Лабораторная работа №2

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

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Задание:

Выбрать набор данных (датасет), содержащий категориальные признаки и пропуски в данных. Для выполнения следующих пунктов можно использовать несколько различных наборов данных (один для обработки пропусков, другой для категориальных признаков и т.д.) Для выбранного датасета (датасетов) на основе материалов лекции решить следующие задачи:

обработку 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
from sklearn.impute import SimpleImputer
from sklearn.impute import MissingIndicator
from sklearn.preprocessing import LabelEncoder, OneHotEncoder
from sklearn.preprocessing import MinMaxScaler, StandardScaler, Normalizer
%matplotlib inline
sns.set(style="whitegrid")
```

In [2]:

```
data = pd.read_csv('data/marvel-wikia-data.csv', sep = ",")
```

In [3]:

```
# Посмотрим первые 5 строк датасета
data.head()
```

Out[3]:

	page_id	name	urlslug	ID	ALIGN	EYE	HAIR	SEX	GSM	ALIVE	APPEARANCES	AI
0	1678	Spider-Man (Peter Parker)	\/Spider-Man_(Peter_Parker)	Secret Identity	Good Characters	Hazel Eyes	Brown Hair	Male Characters	NaN	Living Characters	4043.0	
1	7139	Captain America (Steven Rogers)	\/Captain_America_(Steven_Rogers)	Public Identity	Good Characters	Blue Eyes	White Hair	Male Characters	NaN	Living Characters	3360.0	
2	64786	Wolverine (James \"Logan\" Howlett)	\/Wolverine_(James_%22Logan%22_Howlett)	Public Identity	Neutral Characters	Blue Eyes	Black Hair	Male Characters	NaN	Living Characters	3061.0	
3	1868	Iron Man (Anthony \"Tony\" Stark)	\/Iron_Man_(Anthony_%22Tony%22_Stark)	Public Identity	Good Characters	Blue Eyes	Black Hair	Male Characters	NaN	Living Characters	2961.0	
4	2460	Thor (Thor Odinson)	\/Thor_(Thor_Odinson)	No Dual Identity	Good Characters	Blue Eyes	Blond Hair	Male Characters	NaN	Living Characters	2258.0	

In [4]:

```
# Размер набора данных
data.shape
```

Out[4]:

```
(16376, 13)
```

In [5]:

```
# Посмотрим типы данных
data.dtypes
```

Out[5]:

```
page_id               int64
name                 object
urlslug              object
ID                   object
ALIGN                object
EYE                  object
HAIR                 object
SEX                  object
GSM                  object
ALIVE                object
APPEARANCES         float64
FIRST APPEARANCE     object
Year                float64
dtype: object
```

In [6]:

```
# Выведем количество пропусков в атрибутах
data.isnull().sum()
```

Out[6]:

```
page_id                 0
name                    0
urlslug                 0
ID                   3770
ALIGN                2812
EYE                  9767
HAIR                 4264
SEX                   854
GSM                 16286
ALIVE                   3
APPEARANCES          1096
FIRST APPEARANCE      815
Year                  815
dtype: int64
```

In [7]:

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

```
Всего строк: 16376
```

In [8]:

```
# 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' or dt=='object'):
        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
```

```
Колонка ID. Тип данных object. Количество пустых значений 3770, 23.02%.
Колонка ALIGN. Тип данных object. Количество пустых значений 2812, 17.17%.
Колонка EYE. Тип данных object. Количество пустых значений 9767, 59.64%.
Колонка HAIR. Тип данных object. Количество пустых значений 4264, 26.04%.
Колонка SEX. Тип данных object. Количество пустых значений 854, 5.21%.
Колонка GSM. Тип данных object. Количество пустых значений 16286, 99.45%.
Колонка ALIVE. Тип данных object. Количество пустых значений 3, 0.02%.
Колонка APPEARANCES. Тип данных float64. Количество пустых значений 1096, 6.69%.
Колонка FIRST APPEARANCE. Тип данных object. Количество пустых значений 815, 4.98%.
Колонка Year. Тип данных float64. Количество пустых значений 815, 4.98%.
```

In [9]:

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

Out[9]:

	ID	ALIGN	EYE	HAIR	SEX	GSM	ALIVE	APPEARANCES	FIRST APPEARANCE	Year
0	Secret Identity	Good Characters	Hazel Eyes	Brown Hair	Male Characters	NaN	Living Characters	4043.0	Aug-62	1962.0
1	Public Identity	Good Characters	Blue Eyes	White Hair	Male Characters	NaN	Living Characters	3360.0	Mar-41	1941.0
2	Public Identity	Neutral Characters	Blue Eyes	Black Hair	Male Characters	NaN	Living Characters	3061.0	Oct-74	1974.0
3	Public Identity	Good Characters	Blue Eyes	Black Hair	Male Characters	NaN	Living Characters	2961.0	Mar-63	1963.0
4	No Dual Identity	Good Characters	Blue Eyes	Blond Hair	Male Characters	NaN	Living Characters	2258.0	Nov-50	1950.0
...	...	...	...	...	...	...	...	...	...	...
16371	No Dual Identity	Bad Characters	Green Eyes	No Hair	Male Characters	NaN	Living Characters	NaN	NaN	NaN
16372	No Dual Identity	Good Characters	Blue Eyes	Bald	Male Characters	NaN	Living Characters	NaN	NaN	NaN
16373	Secret Identity	Bad Characters	Black Eyes	Bald	Male Characters	NaN	Living Characters	NaN	NaN	NaN
16374	Secret Identity	Neutral Characters	NaN	NaN	Male Characters	NaN	Living Characters	NaN	NaN	NaN
16375	NaN	Bad Characters	NaN	NaN	NaN	NaN	Living Characters	NaN	NaN	NaN

16376 rows × 10 columns

Обработка пропусков в данных

Удалим колонку GSM, так как он имеет 99% пропусков

In [10]:

```
# GSM имеет 99% пропусков
cat_temp_data = data[['GSM']]
cat_temp_data.head()
```

Out[10]:

	GSM
0	NaN
1	NaN
2	NaN
3	NaN
4	NaN

In [11]:

```
# Выполним удаление данного признака
data.drop(['GSM'], axis=1, inplace=True)
```

In [12]:

```
data.head()
```

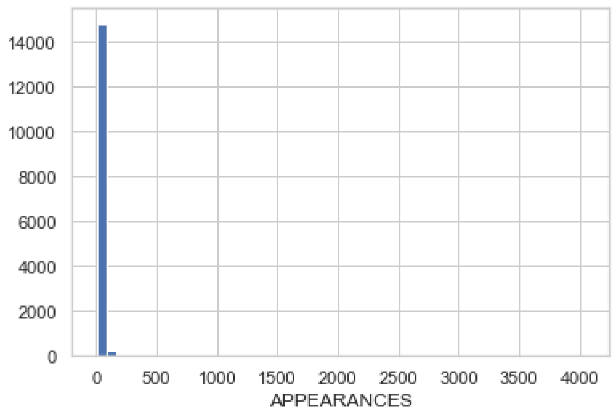
Out[12]:

	page_id	name	urlslug	ID	ALIGN	EYE	HAIR	SEX	ALIVE	APPEARANCES	FI APPEARA
0	1678	Spider-Man (Peter Parker)	\/Spider-Man_(Peter_Parker)	Secret Identity	Good Characters	Hazel Eyes	Brown Hair	Male Characters	Living Characters	4043.0	Au
1	7139	Captain America (Steven Rogers)	\/Captain_America_(Steven_Rogers)	Public Identity	Good Characters	Blue Eyes	White Hair	Male Characters	Living Characters	3360.0	Ma
2	64786	Wolverine (James \"Logan\" Howlett)	\/Wolverine_(James_%22Logan%22_Howlett)	Public Identity	Neutral Characters	Blue Eyes	Black Hair	Male Characters	Living Characters	3061.0	Oc
3	1868	Iron Man (Anthony \"Tony\" Stark)	\/Iron_Man_(Anthony_%22Tony%22_Stark)	Public Identity	Good Characters	Blue Eyes	Black Hair	Male Characters	Living Characters	2961.0	Ma
4	2460	Thor (Thor Odinson)	\/Thor_(Thor_Odinson)	No Dual Identity	Good Characters	Blue Eyes	Blond Hair	Male Characters	Living Characters	2258.0	No

Также рассмотрим колонку APPEARANCES

In [13]:

```
# Гистограмма APPEARANCES
plt.hist(data['APPEARANCES'], 50)
plt.xlabel('APPEARANCES')
plt.show()
```



In [14]:

```
num_data_APPEARANCES = data['APPEARANCES']
num_data_APPEARANCES.head()
```

Out[14]:

```
0    4043.0
1    3360.0
2    3061.0
3    2961.0
4    2258.0
Name: APPEARANCES, dtype: float64
```

In [15]:

```
# Фильтр для проверки заполнения пустых значений
indicator = MissingIndicator()
num_data_APPEARANCES = num_data_APPEARANCES.values.reshape(-1,1)
mask_missing_values_only = indicator.fit_transform(num_data_APPEARANCES)
mask_missing_values_only
```

Out[15]:

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

In [16]:

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

In [17]:

```
def test_num_impute(strat):
    imp_num = SimpleImputer(strategy = strat)
    data_imp_num = imp_num.fit_transform(num_data_APPEARANCES)
    return data_imp_num[mask_missing_values_only]
```

In [18]:

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

Out[18]:

```
('mean',
 array([17.03337696, 17.03337696, 17.03337696, ..., 17.03337696,
        17.03337696, 17.03337696]))
```

In [19]:

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

Out[19]:

```
('median', array([3., 3., 3., ..., 3., 3., 3.]))
```

In [20]:

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

Out[20]:

```
('most_frequent', array([1., 1., 1., ..., 1., 1., 1.]))
```

In [21]:

```
# Более сложная функция, которая позволяет задавать колонку и вид импьютации
def test_num_impute_col(dataset, column, strat):
    temp_data = dataset[[column]]

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

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

    filled_data = data_num_imp[mask_missing_values_only]

    return column, strat, filled_data.size, filled_data[0], filled_data[filled_data.size-1]
```

In [22]:

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

Out[22]:

```
('APPEARANCES', 'mean', 1096, 17.033376963350786, 17.033376963350786)
```

In [23]:

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

Out[23]:

```
('APPEARANCES', 'median', 1096, 3.0, 3.0)
```

In [24]:

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

Out[24]:

```
('APPEARANCES', 'most_frequent', 1096, 1.0, 1.0)
```

Обработка пропусков в категориальных данных

In [26]:

```
num_cols =[]
for col in data.columns:
    count_null = data[data[col].isnull()].shape[0] # кол-во пустых значений
    dt = str(data[col].dtypes)
    if count_null>0 and dt == 'object':
        num_cols.append(col)
        perc_of_missing = round(count_null/total_count * 100, 2)
        print("Колонка: {}. Тип данных: {}. Количество пустых значений: {}, {}%".format(col, dt, count_null, p
```

```
Колонка: ID. Тип данных: object. Количество пустых значений: 3770, 23.02%
Колонка: ALIGN. Тип данных: object. Количество пустых значений: 2812, 17.17%
Колонка: EYE. Тип данных: object. Количество пустых значений: 9767, 59.64%
Колонка: HAIR. Тип данных: object. Количество пустых значений: 4264, 26.04%
Колонка: SEX. Тип данных: object. Количество пустых значений: 854, 5.21%
Колонка: ALIVE. Тип данных: object. Количество пустых значений: 3, 0.02%
Колонка: FIRST APPEARANCE. Тип данных: object. Количество пустых значений: 815, 4.98%
```

Обработаем колонку ALIVE, в которой 0.02% пропусков. Процент пропусков мал, поэтому не будем удалять эту колонку.

In [39]:

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

Out[39]:

	HAIR
0	Brown Hair
1	White Hair
2	Black Hair
3	Black Hair
4	Blond Hair

In [40]:

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

Out[40]:

```
array(['Brown Hair', 'White Hair', 'Black Hair', 'Blond Hair', 'No Hair',
       'Blue Hair', 'Red Hair', 'Bald', 'Auburn Hair', 'Grey Hair',
       'Silver Hair', 'Purple Hair', 'Strawberry Blond Hair',
       'Green Hair', 'Reddish Blond Hair', 'Gold Hair', nan,
       'Orange Hair', 'Pink Hair', 'Variable Hair', 'Yellow Hair',
       'Light Brown Hair', 'Magenta Hair', 'Bronze Hair', 'Dyed Hair',
       'Orange-brown Hair'], dtype=object)
```

In [41]:

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

Out[41]:

```
(4264, 1)
```

In [42]:

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

Out[42]:

```
array([['Brown Hair'],
       ['White Hair'],
       ['Black Hair'],
       ...,
       ['Bald'],
       ['Black Hair'],
       ['Black Hair']], dtype=object)
```

Преобразование категориальных признаков в числовые

In [43]:

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

Out[43]:

	c1
0	Brown Hair
1	White Hair
2	Black Hair
3	Black Hair
4	Blond Hair
...	...
16371	No Hair
16372	Bald
16373	Bald
16374	Black Hair
16375	Black Hair

16376 rows × 1 columns

In [44]:

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

In [45]:

```
# Список имеющихся уникальных значений
cat_enc['c1'].unique()
```

Out[45]:

```
array(['Brown Hair', 'White Hair', 'Black Hair', 'Blond Hair', 'No Hair',
       'Blue Hair', 'Red Hair', 'Bald', 'Auburn Hair', 'Grey Hair',
       'Silver Hair', 'Purple Hair', 'Strawberry Blond Hair',
       'Green Hair', 'Reddish Blond Hair', 'Gold Hair', 'Orange Hair',
       'Pink Hair', 'Variable Hair', 'Yellow Hair', 'Light Brown Hair',
       'Magenta Hair', 'Bronze Hair', 'Dyed Hair', 'Orange-brown Hair'],
      dtype=object)
```

In [46]:

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

Out[46]:

```
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])
```

Чтобы не было фиктивной привязки к отношению порядка, будем использовать one-hot encoding

In [47]:

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

In [48]:

```
cat_enc.shape
```

Out[48]:

```
(16376, 1)
```

In [49]:

```
cat_enc_ohe.shape
```

Out[49]:

```
(16376, 25)
```

In [50]:

```
cat_enc_ohe.todense()[0:10] # разреженная матрица
```

Out[50]:

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

In [51]:

```
# Быстрый способ one-hot кодирования
pd.get_dummies(cat_enc).head(13) # нет фиктивного отношения порядка, 0 - отсутствие, 1 - наличие значения
```

Out[51]:

	c1_Auburn Hair	c1_Bald	c1_Black Hair	c1_Blond Hair	c1_Blue Hair	c1_Bronze Hair	c1_Brown Hair	c1_Dyed Hair	c1_Gold Hair	c1_Green Hair	...	c1_Orange-brown Hair	c1_Pink Hair	c1_Purple Hair	c1
0	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	0	0	
2	0	0	1	0	0	0	0	0	0	0	...	0	0	0	
3	0	0	1	0	0	0	0	0	0	0	...	0	0	0	
4	0	0	0	1	0	0	0	0	0	0	...	0	0	0	
5	0	0	0	0	0	0	0	0	0	0	...	0	0	0	
6	0	0	0	0	0	0	1	0	0	0	...	0	0	0	
7	0	0	0	0	0	0	1	0	0	0	...	0	0	0	
8	0	0	0	0	0	0	1	0	0	0	...	0	0	0	
9	0	0	0	1	0	0	0	0	0	0	...	0	0	0	
10	0	0	0	0	1	0	0	0	0	0	...	0	0	0	
11	0	0	0	1	0	0	0	0	0	0	...	0	0	0	
12	0	0	1	0	0	0	0	0	0	0	...	0	0	0	

13 rows × 25 columns

Minmax масштабирование

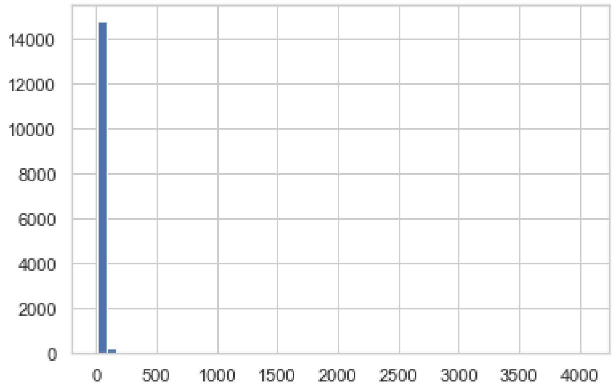
Данные масштабируются в диапазон от 0 до 1

In [53]:

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

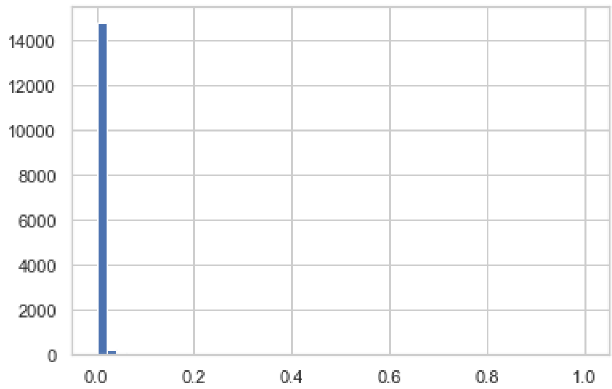
In [54]:

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



In [55]:

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



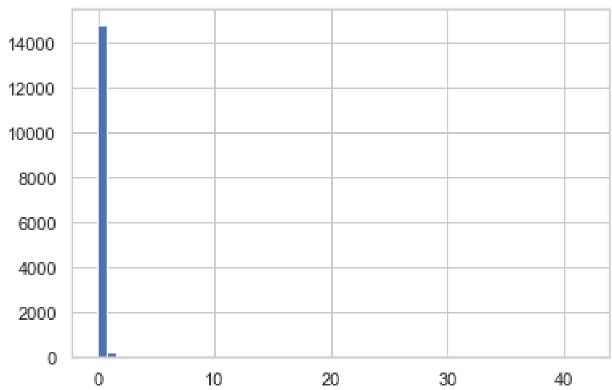
Масштабирование данных на основе Z-оценки

In [56]:

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

In [57]:

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



In [ ]: