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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:

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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="ticks")
```

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%.
```

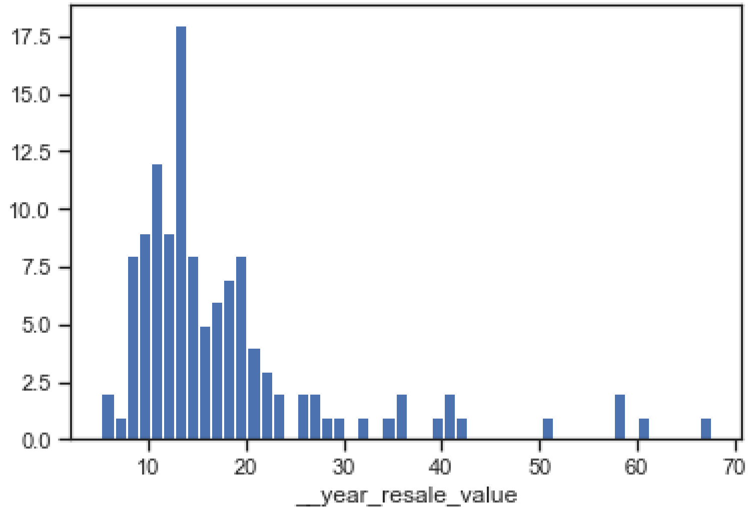
Отфильтруем по столбцам:

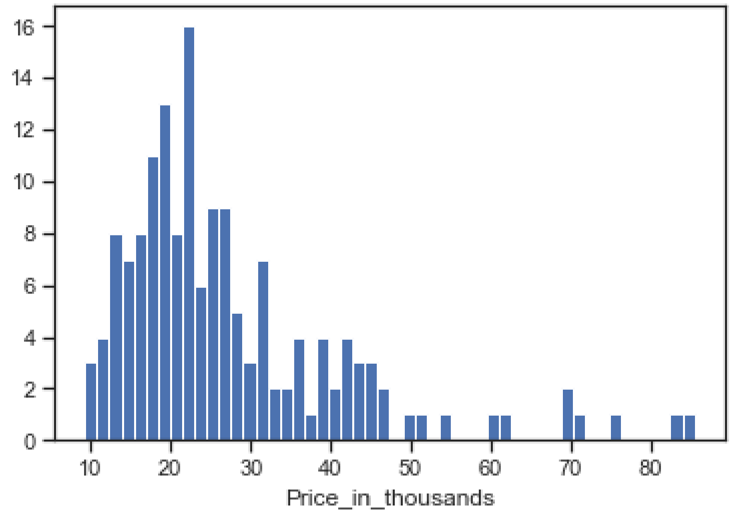
[14]:
```
data_num = data[num_cols]
data_num
```

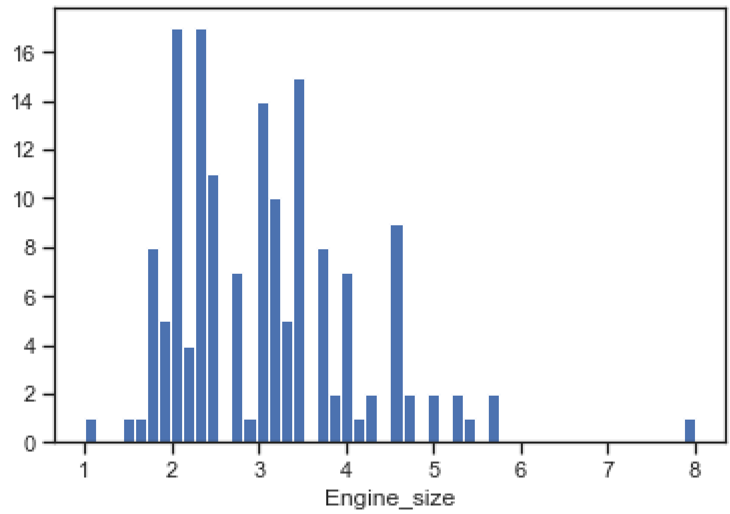
[14]:
```
     __year_resale_value  Price_in_thousands  Engine_size  Horsepower  \
0                 16.360               21.50          1.8       140.0
1                 19.875               28.40          3.2       225.0
2                 18.225                 NaN          3.2       225.0
3                 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]
```

