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Отчет

Лабораторная работа № 3

По курсу «Технологии машинного обучения»

«Изучение библиотек обработки данных»

ИСПОЛНИТЕЛЬ:

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"__"_____2020 г.

ПРЕПОДАВАТЕЛЬ:

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"__"_____2020 г.

Москва 2020

1. Цель работы

Изучение библиотеки обработки данных Pandas.

2. Описание задания

- Выполнить первое демонстрационное задание "demo assignment" под названием "Exploratory data analysis with Pandas" со страницы курса https://mlcourse.ai/assignments.
- Сформировать отчет и разместить его на своем репозитории GitHub

3. Выполнение задания

Подключим выбранный набор данных

1. Загрузка и первичный анализ:

In [16]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
sns.set(style="ticks")
```

In [17]:
```
data = pd.read_csv('../data/vgsales.csv', sep=",", engine="python")
```

In [18]:
```
# Список колонок с типами данных
data.dtypes
```

Out[18]:
```
Rank             int64
Name            object
Platform        object
Year           float64
Genre           object
Publisher       object
NA_Sales       float64
EU_Sales       float64
JP_Sales       float64
Other_Sales    float64
Global_Sales   float64
dtype: object
```

In [19]:
```
# Проверка на пропуски
data.isnull().sum()
```

Out[19]:
```
Rank             0
Name             0
Platform         0
Year           271
Genre            0
Publisher       58
NA_Sales         0
EU_Sales         0
JP_Sales         0
Other_Sales      0
Global_Sales     0
dtype: int64
```

In [20]:
```
# Размер датасета
data.shape
```

Out[20]:
```
(16598, 11)
```

In [21]:
```
data.head()
```

Out[21]:

	Rank	Name	Platform	Year	Genre	Publisher	NA_Sales	EU_Sales	JP_Sales	Other_Sales	Global_Sales
0	1	Wii Sports	Wii	2006.0	Sports	Nintendo	41.49	29.02	3.77	8.46	82.74
1	2	Super Mario Bros.	NES	1985.0	Platform	Nintendo	29.08	3.58	6.81	0.77	40.24
2	3	Mario Kart Wii	Wii	2008.0	Racing	Nintendo	15.85	12.88	3.79	3.31	35.82
3	4	Wii Sports Resort	Wii	2009.0	Sports	Nintendo	15.75	11.01	3.28	2.96	33.00
4	5	Pokemon Red/Pokemon Blue	GB	1996.0	Role-Playing	Nintendo	11.27	8.89	10.22	1.00	31.37

In [103]:
```
total_count = data.shape[0]
print('Всего строк: {}'.format(total_count))
```

```
Всего строк: 16598
```

2. Обработка пропусков

2.1. Простая стратегия – удаление или заполнение нулями

Обработка пропусков в данных

Простые стратегии - удаление или заполнение нулями

In [104]:
```
# Удаление колонок, содержащих пустые значения
data_new_1 = data.dropna(axis=1, how='any')
(data.shape, data_new_1.shape)
```

Out[104]:
```
((16598, 11), (16598, 9))
```

In [105]:
```
# Удаление строк, содержащих пустые значения
data_new_2 = data.dropna(axis=0, how='any')
(data.shape, data_new_2.shape)
```

Out[105]:
```
((16598, 11), (16291, 11))
```

In [106]:
```
data.head()
```

Out[106]:

	Rank	Name	Platform	Year	Genre	Publisher	NA_Sales	EU_Sales	JP_Sales	Other_Sales	Global_Sales
0	1	Wii Sports	Wii	2006.0	Sports	Nintendo	41.49	29.02	3.77	8.46	82.74
1	2	Super Mario Bros.	NES	1985.0	Platform	Nintendo	29.08	3.58	6.81	0.77	40.24
2	3	Mario Kart Wii	Wii	2008.0	Racing	Nintendo	15.85	12.88	3.79	3.31	35.82
3	4	Wii Sports Resort	Wii	2009.0	Sports	Nintendo	15.75	11.01	3.28	2.96	33.00
4	5	Pokemon Red/Pokemon Blue	GB	1996.0	Role-Playing	Nintendo	11.27	8.89	10.22	1.00	31.37

In [107]:
```
# Заполнение всех пропущенных значений нулями
# Некорректно, так как нулями заполняются в том числе категориальные колонки
data_new_3 = data.fillna(0)
data_new_3.head()
```

Out[107]:

	Rank	Name	Platform	Year	Genre	Publisher	NA_Sales	EU_Sales	JP_Sales	Other_Sales	Global_Sales
0	1	Wii Sports	Wii	2006.0	Sports	Nintendo	41.49	29.02	3.77	8.46	82.74
1	2	Super Mario Bros.	NES	1985.0	Platform	Nintendo	29.08	3.58	6.81	0.77	40.24
2	3	Mario Kart Wii	Wii	2008.0	Racing	Nintendo	15.85	12.88	3.79	3.31	35.82
3	4	Wii Sports Resort	Wii	2009.0	Sports	Nintendo	15.75	11.01	3.28	2.96	33.00
4	5	Pokemon Red/Pokemon Blue	GB	1996.0	Role-Playing	Nintendo	11.27	8.89	10.22	1.00	31.37

2.2. Импьютация

2.2.1. Обработка пропусков в числовых данных

"Внедрение значений" - импьютация (imputation)

Обработка пропусков в числовых данных

In [108]:
```
# 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 Year. Тип данных float64. Количество пустых значений 271, 1.63%.
```

In [109]:
```
# Фильтр по колонкам с пропущенными значениями
data_num = data[num_cols]
data_num
```

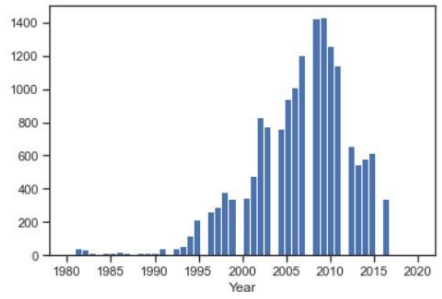
Out[109]:

	Year
0	2006.0
1	1985.0
2	2008.0
3	2009.0
4	1996.0
...	...
16593	2002.0
16594	2003.0
16595	2008.0
16596	2010.0
16597	2003.0

16598 rows × 1 columns

In [110]:
```
# Гистограмма по признакам
for col in data_num:
    plt.hist(data[col], 50)
    plt.xlabel(col)
    plt.show()
```

```
c:\users\administrator\pycharmprojects\rk_tmm\venv\lib\site-packages\numpy\lib\histograms.py:839: RuntimeWarning: invalid value encountered in greater_equal
  keep = (tmp_a >= first_edge)
c:\users\administrator\pycharmprojects\rk_tmm\venv\lib\site-packages\numpy\lib\histograms.py:840: RuntimeWarning: invalid value encountered in less_equal
  keep &= (tmp_a <= last_edge)
```



In [111]:
```
# Фильтр по пустым значениям поля Year
data[data['Year'].isnull()]
```

Out[111]:

	Rank	Name	Platform	Year	Genre	Publisher	NA_Sales	EU_Sales	JP_Sales	Other_Sales	Global_Sales
179	180	Madden NFL 2004	PS2	NaN	Sports	Electronic Arts	4.26	0.26	0.01	0.71	5.23
377	378	FIFA Soccer 2004	PS2	NaN	Sports	Electronic Arts	0.59	2.36	0.04	0.51	3.49
431	432	LEGO Batman: The Videogame	Wii	NaN	Action	Warner Bros. Interactive Entertainment	1.86	1.02	0.00	0.29	3.17
470	471	wwe Smackdown vs. Raw 2006	PS2	NaN	Fighting	NaN	1.57	1.02	0.00	0.41	3.00
607	608	Space Invaders	2600	NaN	Shooter	Atari	2.36	0.14	0.00	0.03	2.53
...	...	...	...	...	...	...	...	...	...	...	...
16307	16310	Freaky Flyers	GC	NaN	Racing	Unknown	0.01	0.00	0.00	0.00	0.01
16327	16330	Inversion	PC	NaN	Shooter	Namco Bandai Games	0.01	0.00	0.00	0.00	0.01
16366	16369	Hakuouki: Shinsengumi Kitan	PS3	NaN	Adventure	Unknown	0.01	0.00	0.00	0.00	0.01
16427	16430	Virtua Quest	GC	NaN	Role-Playing	Unknown	0.01	0.00	0.00	0.00	0.01
16493	16496	The Smurfs	3DS	NaN	Action	Unknown	0.00	0.01	0.00	0.00	0.01

271 rows × 11 columns

In [112]:
```
# Запоминаем индексы строк с пустыми значениями
flt_index = data[data['Year'].isnull()].index
flt_index
```

Out[112]:
```
Int64Index([  179,   377,   431,   470,   607,   624,   649,   652,   711,
              782,
            ...
            16191, 16194, 16198, 16229, 16246, 16307, 16327, 16366, 16427,
            16493],
           dtype='int64', length=271)
```

In [113]:
```
# Проверяем что выводятся нужные строки
data[data.index.isin(flt_index)]
```

Out[113]:

	Rank	Name	Platform	Year	Genre	Publisher	NA_Sales	EU_Sales	JP_Sales	Other_Sales	Global_Sales
179	180	Madden NFL 2004	PS2	NaN	Sports	Electronic Arts	4.26	0.26	0.01	0.71	5.23
377	378	FIFA Soccer 2004	PS2	NaN	Sports	Electronic Arts	0.59	2.36	0.04	0.51	3.49
431	432	LEGO Batman: The Videogame	Wii	NaN	Action	Warner Bros. Interactive Entertainment	1.86	1.02	0.00	0.29	3.17
470	471	wwe Smackdown vs. Raw 2006	PS2	NaN	Fighting	NaN	1.57	1.02	0.00	0.41	3.00
607	608	Space Invaders	2600	NaN	Shooter	Atari	2.36	0.14	0.00	0.03	2.53
...	...	...	...	...	...	...	...	...	...	...	...
16307	16310	Freaky Flyers	GC	NaN	Racing	Unknown	0.01	0.00	0.00	0.00	0.01
16327	16330	Inversion	PC	NaN	Shooter	Namco Bandai Games	0.01	0.00	0.00	0.00	0.01
16366	16369	Hakuouki: Shinsengumi Kitan	PS3	NaN	Adventure	Unknown	0.01	0.00	0.00	0.00	0.01
16427	16430	Virtua Quest	GC	NaN	Role-Playing	Unknown	0.01	0.00	0.00	0.00	0.01
16493	16496	The Smurfs	3DS	NaN	Action	Unknown	0.00	0.01	0.00	0.00	0.01

271 rows × 11 columns

In [114]:
```
# фильтр по колонке
data_num[data_num.index.isin(flt_index)]['Year']
```

Out[114]:
```
179      NaN
377      NaN
431      NaN
470      NaN
607      NaN
          ..
16307    NaN
16327    NaN
16366    NaN
16427    NaN
16493    NaN
Name: Year, Length: 271, dtype: float64
```

In [115]:
```
data_num_Year = data_num[['Year']]
data_num_Year.head()
```

Out[115]:

	Year
0	2006.0
1	1985.0
2	2008.0
3	2009.0
4	1996.0

In [116]:
```
from sklearn.impute import SimpleImputer
from sklearn.impute import MissingIndicator
```

In [117]:
```
# Фильтр для проверки заполнения пустых значений
indicator = MissingIndicator()
mask_missing_values_only = indicator.fit_transform(data_num_Year)
mask_missing_values_only
```

Out[117]:
```
array([[False],
       [False],
       [False],
       ...,
       [False],
       [False],
       [False]])
```

In [118]:
```
strategies=['mean', 'median','most_frequent']
def test_num_impute(strategy_param):
    imp_num = SimpleImputer(strategy=strategy_param)
    data_num_imp = imp_num.fit_transform(data_num_Year)
    return data_num_imp[mask_missing_values_only]
```

In [119]:
```
strategies[0], test_num_impute(strategies[0])
```

Out[119]:
```
('mean',
 array([2006.40644331, 2006.40644331, 2006.40644331, 2006.40644331,
        2006.40644331, 2006.40644331, 2006.40644331, 2006.40644331,
        2006.40644331, 2006.40644331, 2006.40644331, 2006.40644331,
        2006.40644331, 2006.40644331, 2006.40644331, 2006.40644331,
        2006.40644331, 2006.40644331, 2006.40644331, 2006.40644331,
        2006.40644331, 2006.40644331, 2006.40644331, 2006.40644331,
        2006.40644331, 2006.40644331, 2006.40644331, 2006.40644331,
        2006.40644331, 2006.40644331, 2006.40644331, 2006.40644331,
        2006.40644331, 2006.40644331, 2006.40644331, 2006.40644331,
        2006.40644331, 2006.40644331, 2006.40644331, 2006.40644331,
        2006.40644331, 2006.40644331, 2006.40644331, 2006.40644331,
        2006.40644331, 2006.40644331, 2006.40644331, 2006.40644331,
        2006.40644331, 2006.40644331, 2006.40644331, 2006.40644331,
        2006.40644331, 2006.40644331, 2006.40644331, 2006.40644331,
        2006.40644331, 2006.40644331, 2006.40644331, 2006.40644331,
        2006.40644331, 2006.40644331, 2006.40644331, 2006.40644331,
        2006.40644331, 2006.40644331, 2006.40644331, 2006.40644331,
```

In [120]:
```
strategies[1], test_num_impute(strategies[1])
```

Out[120]:
```
('median',
 array([2007., 2007., 2007., 2007., 2007., 2007., 2007., 2007., 2007.,
        2007., 2007., 2007., 2007., 2007., 2007., 2007., 2007., 2007.,
        2007., 2007., 2007., 2007., 2007., 2007., 2007., 2007., 2007.,
        2007., 2007., 2007., 2007., 2007., 2007., 2007., 2007., 2007.,
        2007., 2007., 2007., 2007., 2007., 2007., 2007., 2007., 2007.,
        2007., 2007., 2007., 2007., 2007., 2007., 2007., 2007., 2007.,
        2007., 2007., 2007., 2007., 2007., 2007., 2007., 2007., 2007.,
        2007., 2007., 2007., 2007., 2007., 2007., 2007., 2007., 2007.,
        2007., 2007., 2007., 2007., 2007., 2007., 2007., 2007., 2007.,
        2007., 2007., 2007., 2007., 2007., 2007., 2007., 2007., 2007.,
        2007., 2007., 2007., 2007., 2007., 2007., 2007., 2007., 2007.,
        2007., 2007., 2007., 2007., 2007., 2007., 2007., 2007., 2007.,
        2007., 2007., 2007., 2007., 2007., 2007., 2007., 2007., 2007.,
        2007., 2007., 2007., 2007., 2007., 2007., 2007., 2007., 2007.,
        2007., 2007., 2007., 2007., 2007., 2007., 2007., 2007., 2007.,
        2007., 2007., 2007., 2007., 2007., 2007., 2007., 2007., 2007.,
        2007., 2007., 2007., 2007., 2007., 2007., 2007., 2007., 2007.,
        2007., 2007., 2007., 2007., 2007., 2007., 2007., 2007., 2007.,
```

```
In [121]: strategies[2], test_num_impute(strategies[2])
```

```
Out[121]: ('most_frequent',
           array([2009., 2009., 2009., 2009., 2009., 2009., 2009., 2009., 2009.,
                  2009., 2009., 2009., 2009., 2009., 2009., 2009., 2009., 2009.,
                  2009., 2009., 2009., 2009., 2009., 2009., 2009., 2009., 2009.,
                  2009., 2009., 2009., 2009., 2009., 2009., 2009., 2009., 2009.,
                  2009., 2009., 2009., 2009., 2009., 2009., 2009., 2009., 2009.,
                  2009., 2009., 2009., 2009., 2009., 2009., 2009., 2009., 2009.,
                  2009., 2009., 2009., 2009., 2009., 2009., 2009., 2009., 2009.,
                  2009., 2009., 2009., 2009., 2009., 2009., 2009., 2009., 2009.,
                  2009., 2009., 2009., 2009., 2009., 2009., 2009., 2009., 2009.,
                  2009., 2009., 2009., 2009., 2009., 2009., 2009., 2009., 2009.,
```

```
In [122]: # 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 [123]: data[['Year']].describe()
```

Out[123]:

	Year
count	16327.000000
mean	2006.406443
std	5.828981
min	1980.000000
25%	2003.000000
50%	2007.000000
75%	2010.000000
max	2020.000000

```
In [124]: test_num_impute_col(data, 'Year', strategies[0])

Out[124]: ('Year', 'mean', 271, 2006.4064433147546, 2006.4064433147546)
```

```
In [125]: test_num_impute_col(data, 'Year', strategies[1])
Out[125]: ('Year', 'median', 271, 2007.0, 2007.0)
```

```
In [126]: test_num_impute_col(data, 'Year', strategies[2])
Out[126]: ('Year', 'most_frequent', 271, 2009.0, 2009.0)
```

2.2.2. Обработка пропусков в категориальных данных

Обработка пропусков в категориальных данных

```
In [127]: # 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 Publisher. Тип данных object. Количество пустых значений 58, 0.35%.
```

```
In [128]: cat_temp_data = data[['Publisher']]
cat_temp_data.head()
```

Out[128]:

	Publisher
0	Nintendo
1	Nintendo
2	Nintendo
3	Nintendo
4	Nintendo

```
In [129]: cat_temp_data['Publisher'].unique()
```

Out[129]:
```
array(['Nintendo', 'Microsoft Game Studios', 'Take-Two Interactive',
       'Sony Computer Entertainment', 'Activision', 'Ubisoft',
       'Bethesda Softworks', 'Electronic Arts', 'Sega', 'SquareSoft',
       'Atari', '505 Games', 'Capcom', 'GT Interactive',
       'Konami Digital Entertainment',
       'Sony Computer Entertainment Europe', 'Square Enix', 'LucasArts',
       'Virgin Interactive', 'Warner Bros. Interactive Entertainment',
       'Universal Interactive', 'Eidos Interactive', 'RedOctane',
       'Vivendi Games', 'Enix Corporation', 'Namco Bandai Games',
       'Palcom', 'Hasbro Interactive', 'THQ', 'Fox Interactive',
       'Acclaim Entertainment', 'MTV Games', 'Disney Interactive Studios',
       nan, 'Majesco Entertainment', 'Codemasters', 'Red Orb', 'Level 5',
       'Arena Entertainment', 'Midway Games', 'JVC', 'Deep Silver',
       '989 Studios', 'NCSoft', 'UEP Systems', 'Parker Bros.', 'Maxis',
       'Imagic', 'Tecmo Koei', 'Valve Software', 'ASCII Entertainment',
       'Mindscape', 'Infogrames', 'Unknown', 'Square', 'Valve',
       'Activision Value', 'Banpresto', 'D3Publisher',
       'Oxygen Interactive', 'Red Storm Entertainment', 'Video System',
       'Hello Games', 'Global Star', 'Gotham Games', 'Westwood Studios',
       'GungHo', 'Crave Entertainment', 'Hudson Soft', 'Coleco'
```

In [130]:
```
cat_temp_data[cat_temp_data['Publisher'].isnull()].shape
```

Out[130]:
```
(58, 1)
```

In [131]:
```
# Импьютация наиболее частыми значениями
imp2 = SimpleImputer(missing_values=np.nan, strategy='most_frequent')
data_imp2 = imp2.fit_transform(cat_temp_data)
data_imp2
```

Out[131]:
```
array([['Nintendo'],
       ['Nintendo'],
       ['Nintendo'],
       ...,
       ['Activision'],
       ['7G//AMES'],
       ['Wanadoo']], dtype=object)
```

In [132]:
```
# Пустые значения отсутствуют
np.unique(data_imp2)
```

Out[132]:
```
array(['10TACLE Studios', '1C Company', '20th Century Fox Video Games',
       '2D Boy', '3DO', '49Games', '505 Games', '5pb', '7G//AMES',
       '989 Sports', '989 Studios', 'AQ Interactive', 'ASC Games',
       'ASCII Entertainment', 'ASCII Media Works', 'ASK', 'Abylight',
       'Acclaim Entertainment', 'Accolade', 'Ackkstudios', 'Acquire',
       'Activision', 'Activision Blizzard', 'Activision Value',
       'Adeline Software', 'Aerosoft', 'Agatsuma Entertainment', 'Agetec',
       'Aksys Games', 'Alawar Entertainment', 'Alchemist',
       'Alternative Software', 'Altron', 'Alvion', 'American Softworks',
       'Angel Studios', 'Answer Software', 'Aqua Plus', 'Aques',
       'Arc System Works', 'Arena Entertainment', 'Aria', 'Arika',
       'ArtDink', 'Aruze Corp', 'Ascaron Entertainment',
       'Ascaron Entertainment GmbH', 'Asgard', 'Asmik Ace Entertainment',
       'Asmik Corp', 'Aspyr', 'Astragon', 'Asylum Entertainment', 'Atari',
       'Athena', 'Atlus', 'Avalon Interactive', 'Avanquest',
       'Avanquest Software', 'Axela', 'BAM! Entertainment',
       'BMG Interactive Entertainment', 'BPS', 'Banpresto', 'Benesse',
       'Berkeley', 'Bethesda Softworks', 'Big Ben Interactive',
       'Big Fish Games', 'Bigben Interactive', 'Black Bean Games',
       'Black Label Games', 'Blast! Entertainment Ltd', 'Blue Byte',
```

In [133]:
```
# Импьютация константой
imp3 = SimpleImputer(missing_values=np.nan, strategy='constant', fill_value='EA')
data_imp3 = imp3.fit_transform(cat_temp_data)
data_imp3
```

Out[133]:
```
array([['Nintendo'],
       ['Nintendo'],
       ['Nintendo'],
       ...,
       ['Activision'],
       ['7G//AMES'],
       ['Wanadoo']], dtype=object)
```

In [134]:
```
np.unique(data_imp3)
```

Out[134]:
```
array(['10TACLE Studios', '1C Company', '20th Century Fox Video Games',
       '2D Boy', '3DO', '49Games', '505 Games', '5pb', '7G//AMES',
       '989 Sports', '989 Studios', 'AQ Interactive', 'ASC Games',
       'ASCII Entertainment', 'ASCII Media Works', 'ASK', 'Abylight',
       'Acclaim Entertainment', 'Accolade', 'Ackkstudios', 'Acquire',
       'Activision', 'Activision Blizzard', 'Activision Value',
       'Adeline Software', 'Aerosoft', 'Agatsuma Entertainment', 'Agetec',
       'Aksys Games', 'Alawar Entertainment', 'Alchemist',
       'Alternative Software', 'Altron', 'Alvion', 'American Softworks',
       'Angel Studios', 'Answer Software', 'Aqua Plus', 'Aques',
       'Arc System Works', 'Arena Entertainment', 'Aria', 'Arika',
       'ArtDink', 'Aruze Corp', 'Ascaron Entertainment',
       'Ascaron Entertainment GmbH', 'Asgard', 'Asmik Ace Entertainment',
       'Asmik Corp', 'Aspyr', 'Astragon', 'Asylum Entertainment', 'Atari',
       'Athena', 'Atlus', 'Avalon Interactive', 'Avanquest',
       'Avanquest Software', 'Axela', 'BAM! Entertainment',
       'BMG Interactive Entertainment', 'BPS', 'Banpresto', 'Benesse',
```

```
In [135]: data_imp3[data_imp3=='EA'].size
Out[135]: 58
```

3. Преобразование категориальных признаков в числовые

Преобразование категориальных признаков в числовые

```
In [136]: cat_enc = pd.DataFrame({'c1':data_imp2.T[0]})
          cat_enc
```

Out[136]:

	c1
0	Nintendo
1	Nintendo
2	Nintendo
3	Nintendo
4	Nintendo
...	...
16593	Kemco
16594	Infogrames
16595	Activision
16596	7G//AMES
16597	Wanadoo

16598 rows × 1 columns

3.1. Кодирование категорий целочисленными значениями – label encoding

Кодирование категорий целочисленными значениями - label encoding

```
In [137]: from sklearn.preprocessing import LabelEncoder, OneHotEncoder
          le = LabelEncoder()
          cat_enc_le = le.fit_transform(cat_enc['c1'])

In [138]: cat_enc['c1'].unique()
```

```
Out[138]: array(['Nintendo', 'Microsoft Game Studios', 'Take-Two Interactive',
                 'Sony Computer Entertainment', 'Activision', 'Ubisoft',
                 'Bethesda Softworks', 'Electronic Arts', 'Sega', 'SquareSoft',
                 'Atari', '505 Games', 'Capcom', 'GT Interactive',
                 'Konami Digital Entertainment',
                 'Sony Computer Entertainment Europe', 'Square Enix', 'LucasArts',
                 'Virgin Interactive', 'Warner Bros. Interactive Entertainment',
                 'Universal Interactive', 'Eidos Interactive', 'RedOctane',
                 'Vivendi Games', 'Enix Corporation', 'Namco Bandai Games',
                 'Palcom', 'Hasbro Interactive', 'THQ', 'Fox Interactive',
                 'Acclaim Entertainment', 'MTV Games', 'Disney Interactive Studios',
                 'Majesco Entertainment', 'Codemasters', 'Red Orb', 'Level 5',
                 'Arena Entertainment', 'Midway Games', 'JVC', 'Deep Silver',
                 '989 Studios', 'NCSoft', 'UEP Systems', 'Parker Bros.', 'Maxis',
                 'Imagic', 'Tecmo Koei', 'Valve Software', 'ASCII Entertainment',
                 'Mindscape', 'Infogrames', 'Unknown', 'Square', 'Valve',
                 'Activision Value', 'Banpresto', 'D3Publisher',
                 'Oxygen Interactive', 'Red Storm Entertainment', 'Video System',
                 'Hello Games', 'Global Star', 'Gotham Games', 'Westwood Studios',
                 'GungHo', 'Crave Entertainment', 'Hudson Soft', 'Coleco',
```

In [139]:
```
np.unique(cat_enc_le)
```

Out[139]:
```
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, 280, 281, 282, 283, 284, 285,
       286, 287, 288, 289, 290, 291, 292, 293, 294, 295, 296, 297, 298,
       299, 300, 301, 302, 303, 304, 305, 306, 307, 308, 309, 310, 311,
       312, 313, 314, 315, 316, 317, 318, 319, 320, 321, 322, 323, 324,
       325, 326, 327, 328, 329, 330, 331, 332, 333, 334, 335, 336, 337,
       338, 339, 340, 341, 342, 343, 344, 345, 346, 347, 348, 349, 350,
       351, 352, 353, 354, 355, 356, 357, 358, 359, 360, 361, 362, 363,
       364, 365, 366, 367, 368, 369, 370, 371, 372, 373, 374, 375, 376,
       377, 378, 379, 380, 381, 382, 383, 384, 385, 386, 387, 388, 389,
       390, 391, 392, 393, 394, 395, 396, 397, 398, 399, 400, 401, 402,
       403, 404, 405, 406, 407, 408, 409, 410, 411, 412, 413, 414, 415,
       416, 417, 418, 419, 420, 421, 422, 423, 424, 425, 426, 427, 428,
       429, 430, 431, 432, 433, 434, 435, 436, 437, 438, 439, 440, 441,
       442, 443, 444, 445, 446, 447, 448, 449, 450, 451, 452, 453, 454,
       455, 456, 457, 458, 459, 460, 461, 462, 463, 464, 465, 466, 467,
       468, 469, 470, 471, 472, 473, 474, 475, 476, 477, 478, 479, 480,
       481, 482, 483, 484, 485, 486, 487, 488, 489, 490, 491, 492, 493,
       494, 495, 496, 497, 498, 499, 500, 501, 502, 503, 504, 505, 506,
       507, 508, 509, 510, 511, 512, 513, 514, 515, 516, 517, 518, 519,
       520, 521, 522, 523, 524, 525, 526, 527, 528, 529, 530, 531, 532,
       533, 534, 535, 536, 537, 538, 539, 540, 541, 542, 543, 544, 545,
       546, 547, 548, 549, 550, 551, 552, 553, 554, 555, 556, 557, 558,
       559, 560, 561, 562, 563, 564, 565, 566, 567, 568, 569, 570, 571,
       572, 573, 574, 575, 576, 577])
```

In [140]:
```
le.inverse_transform([0, 1, 2, 3])
```

Out[140]:
```
array(['10TACLE Studios', '1C Company', '20th Century Fox Video Games',
       '2D Boy'], dtype=object)
```

3.2. Кодирование категорий наборами бинарных значений – one-hot encoding

Кодирование категорий наборами бинарных значений - one-hot encoding

In [141]:
```
ohe = OneHotEncoder()
cat_enc_ohe = ohe.fit_transform(cat_enc[['c1']])
```

In [142]:
```
cat_enc.shape
```

Out[142]:
```
(16598, 1)
```

In [143]:
```
cat_enc_ohe.shape
```

Out[143]:
```
(16598, 578)
```

In [144]:
```
cat_enc_ohe
```

Out[144]:
```
<16598x578 sparse matrix of type '<class 'numpy.float64'>'
        with 16598 stored elements in Compressed Sparse Row format>
```

In [145]:
```
cat_enc_ohe.todense()[0:10]
```

Out[145]:
```
matrix([[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 [146]:
```
cat_enc.head(10)
```

Out[146]:

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

3.3. Pandas_get_dummies – быстрый вариант one-hot кодирования

Pandas get_dummies - быстрый вариант one-hot кодирования

In [147]:
```
pd.get_dummies(cat_enc).head()
```

Out[147]:

	c1_10TACLE Studios	c1_1C Company	c1_20th Century Fox Video Games	c1_2D Boy	c1_3DO	c1_49Games	c1_505 Games	c1_5pb	c1_7G//AMES	c1_989 Sports	...	c1_Zushi Games	c1_bitComposer Games	c1_dramatic create	c1_fon
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	
2	0	0	0	0	0	0	0	0	0	0	...	0	0	0	
3	0	0	0	0	0	0	0	0	0	0	...	0	0	0	
4	0	0	0	0	0	0	0	0	0	0	...	0	0	0	

5 rows × 578 columns

In [148]:
```
pd.get_dummies(cat_temp_data, dummy_na=True).head()
```

Out[148]:

	Publisher_10TACLE Studios	Publisher_1C Company	Publisher_20th Century Fox Video Games	Publisher_2D Boy	Publisher_3DO	Publisher_49Games	Publisher_505 Games	Publisher_5pb	Publisher_7G//AMES	Pu
0	0	0	0	0	0	0	0	0	0	
1	0	0	0	0	0	0	0	0	0	
2	0	0	0	0	0	0	0	0	0	
3	0	0	0	0	0	0	0	0	0	
4	0	0	0	0	0	0	0	0	0	

5 rows × 579 columns

4. Масштабирование данных

4.1. MinMax масштабирование

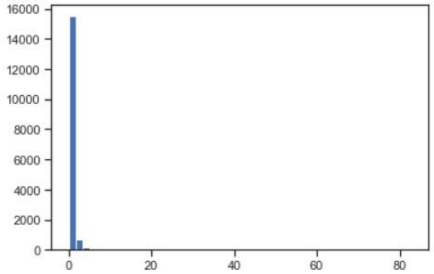
Масштабирование данных

In [159]:
```
from sklearn.preprocessing import MinMaxScaler, StandardScaler, Normalizer
```

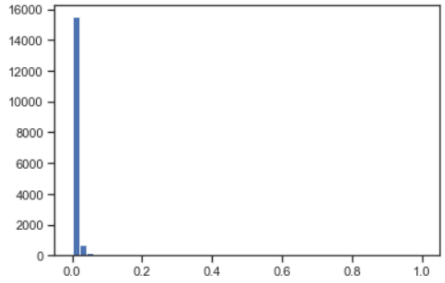
MinMax масштабирование

In [160]:
```
sc1 = MinMaxScaler()
sc1_data = sc1.fit_transform(data[['Global_Sales']])
```

In [161]:
```
plt.hist(data['Global_Sales'], 50)
plt.show()
```



In [162]:
```
plt.hist(sc1_data, 50)
plt.show()
```

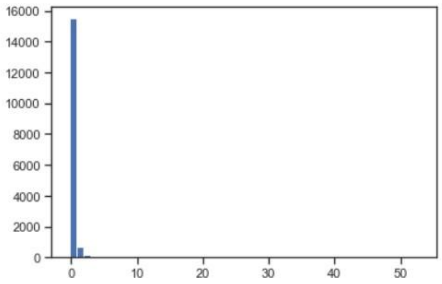


4.2. Масштабирование данных на основе Z-оценки – StandardScaler

Масштабирование данных на основе Z-оценки - StandardScaler

In [163]:
```
sc2 = StandardScaler()
sc2_data = sc2.fit_transform(data[['Global_Sales']])
```

In [164]:
```
plt.hist(sc2_data, 50)
plt.show()
```



4.3. Нормализация данных

Нормализация данных

In [165]:
```
sc3 = Normalizer()
sc3_data = sc3.fit_transform(data[['Global_Sales']])
```

In [166]:
```
plt.hist(sc3_data, 50)
plt.show()
```