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ФАКУЛЬТЕТ ГОЛОВНОЙ УЧЕБНО-ИССЛЕДОВАТЕЛЬСКИЙ И МЕТОДИЧЕСКИЙ ЦЕНТР ПРОФЕССИОНАЛЬНОЙ РЕАБИЛИТАЦИИ ЛИЦ С ОГРАНИЧЕННЫМИ ВОЗМОЖНОСТЯМИ ЗДОРОВЬЯ

КАФЕДРА СИСТЕМЫ ОБРАБОТКИ ИНФОРМАЦИИ И УПРАВЛЕНИЯ

Отчёт по лабораторной работе №2 по курсу «Технологии машинного обучения».

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

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Подпись и дата:

Подпись и дата:

2025 г.

1. Задание лабораторной работы

- 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.

2. Ячейки Jupyter-ноутбука

2.1. Выбор и загрузка данных

В качестве датасета будем использовать набор данных, содержащий данные по продажам автомобилей в США. Данный набор доступен по адресу: https://www.kaggle.com/datasets/gagandeep16/car-sales

Набор данных имеет следующие атрибуты:

- Manufacturer - марка
- Model - модель
- Sales_in_thousands - продажи в тысячах
- year_resale_value - годовой объем продаж
- Vehicle_type - тип автомобиля
- Price_in_thousands - цена в тысячах
- Engine_size - объем двигателя
- Horsepower - лошадиные силы
- Wheelbase - колесная база
- Width - ширина
- Length - длина
- Curb_weight - масса
- Fuel_capacity - топливный бак
- Fuel_efficiency - расход топлива
- Latest_Launch - начало производства модели
- Power_perf_factor - мощностной коэффициент

2.1.1. Импорт библиотек

Импортируем библиотеки с помощью команды import:

[1]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
sns.set(style=DticksD)
```

2.1.2. Загрузка данных

Загрузим набор данных:

[2]:
```
data = pd.read_csv('Car_sales.csv')
```

2.2. Первичный анализ данных

Выведем первые 5 строк датасета:

[3]:
```
data.head()
```

[3]:

	Manufacturer	Model	Sales_in_thousands	__year_resale_value	Vehicle_type	\
0	Acura	Integra	16.919	16.360	Passenger	
1	Acura	TL	39.384	19.875	Passenger	
2	Acura	CL	14.114	18.225	Passenger	
3	Acura	RL	8.588	29.725	Passenger	
4	Audi	A4	20.397	22.255	Passenger	

	Price_in_thousands	Engine_size	Horsepower	Wheelbase	Width	Length	\
0	21.50	1.8	140.0	101.2	67.3	172.4	
1	28.40	3.2	225.0	108.1	70.3	192.9	
2	NaN	3.2	225.0	106.9	70.6	192.0	
3	42.00	3.5	210.0	114.6	71.4	196.6	
4	23.99	1.8	150.0	102.6	68.2	178.0	

	Curb_weight	Fuel_capacity	Fuel_efficiency	Latest_Launch	\
0	2.639	13.2	28.0	2/2/2012	
1	3.517	17.2	25.0	6/3/2011	
2	3.470	17.2	26.0	1/4/2012	
3	3.850	18.0	22.0	3/10/2011	
4	2.998	16.4	27.0	10/8/2011	

	Power_perf_factor
0	58.280150
1	91.370778
2	NaN
3	91.389779
4	62.777639

Определим размер датасета:

[4]:
```
data.shape
```

[4]: (157, 16)

В датасете 157 строк и 16 столбцов. Определим тип столбцов:

[5]:
```
data.dtypes
```

[5]:
```
Manufacturer          object
Model                 object
Sales_in_thousands   float64
__year_resale_value  float64

Vehicle_type          object
Price_in_thousands   float64
Engine_size          float64
Horsepower           float64
Wheelbase            float64
Width                float64
Length               float64
Curb_weight          float64
```

Fuel_capacity	float64

```
Fuel_efficiency      float64
Latest_Launch         object
Power_perf_factor    float64
dtype: object
```

Проверим наличие пропусков:

[6] :
```
data.isnull().sum()
```

[6] :
```
Manufacturer          0
Model                 0
Sales_in_thousands    0
__year_resale_value   36
Vehicle_type          0
Price_in_thousands    2
Engine_size           1
Horsepower            1
Wheelbase             1
Width                 1
Length                1
Curb_weight           2
Fuel_capacity         1
Fuel_efficiency       3
Latest_Launch         0
Power_perf_factor     2
dtype: int64
```

Видим, что пропуски наблюдаются в множестве столбцов.

2.3. Обработка пропусков данных

Удалим колонки, содержащие пустые значения:

[7] :
```
data_new_1 = data.dropna(axis=1, how='any')
(data.shape, data_new_1.shape)
```

[7] :
```
((157, 16), (157, 5))
```

Выведем первые строки датасета на экран:

[8] :
```
data_new_1
```

[8]:

	Manufacturer	Model	Sales_in_thousands	Vehicle_type	Latest_Launch
0	Acura	Integra	16.919	Passenger	2/2/2012
1	Acura	TL	39.384	Passenger	6/3/2011
2	Acura	CL	14.114	Passenger	1/4/2012
3	Acura	RL	8.588	Passenger	3/10/2011
4	Audi	A4	20.397	Passenger	10/8/2011
..	...	...	...	...	...
152	Volvo	V40	3.545	Passenger	9/21/2011
153	Volvo	S70	15.245	Passenger	11/24/2012
154	Volvo	V70	17.531	Passenger	6/25/2011
155	Volvo	C70	3.493	Passenger	4/26/2011
156	Volvo	S80	18.969	Passenger	11/14/2011

[157 rows x 5 columns]

Удалим строки, содержащие пустые значения:

[9] :
```
data_new_2 = data.dropna(axis=0, how='any')
(data.shape, data_new_2.shape)
```

[9] : ((157, 16), (117, 16))

[10] :
```
data_new_2.head()
```

[10]:

	Manufacturer	Model	Sales_in_thousands	__year_resale_value	Vehicle_type	\
0	Acura	Integra	16.919	16.360	Passenger	
1	Acura	TL	39.384	19.875	Passenger	
3	Acura	RL	8.588	29.725	Passenger	
4	Audi	A4	20.397	22.255	Passenger	
5	Audi	A6	18.780	23.555	Passenger	

	Price_in_thousands	Engine_size	Horsepower	Wheelbase	Width	Length	\
0	21.50	1.8	140.0	101.2	67.3	172.4	
1	28.40	3.2	225.0	108.1	70.3	192.9	
3	42.00	3.5	210.0	114.6	71.4	196.6	
4	23.99	1.8	150.0	102.6	68.2	178.0	
5	33.95	2.8	200.0	108.7	76.1	192.0	

	Curb_weight	Fuel_capacity	Fuel_efficiency	Latest_Launch	\
0	2.639	13.2	28.0	2/2/2012	
1	3.517	17.2	25.0	6/3/2011	
3	3.850	18.0	22.0	3/10/2011	
4	2.998	16.4	27.0	10/8/2011	
5	3.561	18.5	22.0	8/9/2011	

	Power_perf_factor
0	58.280150
1	91.370778
3	91.389779
4	62.777639
5	84.565105

Заполним все пропущенные значения нулями:

[11] :
```
data_new_3 = data.fillna(0)
```

Выведем на экран:

[12] :
```
data_new_3.head()
```

[12]:

	Manufacturer	Model	Sales_in_thousands	__year_resale_value	Vehicle_type	\
0	Acura	Integra	16.919	16.360	Passenger	
1	Acura	TL	39.384	19.875	Passenger	
2	Acura	CL	14.114	18.225	Passenger	
3	Acura	RL	8.588	29.725	Passenger	
4	Audi	A4	20.397	22.255	Passenger	

	Price_in_thousands	Engine_size	Horsepower	Wheelbase	Width	Length	\
0	21.50	1.8	140.0	101.2	67.3	172.4	
1	28.40	3.2	225.0	108.1	70.3	192.9	
2	0.00	3.2	225.0	106.9	70.6	192.0	
3	42.00	3.5	210.0	114.6	71.4	196.6	

```
4                 23.99          1.8        150.0        102.6     68.2     178.0

   Curb_weight  Fuel_capacity   Fuel_efficiency  Latest_Launch  \
0        2.639           13.2              28.0       2/2/2012
1        3.517           17.2              25.0       6/3/2011
2        3.470           17.2              26.0       1/4/2012
3        3.850           18.0              22.0      3/10/2011
4        2.998           16.4              27.0      10/8/2011

   Power_perf_factor
0          58.280150
1          91.370778
2           0.000000
3          91.389779
4          62.777639
```

2.3.1. Импьютация данных

2.3.2. Обработка пропусков в числовых данных

Выберем числовые столбцы с пропущенными значениями и посчитаем количество пустых значений:

[13] :
```
num_cols = []
for col in data.columns:
    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 / data.shape[0]) * 100.0, 2)
        print('Столбец {}. Тип данных {}. Количество пустых значений {}, {}%.'.
↪format(col, dt, temp_null_count, temp_perc))
```

```
Столбец __year_resale_value. Тип данных float64. Количество пустых значений 36,
22.93%.
Столбец Price_in_thousands. Тип данных float64. Количество пустых значений 2,
1.27%.
Столбец Engine_size. Тип данных float64. Количество пустых значений 1, 0.64%.
Столбец Horsepower. Тип данных float64. Количество пустых значений 1, 0.64%.
Столбец Wheelbase. Тип данных float64. Количество пустых значений 1, 0.64%.
Столбец Width. Тип данных float64. Количество пустых значений 1, 0.64%.
Столбец Length. Тип данных float64. Количество пустых значений 1, 0.64%.
Столбец Curb_weight. Тип данных float64. Количество пустых значений 2, 1.27%.
Столбец Fuel_capacity. Тип данных float64. Количество пустых значений 1, 0.64%.
Столбец Fuel_efficiency. Тип данных float64. Количество пустых значений 3,
1.91%.
Столбец Power_perf_factor. Тип данных float64. Количество пустых значений 2,
1.27%.
```

Отфильтруем по столбцам:

[14] :
```
data_num = data[num_cols]
data_num
```

[14]:

	__year_resale_value	Price_in_thousands	Engine_size	Horsepower	\
0	16.360	21.50	1.8	140.0	
1	19.875	28.40	3.2	225.0	
2	18.225	NaN	3.2	225.0	
3	29.725	42.00	3.5	210.0	
4	22.255	23.99	1.8	150.0	
..	...	...	...	...	
152	NaN	24.40	1.9	160.0	
153	NaN	27.50	2.4	168.0	
154	NaN	28.80	2.4	168.0	
155	NaN	45.50	2.3	236.0	
156	NaN	36.00	2.9	201.0	

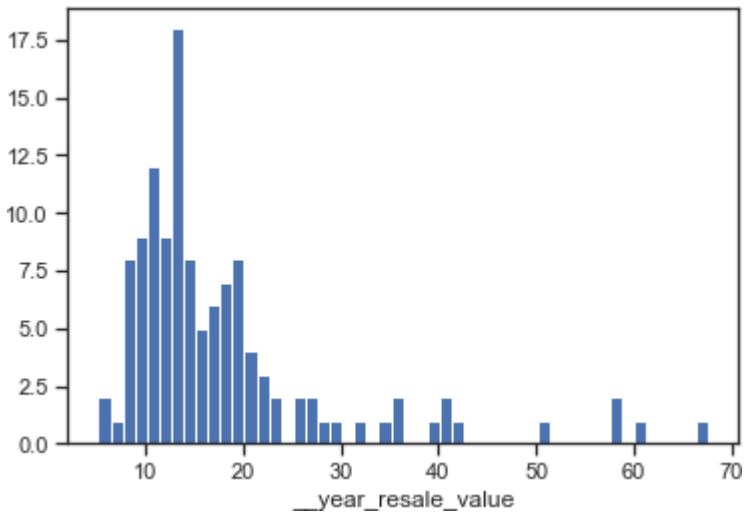
	Wheelbase	Width	Length	Curb_weight	Fuel_capacity	Fuel_efficiency	\
0	101.2	67.3	172.4	2.639	13.2	28.0	
1	108.1	70.3	192.9	3.517	17.2	25.0	
2	106.9	70.6	192.0	3.470	17.2	26.0	
3	114.6	71.4	196.6	3.850	18.0	22.0	
4	102.6	68.2	178.0	2.998	16.4	27.0	
..	...	...	...	...	...	...	
152	100.5	67.6	176.6	3.042	15.8	25.0	
153	104.9	69.3	185.9	3.208	17.9	25.0	
154	104.9	69.3	186.2	3.259	17.9	25.0	
155	104.9	71.5	185.7	3.601	18.5	23.0	
156	109.9	72.1	189.8	3.600	21.1	24.0	

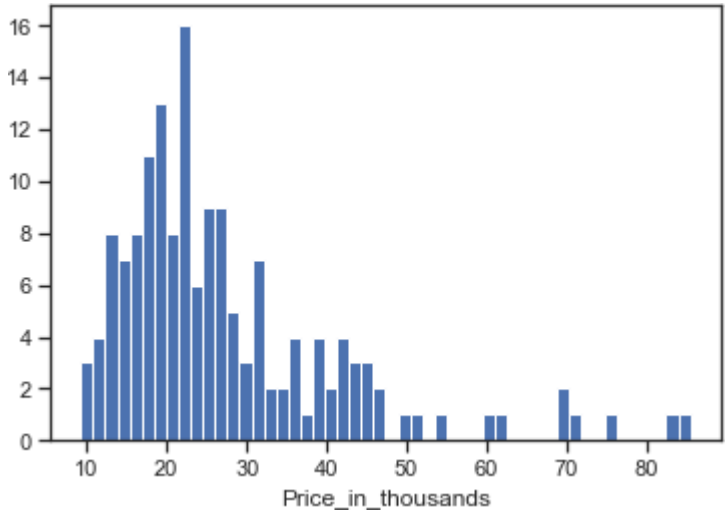
	Power_perf_factor
0	58.280150
1	91.370778
2	NaN
3	91.389779
4	62.777639
..	...
152	66.498812
153	70.654495
154	71.155978
155	101.623357
156	85.735655

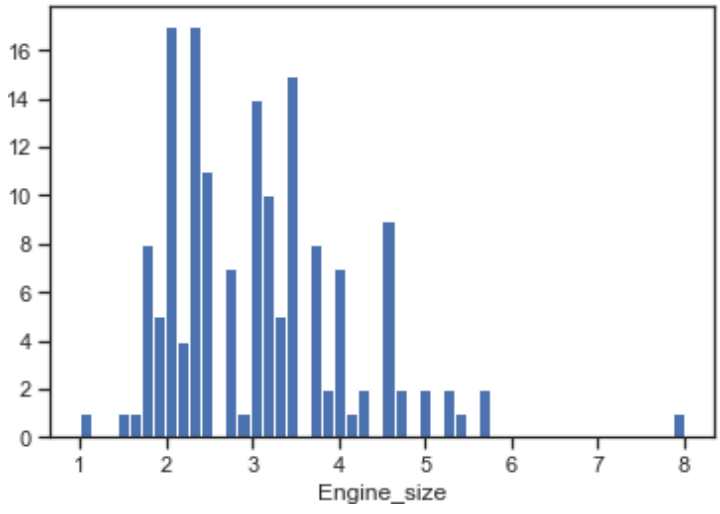
[157 rows x 11 columns]

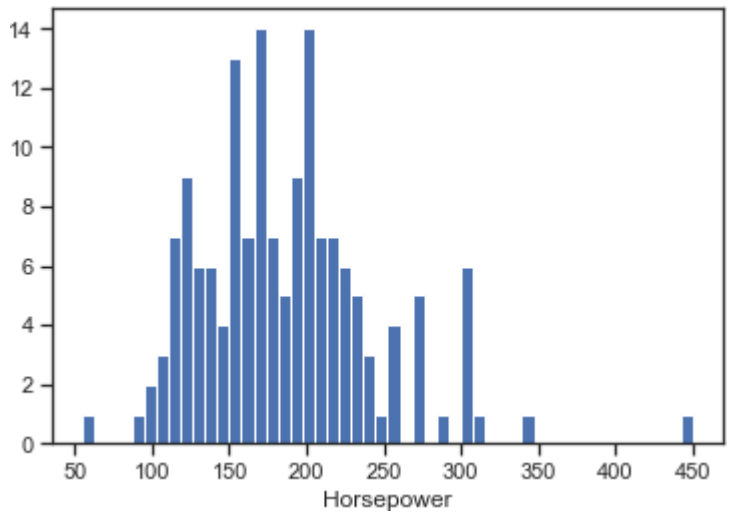
Гистограмма по признакам:

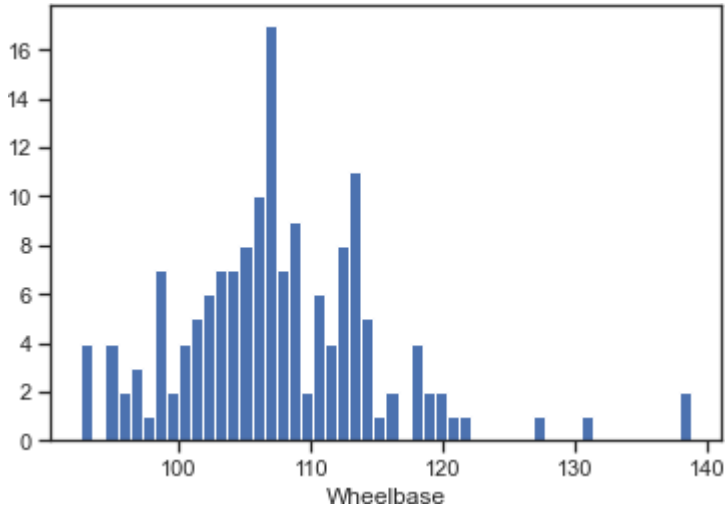
[15] :
```
for col in data_num:
    plt.hist(data[col], 50)
    plt.xlabel(col)
    plt.show()
```

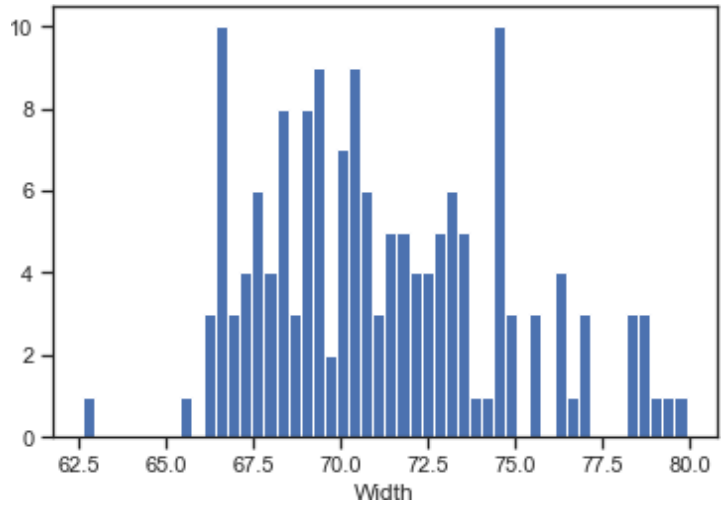

17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0
10
20
30
40
50
60
70
__year_resale_value

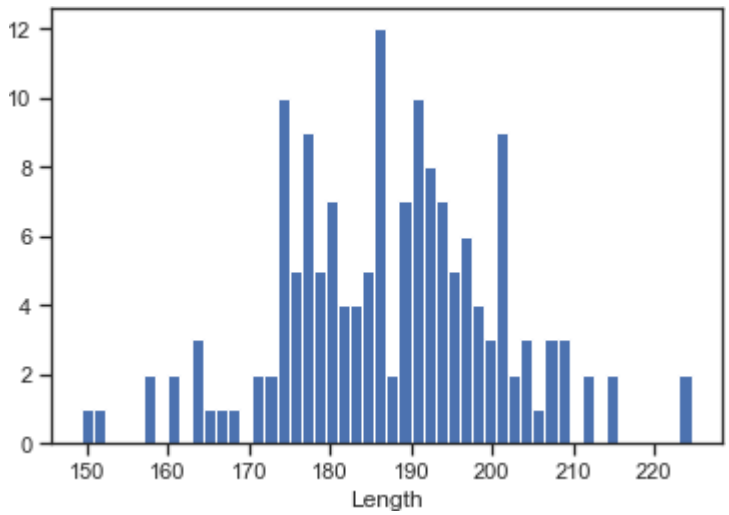

16
14
12
10
8
6
4
2
0
10
20
30
40
50
60
70
80
Price_in_thousands

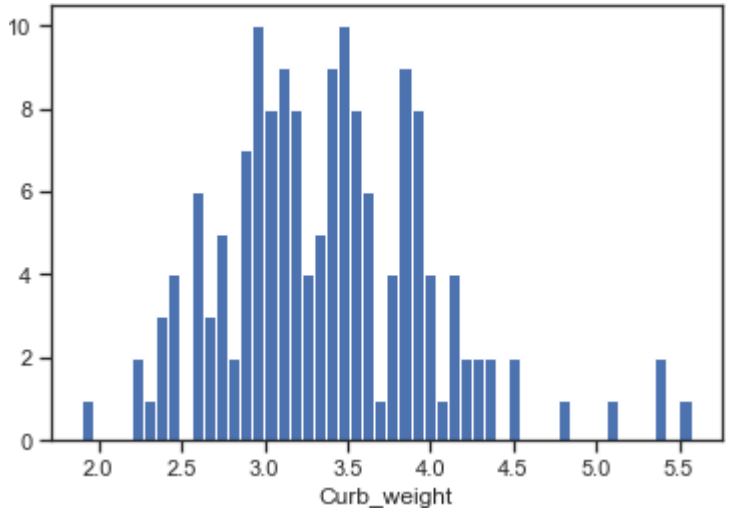

16
14
12
10
8
6
4
2
0
1
2
3
4
5
6
7
8
Engine_size

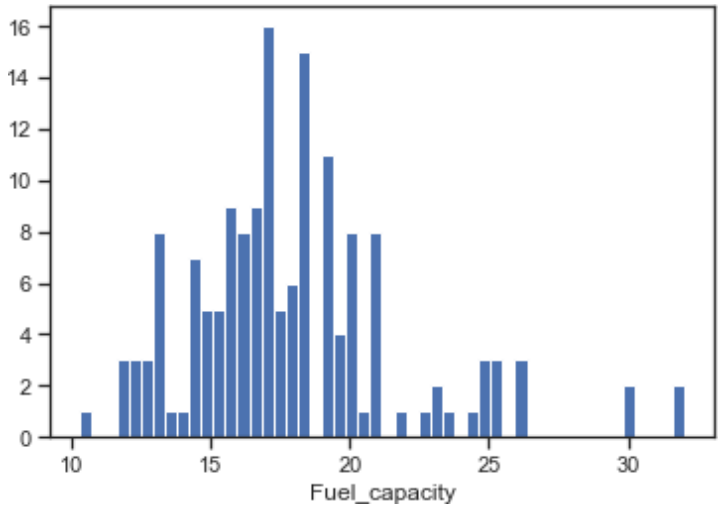

14
12
10
8
6
4
2
0
50
100
150
200
250
300
350
400
450
Horsepower

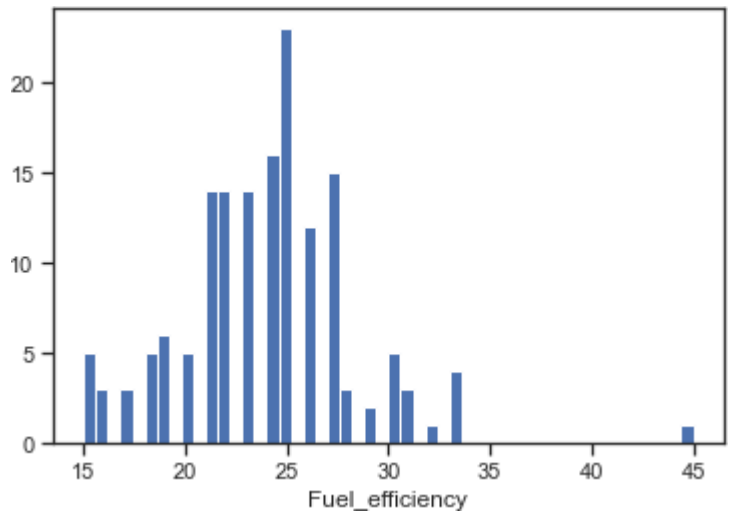

16
14
12
10
8
6
4
2
0
100
110
120
130
140
Wheelbase

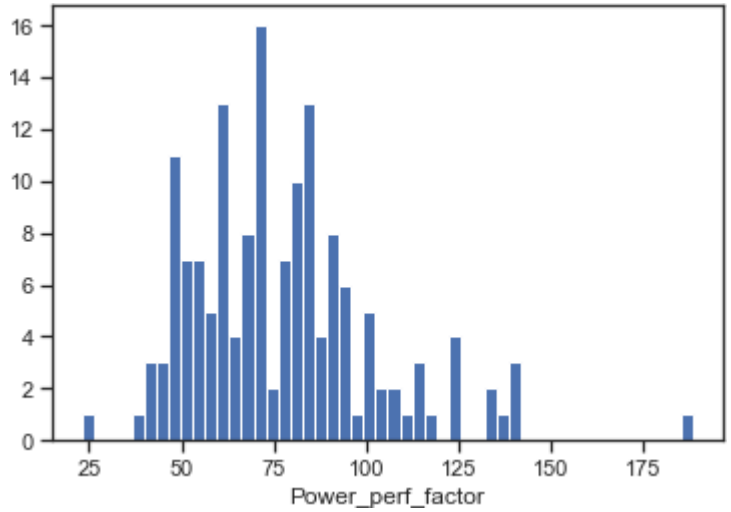

10
8
6
4
2
0
62.5
65.0
67.5
70.0
72.5
75.0
77.5
80.0
Width


12
10
8
6
4
2
0
150
160
170
180
190
200
210
220
Length


10
8
6
4
2
0
2.0
2.5
3.0
3.5
4.0
4.5
5.0
5.5
Curb_weight


16
14
12
10
8
6
4
2
0
10
15
20
25
30
Fuel_capacity





Будем использовать встроенные средства импьютации библиотеки scikit-learn, доступные по адресу: https://scikit-learn.org/stable/modules/impute.html

[16] :
```
data_num_pit = data_num[['Price_in_thousands']]
```

[17] :
```
from sklearn.impute import SimpleImputer
from sklearn.impute import MissingIndicator
```

Фильтр для проверки заполнения пустых значений:

[18] :
```
indicator = MissingIndicator()
mask_missing_values_only = indicator.fit_transform(data_num_pit)
mask_missing_values_only
```

[18] :
```
array([[False],
       [False],
       [ True],
       [False],
       [False],
```

```
[False],
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```
        [False],
        [False],
        [False],
        [False],
        [False],
        [False],
        [False],
        [False],
        [False],
        [False],
        [False],
        [False],
        [False],
        [False],
        [False],
        [False],
        [False],
        [False],
        [False],
        [False],
        [False],
        [False],
        [False],
        [False],
        [False],
        [False],
        [False],
        [False],
        [False],
        [False],
        [False],
        [False],
        [False],
        [False],
        [False],
        [False],
        [False],
        [False],
        [False],
        [False],
        [False],
        [False],
        [False],
        [False],
        [False],
        [False]])
```

Проведем импьютацию различными показателями центра распределения:

[19]:
```
strategies=['mean', 'median', 'most_frequent']
```

[20]:
```
def test_num_impute(strategy_param):
    imp_num = SimpleImputer(strategy=strategy_param)
    data_num_imp = imp_num.fit_transform(data_num_pit)
```

```
    return data_num_imp[mask_missing_values_only]
```

[21] :
```
strategies[0], test_num_impute(strategies[0])
```

[21] : ('mean', array([27.39075484, 27.39075484]))

[22] :
```
strategies[1], test_num_impute(strategies[1])
```

[22] : ('median', array([22.799, 22.799]))

[23] :
```
strategies[2], test_num_impute(strategies[2])
```

[23] : ('most_frequent', array([12.64, 12.64]))

Создадим функцию, позволяющую задавать столбец и вид импьютации:

[24] :
```
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]
```

Проверим работу функции по продажам автомобилей:

[25] :
```
data[['__year_resale_value']].describe()
```

[25]:

	__year_resale_value
count	121.000000
mean	18.072975
std	11.453384
min	5.160000
25%	11.260000
50%	14.180000
75%	19.875000
max	67.550000

[26] :
```
test_num_impute_col(data, '__year_resale_value', strategies[0])
```

[26] : ('__year_resale_value', 'mean', 36, 18.07297520661157, 18.07297520661157)

[27] :
```
test_num_impute_col(data, '__year_resale_value', strategies[1])
```

[27] : ('__year_resale_value', 'median', 36, 14.18, 14.18)

[28] :
```
test_num_impute_col(data, '__year_resale_value', strategies[2])
```

[28] : ('__year_resale_value', 'most_frequent', 36, 7.75, 7.75)

2.3.3. Обработка пропусков в категориальных данных

Так как в датасете нет пропусков среди столбца “Производитель”, то искуственно подправим датасет и загрузим его:

[29] :
```
data_mod = pd.read_csv('Car_sales_mod.csv')
```

Проверим категориальный признак:

[30] :
```
cat_cols = []
for col in data.columns:
    temp_null_count = data_mod[data_mod[col].isnull()].shape[0]
    dt = str(data_mod[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('Столбец {}. Тип данных {}. Количество пустых значений {}, {}%.'.
↪format(col, dt, temp_null_count, temp_perc))
```

Столбец Manufacturer. Тип данных object. Количество пустых значений 15, 9.55%.

Его и будем использовать:

[31] :
```
cat_temp_data = data_mod[['Manufacturer']]
cat_temp_data.head()
```

[31]:

	Manufacturer
0	Acura
1	Acura
2	Acura
3	Acura
4	Audi

[32] :
```
cat_temp_data['Manufacturer'].unique()
```

[32] :
```
array(['Acura', 'Audi', 'BMW', 'Buick', 'Cadillac', 'Chevrolet', nan,
       'Dodge', 'Ford', 'Honda', 'Hyundai', 'Infiniti', 'Jaguar', 'Jeep',
       'Lexus', 'Mitsubishi', 'Mercury', 'Mercedes-B', 'Nissan',
       'Oldsmobile', 'Plymouth', 'Pontiac', 'Porsche', 'Saab', 'Subaru',
       'Toyota', 'Volkswagen', 'Volvo'], dtype=object)
```

[33] :
```
cat_temp_data[cat_temp_data['Manufacturer'].isnull()].shape
```

[33]: (15, 1)

Импьютация наиболее частыми значениями:

[34] :
```
imp2 = SimpleImputer(missing_values=np.nan, strategy='most_frequent')
data_imp2 = imp2.fit_transform(cat_temp_data)
data_imp2
```

[34] :
```
array([['Acura'],
       ['Acura'],
       ['Acura'],
       ['Acura'],
       ['Audi'],
       ['Audi'],
```

['Audi'],
['BMW'],
['BMW'],
['BMW'],
['Buick'],
['Buick'],
['Buick'],
['Buick'],
['Cadillac'],
['Cadillac'],
['Cadillac'],
['Cadillac'],
['Cadillac'],
['Chevrolet'],
['Chevrolet'],
['Chevrolet'],
['Chevrolet'],
['Chevrolet'],
['Chevrolet'],
['Chevrolet'],
['Chevrolet'],
['Chevrolet'],
['Dodge'],
['Dodge'],
['Dodge'],
['Dodge'],
['Dodge'],
['Dodge'],
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['Dodge'],
['Dodge'],
['Dodge'],
['Dodge'],
['Dodge'],
['Dodge'],
['Dodge'],
['Dodge'],
['Dodge'],
['Dodge'],
['Ford'],
['Ford'],
['Ford'],
['Ford'],
['Ford'],
['Ford'],
['Ford'],
['Ford'],
['Ford'],
['Ford'],
['Ford'],
['Honda'],
['Honda'],

['Honda'],
['Honda'],
['Honda'],
['Hyundai'],
['Hyundai'],
['Hyundai'],
['Infiniti'],
['Jaguar'],
['Jeep'],
['Jeep'],
['Jeep'],
['Lexus'],
['Lexus'],
['Lexus'],
['Lexus'],
['Lexus'],
['Lexus'],
['Dodge'],
['Dodge'],
['Dodge'],
['Mitsubishi'],
['Mitsubishi'],
['Mitsubishi'],
['Mitsubishi'],
['Mitsubishi'],
['Mitsubishi'],
['Mitsubishi'],
['Mercury'],
['Mercury'],
['Mercury'],
['Mercury'],
['Mercury'],
['Mercury'],
['Mercedes-B'],
['Mercedes-B'],
['Mercedes-B'],
['Mercedes-B'],
['Mercedes-B'],
['Mercedes-B'],
['Mercedes-B'],
['Mercedes-B'],
['Mercedes-B'],
['Nissan'],
['Nissan'],
['Nissan'],
['Nissan'],
['Nissan'],
['Nissan'],
['Nissan'],
['Oldsmobile'],
['Oldsmobile'],
['Oldsmobile'],
['Oldsmobile'],

```
       ['Oldsmobile'],
       ['Oldsmobile'],
       ['Plymouth'],
       ['Plymouth'],
       ['Plymouth'],
       ['Plymouth'],
       ['Pontiac'],
       ['Pontiac'],
       ['Pontiac'],
       ['Pontiac'],
       ['Pontiac'],
       ['Pontiac'],
       ['Porsche'],
       ['Porsche'],
       ['Porsche'],
       ['Saab'],
       ['Saab'],
       ['Dodge'],
       ['Dodge'],
       ['Dodge'],
       ['Dodge'],
       ['Dodge'],
       ['Subaru'],
       ['Subaru'],
       ['Toyota'],
       ['Toyota'],
       ['Toyota'],
       ['Toyota'],
       ['Toyota'],
       ['Toyota'],
       ['Toyota'],
       ['Toyota'],
       ['Toyota'],
       ['Toyota'],
       ['Volkswagen'],
       ['Volkswagen'],
       ['Volkswagen'],
       ['Volkswagen'],
       ['Volkswagen'],
       ['Volkswagen'],
       ['Volvo'],
       ['Volvo'],
       ['Volvo'],
       ['Volvo'],
       ['Volvo'],
       ['Volvo']],   dtype=object)
```

[35] :
```
np.unique(data_imp2)
```

[35] :
```
array(['Acura', 'Audi', 'BMW', 'Buick', 'Cadillac', 'Chevrolet', 'Dodge',
       'Ford', 'Honda', 'Hyundai', 'Infiniti', 'Jaguar', 'Jeep', 'Lexus',
       'Mercedes-B', 'Mercury', 'Mitsubishi', 'Nissan', 'Oldsmobile',
       'Plymouth', 'Pontiac', 'Porsche', 'Saab', 'Subaru', 'Toyota',
       'Volkswagen', 'Volvo'], dtype=object)
```

Наблюдаем отсутствие пустых значений.
Импьютация константой:

[36] :
```
imp3 = SimpleImputer(missing_values=np.nan, strategy='constant', fill_value='???')
data_imp3 = imp3.fit_transform(cat_temp_data)
data_imp3
```

[36] :
```
array([['Acura'],
       ['Acura'],
       ['Acura'],
       ['Acura'],
       ['Audi'],
       ['Audi'],
       ['Audi'],
       ['BMW'],
       ['BMW'],
       ['BMW'],
       ['Buick'],
       ['Buick'],
       ['Buick'],
       ['Buick'],
       ['Cadillac'],
       ['Cadillac'],
       ['Cadillac'],
       ['Cadillac'],
       ['Cadillac'],
       ['Chevrolet'],
       ['Chevrolet'],
       ['Chevrolet'],
       ['Chevrolet'],
       ['Chevrolet'],
       ['Chevrolet'],
       ['Chevrolet'],
       ['Chevrolet'],
       ['???'],
       ['???'],
       ['???'],
       ['???'],
       ['???'],
       ['???'],
       ['???'],
       ['Dodge'],
       ['Dodge'],
       ['Dodge'],
       ['Dodge'],
       ['Dodge'],
       ['Dodge'],
       ['Dodge'],
       ['Dodge'],
       ['Dodge'],
       ['Dodge'],
       ['Dodge'],
       ['Dodge'],
       ['Ford'],
```

['Ford'],
['Ford'],
['Ford'],
['Ford'],
['Ford'],
['Ford'],
['Ford'],
['Ford'],
['Ford'],
['Ford'],
['Honda'],
['Honda'],
['Honda'],
['Honda'],
['Honda'],
['Hyundai'],
['Hyundai'],
['Hyundai'],
['Infiniti'],
['Jaguar'],
['Jeep'],
['Jeep'],
['Jeep'],
['Lexus'],
['Lexus'],
['Lexus'],
['Lexus'],
['Lexus'],
['Lexus'],
['???'],
['???'],
['???'],
['Mitsubishi'],
['Mitsubishi'],
['Mitsubishi'],
['Mitsubishi'],
['Mitsubishi'],
['Mitsubishi'],
['Mitsubishi'],
['Mercury'],
['Mercury'],
['Mercury'],
['Mercury'],
['Mercury'],
['Mercury'],
['Mercedes-B'],
['Mercedes-B'],
['Mercedes-B'],
['Mercedes-B'],
['Mercedes-B'],
['Mercedes-B'],
['Mercedes-B'],
['Mercedes-B'],

['Mercedes-B'],
['Nissan'],
['Nissan'],
['Nissan'],
['Nissan'],
['Nissan'],
['Nissan'],
['Nissan'],
['Oldsmobile'],
['Oldsmobile'],
['Oldsmobile'],
['Oldsmobile'],
['Oldsmobile'],
['Oldsmobile'],
['Plymouth'],
['Plymouth'],
['Plymouth'],
['Plymouth'],
['Pontiac'],
['Pontiac'],
['Pontiac'],
['Pontiac'],
['Pontiac'],
['Pontiac'],
['Porsche'],
['Porsche'],
['Porsche'],
['Saab'],
['Saab'],
['???'],
['???'],
['???'],
['???'],
['???'],
['Subaru'],
['Subaru'],
['Toyota'],
['Toyota'],
['Toyota'],
['Toyota'],
['Toyota'],
['Toyota'],
['Toyota'],
['Toyota'],
['Toyota'],
['Toyota'],
['Volkswagen'],
['Volkswagen'],
['Volkswagen'],
['Volkswagen'],
['Volkswagen'],
['Volkswagen'],
['Volvo'],
['Volvo'],

```
       ['Volvo'],
       ['Volvo'],
       ['Volvo'],
       ['Volvo']],  dtype=object)
```

[37] :
```
np.unique(data_imp3)
```

[37] :
```
array(['???', 'Acura', 'Audi', 'BMW', 'Buick', 'Cadillac', 'Chevrolet',
       'Dodge', 'Ford', 'Honda', 'Hyundai', 'Infiniti', 'Jaguar', 'Jeep',
       'Lexus', 'Mercedes-B', 'Mercury', 'Mitsubishi', 'Nissan',
       'Oldsmobile', 'Plymouth', 'Pontiac', 'Porsche', 'Saab', 'Subaru',
       'Toyota', 'Volkswagen', 'Volvo'], dtype=object)
```

[38] :
```
data_imp3[data_imp3==0].size
```

[38]:
```
0
```

Значения были заменены на “???”.

2.3.4. Преобразование категориальных признаков в числовые

[39] :
```
cat_enc = pd.DataFrame({'c1':data_imp2.T[0]})
cat_enc
```

[39]:

	c1
0	Acura
1	Acura
2	Acura
3	Acura
4	Audi
..	...
152	Volvo
153	Volvo
154	Volvo
155	Volvo
156	Volvo

[157 rows x 1 columns]

2.4. Кодирование категорий целочисленными значениями

2.4.1. LabelEncoder

[40] :
```
from sklearn.preprocessing import LabelEncoder
```

[41] :
```
cat_enc['c1'].unique()
```

[41] :
```
array(['Acura', 'Audi', 'BMW', 'Buick', 'Cadillac', 'Chevrolet', 'Dodge',
       'Ford', 'Honda', 'Hyundai', 'Infiniti', 'Jaguar', 'Jeep', 'Lexus',
       'Mitsubishi', 'Mercury', 'Mercedes-B', 'Nissan', 'Oldsmobile',
       'Plymouth', 'Pontiac', 'Porsche', 'Saab', 'Subaru', 'Toyota',
       'Volkswagen', 'Volvo'], dtype=object)
```

[42] :
```
le = LabelEncoder()
```

[43] :
```
cat_enc_le = le.fit_transform(cat_enc['c1'])
```

[44] :
```
le.classes_
```

[44]:
```
array(['Acura', 'Audi', 'BMW', 'Buick', 'Cadillac', 'Chevrolet', 'Dodge',
       'Ford', 'Honda', 'Hyundai', 'Infiniti', 'Jaguar', 'Jeep', 'Lexus',
       'Mercedes-B', 'Mercury', 'Mitsubishi', 'Nissan', 'Oldsmobile',
       'Plymouth', 'Pontiac', 'Porsche', 'Saab', 'Subaru', 'Toyota',
       'Volkswagen', 'Volvo'], dtype=object)
```

[45]:
```
cat_enc_le
```

[45]:
```
array([ 0,  0,  0,  0,  1,  1,  1,  2,  2,  2,  3,  3,  3,  3,  4,  4,  4,
        4,  4,  5,  5,  5,  5,  5,  5,  5,  5,  5,  6,  6,  6,  6,  6,  6,
        6,  6,  6,  6,  6,  6,  6,  6,  6,  6,  6,  6,  7,  7,  7,  7,  7,
        7,  7,  7,  7,  7,  7,  8,  8,  8,  8,  8,  9,  9,  9, 10, 11, 12,
       12, 12, 13, 13, 13, 13, 13, 13,  6,  6,  6, 16, 16, 16, 16, 16, 16,
       16, 15, 15, 15, 15, 15, 15, 14, 14, 14, 14, 14, 14, 14, 14, 14, 17,
       17, 17, 17, 17, 17, 17, 18, 18, 18, 18, 18, 18, 19, 19, 19, 19, 20,
       20, 20, 20, 20, 20, 21, 21, 21, 22, 22,  6,  6,  6,  6,  6, 23, 23,
       24, 24, 24, 24, 24, 24, 24, 24, 24, 25, 25, 25, 25, 25, 25, 26, 26,
       26, 26, 26, 26])
```

[46]:
```
np.unique(cat_enc_le)
```

[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, 25, 26])
```

[47]:
```
le.inverse_transform([ 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])
```

[47] :
```
array(['Acura', 'Audi', 'BMW', 'Buick', 'Cadillac', 'Chevrolet', 'Dodge',
       'Ford', 'Honda', 'Hyundai', 'Infiniti', 'Jaguar', 'Jeep', 'Lexus',
       'Mercedes-B', 'Mercury', 'Mitsubishi', 'Nissan', 'Oldsmobile',
       'Plymouth', 'Pontiac', 'Porsche', 'Saab', 'Subaru', 'Toyota',
       'Volkswagen', 'Volvo'], dtype=object)
```

2.4.2. OrdinalEncoder

[48] :
```
from sklearn.preprocessing import OrdinalEncoder
```

[49] :
```
data_oe = data_mod[['Manufacturer', 'Model']]
data_oe.head()
```

[49] :

	Manufacturer	Model
0	Acura	Integra
1	Acura	TL
2	Acura	CL
3	Acura	RL
4	Audi	A4

[50] :
```
imp4 = SimpleImputer(missing_values=np.nan, strategy='constant', fill_value='???')
data_oe_filled = imp4.fit_transform(data_oe)
```

```
data_oe_filled
```

[50] :
```
array([['Acura', 'Integra'],
       ['Acura', 'TL'],
       ['Acura', 'CL'],
       ['Acura', 'RL'],
       ['Audi', 'A4'],
       ['Audi', 'A6'],
       ['Audi', 'A8'],
       ['BMW', '323i'],
       ['BMW', '328i'],
       ['BMW', '528i'],
       ['Buick', 'Century'],
       ['Buick', 'Regal'],
       ['Buick', 'Park Avenue'],
       ['Buick', 'LeSabre'],
       ['Cadillac', 'DeVille'],
       ['Cadillac', 'Seville'],
       ['Cadillac', 'Eldorado'],
       ['Cadillac', 'Catera'],
       ['Cadillac', 'Escalade'],
       ['Chevrolet', 'Cavalier'],
       ['Chevrolet', 'Malibu'],
       ['Chevrolet', 'Lumina'],
       ['Chevrolet', 'Monte Carlo'],
       ['Chevrolet', 'Camaro'],
       ['Chevrolet', 'Corvette'],
       ['Chevrolet', 'Prizm'],
       ['Chevrolet', 'Metro'],
       ['Chevrolet', 'Impala'],
       ['???', 'Sebring Coupe'],
       ['???', 'Sebring Conv.'],
       ['???', 'Concorde'],
       ['???', 'Cirrus'],
       ['???', 'LHS'],
       ['???', 'Town & Country'],
       ['???', '300M'],
       ['Dodge', 'Neon'],
       ['Dodge', 'Avenger'],
       ['Dodge', 'Stratus'],
       ['Dodge', 'Intrepid'],
       ['Dodge', 'Viper'],
       ['Dodge', 'Ram Pickup'],
       ['Dodge', 'Ram Wagon'],
       ['Dodge', 'Ram Van'],
       ['Dodge', 'Dakota'],
       ['Dodge', 'Durango'],
       ['Dodge', 'Caravan'],
       ['Ford', 'Escort'],
       ['Ford', 'Mustang'],
       ['Ford', 'Contour'],
       ['Ford', 'Taurus'],
       ['Ford', 'Focus'],
```

['Ford', 'Crown Victoria'],
['Ford', 'Explorer'],
['Ford', 'Windstar'],
['Ford', 'Expedition'],
['Ford', 'Ranger'],
['Ford', 'F-Series'],
['Honda', 'Civic'],
['Honda', 'Accord'],
['Honda', 'CR-V'],
['Honda', 'Passport'],
['Honda', 'Odyssey'],
['Hyundai', 'Accent'],
['Hyundai', 'Elantra'],
['Hyundai', 'Sonata'],
['Infiniti', 'I30'],
['Jaguar', 'S-Type'],
['Jeep', 'Wrangler'],
['Jeep', 'Cherokee'],
['Jeep', 'Grand Cherokee'],
['Lexus', 'ES300'],
['Lexus', 'GS300'],
['Lexus', 'GS400'],
['Lexus', 'LS400'],
['Lexus', 'LX470'],
['Lexus', 'RX300'],
['???', 'Continental'],
['???', 'Town car'],
['???', 'Navigator'],
['Mitsubishi', 'Mirage'],
['Mitsubishi', 'Eclipse'],
['Mitsubishi', 'Galant'],
['Mitsubishi', 'Diamante'],
['Mitsubishi', '3000GT'],
['Mitsubishi', 'Montero'],
['Mitsubishi', 'Montero Sport'],
['Mercury', 'Mystique'],
['Mercury', 'Cougar'],
['Mercury', 'Sable'],
['Mercury', 'Grand Marquis'],
['Mercury', 'Mountaineer'],
['Mercury', 'Villager'],
['Mercedes-B', 'C-Class'],
['Mercedes-B', 'E-Class'],
['Mercedes-B', 'S-Class'],
['Mercedes-B', 'SL-Class'],
['Mercedes-B', 'SLK'],
['Mercedes-B', 'SLK230'],
['Mercedes-B', 'CLK Coupe'],
['Mercedes-B', 'CL500'],
['Mercedes-B', 'M-Class'],
['Nissan', 'Sentra'],
['Nissan', 'Altima'],
['Nissan', 'Maxima'],

['Nissan', 'Quest'],
['Nissan', 'Pathfinder'],
['Nissan', 'Xterra'],
['Nissan', 'Frontier'],
['Oldsmobile', 'Cutlass'],
['Oldsmobile', 'Intrigue'],
['Oldsmobile', 'Alero'],
['Oldsmobile', 'Aurora'],
['Oldsmobile', 'Bravada'],
['Oldsmobile', 'Silhouette'],
['Plymouth', 'Neon'],
['Plymouth', 'Breeze'],
['Plymouth', 'Voyager'],
['Plymouth', 'Prowler'],
['Pontiac', 'Sunfire'],
['Pontiac', 'Grand Am'],
['Pontiac', 'Firebird'],
['Pontiac', 'Grand Prix'],
['Pontiac', 'Bonneville'],
['Pontiac', 'Montana'],
['Porsche', 'Boxter'],
['Porsche', 'Carrera Coupe'],
['Porsche', 'Carrera Cabrio'],
['Saab', '5-Sep'],
['Saab', '3-Sep'],
['???', 'SL'],
['???', 'SC'],
['???', 'SW'],
['???', 'LW'],
['???', 'LS'],
['Subaru', 'Outback'],
['Subaru', 'Forester'],
['Toyota', 'Corolla'],
['Toyota', 'Camry'],
['Toyota', 'Avalon'],
['Toyota', 'Celica'],
['Toyota', 'Tacoma'],
['Toyota', 'Sienna'],
['Toyota', 'RAV4'],
['Toyota', '4Runner'],
['Toyota', 'Land Cruiser'],
['Volkswagen', 'Golf'],
['Volkswagen', 'Jetta'],
['Volkswagen', 'Passat'],
['Volkswagen', 'Cabrio'],
['Volkswagen', 'GTI'],
['Volkswagen', 'Beetle'],
['Volvo', 'S40'],
['Volvo', 'V40'],
['Volvo', 'S70'],
['Volvo', 'V70'],
['Volvo', 'C70'],
['Volvo', 'S80']], dtype=object)

[51] :
```
oe = OrdinalEncoder()
cat_enc_oe = oe.fit_transform(data_oe_filled)
cat_enc_oe
```

[51]:
```
array([[  1.,  79.],
       [  1., 143.],
       [  1.,  25.],
       [  1., 115.],
       [  2.,   8.],
       [  2.,   9.],
       [  2.,  10.],
       [  3.,   3.],
       [  3.,   4.],
       [  3.,   7.],
       [  4.,  38.],
       [  4., 121.],
       [  4., 107.],
       [  4.,  89.],
       [  5.,  51.],
       [  5., 137.],
       [  5.,  58.],
       [  5.,  35.],
       [  5.,  59.],
       [  6.,  36.],
       [  6.,  92.],
       [  6.,  90.],
       [  6.,  97.],
       [  6.,  30.],
       [  6.,  46.],
       [  6., 111.],
       [  6.,  94.],
       [  6.,  78.],
       [  0., 135.],
       [  0., 134.],
       [  0.,  42.],
       [  0.,  40.],
       [  0.,  83.],
       [  0., 146.],
       [  0.,   2.],
       [  7., 104.],
       [  7.,  17.],
       [  7., 141.],
       [  7.,  80.],
       [  7., 151.],
       [  7., 117.],
       [  7., 119.],
       [  7., 118.],
       [  7.,  50.],
       [  7.,  53.],
       [  7.,  32.],
       [  8.,  60.],
       [  8., 101.],
       [  8.,  44.],
```

```
[  8., 145.],
[  8.,  65.],
[  8.,  48.],
[  8.,  62.],
[  8., 153.],
[  8.,  61.],
[  8., 120.],
[  8.,  63.],
[  9.,  41.],
[  9.,  12.],
[  9.,  28.],
[  9., 109.],
[  9., 105.],
[ 10.,  11.],
[ 10.,  57.],
[ 10., 140.],
[ 11.,  77.],
[ 12., 123.],
[ 13., 154.],
[ 13.,  39.],
[ 13.,  74.],
[ 14.,  55.],
[ 14.,  68.],
[ 14.,  69.],
[ 14.,  85.],
[ 14.,  87.],
[ 14., 116.],
[  O.,  43.],
[  O., 147.],
[  O., 103.],
[ 17.,  95.],
[ 17.,  56.],
[ 17.,  71.],
[ 17.,  52.],
[ 17.,   1.],
[ 17.,  98.],
[ 17.,  99.],
[ 16., 102.],
[ 16.,  47.],
[ 16., 133.],
[ 16.,  75.],
[ 16., 100.],
[ 16., 150.],
[ 15.,  23.],
[ 15.,  54.],
[ 15., 122.],
[ 15., 129.],
[ 15., 130.],
[ 15., 131.],
[ 15.,  27.],
[ 15.,  26.],
[ 15.,  91.],
[ 18., 136.],
```

```
[ 18.,  14.],
[ 18.,  93.],
[ 18., 113.],
[ 18., 110.],
[ 18., 155.],
[ 18.,  67.],
[ 19.,  49.],
[ 19.,  81.],
[ 19.,  13.],
[ 19.,  15.],
[ 19.,  21.],
[ 19., 139.],
[ 20., 104.],
[ 20.,  22.],
[ 20., 152.],
[ 20., 112.],
[ 21., 142.],
[ 21.,  73.],
[ 21.,  64.],
[ 21.,  76.],
[ 21.,  19.],
[ 21.,  96.],
[ 22.,  20.],
[ 22.,  34.],
[ 22.,  33.],
[ 23.,   6.],
[ 23.,   0.],
[  0., 128.],
[  0., 127.],
[  0., 132.],
[  0.,  86.],
[  0.,  84.],
[ 24., 106.],
[ 24.,  66.],
[ 25.,  45.],
[ 25.,  31.],
[ 25.,  16.],
[ 25.,  37.],
[ 25., 144.],
[ 25., 138.],
[ 25., 114.],
[ 25.,   5.],
[ 25.,  88.],
[ 26.,  72.],
[ 26.,  82.],
[ 26., 108.],
[ 26.,  29.],
[ 26.,  70.],
[ 26.,  18.],
[ 27., 124.],
[ 27., 148.],
[ 27., 125.],
[ 27., 149.],
```

```
       [ 27.,  24.],
       [ 27., 126.]])
```

Уникальные значения столбца “Производитель”:

[52] :
```
np.unique(cat_enc_oe[:, 0])
```

[52]:
```
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.])
```

Уникальные значения столбца “Модель”:

[53] :
```
np.unique(cat_enc_oe[:, 1])
```

[53]:
```
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.])
```

Все значения:

[54] :
```
oe.categories_
```

[54] :
```
[array(['???', 'Acura', 'Audi', 'BMW', 'Buick', 'Cadillac', 'Chevrolet',
        'Dodge', 'Ford', 'Honda', 'Hyundai', 'Infiniti', 'Jaguar', 'Jeep',
        'Lexus', 'Mercedes-B', 'Mercury', 'Mitsubishi', 'Nissan',
        'Oldsmobile', 'Plymouth', 'Pontiac', 'Porsche', 'Saab', 'Subaru',
        'Toyota', 'Volkswagen', 'Volvo'], dtype=object),
 array(['3-Sep', '3000GT', '300M', '323i', '328i', '4Runner', '5-Sep',
        '528i', 'A4', 'A6', 'A8', 'Accent', 'Accord', 'Alero', 'Altima',
        'Aurora', 'Avalon', 'Avenger', 'Beetle', 'Bonneville', 'Boxter',
        'Bravada', 'Breeze', 'C-Class', 'C70', 'CL', 'CL500', 'CLK Coupe',
        'CR-V', 'Cabrio', 'Camaro', 'Camry', 'Caravan', 'Carrera Cabrio',
        'Carrera Coupe', 'Catera', 'Cavalier', 'Celica', 'Century',
        'Cherokee', 'Cirrus', 'Civic', 'Concorde', 'Continental',
        'Contour', 'Corolla', 'Corvette', 'Cougar', 'Crown Victoria',
        'Cutlass', 'Dakota', 'DeVille', 'Diamante', 'Durango', 'E-Class',
        'ES300', 'Eclipse', 'Elantra', 'Eldorado', 'Escalade', 'Escort',
        'Expedition', 'Explorer', 'F-Series', 'Firebird', 'Focus',
        'Forester', 'Frontier', 'GS300', 'GS400', 'GTI', 'Galant', 'Golf',
        'Grand Am', 'Grand Cherokee', 'Grand Marquis', 'Grand Prix', 'I30',
        'Impala', 'Integra', 'Intrepid', 'Intrigue', 'Jetta', 'LHS', 'LS',
        'LS400', 'LW', 'LX470', 'Land Cruiser', 'LeSabre', 'Lumina',
        'M-Class', 'Malibu', 'Maxima', 'Metro', 'Mirage', 'Montana',
        'Monte Carlo', 'Montero', 'Montero Sport', 'Mountaineer',
```

```
       'Mustang', 'Mystique', 'Navigator', 'Neon', 'Odyssey', 'Outback',
       'Park Avenue', 'Passat', 'Passport', 'Pathfinder', 'Prizm',
       'Prowler', 'Quest', 'RAV4', 'RL', 'RX300', 'Ram Pickup', 'Ram Van',
       'Ram Wagon', 'Ranger', 'Regal', 'S-Class', 'S-Type', 'S40', 'S70',
       'S80', 'SC', 'SL', 'SL-Class', 'SLK', 'SLK230', 'SW', 'Sable',
       'Sebring Conv.', 'Sebring Coupe', 'Sentra', 'Seville', 'Sienna',
       'Silhouette', 'Sonata', 'Stratus', 'Sunfire', 'TL', 'Tacoma',
       'Taurus', 'Town & Country', 'Town car', 'V40', 'V70', 'Villager',
       'Viper', 'Voyager', 'Windstar', 'Wrangler', 'Xterra'], dtype=object)]
```

[55] :
```
oe.inverse_transform(cat_enc_oe)
```

[55] :
```
array([['Acura', 'Integra'],
       ['Acura', 'TL'],
       ['Acura', 'CL'],
       ['Acura', 'RL'],
       ['Audi', 'A4'],
       ['Audi', 'A6'],
       ['Audi', 'A8'],
       ['BMW', '323i'],
       ['BMW', '328i'],
       ['BMW', '528i'],
       ['Buick', 'Century'],
       ['Buick', 'Regal'],
       ['Buick', 'Park Avenue'],
       ['Buick', 'LeSabre'],
       ['Cadillac', 'DeVille'],
       ['Cadillac', 'Seville'],
       ['Cadillac', 'Eldorado'],
       ['Cadillac', 'Catera'],
       ['Cadillac', 'Escalade'],
       ['Chevrolet', 'Cavalier'],
       ['Chevrolet', 'Malibu'],
       ['Chevrolet', 'Lumina'],
       ['Chevrolet', 'Monte Carlo'],
       ['Chevrolet', 'Camaro'],
       ['Chevrolet', 'Corvette'],
       ['Chevrolet', 'Prizm'],
       ['Chevrolet', 'Metro'],
       ['Chevrolet', 'Impala'],
       ['???', 'Sebring Coupe'],
       ['???', 'Sebring Conv.'],
       ['???', 'Concorde'],
       ['???', 'Cirrus'],
       ['???', 'LHS'],
       ['???', 'Town & Country'],
       ['???', '300M'],
       ['Dodge', 'Neon'],
       ['Dodge', 'Avenger'],
       ['Dodge', 'Stratus'],
       ['Dodge', 'Intrepid'],
       ['Dodge', 'Viper'],
       ['Dodge', 'Ram Pickup'],
```

['Dodge', 'Ram Wagon'],
['Dodge', 'Ram Van'],
['Dodge', 'Dakota'],
['Dodge', 'Durango'],
['Dodge', 'Caravan'],
['Ford', 'Escort'],
['Ford', 'Mustang'],
['Ford', 'Contour'],
['Ford', 'Taurus'],
['Ford', 'Focus'],
['Ford', 'Crown Victoria'],
['Ford', 'Explorer'],
['Ford', 'Windstar'],
['Ford', 'Expedition'],
['Ford', 'Ranger'],
['Ford', 'F-Series'],
['Honda', 'Civic'],
['Honda', 'Accord'],
['Honda', 'CR-V'],
['Honda', 'Passport'],
['Honda', 'Odyssey'],
['Hyundai', 'Accent'],
['Hyundai', 'Elantra'],
['Hyundai', 'Sonata'],
['Infiniti', 'I30'],
['Jaguar', 'S-Type'],
['Jeep', 'Wrangler'],
['Jeep', 'Cherokee'],
['Jeep', 'Grand Cherokee'],
['Lexus', 'ES300'],
['Lexus', 'GS300'],
['Lexus', 'GS400'],
['Lexus', 'LS400'],
['Lexus', 'LX470'],
['Lexus', 'RX300'],
['???', 'Continental'],
['???', 'Town car'],
['???', 'Navigator'],
['Mitsubishi', 'Mirage'],
['Mitsubishi', 'Eclipse'],
['Mitsubishi', 'Galant'],
['Mitsubishi', 'Diamante'],
['Mitsubishi', '3000GT'],
['Mitsubishi', 'Montero'],
['Mitsubishi', 'Montero Sport'],
['Mercury', 'Mystique'],
['Mercury', 'Cougar'],
['Mercury', 'Sable'],
['Mercury', 'Grand Marquis'],
['Mercury', 'Mountaineer'],
['Mercury', 'Villager'],
['Mercedes-B', 'C-Class'],
['Mercedes-B', 'E-Class'],

['Mercedes-B', 'S-Class'],
['Mercedes-B', 'SL-Class'],
['Mercedes-B', 'SLK'],
['Mercedes-B', 'SLK230'],
['Mercedes-B', 'CLK Coupe'],
['Mercedes-B', 'CL500'],
['Mercedes-B', 'M-Class'],
['Nissan', 'Sentra'],
['Nissan', 'Altima'],
['Nissan', 'Maxima'],
['Nissan', 'Quest'],
['Nissan', 'Pathfinder'],
['Nissan', 'Xterra'],
['Nissan', 'Frontier'],
['Oldsmobile', 'Cutlass'],
['Oldsmobile', 'Intrigue'],
['Oldsmobile', 'Alero'],
['Oldsmobile', 'Aurora'],
['Oldsmobile', 'Bravada'],
['Oldsmobile', 'Silhouette'],
['Plymouth', 'Neon'],
['Plymouth', 'Breeze'],
['Plymouth', 'Voyager'],
['Plymouth', 'Prowler'],
['Pontiac', 'Sunfire'],
['Pontiac', 'Grand Am'],
['Pontiac', 'Firebird'],
['Pontiac', 'Grand Prix'],
['Pontiac', 'Bonneville'],
['Pontiac', 'Montana'],
['Porsche', 'Boxter'],
['Porsche', 'Carrera Coupe'],
['Porsche', 'Carrera Cabrio'],
['Saab', '5-Sep'],
['Saab', '3-Sep'],
['???', 'SL'],
['???', 'SC'],
['???', 'SW'],
['???', 'LW'],
['???', 'LS'],
['Subaru', 'Outback'],
['Subaru', 'Forester'],
['Toyota', 'Corolla'],
['Toyota', 'Camry'],
['Toyota', 'Avalon'],
['Toyota', 'Celica'],
['Toyota', 'Tacoma'],
['Toyota', 'Sienna'],
['Toyota', 'RAV4'],
['Toyota', '4Runner'],
['Toyota', 'Land Cruiser'],
['Volkswagen', 'Golf'],
['Volkswagen', 'Jetta'],

```
['Volkswagen', 'Passat'],
['Volkswagen', 'Cabrio'],
['Volkswagen', 'GTI'],
['Volkswagen', 'Beetle'],
['Volvo', 'S40'],
['Volvo', 'V40'],
['Volvo', 'S70'],
['Volvo', 'V70'],
['Volvo', 'C70'],
['Volvo', 'S80']], dtype=object)
```

2.4.3. Кодирование шкал порядка

Для кодирования шкал порядка воспользуемся функцией map:

[56] :
```
sizes = ['small', 'medium', 'large', 'small', 'medium', 'large', 'small',
↪'medium', 'large']
```

[57] :
```
pd_sizes = pd.DataFrame(data={'sizes':sizes})
pd_sizes
```

[57]:

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

[58] :
```
pd_sizes['sizes_codes'] = pd_sizes['sizes'].map({'small':1, 'medium':2, 'large':
↪3})
pd_sizes
```

[58]:

	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

[59] :
```
pd_sizes['sizes_decoded'] = pd_sizes['sizes_codes'].map({1:'small', 2:'medium', 3:
↪'large'})
pd_sizes
```

[59] :

	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
```

2.4.4. Кодирование категорий наборами бинарных значений - one-hot encoding

Каждое уникальное значение признака становится новым отдельным признаком:

[60] :
```
from sklearn.preprocessing import OneHotEncoder
```

[61] :
```
ohe = OneHotEncoder()
cat_enc_ohe = ohe.fit_transform(cat_enc[['c1']])
```

[62] :
```
cat_enc.shape
```

[62]:
```
(157, 1)
```

[63] :
```
cat_enc_ohe.shape
```

[63]:
```
(157, 27)
```

[64] :
```
cat_enc_ohe
```

[64] :
```
<157x27 sparse matrix of type '<class 'numpy.float64'>'
        with 157 stored elements in Compressed Sparse Row format>
```

[65] :
```
cat_enc_ohe.todense()[0:10]
```

[65]:
```
matrix([[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.],
        [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.],
        [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.],
        [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., 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., 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., 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., 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., 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., 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.]])
```

[66] :
```
cat_enc.head(10)
```

[66]:

	c1
0	Acura
1	Acura
2	Acura
3	Acura
4	Audi
5	Audi
6	Audi
7	BMW
8	BMW
9	BMW

[67] :
```
pd.get_dummies(cat_enc).head()
```

[67]:

	c1_Acura	c1_Audi	c1_BMW	c1_Buick	c1_Cadillac	c1_Chevrolet	c1_Dodge	\
0	1	0	0	0	0	0	0	
1	1	0	0	0	0	0	0	
2	1	0	0	0	0	0	0	
3	1	0	0	0	0	0	0	
4	0	1	0	0	0	0	0	

	c1_Ford	c1_Honda	c1_Hyundai	...	c1_Nissan	c1_Oldsmobile	c1_Plymouth	\
0	0	0	0	...	0	0	0	
1	0	0	0	...	0	0	0	
2	0	0	0	...	0	0	0	
3	0	0	0	...	0	0	0	
4	0	0	0	...	0	0	0	

	c1_Pontiac	c1_Porsche	c1_Saab	c1_Subaru	c1_Toyota	c1_Volkswagen	\
0	0	0	0	0	0	0	
1	0	0	0	0	0	0	
2	0	0	0	0	0	0	
3	0	0	0	0	0	0	
4	0	0	0	0	0	0	

	c1_Volvo
0	0
1	0
2	0
3	0
4	0

[5 rows x 27 columns]

[68] :
```
pd.get_dummies(cat_temp_data, dummy_na=True).head()
```

[68]:

	Manufacturer_Acura	Manufacturer_Audi	Manufacturer_BMW	\
0	1	0	0	
1	1	0	0	
2	1	0	0	
3	1	0	0	
4	0	1	0	

	Manufacturer_Buick	Manufacturer_Cadillac	Manufacturer_Chevrolet	\

```
0                    0                    0                    0
1                    0                    0                    0
2                    0                    0                    0
3                    0                    0                    0
4                    0                    0                    0

   Manufacturer_Dodge  Manufacturer_Ford  Manufacturer_Honda  \
0                   0                  0                   0
1                   0                  0                   0
2                   0                  0                   0
3                   0                  0                   0
4                   0                  0                   0

   Manufacturer_Hyundai  ...  Manufacturer_Oldsmobile  Manufacturer_Plymouth  \
0                     0  ...                        0                      0
1                     0  ...                        0                      0
2                     0  ...                        0                      0
3                     0  ...                        0                      0
4                     0  ...                        0                      0

   Manufacturer_Pontiac  Manufacturer_Porsche  Manufacturer_Saab \
0                     0                     0                   0
1                     0                     0                   0
2                     0                     0                   0
3                     0                     0                   0
4                     0                     0                   0

   Manufacturer_Subaru  Manufacturer_Toyota  Manufacturer_Volkswagen  \
0                    0                    0                        0
1                    0                    0                        0
2                    0                    0                        0
3                    0                    0                        0
4                    0                    0                        0

   Manufacturer_Volvo  Manufacturer_nan
0                   0                 0
1                   0                 0
2                   0                 0
3                   0                 0
4                   0                 0

[5 rows x 28 columns]
```

2.5. Масштабирование данных

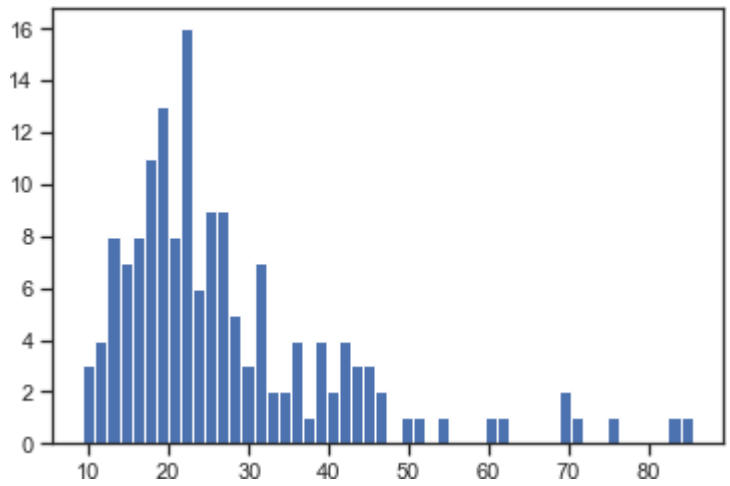
Масштабирование предполагает изменение диапазона измерения величины. Применяют MinMax масштабирование и масштабирование данных на основе Z-оценки.

[69] :
```
from sklearn.preprocessing import MinMaxScaler, StandardScaler, Normalizer
```

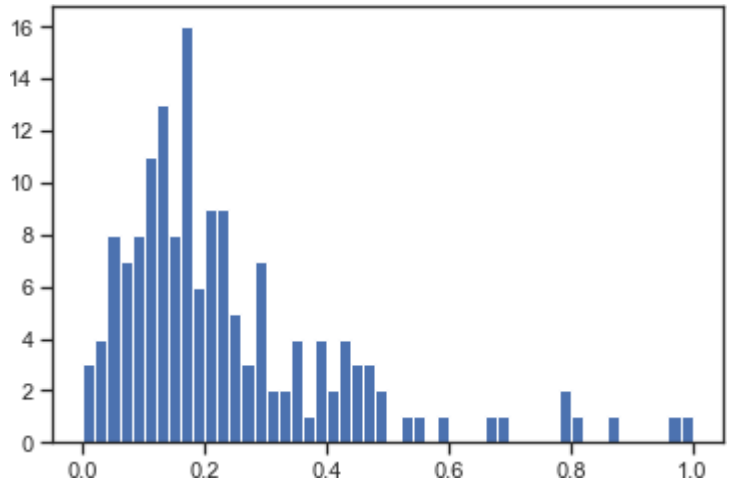
2.5.1. MinMax масштабирование

[70] :
```
sc1 = MinMaxScaler()
sc1_data = sc1.fit_transform(data[['Price_in_thousands']])
```

[71] :
```
plt.hist(data['Price_in_thousands'], 50)
plt.show()
```



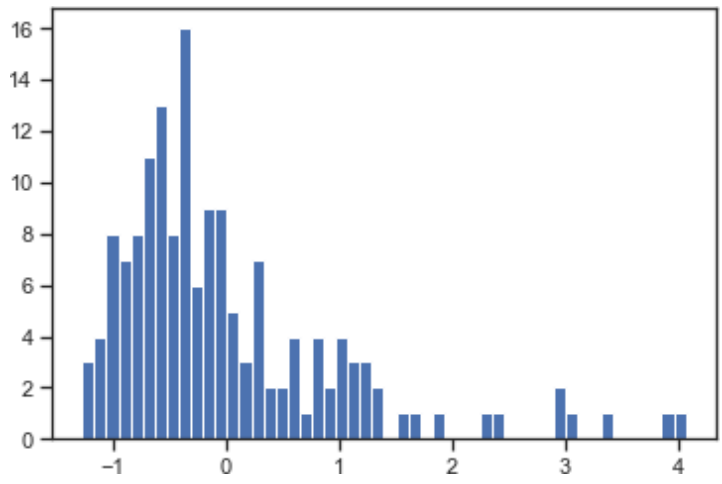
[72] :
```
plt.hist(sc1_data, 50)
plt.show()
```



2.5.2. Масштабирование данных на основе Z-оценки

[73] :
```
sc2 = StandardScaler()
sc2_data = sc2.fit_transform(data[['Price_in_thousands']])
```

[74] :
```
plt.hist(sc2_data, 50)
plt.show()
```


16
14
12
10
8
6
4
2
0
−1
0
1
2
3
4