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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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# 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

### 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

### Импорт библиотек

Импортируем библиотеки с помощью команды import:

In [1]:

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

### Загрузка данных

Загрузим набор данных:

In [2]:

```
data = pd.read_csv('Car_sales.csv')
```

## 2. Первичный анализ данных

Выведем первые 5 строк датасета:

In [3]:

```
data.head()
```

Out[3]:

|   | Manufacturer | Model   | Sales_in_thousands | __year_resale_value | Vehicle_type | Price_in_thousands | Engine_size | Horsepower | Wheel |
|---|--------------|---------|--------------------|---------------------|--------------|--------------------|-------------|------------|-------|
| 0 | Acura        | Integra | 16.919             | 16.360              | Passenger    | 21.50              | 1.8         | 140.0      | 1     |
| 1 | Acura        | TL      | 39.384             | 19.875              | Passenger    | 28.40              | 3.2         | 225.0      | 1     |
| 2 | Acura        | CL      | 14.114             | 18.225              | Passenger    | NaN                | 3.2         | 225.0      | 1     |
| 3 | Acura        | RL      | 8.588              | 29.725              | Passenger    | 42.00              | 3.5         | 210.0      | 1     |
| 4 | Audi         | A4      | 20.397             | 22.255              | Passenger    | 23.99              | 1.8         | 150.0      | 1     |

Определим размер датасета:

In [4]:

```
data.shape
```

Out[4]:

```
(157, 16)
```

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

In [5]:

```
data.dtypes
```

Out[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:

In [6]:

```
data.isnull().sum()
```

Out[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.

### 3. Обработка пропусков данных

Удалим колонки, содержащие пустые значения:

In [7]:

```
data_new_1 = data.dropna(axis=1, how='any')
(data.shape, data_new_1.shape)
```

Out[7]:

```
((157, 16), (157, 5))
```

Выведем первые строки датасета на экран:

In [8]:

```
data_new_1
```

Out[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 × 5 columns

Удалим строки, содержащие пустые значения:

In [9]:

```
data_new_2 = data.dropna(axis=0, how='any')
(data.shape, data_new_2.shape)
```

Out[9]:

```
((157, 16), (117, 16))
```

In [10]:

```
data_new_2.head()
```

Out[10]:

|   | Manufacturer | Model   | Sales_in_thousands | __year_resale_value | Vehicle_type | Price_in_thousands | Engine_size | Horsepower | Wheel |
|---|--------------|---------|--------------------|---------------------|--------------|--------------------|-------------|------------|-------|
| 0 | Acura        | Integra | 16.919             | 16.360              | Passenger    | 21.50              | 1.8         | 140.0      | 1     |
| 1 | Acura        | TL      | 39.384             | 19.875              | Passenger    | 28.40              | 3.2         | 225.0      | 1     |
| 3 | Acura        | RL      | 8.588              | 29.725              | Passenger    | 42.00              | 3.5         | 210.0      | 1     |
| 4 | Audi         | A4      | 20.397             | 22.255              | Passenger    | 23.99              | 1.8         | 150.0      | 1     |
| 5 | Audi         | A6      | 18.780             | 23.555              | Passenger    | 33.95              | 2.8         | 200.0      | 1     |

Заполним все пропущенные значения нулями:

In [11]:

```
data_new_3 = data.fillna(0)
```

Выведем на экран:

In [12]:

```
data_new_3.head()
```

Out[12]:

|   | Manufacturer | Model   | Sales_in_thousands | __year_resale_value | Vehicle_type | Price_in_thousands | Engine_size | Horsepower | Wheel |
|---|--------------|---------|--------------------|---------------------|--------------|--------------------|-------------|------------|-------|
| 0 | Acura        | Integra | 16.919             | 16.360              | Passenger    | 21.50              | 1.8         | 140.0      | 1     |
| 1 | Acura        | TL      | 39.384             | 19.875              | Passenger    | 28.40              | 3.2         | 225.0      | 1     |
| 2 | Acura        | CL      | 14.114             | 18.225              | Passenger    | 0.00               | 3.2         | 225.0      | 1     |
| 3 | Acura        | RL      | 8.588              | 29.725              | Passenger    | 42.00              | 3.5         | 210.0      | 1     |
| 4 | Audi         | A4      | 20.397             | 22.255              | Passenger    | 23.99              | 1.8         | 150.0      | 1     |

## Импьютация данных

### Обработка пропусков в числовых данных

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

In [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:

In [14]:

```
data_num = data[num_cols]
data_num
```

Out[14]:

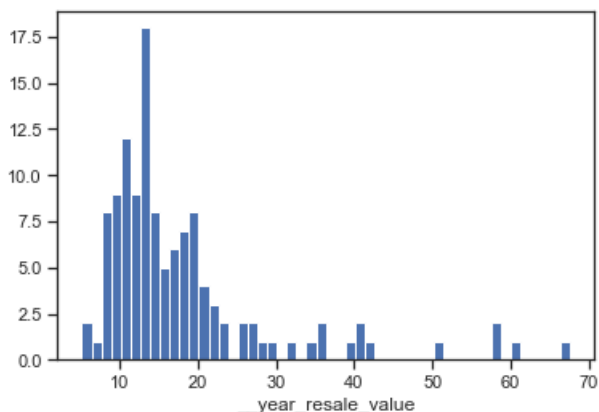
|     | <code>__year_resale_value</code> | <code>Price_in_thousands</code> | <code>Engine_size</code> | <code>Horsepower</code> | <code>Wheelbase</code> | <code>Width</code> | <code>Length</code> | <code>Curb_weight</code> | <code>Fuel_capacity</code> | <code>Fuel_efficiency</code> |
|-----|----------------------------------|---------------------------------|--------------------------|-------------------------|------------------------|--------------------|---------------------|--------------------------|----------------------------|------------------------------|
| 0   | 16.360                           | 21.50                           | 1.8                      | 140.0                   | 101.2                  | 67.3               | 172.4               | 2.639                    | 13.2                       |                              |
| 1   | 19.875                           | 28.40                           | 3.2                      | 225.0                   | 108.1                  | 70.3               | 192.9               | 3.517                    | 17.2                       |                              |
| 2   | 18.225                           | NaN                             | 3.2                      | 225.0                   | 106.9                  | 70.6               | 192.0               | 3.470                    | 17.2                       |                              |
| 3   | 29.725                           | 42.00                           | 3.5                      | 210.0                   | 114.6                  | 71.4               | 196.6               | 3.850                    | 18.0                       |                              |
| 4   | 22.255                           | 23.99                           | 1.8                      | 150.0                   | 102.6                  | 68.2               | 178.0               | 2.998                    | 16.4                       |                              |
| ... | ...                              | ...                             | ...                      | ...                     | ...                    | ...                | ...                 | ...                      | ...                        | ...                          |
| 152 | NaN                              | 24.40                           | 1.9                      | 160.0                   | 100.5                  | 67.6               | 176.6               | 3.042                    | 15.8                       |                              |
| 153 | NaN                              | 27.50                           | 2.4                      | 168.0                   | 104.9                  | 69.3               | 185.9               | 3.208                    | 17.9                       |                              |
| 154 | NaN                              | 28.80                           | 2.4                      | 168.0                   | 104.9                  | 69.3               | 186.2               | 3.259                    | 17.9                       |                              |
| 155 | NaN                              | 45.50                           | 2.3                      | 236.0                   | 104.9                  | 71.5               | 185.7               | 3.601                    | 18.5                       |                              |
| 156 | NaN                              | 36.00                           | 2.9                      | 201.0                   | 109.9                  | 72.1               | 189.8               | 3.600                    | 21.1                       |                              |

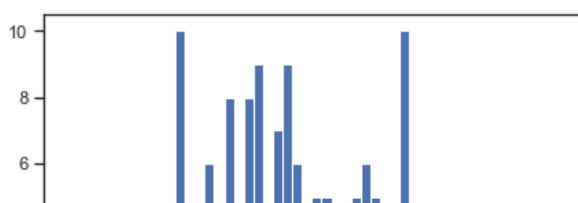
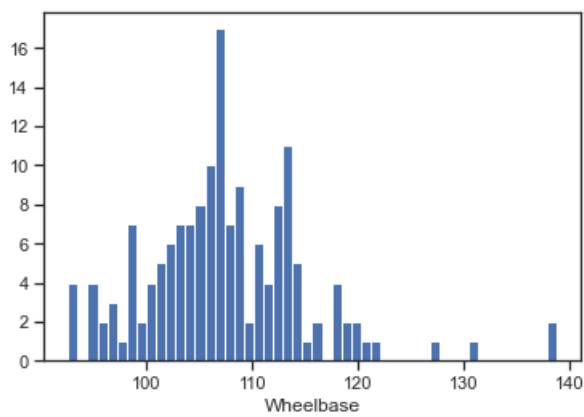
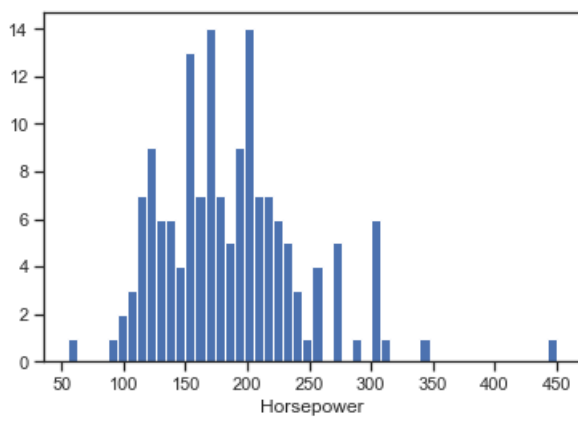
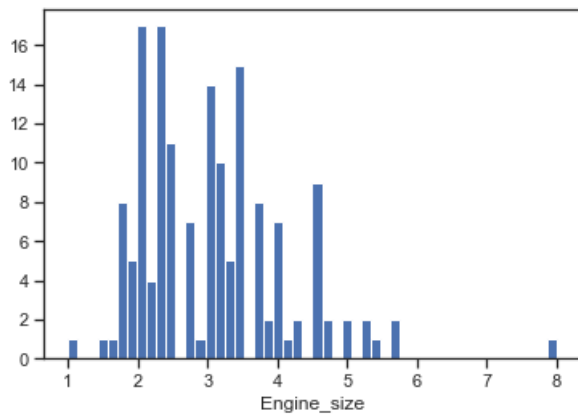
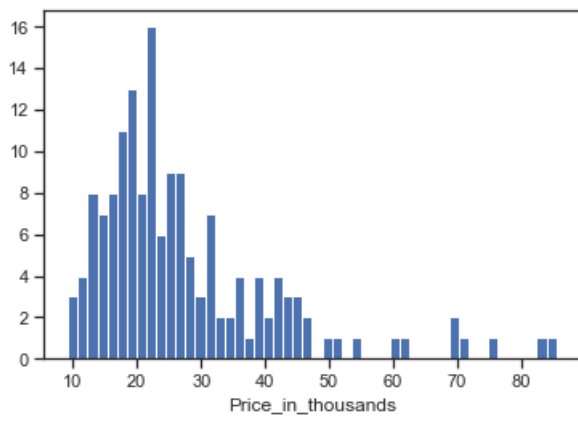
157 rows × 11 columns

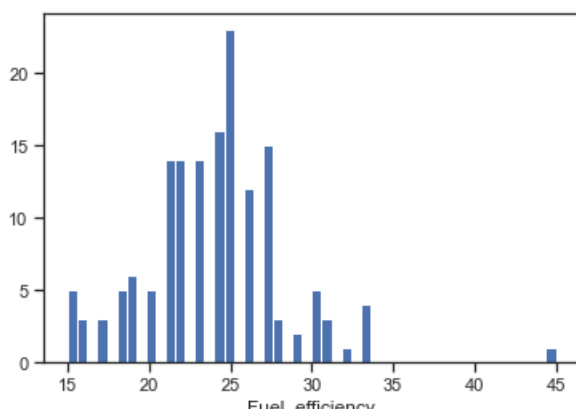
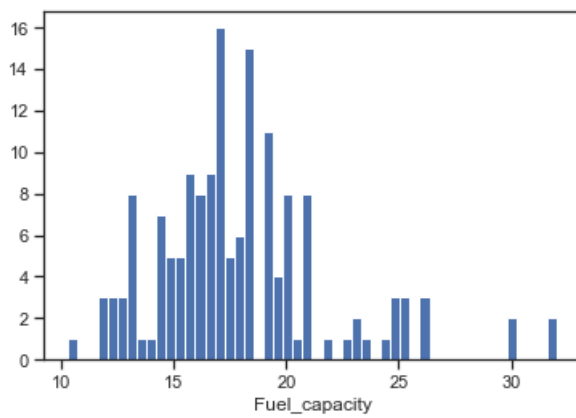
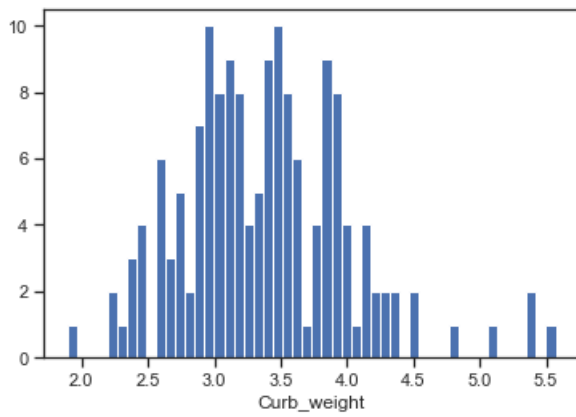
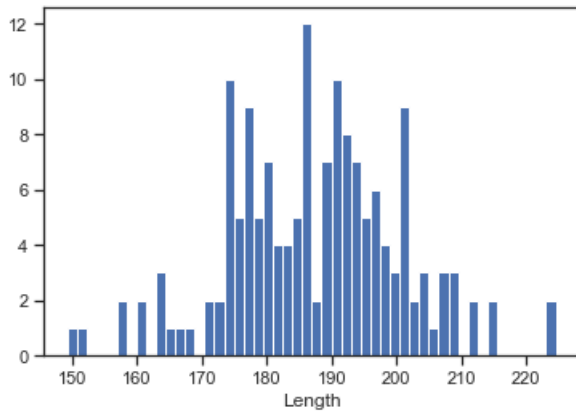
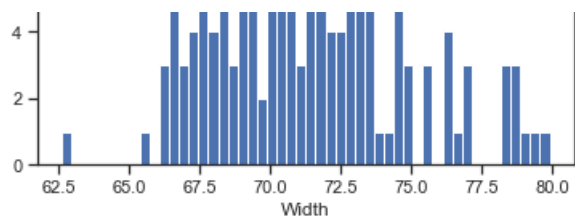
Гистограмма по признакам:

In [15]:

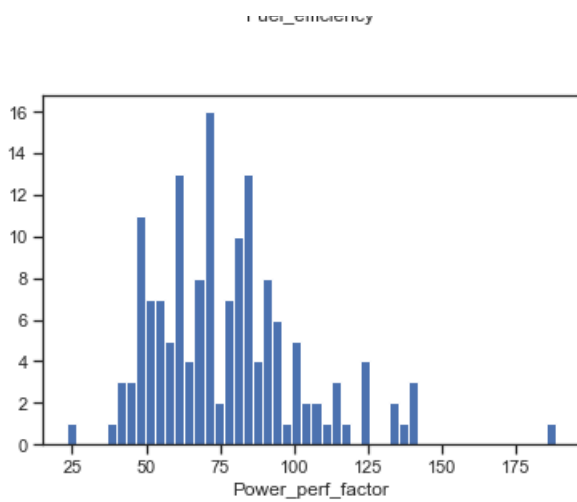
```
for col in data_num:
    plt.hist(data[col], 50)
    plt.xlabel(col)
    plt.show()
```











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

In [16]:

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

In [17]:

```
from sklearn.impute import SimpleImputer
from sklearn.impute import MissingIndicator
```

Фильтр для проверки заполнения пустых значений:

In [18]:

```
indicator = MissingIndicator()
mask_missing_values_only = indicator.fit_transform(data_num_pit)
mask_missing_values_only
```

Out[18]:

[illegible]

[illegible]

[illegible]

Проведем импьютацию различными показателями центра распределения:

In [19]:

```
strategies=['mean', 'median', 'most frequent']
```

In [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]
```

In [21]:

```
strategies[0], test num impute(strategies[0])
```

Out[21]:

```
('mean', array([27.39075484, 27.39075484]))
```

In [22]:

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

Out[22]:

```
('median', array([22.799, 22.799]))
```

In [23]:

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

Out[23]:

```
('most_frequent', array([12.64, 12.64]))
```

Создадим функцию, позволяющую задавать столбец и вид импьютации:

In [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:

In [25]:

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

Out[25]:

|              | <b>__year_resale_value</b> |
|--------------|----------------------------|
| <b>count</b> | 121.000000                 |
| <b>mean</b>  | 18.072975                  |
| <b>std</b>   | 11.453384                  |
| <b>min</b>   | 5.160000                   |
| <b>25%</b>   | 11.260000                  |
| <b>50%</b>   | 14.180000                  |
| <b>75%</b>   | 19.875000                  |
| <b>max</b>   | 67.550000                  |

In [26]:

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

Out[26]:

```
('__year_resale_value', 'mean', 36, 18.07297520661157, 18.07297520661157)
```

In [27]:

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

Out[27]:

```
('__year_resale_value', 'median', 36, 14.18, 14.18)
```

In [28]:

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

Out[28]:

```
('__year_resale_value', 'most_frequent', 36, 7.75, 7.75)
```

## Обработка пропусков в категориальных данных

Так как в датасете нет пропусков среди столбца "Производитель", то искусственно подправим датасет и загрузим его:

In [29]:

```
data_mod = pd.read_csv('Car_sales_mod.csv')
```

Проверим категориальный признак:

In [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:

In [31]:

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

Out[31]:

| Manufacturer |       |
|--------------|-------|
| 0            | Acura |
| 1            | Acura |
| 2            | Acura |
| 3            | Acura |
| 4            | Audi  |

In [32]:

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

Out[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)
```

In [33]:

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

Out[33]:

(15, 1)

Импьютация наиболее частыми значениями:

In [34]:

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

Out[34]:

[illegible]

['Ford'],  
['Ford'],  
['Ford'],  
['Ford'],  
['Ford'],  
['Ford'],  
['Ford'],  
['Ford'],  
['Ford'],  
['Ford'],  
['Honda'],  
['Honda'],  
['Honda'],  
['Honda'],  
['Honda'],  
['Hyundai'],  
['Hyundai'],  
['Hyundai'],  
['Infiniti'],  
['Jaguar'],  
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['Jeep'],  
['Jeep'],  
['Lexus'],  
['Lexus'],  
['Lexus'],  
['Lexus'],  
['Lexus'],  
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['Dodge'],  
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['Mitsubishi'],  
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['Mercedes-B'],  
['Mercedes-B'],  
['Mercedes-B'],  
['Mercedes-B'],  
['Mercedes-B'],  
['Mercedes-B'],  
['Mercedes-B'],  
['Mercedes-B'],  
['Mercedes-B'],  
['Mercedes-B'],  
['Nissan'],  
['Nissan'],  
['Nissan'],  
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['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'],
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['Toyota'],
['Toyota'],
['Volkswagen'],
['Volkswagen'],
['Volkswagen'],
['Volkswagen'],
['Volkswagen'],
['Volkswagen'],
['Volvo'],
['Volvo'],
['Volvo'],
['Volvo'],
['Volvo'],
['Volvo']], dtype=object)

```

In [35]:

```
np.unique(data_imp2)
```

Out[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:

In [36]:

```

imp3 = SimpleImputer(missing_values=np.nan, strategy='constant', fill_value='???')
data_imp3 = imp3.fit_transform(cat_temp_data)
data_imp3

```

Out[36]:

```

array([[ 'Acura'],
       [ 'Acura'],
       [ 'Acura'],
       [ 'Acura'],
       [ 'Audi'],
       [ 'Audi'],
       [ 'Audi'],
       [ 'BMW'],
       [ 'BMW'],
       [ 'BMW'],
       [ 'Buick'],
       [ 'Buick'],
       [ 'Buick'],

```



['Buick'],  
['Cadillac'],  
['Cadillac'],  
['Cadillac'],  
['Cadillac'],  
['Cadillac'],  
['Chevrolet'],  
['Chevrolet'],  
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['Hyundai'],  
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['Hyundai'],  
['Infiniti'],  
['Jaguar'],  
['Jeep'],  
['Jeep'],  
['Jeep'],  
['Lexus'],  
['Lexus'],  
['Lexus'],  
['Lexus'],  
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['Lexus'],  
['???'],  
['???'],  
['???'],  
['Mitsubishi'],  
['Mitsubishi'],  
['Mitsubishi'],  
['Mitsubishi'],  
['Mitsubishi'],  
['Mitsubishi'],  
['Mitsubishi'],  
['Mercury'],  
['Mercury'],  
['Mercury'],  
['Mercury'],

```

['Mercury'],
['Mercury'],
['Mercedes-B'],
['Mercedes-B'],
['Mercedes-B'],
['Mercedes-B'],
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['Mercedes-B'],
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['???'],
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['Toyota'],
['Volkswagen'],
['Volkswagen'],
['Volkswagen'],
['Volkswagen'],
['Volkswagen'],
['Volkswagen'],
['Volvo'],
['Volvo'],
['Volvo'],
['Volvo'],
['Volvo'],
['Volvo']], dtype=object)

```

In [37]:

```
np.unique(data_imp3)
```

Out[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)
```

In [38]:

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

Out[38]:

0

Значения были заменены на "???".

## Преобразование категориальных признаков в числовые

In [39]:

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

Out[39]:

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

157 rows × 1 columns

## 4. Кодирование категорий целочисленными значениями

### LabelEncoder

In [40]:

```
from sklearn.preprocessing import LabelEncoder
```

In [41]:

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

Out[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)
```

```
['volkswagen', 'volvo'], dtype=object)
```

In [42]:

```
le = LabelEncoder()
```

In [43]:

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

In [44]:

```
le.classes_
```

Out[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)
```

In [45]:

```
cat_enc_le
```

Out[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,  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, 13, 6,  6,  6, 16, 16, 16, 16, 16, 16,  
       16, 15, 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, 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])
```

In [46]:

```
np.unique(cat_enc_le)
```

Out[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])
```

In [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])
```

Out[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)
```

## OrdinalEncoder

In [48]:

```
from sklearn.preprocessing import OrdinalEncoder
```

In [49]:

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

Out[49]:

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

In [50]:

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

Out[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)

```

In [51]:

```

oe = OrdinalEncoder()
cat_enc_oe = oe.fit_transform(data_oe_filled)
cat_enc_oe

```

Out[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.],  
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[ 13., 39.],  
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[ 14., 85.],  
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[ 15., 122.],  
[ 15., 129.],  
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[ 15., 131.],  
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[ 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":

In [52]:

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

Out[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":

In [53]:

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

Out[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:

In [54]:

```
oe.categories_
```

Out[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)]

```

In [55]:

```
oe.inverse_transform(cat_enc_oe)
```

Out[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', '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', 'Boxster'],
[ '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)
```

## Кодирование шкал порядка

Для кодирования шкал порядка воспользуемся функцией `map`:

Тн [561]:

```
## [56]:
```

```
sizes = ['small', 'medium', 'large', 'small', 'medium', 'large', 'small', 'medium', 'large']
```

```
In [57]:
```

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

```
Out[57]:
```

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

```
In [58]:
```

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

```
Out[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           |

```
In [59]:
```

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

```
Out[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         |

| 0 | small<br>sizes | 1<br>sizes_codes | small<br>sizes_decoded |
|---|----------------|------------------|------------------------|
| 7 | medium         | 2                | medium                 |
| 8 | large          | 3                | large                  |

## Кодирование категорий наборами бинарных значений - one-hot encoding

Каждое уникальное значение признака становится новым отдельным признаком:

In [60]:

```
from sklearn.preprocessing import OneHotEncoder
```

In [61]:

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

In [62]:

```
cat_enc.shape
```

Out[62]:

```
(157, 1)
```

In [63]:

```
cat_enc_ohe.shape
```

Out[63]:

```
(157, 27)
```

In [64]:

```
cat_enc_ohe
```

Out[64]:

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

In [65]:

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

Out[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., 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., 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., 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.],
 [0., 1., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
        0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.],
 [0., 0., 1., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
        0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.],
 [0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
        0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.]])
```

```
[0., 0., 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.]])
```

In [66]:

```
cat_enc.head(10)
```

Out[66]:

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

In [67]:

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

Out[67]:

|   | c1_Acura | c1_Audi | c1_BMW | c1_Buick | c1_Cadillac | c1_Chevrolet | c1_Dodge | c1_Ford | c1_Honda | c1_Hyundai | ... | c1_Nissan | c1_U |
|---|----------|---------|--------|----------|-------------|--------------|----------|---------|----------|------------|-----|-----------|------|
| 0 | 1        | 0       | 0      | 0        | 0           | 0            | 0        | 0       | 0        | 0          | ... | 0         |      |
| 1 | 1        | 0       | 0      | 0        | 0           | 0            | 0        | 0       | 0        | 0          | ... | 0         |      |
| 2 | 1        | 0       | 0      | 0        | 0           | 0            | 0        | 0       | 0        | 0          | ... | 0         |      |
| 3 | 1        | 0       | 0      | 0        | 0           | 0            | 0        | 0       | 0        | 0          | ... | 0         |      |
| 4 | 0        | 1       | 0      | 0        | 0           | 0            | 0        | 0       | 0        | 0          | ... | 0         |      |

5 rows × 27 columns



In [68]:

```
pd.get_dummies(cat_temp_data, dummy_na=True).head()
```

Out[68]:

|   | Manufacturer_Acura | Manufacturer_Audi | Manufacturer_BMW | Manufacturer_Buick | Manufacturer_Cadillac | Manufacturer_Chevrolet | Manufacturer_Ford | Manufacturer_Honda | Manufacturer_Hyundai | Manufacturer_Nissan | Manufacturer_U |
|---|--------------------|-------------------|------------------|--------------------|-----------------------|------------------------|-------------------|--------------------|----------------------|---------------------|----------------|
| 0 | 1                  | 0                 | 0                | 0                  | 0                     | 0                      | 0                 | 0                  | 0                    | 0                   | 0              |
| 1 | 1                  | 0                 | 0                | 0                  | 0                     | 0                      | 0                 | 0                  | 0                    | 0                   | 0              |
| 2 | 1                  | 0                 | 0                | 0                  | 0                     | 0                      | 0                 | 0                  | 0                    | 0                   | 0              |
| 3 | 1                  | 0                 | 0                | 0                  | 0                     | 0                      | 0                 | 0                  | 0                    | 0                   | 0              |
| 4 | 0                  | 1                 | 0                | 0                  | 0                     | 0                      | 0                 | 0                  | 0                    | 0                   | 0              |

5 rows × 28 columns



## 5. Масштабирование данных

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

In [69]:

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

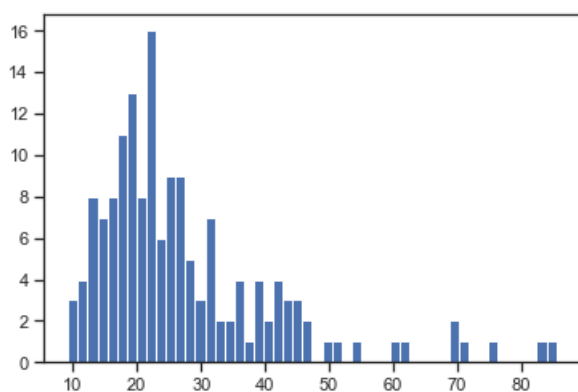
### MinMax масштабирование

In [70]:

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

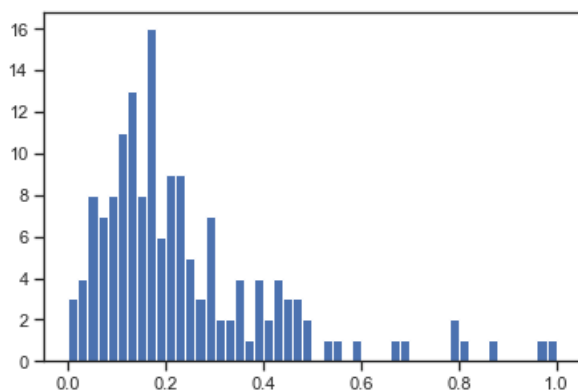
In [71]:

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



In [72]:

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



### Масштабирование данных на основе Z-оценки

In [73]:

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



In [74]:

```
plt.hist(sc2_data, 50)  
plt.show()
```