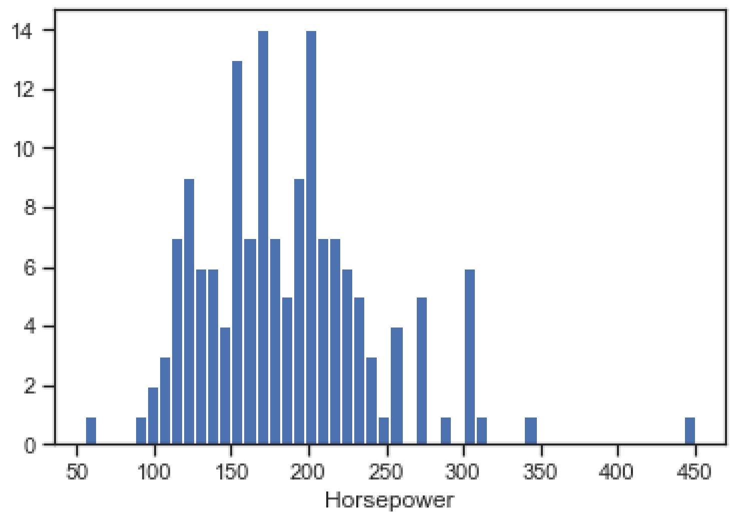
Гистограмма по признакам:

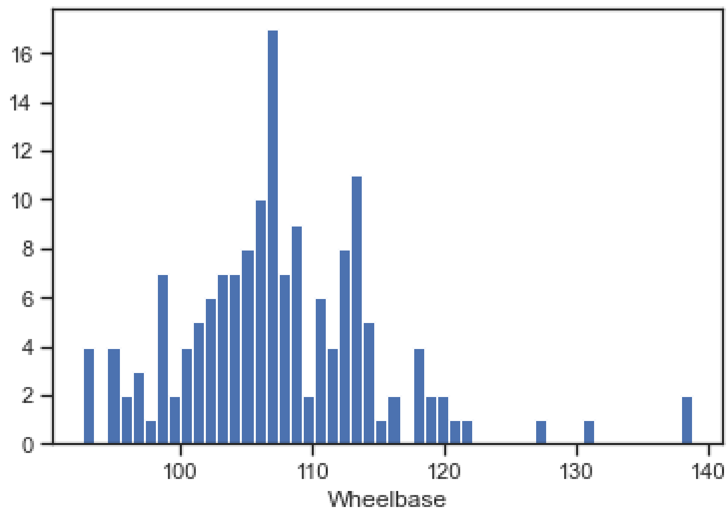
[15]:
```
for col in data_num:
    plt.hist(data[col], 50)
    plt.xlabel(col)
    plt.show()
```

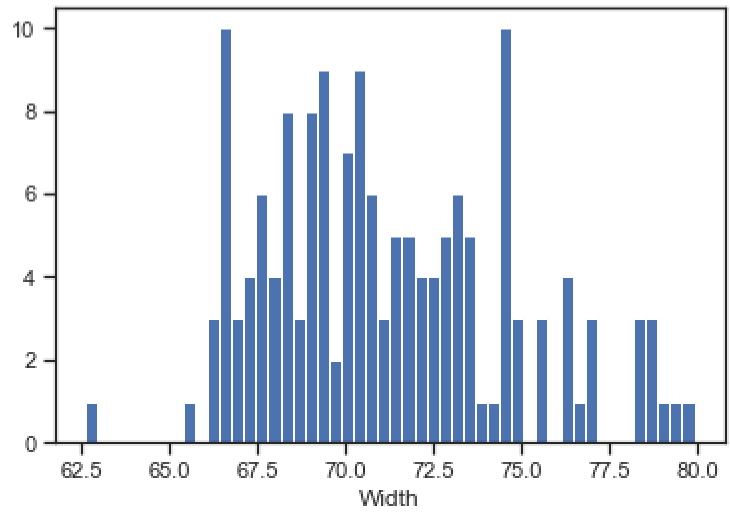

17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0
10
20
30
40
50
60
70
__year_resale_value

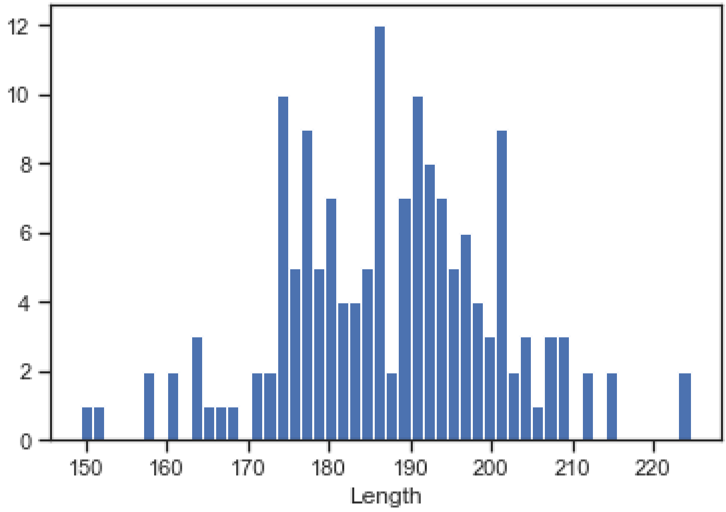

16
14
12
10
8
6
4
2
0
10
20
30
40
50
60
70
80
Price_in_thousands

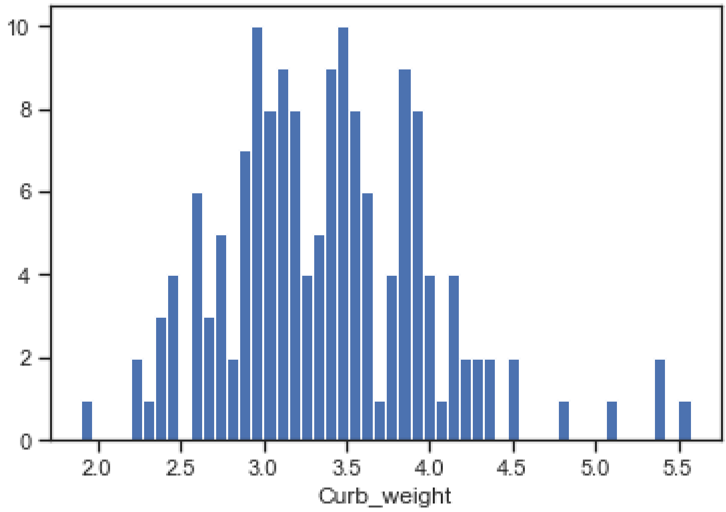

16
14
12
10
8
6
4
2
0
1
2
3
4
5
6
7
8
Engine_size

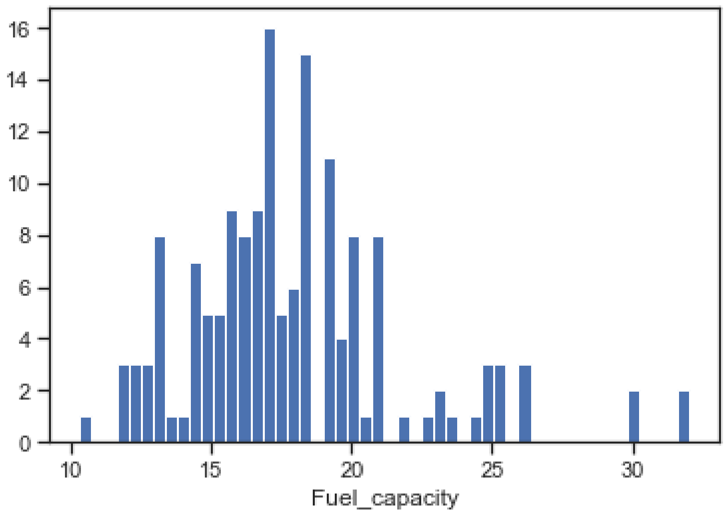

14
12
10
8
6
4
2
0
50
100
150
200
250
300
350
400
450
Horsepower

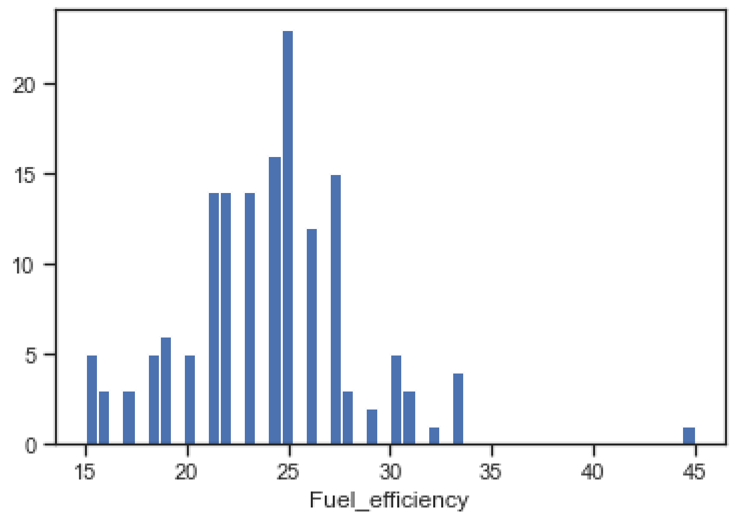

16
14
12
10
8
6
4
2
0
100
110
120
130
140
Wheelbase

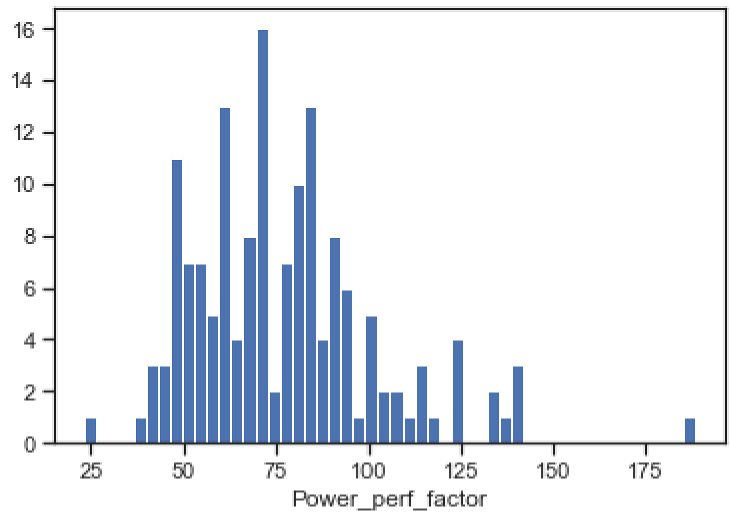

10
8
6
4
2
0
62.5
65.0
67.5
70.0
72.5
75.0
77.5
80.0
Width


Length


Curb_weight


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],
[False],
[False],
[False],
[False],
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        [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'],
['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'],
['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'],
       ['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'],
       ['Chevrolet'],
       ['???'],
       ['???'],
       ['???'],
       ['???'],
       ['???'],
       ['???'],
       ['???'],
       ['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'],
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['Plymouth'],
['Pontiac'],
['Pontiac'],
['Pontiac'],
['Pontiac'],
['Pontiac'],
['Pontiac'],
['Porsche'],
['Porsche'],
['Porsche'],
['Saab'],
['Saab'],
['???'],
['???'],
['???'],
['???'],
['???'],
['Subaru'],
['Subaru'],
['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]:
```python
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.],
[  0.,  43.],
[  0., 147.],
[  0., 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

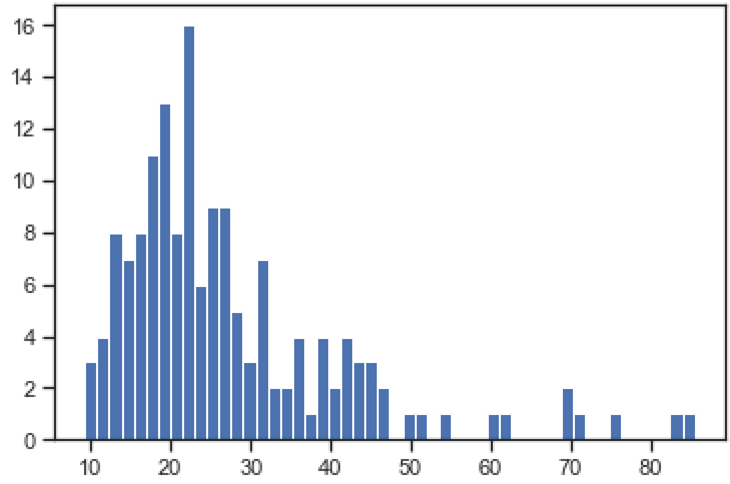
Масштабирование предполагает изменение диапазона измерения величины. Применяют MinMax масштабирование и масштабирование данных на основе Z-оценки.

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

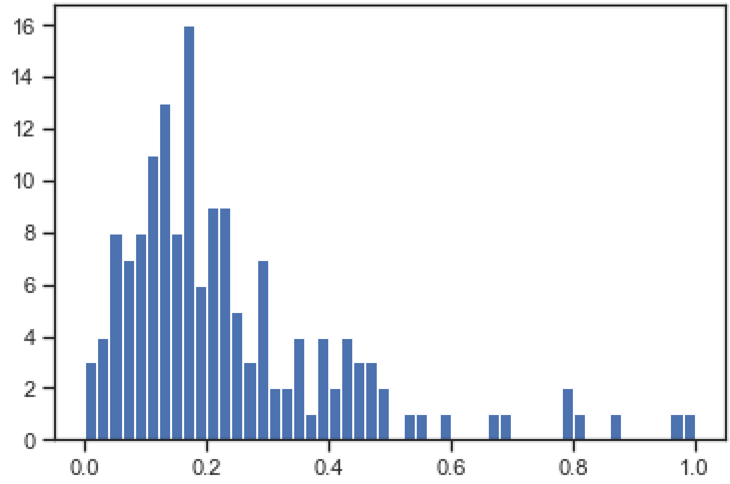
2.5.1. MinMax масштабирование

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

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



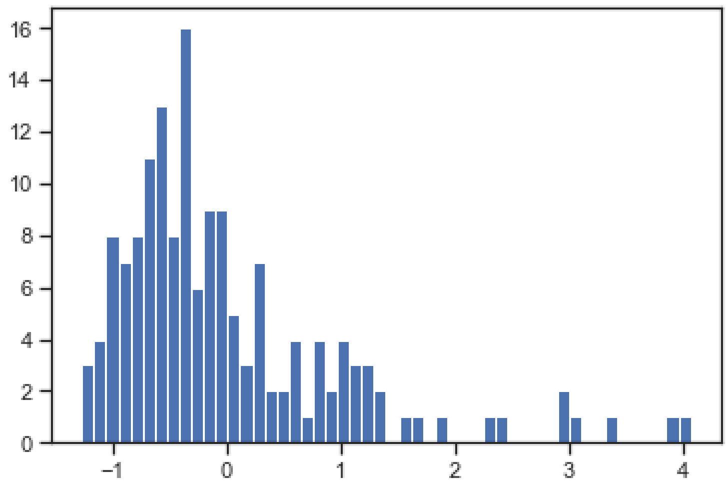

```
[72]: plt.hist(sc1_data, 50)
      plt.show()
```



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