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Факультет «Информатика и системы управления»
Кафедра ИУ5 «Системы обработки информации и управления»

Курс

«Технологии машинного обучения»

Отчет по лабораторной работе №2

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Лабораторная работа №2

Обработка пропусков в данных, кодирование категориальных признаков, масштабирование данных

Задание:

1. 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.)
2. Для выбранного датасета (датасетов) на основе материалов лекции решить следующие задачи:
   - обработку пропусков в данных;
   - кодирование категориальных признаков;
   - масштабирование данных.

В качестве исходных данных возьмём датасет результаты игроков в баскетбол за несколько сезонов

```
#Импорт библиотек
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.impute import SimpleImputer, MissingIndicator
from sklearn.preprocessing import MinMaxScaler, StandardScaler, OneHotEncoder,
LabelEncoder
data = pd.read_csv("combined_seasons.csv")
data.shape
(11606, 32)
data.head()
```

	Rk	Player	Pos	Age	Tm	G	GS	MP	FG	FGA	...	DRB	TRB	AST	STL	B
0	0	Tariq Abdul-Wahad	SG	24	SAC	49	49	24.6	3.6	8.3	...	2.3	3.8	1.0	1.0	0
1	1	Shareef Abdur-Rahim	SF	22	VAN	50	50	40.4	7.7	17.9	...	5.2	7.5	3.4	1.4	1
2	2	Cory Alexander	PG	25	DEN	36	4	21.6	2.7	7.2	...	1.9	2.1	3.3	1.0	0
3	3	Ray Allen*	SG	23	MIL	50	50	34.4	6.1	13.5	...	3.1	4.2	3.6	1.1	0
4	4	Peter Aluma	C	25	SAC	2	0	2.5	0.5	1.0	...	0.5	1.0	0.0	0.5	0

5 rows × 32 columns

```
#Проверка пропусков
data.isnull().sum()
```

```
Rk           0
Player       0
Pos          0
Age          0
Tm           0
G            0
GS           0
MP           0
FG           0
FGA          0
FG%         53
3P           0
3PA          0
3P%       1600
2P           0
2PA          0
2P%        102
eFG%        53
FT           0
FTA          0
FT%        493
ORB          0
DRB          0
TRB          0
AST          0
STL          0
BLK          0
TOV          0
PF           0
PTS          0
Season       0
isMVP        0
dtype: int64
```

```
#Проверка типов
data.dtypes
```

```
Rk          int64
Player     object
Pos        object
Age         int64
Tm         object
G           int64
GS          int64
MP        float64
FG        float64
FGA       float64
FG%       float64
3P        float64
3PA       float64
3P%       float64
2P        float64
2PA       float64
2P%       float64
eFG%      float64
FT        float64
FTA       float64
FT%       float64
ORB       float64
DRB       float64
TRB       float64
AST       float64
```

```
STL       float64
BLK       float64
TOV       float64
PF        float64
PTS       float64
Season     object
isMVP       int64
dtype: object
```

1) Обработка пропусков данных

Обработку пропусков данных можно осуществить следующими способами:

Удаление столбцов или строк, в которых есть пропуски

```
dataWithoutrows = data.dropna(axis=0, how="any")
(dataWithoutrows.shape, data.shape)
((9728, 32), (11606, 32))
```

```
dataWithoutcols = data.dropna(axis=1, how="any")
(dataWithoutcols.shape, data.shape)
((11606, 27), (11606, 32))
```

Заполнение пропусков нулями

```
dataWithNull = data.fillna(0)
```

```
dataWithNull.isnull().sum()
```

```
Rk        0
Player    0
Pos       0
Age       0
Tm        0
G         0
GS        0
MP        0
FG        0
FGA       0
FG%       0
3P        0
3PA       0
3P%       0
2P        0
2PA       0
2P%       0
eFG%      0
FT        0
FTA       0
FT%       0
ORB       0
DRB       0
TRB       0
AST       0
STL       0
BLK       0
TOV       0
PF        0
PTS       0
Season    0
isMVP     0
dtype: int64
```

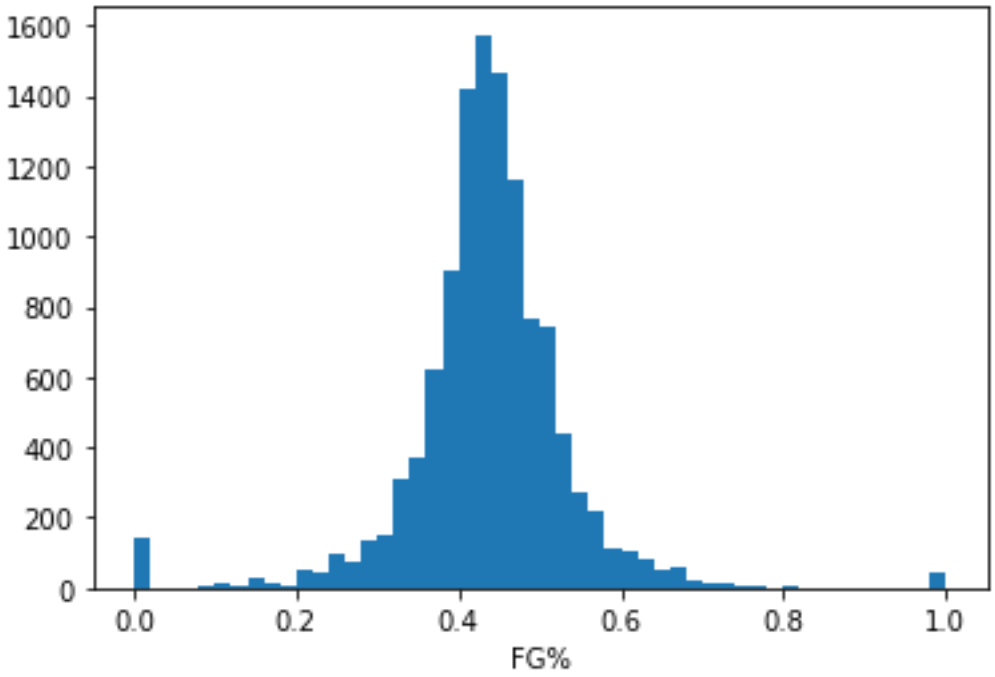
Внедрение значений

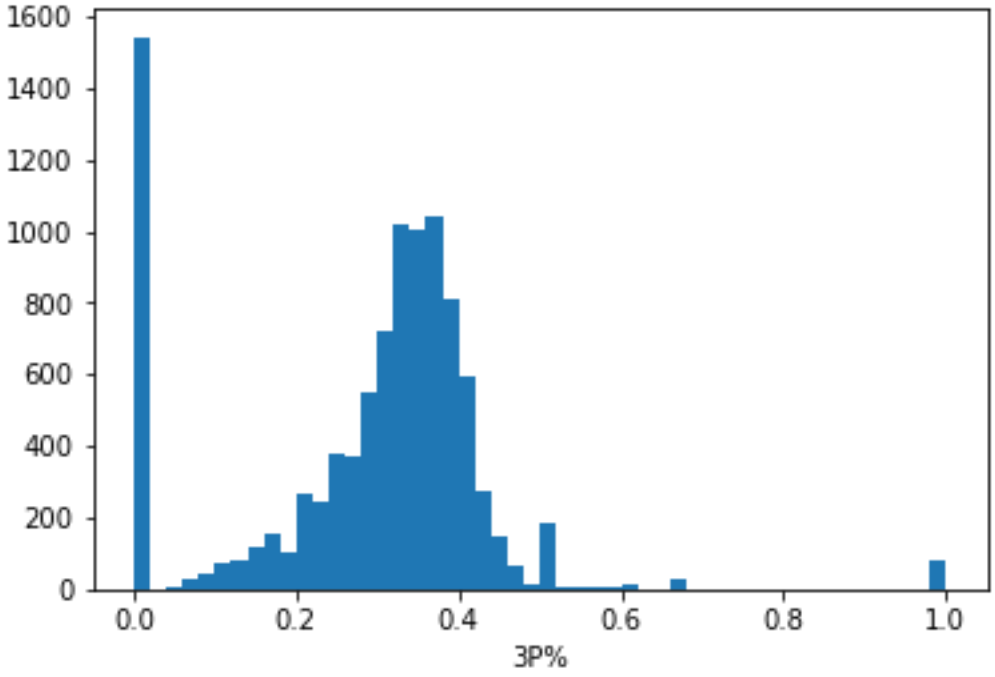
```
nullCol= []
for col in data.columns:
    if data[data[col].isnull()].shape[0] > 0:
        nullCol.append(col)
nullData = data[nullCol]
nullData
```

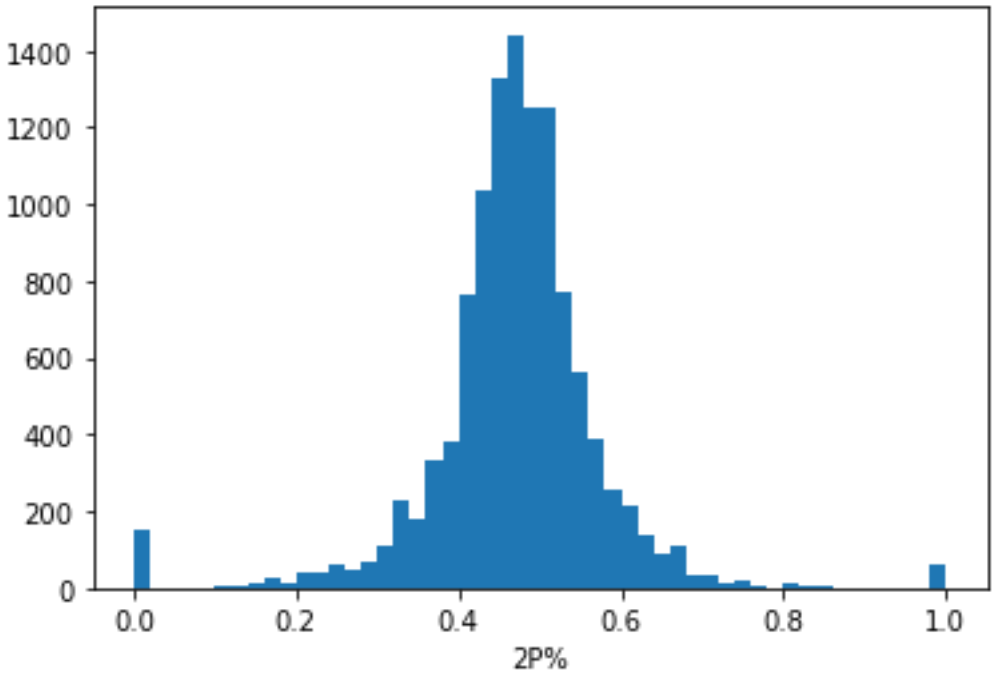
	FG%	3P%	2P%	eFG%	FT%
0	0.435	0.286	0.443	0.442	0.691
1	0.432	0.306	0.438	0.438	0.841
2	0.373	0.286	0.432	0.431	0.841
3	0.450	0.356	0.492	0.505	0.903
4	0.500	NaN	0.500	0.500	NaN
...	...	...	...	...	...
11601	0.436	0.474	0.424	0.494	0.333
11602	0.456	0.380	0.504	0.529	0.900
11603	0.540	0.125	0.556	0.542	0.632
11604	0.567	0.000	0.593	0.567	0.776
11605	0.624	NaN	0.624	0.624	0.734

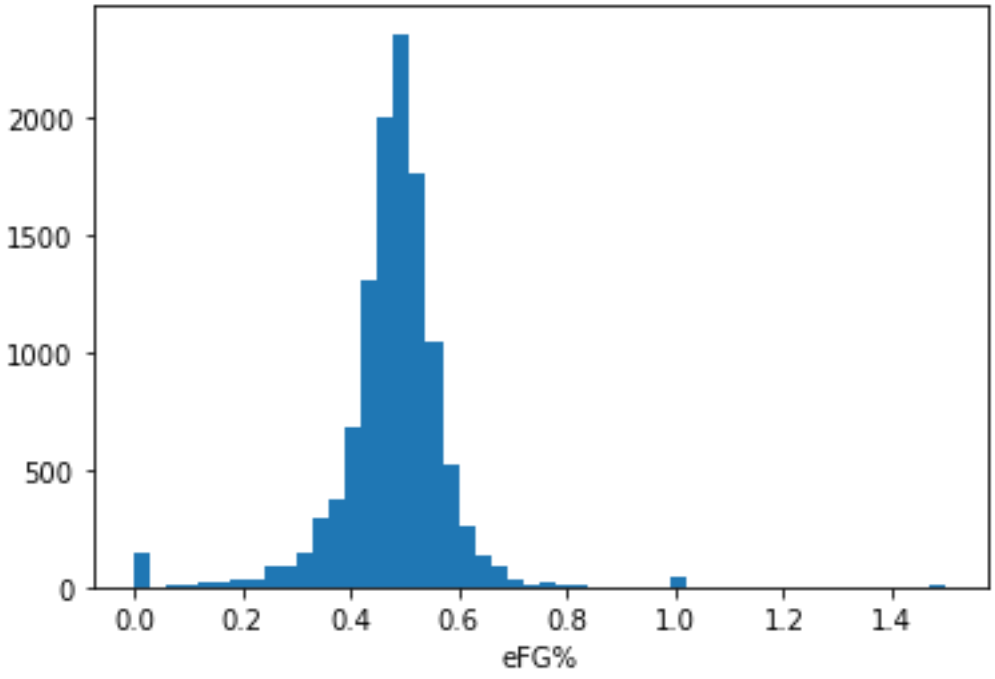
11606 rows × 5 columns

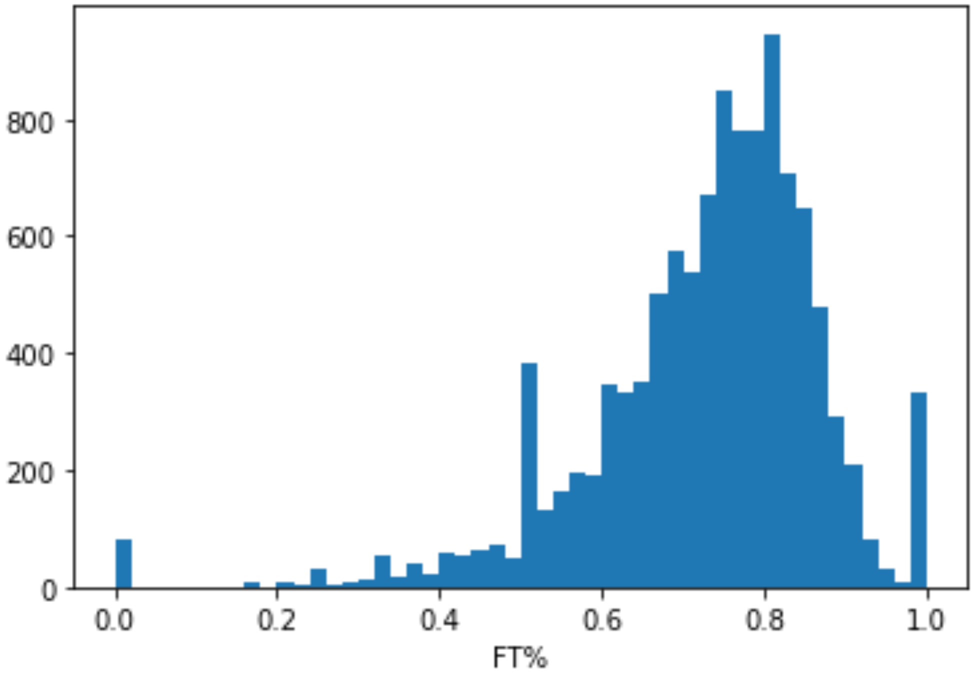
```
#Исходные графики рассматриваемых столбцов
for col in nullData:
    plt.hist(data[col],50)
    plt.xlabel(col)
    plt.show()
```


1600
1400
1200
1000
800
600
400
200
0
0.0
0.2
0.4
0.6
0.8
1.0
FG%


1600
1400
1200
1000
800
600
400
200
0
0.0
0.2
0.4
0.6
0.8
1.0
3P%


1400
1200
1000
800
600
400
200
0
0.0
0.2
0.4
0.6
0.8
1.0
2P%


2000
1500
1000
500
0
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
eFG%




```
#Локальное заполнение пропусков
def test_num_impute(strategy_param, col):
    imp_num=SimpleImputer(strategy=strategy_param)
    indicator = MissingIndicator()
    mask_missing_values_only = indicator.fit_transform(nullData[[col]])
    data_num_imp=imp_num.fit_transform(nullData[[col]])
    return data_num_imp[mask_missing_values_only]
test_num_impute("mean",nullData.columns[0])
array([0.43605791, 0.43605791, 0.43605791, 0.43605791, 0.43605791,
       0.43605791, 0.43605791, 0.43605791, 0.43605791, 0.43605791,
       0.43605791, 0.43605791, 0.43605791, 0.43605791, 0.43605791,
       0.43605791, 0.43605791, 0.43605791, 0.43605791, 0.43605791,
       0.43605791, 0.43605791, 0.43605791, 0.43605791, 0.43605791,
       0.43605791, 0.43605791, 0.43605791, 0.43605791, 0.43605791,
       0.43605791, 0.43605791, 0.43605791, 0.43605791, 0.43605791,
       0.43605791, 0.43605791, 0.43605791, 0.43605791, 0.43605791,
       0.43605791, 0.43605791, 0.43605791, 0.43605791, 0.43605791,
       0.43605791, 0.43605791, 0.43605791, 0.43605791, 0.43605791,
       0.43605791, 0.43605791, 0.43605791])
test_num_impute("median",nullData.columns[1])
array([0.328, 0.328, 0.328, ..., 0.328, 0.328, 0.328])
test_num_impute("mean",nullData.columns[2])
array([0.46879242, 0.46879242, 0.46879242, 0.46879242, 0.46879242,
       0.46879242, 0.46879242, 0.46879242, 0.46879242, 0.46879242,
       0.46879242, 0.46879242, 0.46879242, 0.46879242, 0.46879242,
       0.46879242, 0.46879242, 0.46879242, 0.46879242, 0.46879242,
       0.46879242, 0.46879242, 0.46879242, 0.46879242, 0.46879242,
       0.46879242, 0.46879242, 0.46879242, 0.46879242, 0.46879242,
       0.46879242, 0.46879242, 0.46879242, 0.46879242, 0.46879242,
       0.46879242, 0.46879242, 0.46879242, 0.46879242, 0.46879242,
       0.46879242, 0.46879242, 0.46879242, 0.46879242, 0.46879242,
       0.46879242, 0.46879242, 0.46879242, 0.46879242, 0.46879242,
       0.46879242, 0.46879242, 0.46879242, 0.46879242, 0.46879242,
       0.46879242, 0.46879242, 0.46879242, 0.46879242, 0.46879242,
       0.46879242, 0.46879242, 0.46879242, 0.46879242, 0.46879242,
       0.46879242, 0.46879242, 0.46879242, 0.46879242, 0.46879242,
       0.46879242, 0.46879242, 0.46879242, 0.46879242, 0.46879242,
       0.46879242, 0.46879242, 0.46879242, 0.46879242, 0.46879242,
       0.46879242, 0.46879242, 0.46879242, 0.46879242, 0.46879242,
       0.46879242, 0.46879242, 0.46879242, 0.46879242, 0.46879242,
```

```
       0.46879242, 0.46879242, 0.46879242, 0.46879242, 0.46879242,
       0.46879242, 0.46879242, 0.46879242, 0.46879242, 0.46879242,
       0.46879242, 0.46879242, 0.46879242, 0.46879242, 0.46879242,
       0.46879242, 0.46879242])
 test_num_impute("median",nullData.columns[3])
array([0.486, 0.486, 0.486, 0.486, 0.486, 0.486, 0.486, 0.486, 0.486,
       0.486, 0.486, 0.486, 0.486, 0.486, 0.486, 0.486, 0.486, 0.486,
       0.486, 0.486, 0.486, 0.486, 0.486, 0.486, 0.486, 0.486, 0.486,
       0.486, 0.486, 0.486, 0.486, 0.486, 0.486, 0.486, 0.486, 0.486,
       0.486, 0.486, 0.486, 0.486, 0.486, 0.486, 0.486, 0.486, 0.486,
       0.486, 0.486, 0.486, 0.486, 0.486, 0.486, 0.486, 0.486])
test_num_impute("median",nullData.columns[4])
array([0.752, 0.752, 0.752, 0.752, 0.752, 0.752, 0.752, 0.752, 0.752,
       0.752, 0.752, 0.752, 0.752, 0.752, 0.752, 0.752, 0.752, 0.752,
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       0.752, 0.752, 0.752, 0.752, 0.752, 0.752, 0.752, 0.752, 0.752,
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       0.752, 0.752, 0.752, 0.752, 0.752, 0.752, 0.752, 0.752, 0.752,
       0.752, 0.752, 0.752, 0.752, 0.752, 0.752, 0.752, 0.752, 0.752,
       0.752, 0.752, 0.752, 0.752, 0.752, 0.752, 0.752, 0.752, 0.752,
       0.752, 0.752, 0.752, 0.752, 0.752, 0.752, 0.752, 0.752, 0.752,
       0.752, 0.752, 0.752, 0.752, 0.752, 0.752, 0.752, 0.752, 0.752,
       0.752, 0.752, 0.752, 0.752, 0.752, 0.752, 0.752, 0.752, 0.752,
       0.752, 0.752, 0.752, 0.752, 0.752, 0.752, 0.752, 0.752, 0.752,
       0.752, 0.752, 0.752, 0.752, 0.752, 0.752, 0.752, 0.752, 0.752,
```
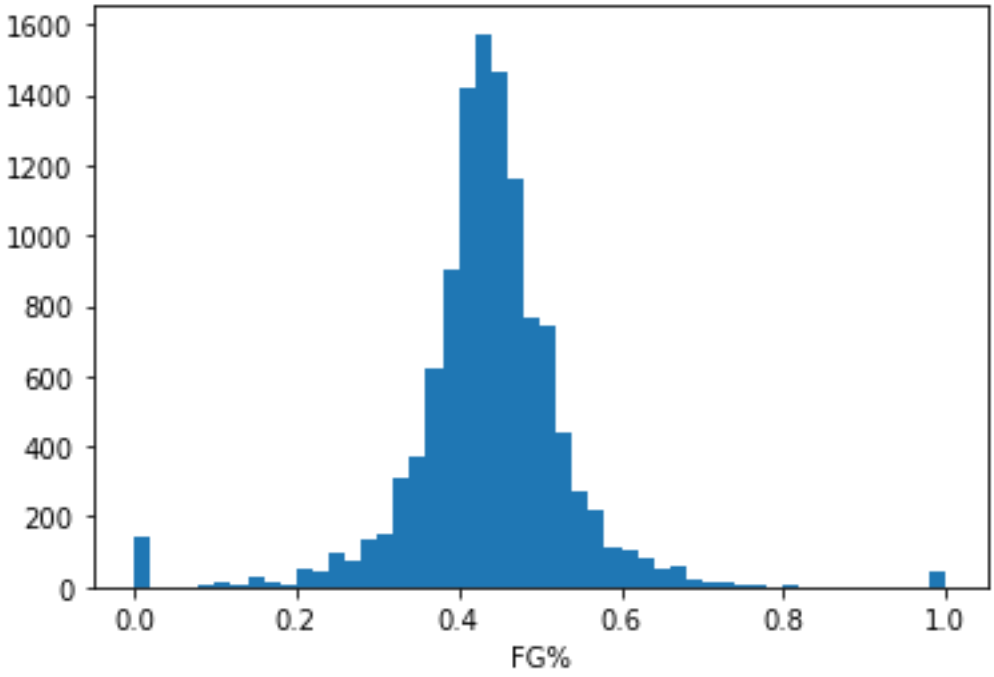
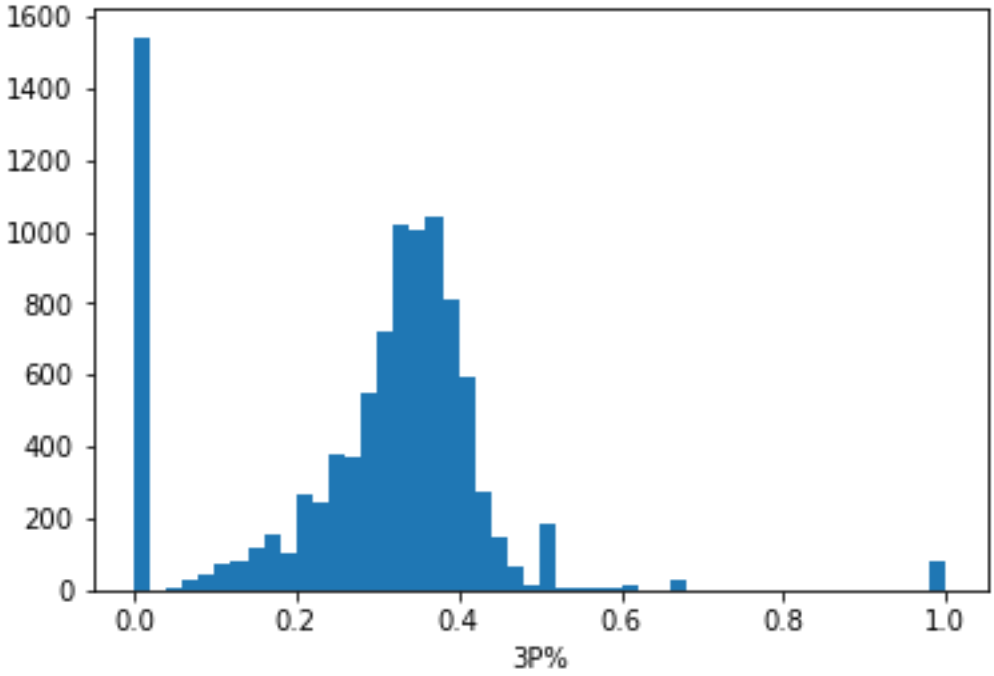
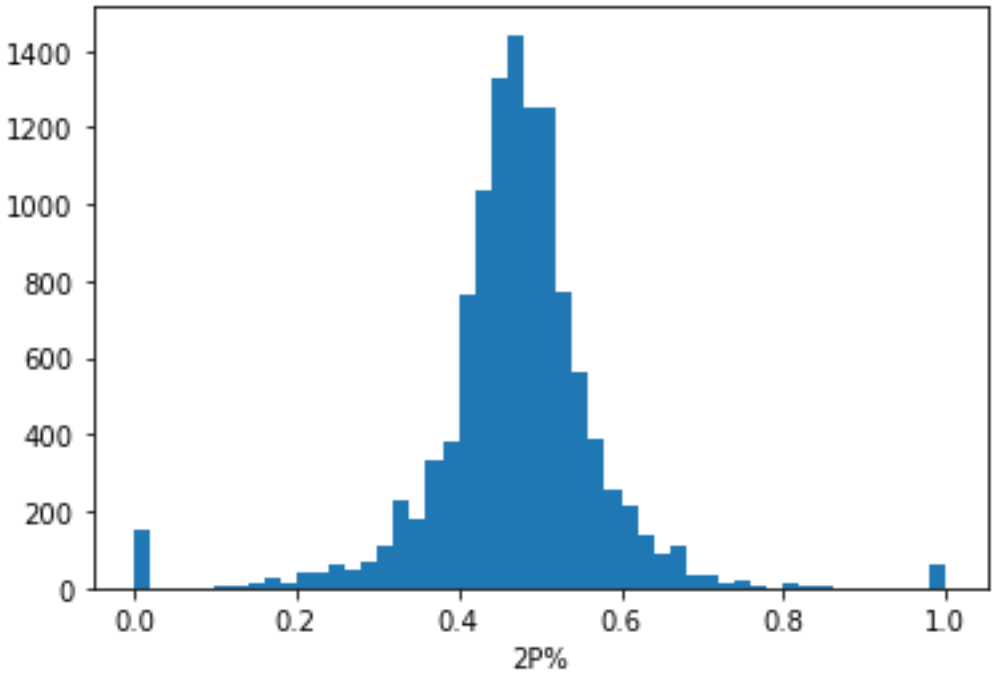
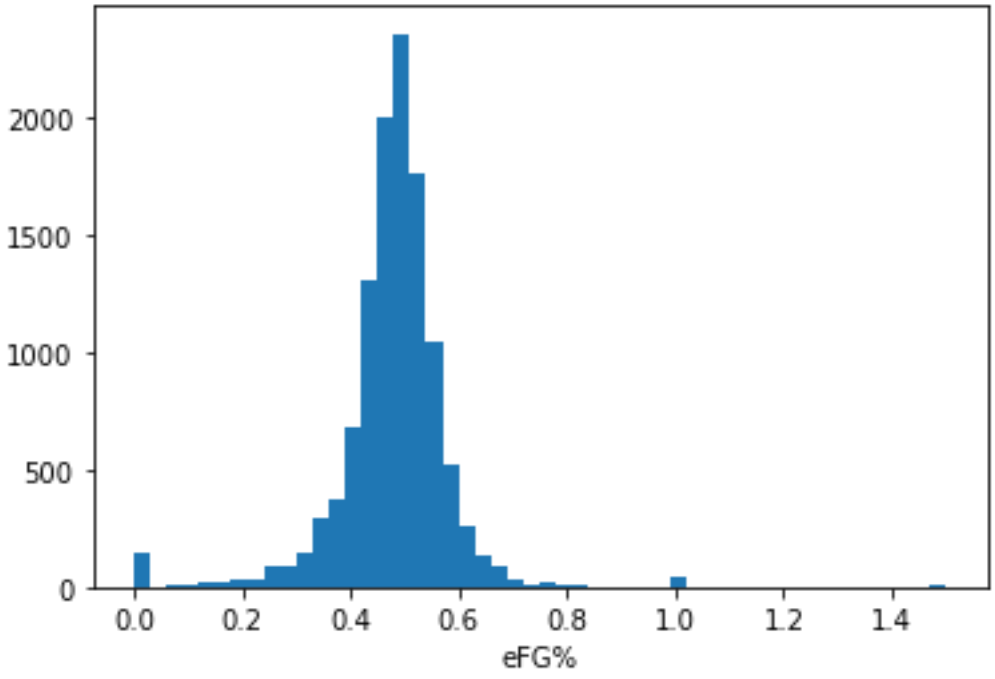
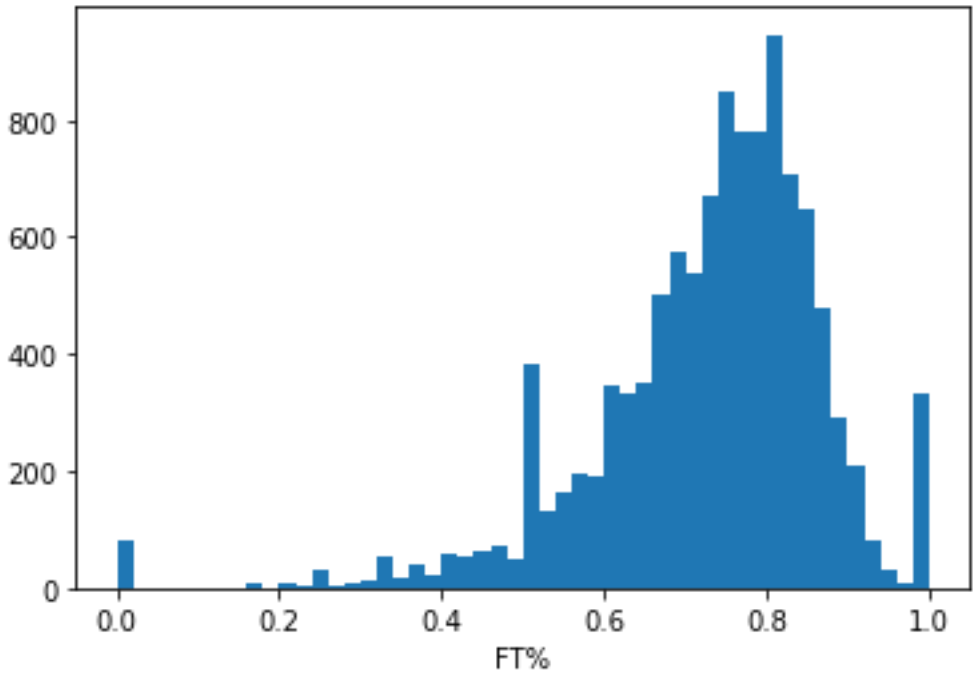

```
       0.752, 0.752, 0.752, 0.752, 0.752, 0.752, 0.752, 0.752, 0.752,
       0.752, 0.752, 0.752, 0.752, 0.752, 0.752, 0.752])
#Полученные графики после заполнения пустых значений
for col in nullData:
    plt.hist(data[col],50)
    plt.xlabel(col)
    plt.show()
```






1400
1200
1000
800
600
400
200
0
0.0
0.2
0.4
0.6
0.8
1.0
2P%


2000
1500
1000
500
0
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
eFG%



2) Кодирование категориальных признаков

LabelEncoder

Для этой задачи возмём датасет информации о посетителях библиотеки

```
data = pd.read_csv("Library_Usage.csv")
#Определение пустых значений
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 / data.shape[0]) * 100.0, 2)
        print('Колонка {}. Тип данных {}. Количество пустых
значений {}, {}%.'.format(col, dt, temp_null_count, temp_perc))
```

```
Колонка Age Range. Тип данных object. Количество пустых значений 215, 0.05%.
Колонка Home Library Code. Тип данных object. Количество пустых значений 40,
0.01%.
```

```
#Найдём уникальные значения столбца
data["Age Range"].unique()
```

```
array(['20 to 24 years', '25 to 34 years', '45 to 54 years',
       '65 to 74 years', '60 to 64 years', '35 to 44 years', nan,
       '55 to 59 years', '10 to 19 years', '0 to 9 years',
       '75 years and over'], dtype=object)
```

```
#Кодирование
le = LabelEncoder()
cat_enc_le = le.fit_transform(data["Age Range"])
#Новые уникальные значения столбца
np.unique(cat_enc_le)
```

```
array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10])
```

```
#Раскодировка
le.inverse_transform([0, 1, 2, 3])
array(['0 to 9 years', '10 to 19 years', '20 to 24 years',
       '25 to 34 years'], dtype=object)
```

OneHotEncoder

```
#Найдём уникальные значения столбца
data["Home Library Code"].unique()
array(['P1', 'S7', 'X', 'M2', 'C2', 'P5', 'A5', 'M6', 'P7', 'P3', 'M4',
       'N6', 'O7', 'P9', 'R3', 'YB', 'M8', 'G6', 'E9', 'I5', 'W2', 'O2',
       'G4', 'B4', 'V3', 'W4', 'B2', 'N4', 'E7', 'YB4', 'YLW', 'YB9',
       'G4AAA', 'YJJ', 'R3J', 'YB2', 'XFFL', 'B4AAA', 'S7J', 'YB1', 'YB7',
       'B2AAA', 'YB8', 'O2AAA', 'YB3', 'XFSAA', 'M8AAA', nan, 'N6AAA',
       'C2J', 'NONE', 'M6AAA', 'YJJAA', 'E9AAA', 'P1AAA', 'YB6', 'W2AAA',
       'B2AZZ', 'M4AAA', 'P3AAA', 'N4AAA', 'P7J', 'I7', 'M2AAA', 'YLWAA',
       'O7AAA', 'YBJ', 'S7AAA', 'M6ABU', 'P7AAA', 'R3AAA', 'YB5', 'P1J',
       'YB10', 'M8J', 'N6J', 'AQUIS', 'E7J', 'W2J', 'O7J'], dtype=object)
#Кодирование
ohe = OneHotEncoder()
cat_enc_ohe = ohe.fit_transform(data[["Home Library Code"]])
cat_enc_ohe.todense()[1:5]
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., 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., 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., 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., 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., 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., 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., 0.,
         0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.]])
#OHE в виде DataFrame
pd.get_dummies(data["Home Library Code"])
```

	A5	AQUIS	B2	B2AAA	B2AZZ	B4	B4AAA	C2	C2J	E7	...	YB5	YB6	YB7
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

	A5	AQUIS	B2	B2AAA	B2AZZ	B4	B4AAA	C2	C2J	E7	...	YB5	YB6	YB7
4	0	0	0	0	0	0	0	0	0	0	...	0	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
423443	0	0	0	0	0	0	0	0	0	0	...	0	0	0
423444	0	0	0	0	0	0	0	0	0	0	...	0	0	0
423445	0	0	0	0	0	1	0	0	0	0	...	0	0	0
423446	0	0	0	0	0	0	0	0	0	0	...	0	0	0
423447	0	0	0	0	0	0	0	0	0	1	...	0	0	0

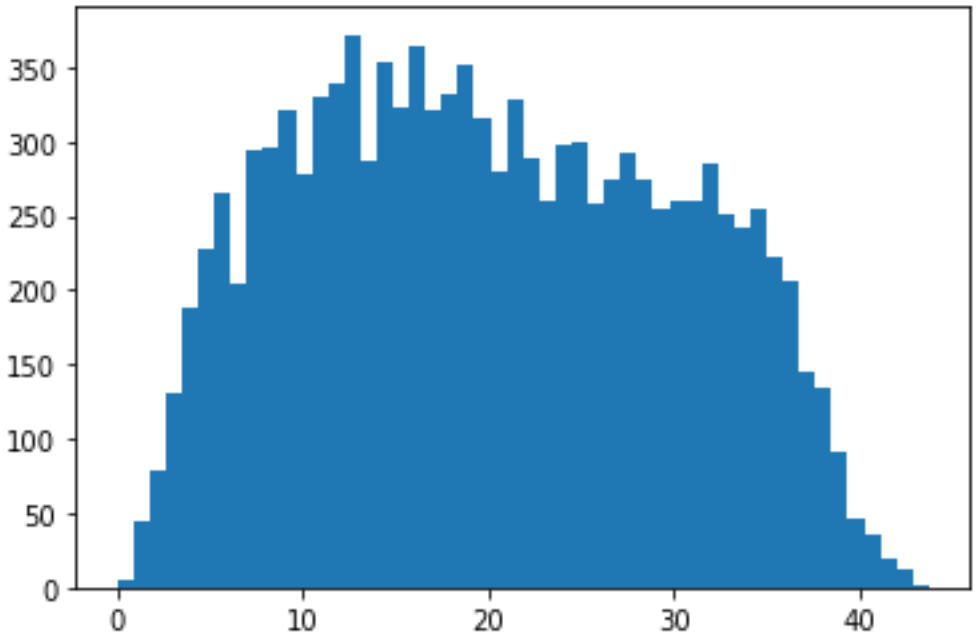
423448 rows × 79 columns

3) Масштабирование данных

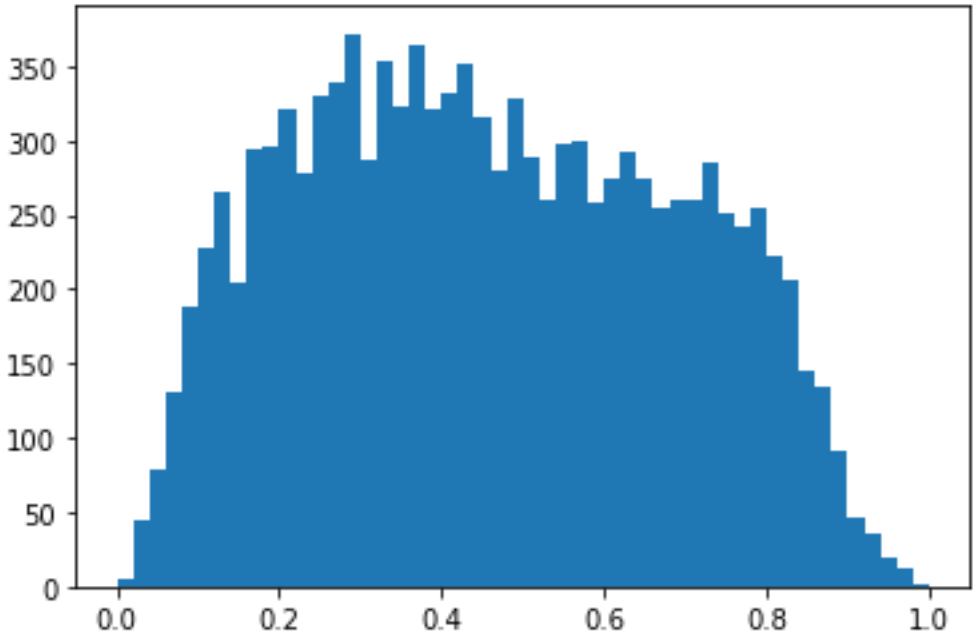
MinMax масштабирование (от 0 до 1)

Для масштабирования снова возьмём датасет результаты игроков в баскетбол за несколько сезонов

```
data = pd.read_csv("combined_seasons.csv")
#Масштабирование
sc1 = MinMaxScaler()
sc1_data = sc1.fit_transform(data[['MP']])
plt.hist(data['MP'], 50)
plt.show()
```

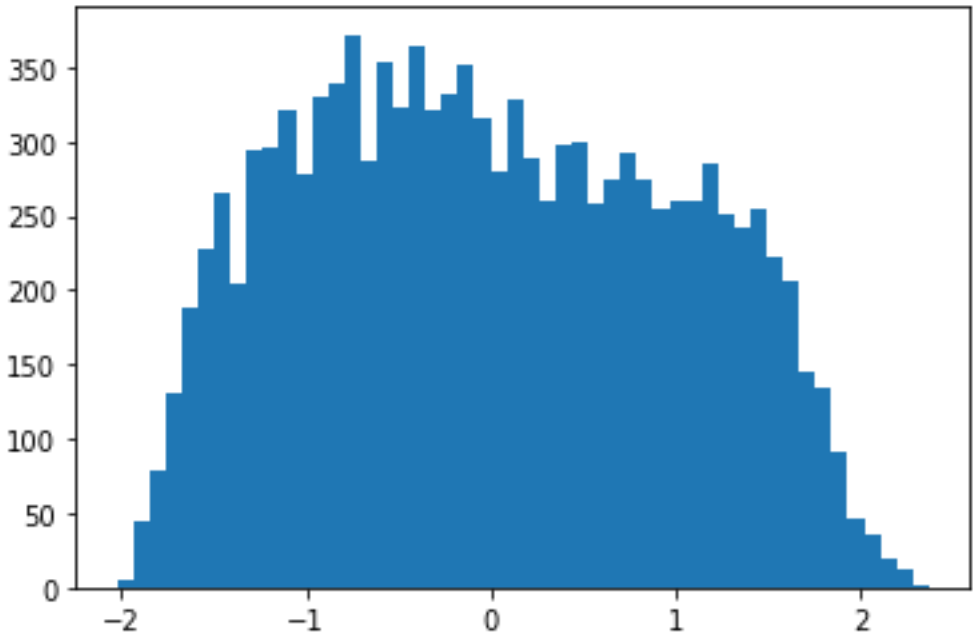



```
plt.hist(sc1_data, 50)
plt.show()
```



На основе Z-оценки

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


350
300
250
200
150
100
50
0
−2
−1
0
1
2