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Методы машинного обучения

Отчёт по лабораторной работе № 3

«Обработка пропусков в данных, кодирование категориальных признаков, масштабирование данных»

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In [168]:

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

In [253]:

```
data = pd.read_csv('titanic.csv')
games = pd.read_csv('vgsales.csv')
data.head()
```

Out[253]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	C
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	

Проверим набор данных пассажиров Титаника на наличие пропусков данных

In [170]:

```
for col in data.columns:
    count = data[data[col].isnull()].shape[0]
    print('{}  -  {}'.format(col, count))
print ('{} - размер датасета'.format(data.shape))
```

```
PassengerId  -  0
Survived  -  0
Pclass  -  0
Name  -  0
Sex  -  0
Age  -  177
SibSp  -  0
Parch  -  0
Ticket  -  0
Fare  -  0
Cabin  -  687
Embarked  -  2
(891, 12) - размер датасета
```

Можно заметить, что пропущены 177 значений столбца Age, 2 значения столбца Embarked и целых 687 значений столбца Cabin. Исходя из полученных данных целесообразным будет полное удаление столбца Cabin. Для столбцов Age и Embarked следует удалить строки с пропущенными значениями

In [171]:

```
del data['Cabin']
data
```

Out[171]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500
...	...	...	...	...	...	...	...	...	...	...
886	887	0	2	Montvila, Rev. Juozas	male	27.0	0	0	211536	13.0000
887	888	1	1	Graham, Miss. Margaret Edith	female	19.0	0	0	112053	30.0000
888	889	0	3	Johnston, Miss. Catherine Helen "Carrie"	female	NaN	1	2	W./C. 6607	23.4500
889	890	1	1	Behr, Mr. Karl Howell	male	26.0	0	0	111369	30.0000
890	891	0	3	Dooley, Mr. Patrick	male	32.0	0	0	370376	7.7500

891 rows × 11 columns

После удаления столбца Cabin воспользуемся методом dropna() для удаления строк, содержащих пропуски данных

In [172]:

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

Out[172]:

```
((891, 11), (712, 11))
```

In [173]:

```
data_.dropna(inplace=True)
data_.reset_index(drop=True, inplace=True)
data_
```

```
c:\users\timofey\virtln\mmo\lib\site-packages\ipykernel_launcher.py:1: Setti
ngWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/
stable/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pand
as.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-v
ersus-a-copy)
  """Entry point for launching an IPython kernel.
```

Out[173]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500
...	...	...	...	...	...	...	...	...	...	...
707	886	0	3	Rice, Mrs. William (Margaret Norton)	female	39.0	0	5	382652	29.1250
708	887	0	2	Montvila, Rev. Juozas	male	27.0	0	0	211536	13.0000
709	888	1	1	Graham, Miss. Margaret Edith	female	19.0	0	0	112053	30.0000
710	890	1	1	Behr, Mr. Karl Howell	male	26.0	0	0	111369	30.0000
711	891	0	3	Dooley, Mr. Patrick	male	32.0	0	0	370376	7.7500

712 rows × 11 columns

Можно заметить, что размер набора данных уменьшился на 179 строк.

In [ ]:

```
```

В исходном наборе данных присутствуют категориальные признаки, которые необходимо преобразовать в числовые

Узнаем количество уникальных значений каждого категориального признака

In [175]:

```
print ('{} - {}'.format(data_['Sex'].unique(), data_['Embarked'].unique()))
```

```
['male' 'female'] - ['S' 'C' 'Q']
```

In [176]:

```
from sklearn.preprocessing import LabelEncoder, OneHotEncoder
le = LabelEncoder()
ohe = OneHotEncoder()
```

Воспользуемся двумя методами кодирования: Label encoding и One-hot encoding. Признак Sex закодируем первым методом, а признак Embarked - вторым

In [177]:

```
sex = le.fit_transform(data_['Sex'])
np.unique(sex)
```

Out[177]:

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

In [178]:

```
sex
```

Out[178]:

```
array([1, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 1, 1, 0, 0, 1, 0, 1, 1, 0, 1, 0,
       0, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 1, 0, 1, 0,
       1, 1, 1, 1, 0, 1, 0, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 0, 1,
       0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 0, 1, 1, 1, 1, 0, 1, 1, 0, 1, 0,
       0, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 0, 1, 1, 0, 1, 1,
       1, 0, 0, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 1, 1, 0, 1, 1, 0, 1, 1, 1,
       1, 0, 1, 1, 1, 0, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 0, 1,
       0, 0, 1, 0, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 0, 1, 1, 0, 0, 1, 0, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0,
       0, 1, 1, 0, 1, 1, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 0, 0, 1, 0, 1,
       0, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 1, 0, 1, 1, 0, 0, 1,
       1, 0, 1, 0, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 1, 0, 0,
       0, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 0,
       0, 1, 1, 0, 1, 1, 0, 0, 1, 1, 1, 1, 0, 0, 1, 1, 1, 0, 0, 1, 0, 1,
       1, 0, 0, 1, 1, 1, 0, 0, 1, 0, 1, 1, 0, 1, 1, 0, 1, 0, 1, 1, 1, 1,
       0, 1, 0, 0, 1, 0, 1, 1, 0, 1, 0, 0, 1, 1, 0, 1, 1, 0, 0, 0, 1, 1,
       0, 1, 1, 0, 1, 0, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0,
```

In [83]:

```
sex = pd.DataFrame({'Sex':sex.T})
sex
```

Out[83]:

	Sex
0	1
1	0
2	0
3	0
4	1
...	...
707	0
708	1
709	0
710	1
711	1

712 rows × 1 columns

Удалим столбец Sex, в исходном наборе данных и заменим его на новый с числовыми значениями

In [84]:

```
del data_['Sex']
data_j1 = data_.join(sex)
data_j1
```

. . .

Метод One-Hot Encoding

In [215]:

```
cat_data = data_j1['Embarked']
```

In [216]:

```
cat_enc = pd.DataFrame({'Embarked':cat_data.T})
cat_enc
```

Out[216]:

	Embarked
0	S
1	C
2	S
3	S
4	S
...	...
707	Q
708	S
709	S
710	C
711	Q

712 rows × 1 columns

In [217]:

```
cat_enc.shape
```

Out[217]:

```
(712, 1)
```

In [218]:

```
embarked = ohe.fit_transform(cat_enc[['Embarked']])
```

In [219]:

```
ohe.categories_
```

Out[219]:

```
[array(['C', 'Q', 'S'], dtype=object)]
```

In [220]:

```
embarked.todense()[0:5]
```

Out[220]:

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

In [221]:

```
embarked.toarray()
```

Out[221]:

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

In [222]:

```
e = embarked.transpose()
e.toarray()
```

Out[222]:

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

In [223]:

```
e0 = e[0].toarray()
e0
```

Out[223]:

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

In [224]:

```
e1 = e[1].toarray()
e2 = e[2].toarray()
```

In [225]:

```
data_j2 = pd.DataFrame({'E1':e0[0],'E2':e1[0],'E3':e2[0]})
data_j2
```

Out[225]:

	E1	E2	E3
0	0.0	0.0	1.0
1	1.0	0.0	0.0
2	0.0	0.0	1.0
3	0.0	0.0	1.0
4	0.0	0.0	1.0
...	...	...	...
707	0.0	1.0	0.0
708	0.0	0.0	1.0
709	0.0	0.0	1.0
710	1.0	0.0	0.0
711	0.0	1.0	0.0

712 rows × 3 columns

In [231]:

```
data_j2.dtypes
```

Out[231]:

```
E1    float64
E2    float64
E3    float64
dtype: object
```

Изменим тип признаков датафрейма на с float64 на int

In [237]:

```
data_j2['E1'] = data_j2['E1'].astype('int')
data_j2['E2'] = data_j2['E2'].astype('int')
data_j2['E3'] = data_j2['E3'].astype('int')
```

In [238]:

```
data_j2
```

Out[238]:

	E1	E2	E3
0	0	0	1
1	1	0	0
2	0	0	1
3	0	0	1
4	0	0	1
...	...	...	...
707	0	1	0
708	0	0	1
709	0	0	1
710	1	0	0
711	0	1	0

712 rows × 3 columns

Объединим датафреймы

In [239]:

```
del data_j1['Embarked']
new_data = data_j1.join(data_j2)
new_data
```

Out[239]:

	PassengerId	Survived	Pclass	Name	Age	SibSp	Parch	Ticket	Fare	Sex	E
0	1	0	3	Braund, Mr. Owen Harris	22.0	1	0	A/5 21171	7.2500	1	
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	38.0	1	0	PC 17599	71.2833	0	
2	3	1	3	Heikkinen, Miss. Laina	26.0	0	0	STON/O2. 3101282	7.9250	0	
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	35.0	1	0	113803	53.1000	0	
4	5	0	3	Allen, Mr. William Henry	35.0	0	0	373450	8.0500	1	
...	...	...	...	...	...	...	...	...	...	...	
707	886	0	3	Rice, Mrs. William (Margaret Norton)	39.0	0	5	382652	29.1250	0	
708	887	0	2	Montvila, Rev. Juozas	27.0	0	0	211536	13.0000	1	
709	888	1	1	Graham, Miss. Margaret Edith	19.0	0	0	112053	30.0000	0	
710	890	1	1	Behr, Mr. Karl Howell	26.0	0	0	111369	30.0000	1	
711	891	0	3	Dooley, Mr. Patrick	32.0	0	0	370376	7.7500	1	

712 rows × 13 columns

Также возможно использование быстрого варианта one-hot кодирования с помощью pandas get_dummies()

In [229]:

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

Out[229]:

	Embarked_C	Embarked_Q	Embarked_S
0	0	0	1
1	1	0	0
2	0	0	1
3	0	0	1
4	0	0	1
...	...	...	...
707	0	1	0
708	0	0	1
709	0	0	1
710	1	0	0
711	0	1	0

712 rows × 3 columns

Масштабирование

In [240]:

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

MinMax масштабирование

In [241]:

```
sc1 = MinMaxScaler()
sc1_data = sc1.fit_transform(new_data[['Fare']])
```

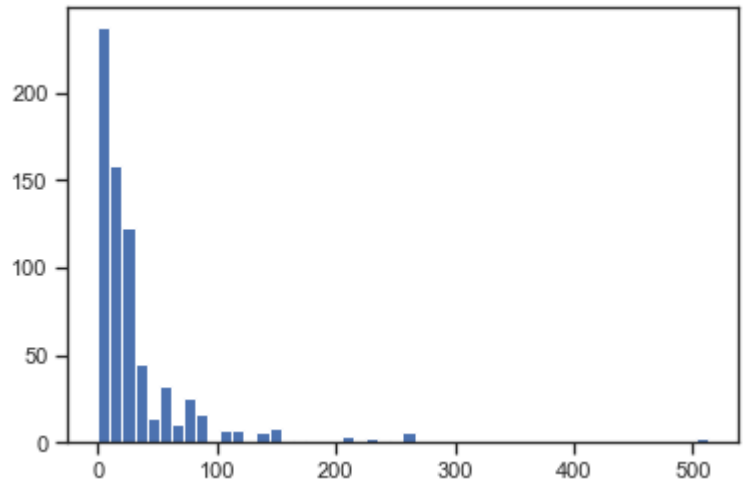
In [246]:

```
print(new_data['Fare'].mean())
```

```
34.567251404494385
```

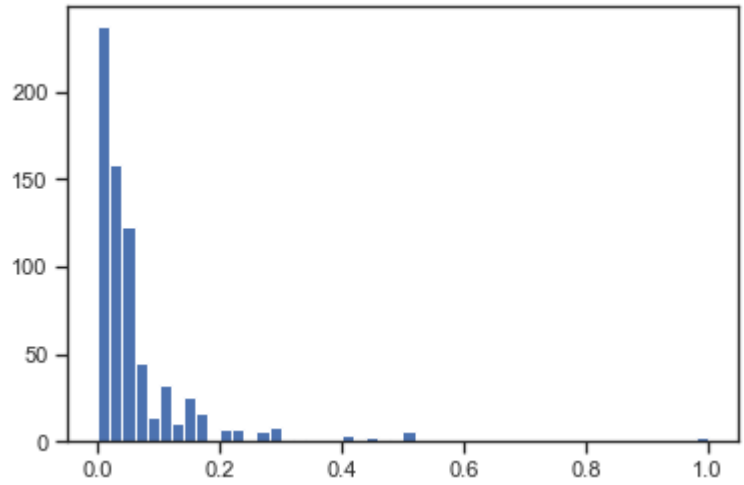
In [243]:

```
plt.hist(new_data['Fare'], 50)
plt.show()
```



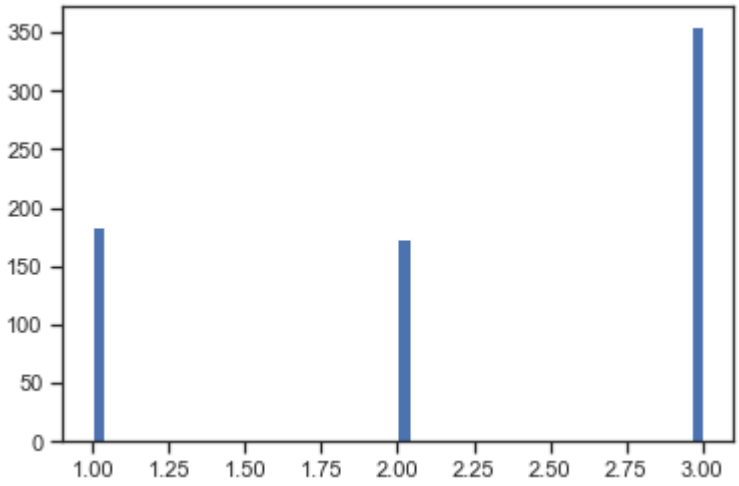
In [247]:

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



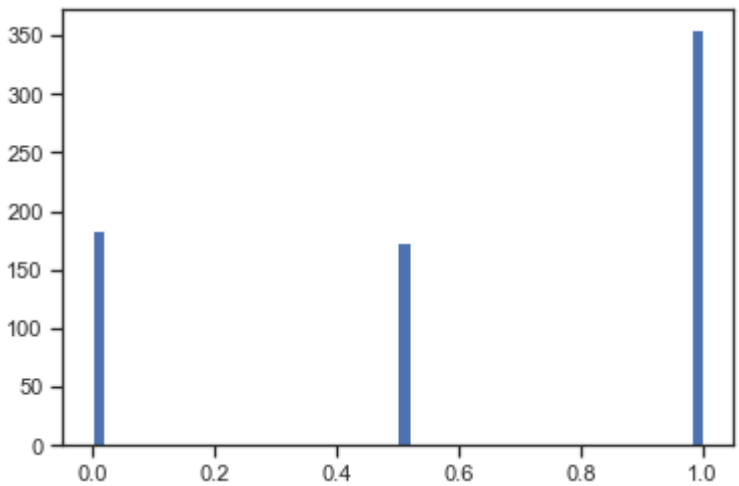
In [250]:

```
plt.hist(new_data['Pclass'], 50)
plt.show()
```



In [252]:

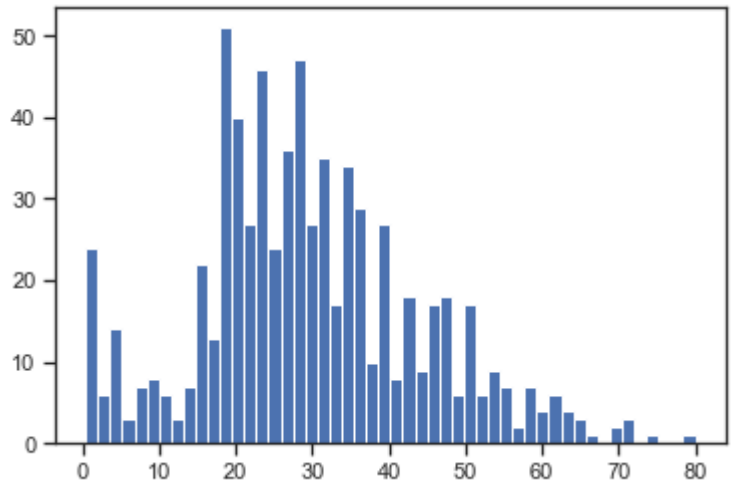
```
sc11 = MinMaxScaler()
sc11_data = sc1.fit_transform(new_data[['Pclass']])
plt.hist(sc11_data, 50)
plt.show()
```



Масштабирование данных на основе Z-оценки

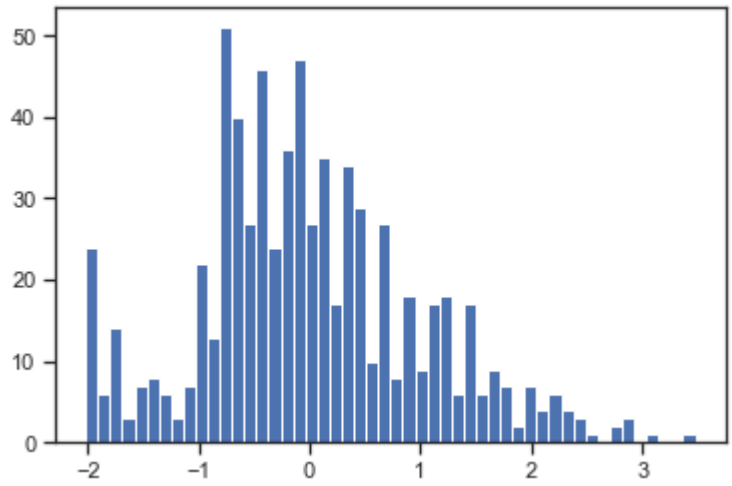
In [249]:

```
plt.hist(new_data['Age'], 50)
plt.show()
```



In [248]:

```
sc2 = StandardScaler()
sc2_data = sc2.fit_transform(new_data[['Age']])
plt.hist(sc2_data, 50)
plt.show()
```



Дополнительно поработаем со вторым набором данных о видеоиграх

In [257]:

```
games.head()
```

Out[257]:

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

Проверим набор данных видеоигр на наличие пропусков данных

In [267]:

```
for co in games.columns:
    counter = games[games[co].isnull()].shape[0]
    print('{}  -  {}'.format(co, counter))
print ('{} - размер датасета'.format(games.shape))
```

```
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
(16598, 11) - размер датасета
```

In [272]:

```
games['Year'].unique()
```

Out[272]:

```
array([2006., 1985., 2008., 2009., 1996., 1989., 1984., 2005., 1999.,
       2007., 2010., 2013., 2004., 1990., 1988., 2002., 2001., 2011.,
       1998., 2015., 2012., 2014., 1992., 1997., 1993., 1994., 1982.,
       2003., 1986., 2000.,   nan, 1995., 2016., 1991., 1981., 1987.,
       1980., 1983., 2020., 2017.])
```

Проведем импьютацию пропущенных значений

In [274]:

```
from sklearn.impute import SimpleImputer
from sklearn.impute import MissingIndicator
data_imput = games['Year']
data_imput
```

Out[274]:

```
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
Name: Year, Length: 16598, dtype: float64
```

In [275]:

```
data_imput = pd.DataFrame({'Year':data_imput.T})
data_imput
```

Out[275]:

	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 [276]:

```
data_imput.shape
```

Out[276]:

```
(16598, 1)
```

In [277]:

```
indicator = MissingIndicator()
missing_value = indicator.fit_transform(data_imput)
missing_value
```

Out[277]:

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

In [278]:

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

In [279]:

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

In [285]:

```
def test_num_impute_col(dataset, column, strategy_param):
    temp_data = dataset[[column]]

    indicator = MissingIndicator()
    missing_value = 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[missing_value]

    return column, strategy_param, filled_data.size, filled_data[0], filled_data[filled_dat
```

In [284]:

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

...

In [287]:

```
test_num_impute_col(data_imput,'Year', strategies[0])
```

Out[287]:

```
('Year', 'mean', 271, 2006.4064433147546, 2006.4064433147546)
```

In [288]:

```
test_num_impute_col(data_imput,'Year', strategies[1])
```

Out[288]:

```
('Year', 'median', 271, 2007.0, 2007.0)
```

In [289]:

```
test_num_impute_col(data_imput,'Year', strategies[2])
```

Out[289]:

```
('Year', 'most_frequent', 271, 2009.0, 2009.0)
```