
       'WITHDRAWN'], dtype=object)
```

In [73]:

```
cat_enc_le
```

Out[73]:

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

In [74]:

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

Out[74]:

```
array([0, 1, 2, 3, 4, 5, 6])
```

In [77]:

```
# В этом примере видно, что перед кодированием
# уникальные значения признака сортируются в лексикографическом порядке
le.inverse_transform([0, 1, 2, 3, 4, 5, 6])
```

Out[77]:

```
array(['CERTIFIED', 'CERTIFIED-WITHDRAWN', 'DENIED', 'INVALIDATED',
       'PENDING QUALITY AND COMPLIANCE REVIEW - UNASSIGNED', 'REJECTED',
       'WITHDRAWN'], dtype=object)
```

- Использование **OrdinalEncoder**

In [78]:

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

In [79]:

```
data_oe = data[['EMPLOYER_NAME', 'JOB_TITLE', 'FULL_TIME_POSITION']]
data_oe.head()
```

Out[79]:

	EMPLOYER_NAME	JOB_TITLE	FULL_TIME_POSITION
0	UNIVERSITY OF MICHIGAN	POSTDOCTORAL RESEARCH FELLOW	N
1	GOODMAN NETWORKS, INC.	CHIEF OPERATING OFFICER	Y
2	PORTS AMERICA GROUP, INC.	CHIEF PROCESS OFFICER	Y
3	GATES CORPORATION, A WHOLLY-OWNED SUBSIDIARY O...	REGIONAL PRESIDEN, AMERICAS	Y
4	PEABODY INVESTMENTS CORP.	PRESIDENT MONGOLIA AND INDIA	Y

In [80]:

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

Out[80]:

```
array([['UNIVERSITY OF MICHIGAN', 'POSTDOCTORAL RESEARCH FELLOW', 'N'],
       ['GOODMAN NETWORKS, INC.', 'CHIEF OPERATING OFFICER', 'Y'],
       ['PORTS AMERICA GROUP, INC.', 'CHIEF PROCESS OFFICER', 'Y'],
       ...,
       ['NA', 'NA', 'NA'],
       ['NA', 'NA', 'NA'],
       ['NA', 'NA', 'NA']], dtype=object)
```

In [81]:

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

Out[81]:

```
array([[2.19673e+05, 1.63538e+05, 0.00000e+00],
       [8.60970e+04, 4.32620e+04, 2.00000e+00],
```

```
       [1.63481e+05, 4.33370e+04, 2.00000e+00],
       ...,
       [1.41740e+05, 1.47991e+05, 1.00000e+00],
       [1.41740e+05, 1.47991e+05, 1.00000e+00],
       [1.41740e+05, 1.47991e+05, 1.00000e+00]])
```

In [82]:

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

Out[82]:

```
array([0.00000e+00, 1.00000e+00, 2.00000e+00, ..., 2.36011e+05,
       2.36012e+05, 2.36013e+05])
```

In [83]:

```
# Уникальные значения 2 признака
np.unique(cat_enc_oe[:, 1])
```

Out[83]:

```
array([0.00000e+00, 1.00000e+00, 2.00000e+00, ..., 2.87547e+05,
       2.87548e+05, 2.87549e+05])
```

In [84]:

```
oe.categories_
```

Out[84]:

```
[array(['"EXCELLENT COMPUTING DISTRIBUTORS INC"',
        '"I HAVE A DREAM" FOUNDATION', '"K" LINE AMERICA', ...,
        'ÉTUDES LLC', 'ÉTUDES, LLC', 'ÈNIMAI, INC.'], dtype=object),
 array(['"BUSINESS SYSTEM ANALYST', '"SALES MANAGER',
        '"TEST" SENIOR SCIENTIST', ..., '\xa0TEAM LEAD - US',
        '\xa0TECHNOLOGY ARCHITECT - US', '\xa0TEST ANALYST - US'],
       dtype=object),
 array(['N', 'NA', 'Y'], dtype=object)]
```

In [85]:

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

Out[85]:

```
array([['UNIVERSITY OF MICHIGAN', 'POSTDOCTORAL RESEARCH FELLOW', 'N'],
       ['GOODMAN NETWORKS, INC.', 'CHIEF OPERATING OFFICER', 'Y'],
       ['PORTS AMERICA GROUP, INC.', 'CHIEF PROCESS OFFICER', 'Y'],
       ...,
       ['NA', 'NA', 'NA'],
       ['NA', 'NA', 'NA'],
       ['NA', 'NA', 'NA']], dtype=object)
```

Кодирование шкал порядка

In [86]:

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

In [87]:

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

Out[87]:

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

In [88]:

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

Out[88]:

	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 [89]:

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

Out[89]:

	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

Кодирование категорий наборами бинарных значений - **one-hot encoding**

In [90]:

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

In [91]:

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

In [92]:

```
cat_enc.shape
```

Out[92]:

```
(3002458, 1)
```

In [93]:

```
cat_enc_ohe.shape
```

Out[93]:

```
(3002458, 7)
```

In [94]:

```
cat_enc_ohe
```

Out[94]:

```
<3002458x7 sparse matrix of type '<class 'numpy.float64'>'
 with 3002458 stored elements in Compressed Sparse Row format>
```

In [95]:

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

Out[95]:

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

In [96]:

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

Out[96]:

	c1
0	CERTIFIED-WITHDRAWN
1	CERTIFIED-WITHDRAWN
2	CERTIFIED-WITHDRAWN
3	CERTIFIED-WITHDRAWN
4	WITHDRAWN
5	CERTIFIED-WITHDRAWN
6	CERTIFIED-WITHDRAWN
7	CERTIFIED-WITHDRAWN
8	CERTIFIED-WITHDRAWN

	c1
9	WITHDRAWN

Pandas get_dummies - быстрый вариант **one-hot** кодирования

In [97]:

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

Out[97]:

	c1_CERTIFIED	c1_CERTIFIED-WITHDRAWN	c1_DENIED	c1_INVALIDATED	c1_PENDING QUALITY AND COMPLIANCE REVIEW - UNASSIGNED	c1_REJECTED	c1_WITHDRAWN
0	False	True	False	False	False	False	False
1	False	True	False	False	False	False	False
2	False	True	False	False	False	False	False
3	False	True	False	False	False	False	False
4	False	False	False	False	False	False	True

In [100]:

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

Out[100]:

	CASE_STATUS_CERTIFIED	CASE_STATUS_CERTIFIED-WITHDRAWN	CASE_STATUS_DENIED	CASE_STATUS_INVALIDATED	CASE_STATU QU COMPLIANC U
0	False	True	False	False	
1	False	True	False	False	
2	False	True	False	False	
3	False	True	False	False	
4	False	False	False	False	

Масштабирование данных

- **MinMax** масштабирование

In [101]:

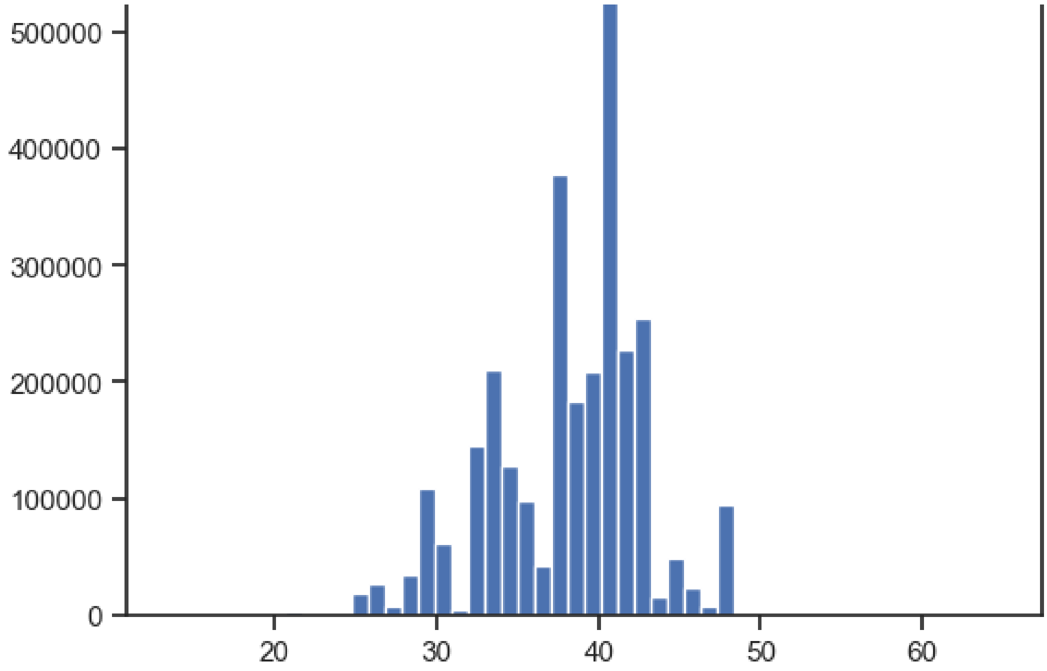
```
from sklearn.preprocessing import MinMaxScaler, StandardScaler, Normalizer
```

In [106]:

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

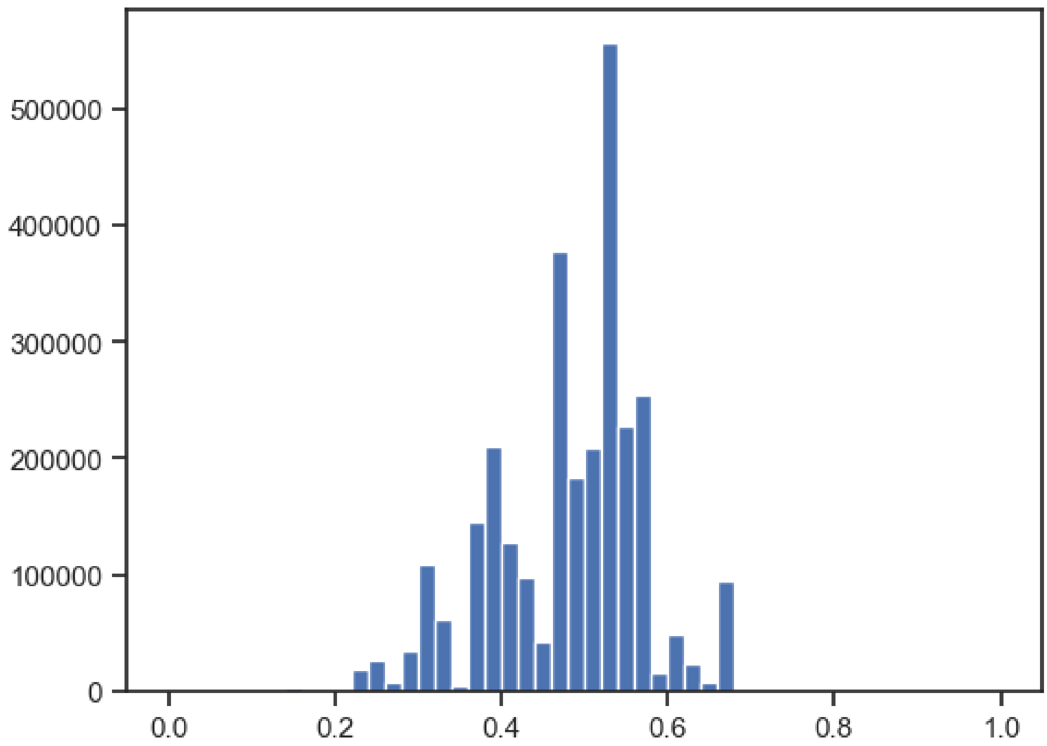
In [107]:

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



In [108]:

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



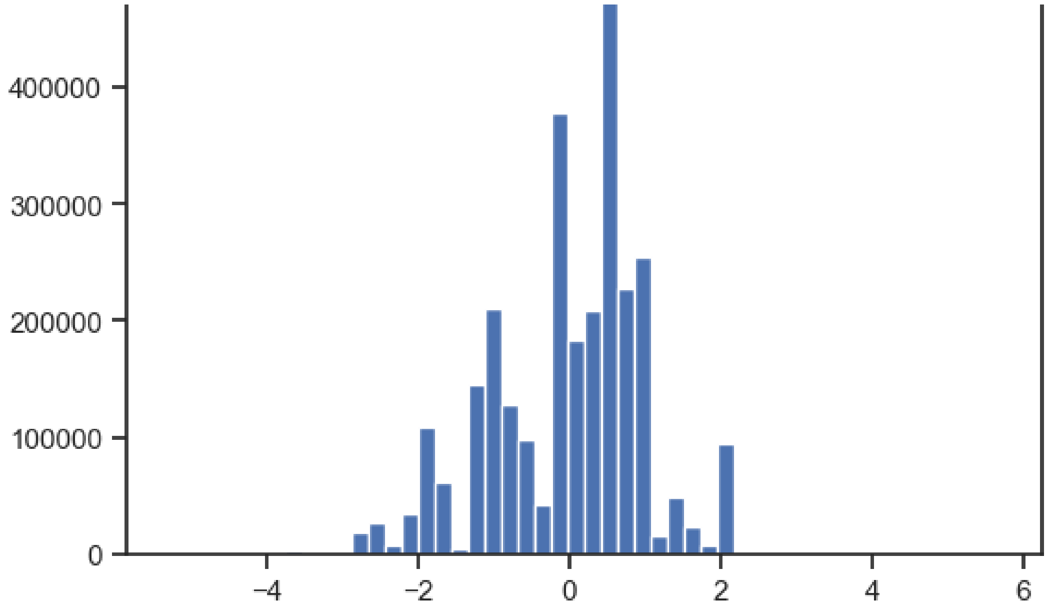
- Масштабирование данных на основе **Z-**оценки **- StandardScaler**

In [109]:

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

In [110]:

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



In [ ]: