Московский государственный технический университет им. Н.Э. Баумана
Кафедра «Системы обработки информации и управления»

Лабораторная работа №3
по дисциплине
«Методы машинного обучения»
на тему
«Обработка пропусков в данных, кодирование категориальных признаков, масштабирование данных»

Выполнил:
студент группы ИУ5-21М
Сефербеков М.С

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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")
```

In [2]:

```
# Будем использовать только обучающую выборку
data = pd.read_csv('Building_Permits.csv', sep=",")
```

```
c:\users\innap\miniconda3\lib\site-packages\IPython\core\interactiveshell.
py:3063: DtypeWarning: Columns (22,32) have mixed types. Specify dtype opt
ion on import or set low_memory=False.
  interactivity=interactivity, compiler=compiler, result=result)
```

In [3]:

```
data.head()
```

Out[3]:

	Permit Number	Permit Type	Permit Type Definition	Permit Creation Date	Block	Lot	Street Number	Street Number Suffix	Street Name	Stre Suff
0	201505065519	4	sign - erect	05/06/2015	0326	023	140	NaN	Ellis	
1	201604195146	4	sign - erect	04/19/2016	0306	007	440	NaN	Geary	
2	201605278609	3	additions alterations or repairs	05/27/2016	0595	203	1647	NaN	Pacific	/
3	201611072166	8	otc alterations permit	11/07/2016	0156	011	1230	NaN	Pacific	/
4	201611283529	6	demolitions	11/28/2016	0342	001	950	NaN	Market	

5 rows × 43 columns

In [4]:

```
data.shape
```

Out[4]:

```
(198900, 43)
```

In [5]:

```
data.dtypes
```

Out[5]:

```
Permit Number                                 object
Permit Type                                    int64
Permit Type Definition                        object
Permit Creation Date                          object
Block                                         object
Lot                                           object
Street Number                                  int64
Street Number Suffix                          object
Street Name                                   object
Street Suffix                                 object
Unit                                         float64
Unit Suffix                                   object
Description                                   object
Current Status                                object
Current Status Date                           object
Filed Date                                    object
Issued Date                                   object
Completed Date                                object
First Construction Document Date              object
Structural Notification                       object
Number of Existing Stories                   float64
Number of Proposed Stories                   float64
Voluntary Soft-Story Retrofit                 object
Fire Only Permit                              object
Permit Expiration Date                        object
Estimated Cost                               float64
Revised Cost                                 float64
Existing Use                                  object
Existing Units                               float64
Proposed Use                                  object
Proposed Units                               float64
Plansets                                     float64
TIDF Compliance                               object
Existing Construction Type                   float64
Existing Construction Type Description        object
Proposed Construction Type                   float64
Proposed Construction Type Description        object
Site Permit                                   object
Supervisor District                          float64
Neighborhoods - Analysis Boundaries           object
Zipcode                                      float64
Location                                      object
Record ID                                      int64
dtype: object
```

In [6]:

```
# проверим есть ли пропущенные значения
data.isnull().sum()
```

Out[6]:

```
Permit Number                                0
Permit Type                                  0
Permit Type Definition                       0
Permit Creation Date                         0
Block                                        0
Lot                                          0
Street Number                                0
Street Number Suffix                    196684
Street Name                                  0
Street Suffix                             2768
Unit                                    169421
Unit Suffix                             196939
Description                                290
Current Status                               0
Current Status Date                          0
Filed Date                                   0
Issued Date                              14940
Completed Date                          101709
First Construction Document Date         14946
Structural Notification                 191978
Number of Existing Stories               42784
Number of Proposed Stories               42868
Voluntary Soft-Story Retrofit           198865
Fire Only Permit                        180073
Permit Expiration Date                   51880
Estimated Cost                           38066
Revised Cost                              6066
Existing Use                             41114
Existing Units                           51538
Proposed Use                             42439
Proposed Units                           50911
Plansets                                 37309
TIDF Compliance                         198898
Existing Construction Type               43366
Existing Construction Type Description   43366
Proposed Construction Type               43162
Proposed Construction Type Description   43162
Site Permit                             193541
Supervisor District                       1717
Neighborhoods - Analysis Boundaries       1725
Zipcode                                   1716
Location                                  1700
Record ID                                    0
dtype: int64
```

In [7]:

```
total_count = data.shape[0]
print('Всего строк: {}'.format(total_count))
```

```
Всего строк: 198900
```

1. Обработка пропусков в данных

1.1. Простые стратегии - удаление или заполнение нулями

In [8]:

```
# Удаление колонок, содержащих пустые значения
data_new_1 = data.dropna(axis=1, how='any')
(data.shape, data_new_1.shape)
```

Out[8]:

```
((198900, 43), (198900, 12))
```

In [9]:

```
# Удаление строк, содержащих пустые значения
data_new_2 = data.dropna(axis=0, how='any')
(data.shape, data_new_2.shape)
```

Out[9]:

```
((198900, 43), (0, 43))
```

In [10]:

```
data.head()
```

Out[10]:

	Permit Number	Permit Type	Permit Type Definition	Permit Creation Date	Block	Lot	Street Number	Street Number Suffix	Street Name	Stre Suff
0	201505065519	4	sign - erect	05/06/2015	0326	023	140	NaN	Ellis	
1	201604195146	4	sign - erect	04/19/2016	0306	007	440	NaN	Geary	
2	201605278609	3	additions alterations or repairs	05/27/2016	0595	203	1647	NaN	Pacific	/
3	201611072166	8	otc alterations permit	11/07/2016	0156	011	1230	NaN	Pacific	/
4	201611283529	6	demolitions	11/28/2016	0342	001	950	NaN	Market	

5 rows × 43 columns

In [11]:

```
# Заполнение всех пропущенных значений нулями
# В данном случае это некорректно, так как нулями заполняются в том числе категориальны
е колонки
data_new_3 = data.fillna(0)
data_new_3.head()
```

Out[11]:

	Permit Number	Permit Type	Permit Type Definition	Permit Creation Date	Block	Lot	Street Number	Street Number Suffix	Street Name	Stre Suff
0	201505065519	4	sign - erect	05/06/2015	0326	023	140	0	Ellis	
1	201604195146	4	sign - erect	04/19/2016	0306	007	440	0	Geary	
2	201605278609	3	additions alterations or repairs	05/27/2016	0595	203	1647	0	Pacific	/
3	201611072166	8	otc alterations permit	11/07/2016	0156	011	1230	0	Pacific	/
4	201611283529	6	demolitions	11/28/2016	0342	001	950	0	Market	

5 rows × 43 columns

1.2. "Внедрение значений" - импьютация (imputation)

1.2.1. Обработка пропусков в числовых данных

In [12]:

```
# Выберем числовые колонки с пропущенными значениями
# Цикл по колонкам датасета
num_cols = []
for col in data.columns:
    # Количество пустых значений
    temp_null_count = data[data[col].isnull()].shape[0]
    dt = str(data[col].dtype)
    if temp_null_count>0 and (dt=='float64' or dt=='int64'):
        num_cols.append(col)
        temp_perc = round((temp_null_count / total_count) * 100.0, 2)
        print('Колонка {}. Тип данных {}. Количество пустых значений {}, {}%.'.format(c
ol, dt, temp_null_count, temp_perc))
```

```
Колонка Unit. Тип данных float64. Количество пустых значений 169421, 85.1
8%.
Колонка Number of Existing Stories. Тип данных float64. Количество пустых
значений 42784, 21.51%.
Колонка Number of Proposed Stories. Тип данных float64. Количество пустых
значений 42868, 21.55%.
Колонка Estimated Cost. Тип данных float64. Количество пустых значений 380
66, 19.14%.
Колонка Revised Cost. Тип данных float64. Количество пустых значений 6066,
3.05%.
Колонка Existing Units. Тип данных float64. Количество пустых значений 515
38, 25.91%.
Колонка Proposed Units. Тип данных float64. Количество пустых значений 509
11, 25.6%.
Колонка Plansets. Тип данных float64. Количество пустых значений 37309, 1
8.76%.
Колонка Existing Construction Type. Тип данных float64. Количество пустых
значений 43366, 21.8%.
Колонка Proposed Construction Type. Тип данных float64. Количество пустых
значений 43162, 21.7%.
Колонка Supervisor District. Тип данных float64. Количество пустых значени
й 1717, 0.86%.
Колонка Zipcode. Тип данных float64. Количество пустых значений 1716, 0.8
6%.
```

In [13]:

```
# Фильтр по колонкам с пропущенными значениями
data_num = data[num_cols]
data_num
```

Out[13]:

	Unit	Number of Existing Stories	Number of Proposed Stories	Estimated Cost	Revised Cost	Existing Units	Proposed Units	Plansets	Con
0	NaN	6.0	NaN	4000.00	4000.00	143.0	NaN	2.0	
1	0.0	7.0	NaN	1.00	500.00	NaN	NaN	2.0	
2	NaN	6.0	6.0	20000.00	NaN	39.0	39.0	2.0	
3	0.0	2.0	2.0	2000.00	2000.00	1.0	1.0	2.0	
4	NaN	3.0	NaN	100000.00	100000.00	NaN	NaN	2.0	
5	NaN	5.0	5.0	4000.00	4000.00	326.0	326.0	2.0	
6	0.0	3.0	3.0	12000.00	12000.00	5.0	5.0	0.0	
7	NaN	NaN	NaN	NaN	0.00	NaN	NaN	NaN	
8	NaN	NaN	NaN	NaN	1.00	NaN	NaN	NaN	
9	NaN	NaN	NaN	NaN	0.00	NaN	NaN	NaN	
10	NaN	NaN	NaN	NaN	1.00	NaN	NaN	NaN	
11	NaN	NaN	NaN	NaN	1.00	NaN	NaN	NaN	
12	NaN	NaN	NaN	NaN	1.00	NaN	NaN	NaN	
13	NaN	2.0	2.0	30000.00	0.00	1.0	1.0	2.0	
14	NaN	NaN	NaN	NaN	1.00	NaN	NaN	NaN	
15	301.0	NaN	NaN	NaN	1.00	NaN	NaN	NaN	
16	NaN	NaN	NaN	NaN	1.00	NaN	NaN	NaN	
17	0.0	NaN	NaN	NaN	1.00	NaN	NaN	NaN	
18	1.0	4.0	4.0	75000.00	0.00	6.0	6.0	2.0	
19	0.0	NaN	NaN	NaN	1.00	NaN	NaN	NaN	
20	NaN	NaN	NaN	NaN	1.00	NaN	NaN	NaN	
21	NaN	2.0	2.0	100000.00	0.00	2.0	2.0	2.0	
22	NaN	3.0	3.0	100000.00	NaN	6.0	6.0	2.0	
23	NaN	NaN	NaN	NaN	1.00	NaN	NaN	NaN	
24	NaN	4.0	4.0	64650.00	64650.00	9.0	9.0	0.0	
25	NaN	2.0	2.0	7000.00	7000.00	1.0	1.0	0.0	
26	NaN	NaN	NaN	NaN	1.00	NaN	NaN	NaN	
27	NaN	NaN	NaN	NaN	1.00	NaN	NaN	NaN	
28	NaN	NaN	NaN	NaN	1.00	NaN	NaN	NaN	
29	NaN	NaN	NaN	NaN	1.00	NaN	NaN	NaN	
...	...	...	...	...	...	...	...	...	
198870	NaN	NaN	NaN	NaN	1.00	NaN	NaN	NaN	
198871	NaN	NaN	NaN	NaN	1.00	NaN	NaN	NaN	
198872	NaN	2.0	2.0	10000.00	0.00	NaN	NaN	2.0	
198873	0.0	2.0	2.0	1.00	1.00	1.0	1.0	0.0	

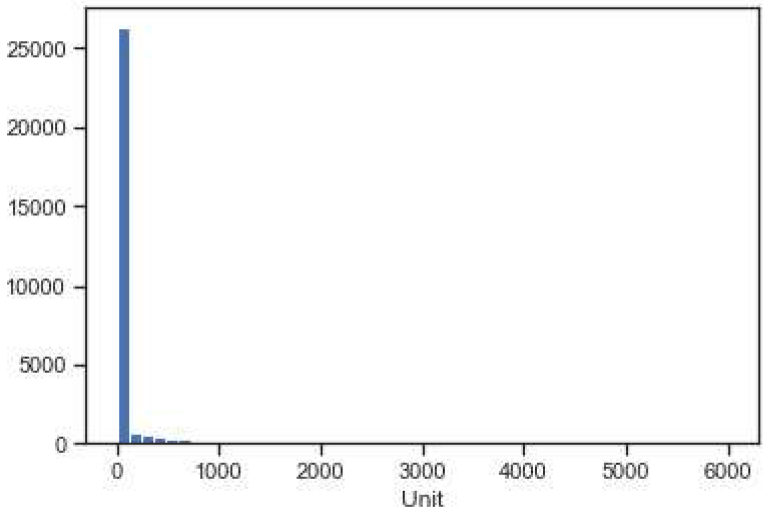
	Unit	Number of Existing Stories	Number of Proposed Stories	Estimated Cost	Revised Cost	Existing Units	Proposed Units	Plansets	Con
198874	0.0	3.0	3.0	10000.00	15000.00	3.0	3.0	0.0	
198875	NaN	NaN	5.0	1.00	0.00	NaN	29.0	2.0	
198876	NaN	NaN	NaN	NaN	0.00	NaN	NaN	NaN	
198877	NaN	2.0	2.0	1000.00	1000.00	1.0	1.0	0.0	
198878	0.0	2.0	2.0	20000.00	0.00	4.0	4.0	2.0	
198879	NaN	2.0	2.0	18453.12	18453.12	1.0	1.0	0.0	
198880	NaN	NaN	NaN	NaN	1.00	NaN	NaN	NaN	
198881	NaN	NaN	NaN	NaN	1.00	NaN	NaN	NaN	
198882	NaN	2.0	2.0	1.00	1.00	1.0	1.0	0.0	
198883	NaN	NaN	NaN	NaN	1.00	NaN	NaN	NaN	
198884	NaN	NaN	NaN	NaN	1.00	NaN	NaN	NaN	
198885	NaN	2.0	2.0	5000.00	0.00	1.0	1.0	2.0	
198886	NaN	3.0	3.0	65000.00	65000.00	6.0	6.0	2.0	
198887	NaN	4.0	4.0	30000.00	30000.00	191.0	191.0	2.0	
198888	NaN	9.0	9.0	18000.00	30000.00	78.0	78.0	0.0	
198889	NaN	1.0	1.0	20000.00	20000.00	1.0	1.0	0.0	
198890	NaN	6.0	6.0	750000.00	750000.00	NaN	NaN	2.0	
198891	NaN	2.0	2.0	1.00	1.00	0.0	0.0	2.0	
198892	NaN	3.0	3.0	55000.00	38000.00	5.0	5.0	2.0	
198893	NaN	3.0	3.0	2800.00	2800.00	3.0	3.0	0.0	
198894	NaN	2.0	2.0	7400.00	7400.00	2.0	2.0	0.0	
198895	NaN	NaN	NaN	NaN	1.00	NaN	NaN	NaN	
198896	NaN	4.0	4.0	5000.00	5000.00	4.0	4.0	2.0	
198897	NaN	NaN	NaN	NaN	1.00	NaN	NaN	NaN	
198898	NaN	NaN	NaN	NaN	1.00	NaN	NaN	NaN	
198899	NaN	NaN	NaN	NaN	1.00	NaN	NaN	NaN	

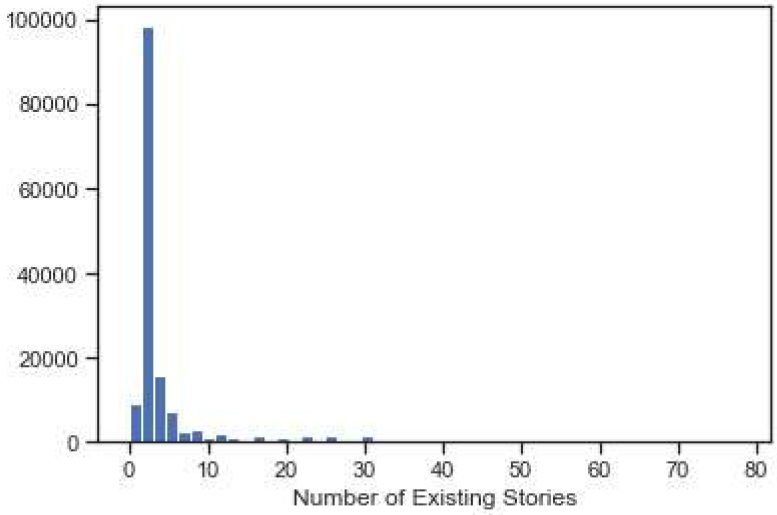
198900 rows × 12 columns

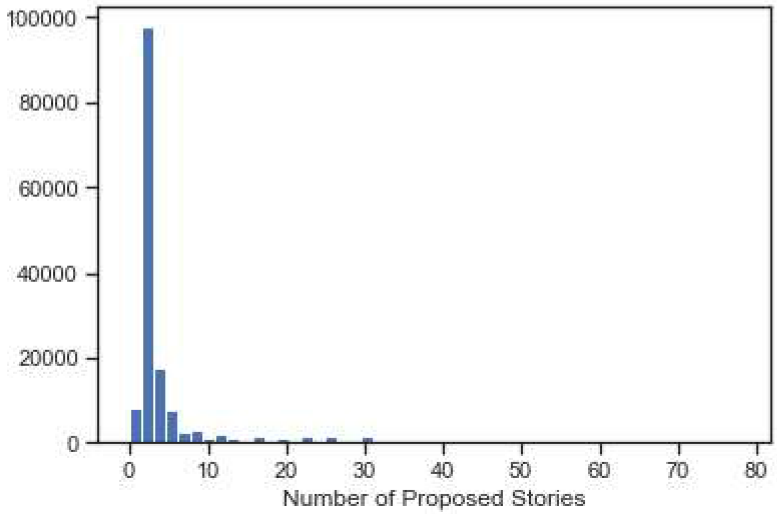
In [14]:

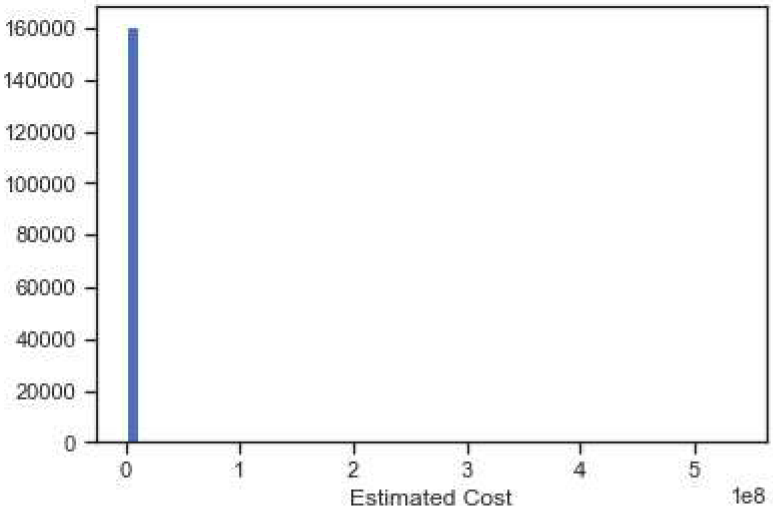
```
# Гистограмма по признакам
for col in data_num:
    plt.hist(data[col], 50)
    plt.xlabel(col)
    plt.show()
```

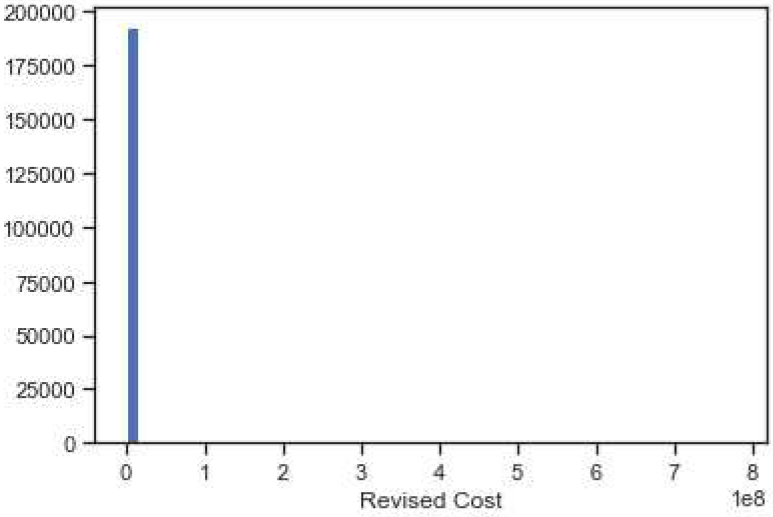
```
c:\users\innap\miniconda3\lib\site-packages\numpy\lib\histograms.py:824: R
untimeWarning: invalid value encountered in greater_equal
  keep = (tmp_a >= first_edge)
c:\users\innap\miniconda3\lib\site-packages\numpy\lib\histograms.py:825: R
untimeWarning: invalid value encountered in less_equal
  keep &= (tmp_a <= last_edge)
```

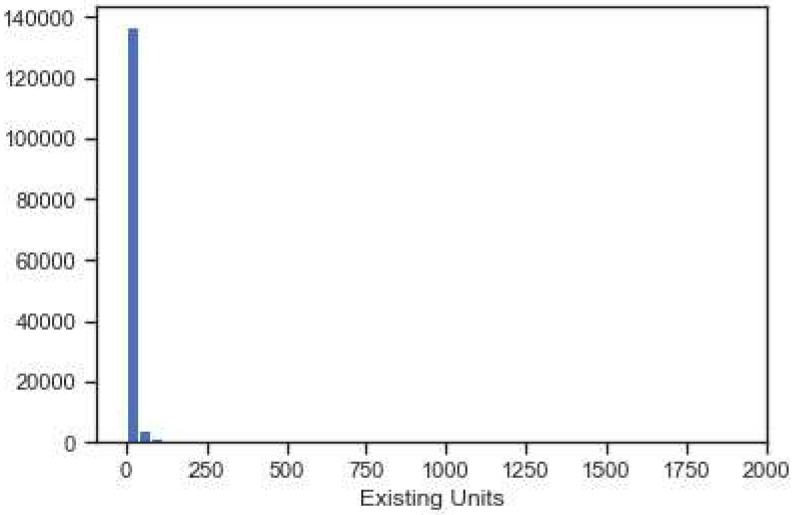


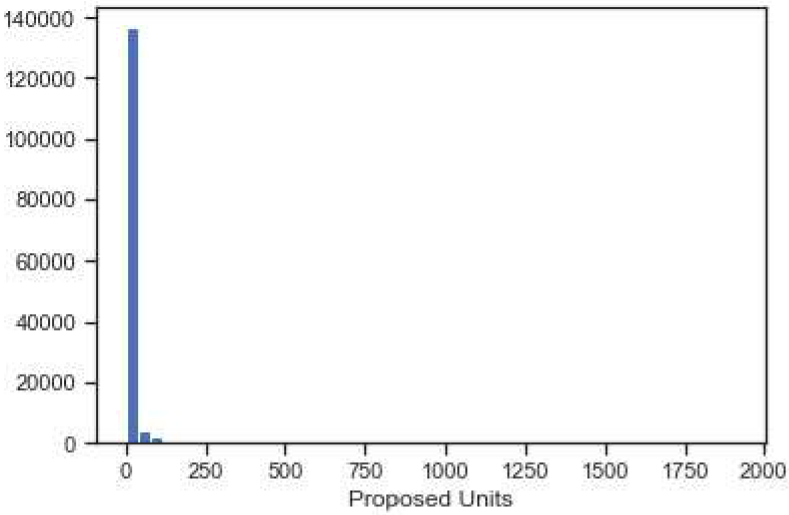


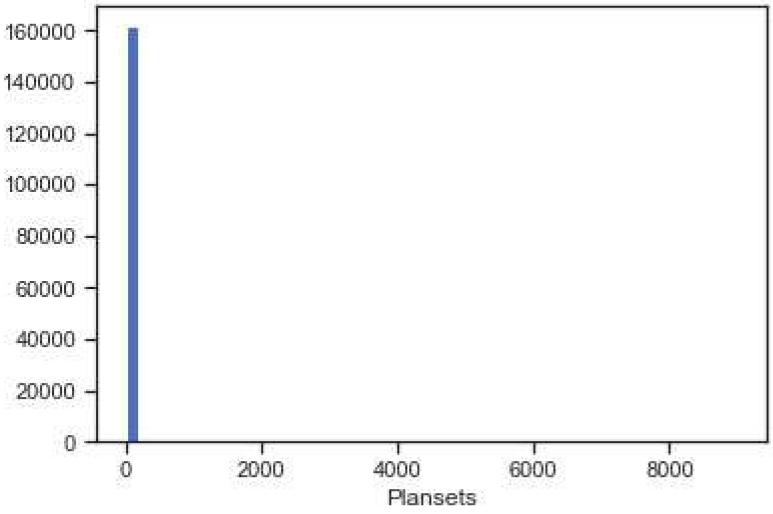


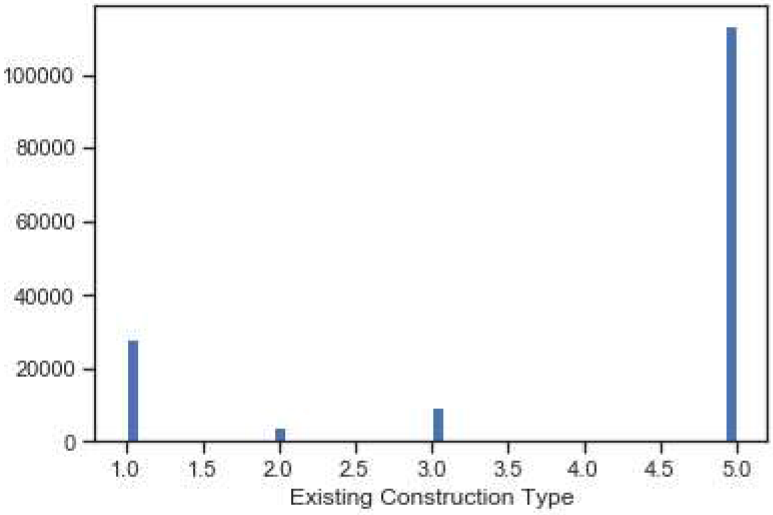

160000
140000
120000
100000
80000
60000
40000
20000
0
0
1
2
3
4
5
Estimated Cost
1e8

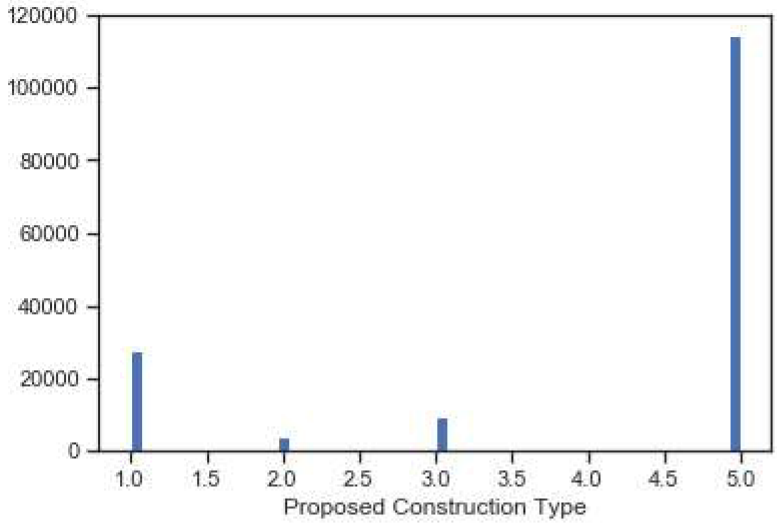

200000
175000
150000
125000
100000
75000
50000
25000
0
0
1
2
3
4
5
6
7
8
Revised Cost
1e8

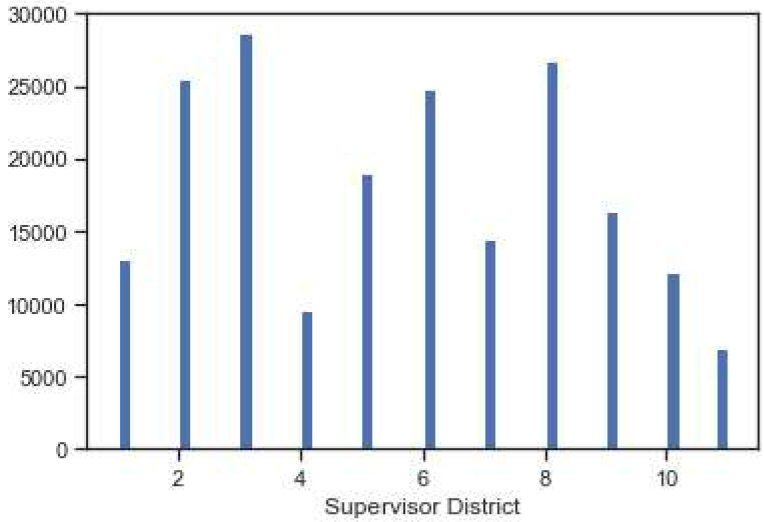

140000
120000
100000
80000
60000
40000
20000
0
0
250
500
750
1000
1250
1500
1750
2000
Existing Units

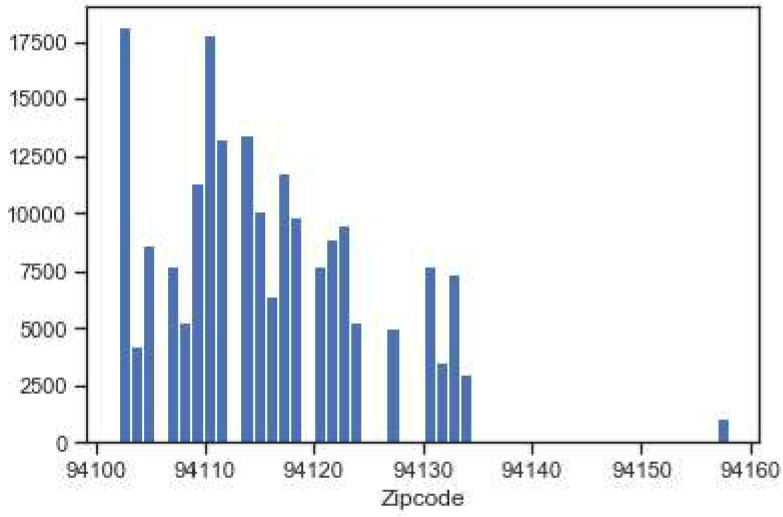

140000
120000
100000
80000
60000
40000
20000
0
0
250
500
750
1000
1250
1500
1750
2000
Proposed Units


160000
140000
120000
100000
80000
60000
40000
20000
0
0
2000
4000
6000
8000
Plansets


100000
80000
60000
40000
20000
0
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0
Existing Construction Type


120000
100000
80000
60000
40000
20000
0
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0
Proposed Construction Type


30000
25000
20000
15000
10000
5000
0
2
4
6
8
10
Supervisor District


17500
15000
12500
10000
7500
5000
2500
0
94100
94110
94120
94130
94140
94150
94160
Zipcode

In [15]:

```
# Фильтр по пустым значениям поля Estimated Cost
data[data['Estimated Cost'].isnull()]
```

Out[15]:

	Permit Number	Permit Type	Permit Type Definition	Permit Creation Date	Block	Lot	Street Number	Street Number Suffix	S
7	M803667	8	otc alterations permit	06/30/2017	4789	014	1465	NaN	R
8	M804227	8	otc alterations permit	07/05/2017	1212	054	2094	NaN	
9	M804767	8	otc alterations permit	07/06/2017	1259	016	89	NaN	/
10	M805287	8	otc alterations permit	07/06/2017	3541	001	106	NaN	Sa
11	M805907	8	otc alterations permit	07/07/2017	0829	021	675	NaN	
12	M806447	8	otc alterations permit	07/10/2017	6537	023	4082	NaN	
14	M813729	8	otc alterations permit	07/26/2017	1049	027	2761	NaN	
15	M813907	8	otc alterations permit	07/27/2017	0243	043	840	NaN	F
16	M813967	8	otc alterations permit	07/27/2017	0268	008	220	NaN	Montg
17	M814148	8	otc alterations permit	07/27/2017	3621	097	3707	NaN	
19	M814368	8	otc alterations permit	07/28/2017	2659	001	263	NaN	C
20	M814967	8	otc alterations permit	07/31/2017	1176	068	1624	NaN	F
23	M816927	8	otc alterations permit	08/07/2017	0941	012	2824	NaN	F
26	M820728	8	otc alterations permit	08/18/2017	1449	006	331	NaN	
27	M821207	8	otc alterations permit	08/21/2017	1193	024	120	NaN	Sh
28	M821268	8	otc alterations permit	08/21/2017	1851	012	1512	NaN	
29	M821847	8	otc alterations permit	08/22/2017	0326	001	165	NaN	F

	Permit Number	Permit Type	Permit Type Definition	Permit Creation Date	Block	Lot	Street Number	Street Number Suffix	S
30	M822307	8	otc alterations permit	08/23/2017	0182	004	1441	NaN	
31	M822487	8	otc alterations permit	08/23/2017	3580	017	3830	NaN	
32	M822707	8	otc alterations permit	08/23/2017	3610	041	563	NaN	
34	M823847	8	otc alterations permit	08/25/2017	3545	018A	1810	NaN	
35	M824007	8	otc alterations permit	08/25/2017	0749	006A	1445	NaN	
36	M824127	8	otc alterations permit	08/28/2017	6551	023	1383	NaN	C
37	M824927	8	otc alterations permit	08/29/2017	6597	024	681	NaN	Sar
38	M825267	8	otc alterations permit	08/29/2017	1572	017	606	NaN	
39	M828787	8	otc alterations permit	09/07/2017	0177	022	655	NaN	F
40	M829567	8	otc alterations permit	09/08/2017	0490	002	3325	NaN	S
41	M832207	8	otc alterations permit	09/15/2017	1609	021F	700	NaN	
43	M833229	8	otc alterations permit	09/19/2017	0605	028	2379	NaN	Ja
44	M834107	8	otc alterations permit	09/21/2017	7151	014	247	NaN	Cl
...	...	...	...	...	...	...	...	...	
198822	M892988	8	otc alterations permit	02/23/2018	5811	042	815	NaN	M
198824	M893007	8	otc alterations permit	02/23/2018	5880	007	36	NaN	
198830	M893027	8	otc alterations permit	02/23/2018	6474	014	680	NaN	Brun
198831	M893047	8	otc alterations permit	02/23/2018	4343	029	2587	NaN	

	Permit Number	Permit Type	Permit Type Definition	Permit Creation Date	Block	Lot	Street Number	Street Number Suffix	S I
198833	M893067	8	otc alterations permit	02/23/2018	1523	031	462	NaN	
198837	M893087	8	otc alterations permit	02/23/2018	1144	001B	222	NaN	St
198840	M893107	8	otc alterations permit	02/23/2018	0576	011	1856	NaN	F
198841	M893127	8	otc alterations permit	02/23/2018	0652	032	2215	NaN	Cali
198842	M893147	8	otc alterations permit	02/23/2018	0191	018	1242	NaN	N
198843	M893167	8	otc alterations permit	02/23/2018	0852	042	221	NaN	
198847	M893187	8	otc alterations permit	02/23/2018	1205	035	403	NaN	Bro
198850	M893207	8	otc alterations permit	02/23/2018	3644	015	143	NaN	Sar
198858	M893227	8	otc alterations permit	02/23/2018	0652	005	2007	NaN	Buch
198859	M893247	8	otc alterations permit	02/23/2018	3504	030	1699	NaN	N
198861	M893267	8	otc alterations permit	02/23/2018	0309	009	156	NaN	
198862	201802232161	8	otc alterations permit	02/23/2018	0670	004	1233	NaN	
198865	M893307	8	otc alterations permit	02/23/2018	1070	001A	2750	NaN	
198868	M893327	8	otc alterations permit	02/23/2018	5744	021	311	NaN	Cre
198869	M893328	8	otc alterations permit	02/23/2018	0025	024	884	NaN	North
198870	M893328	8	otc alterations permit	02/23/2018	0025	024	888	NaN	North
198871	M893347	8	otc alterations permit	02/23/2018	1253	001	701	NaN	Cl
198876	M893367	8	otc alterations permit	02/23/2018	1213	013	500	NaN	St

	Permit Number	Permit Type	Permit Type Definition	Permit Creation Date	Block	Lot	Street Number	Street Number Suffix	S I
198880	M893387	8	otc alterations permit	02/23/2018	1841	025D	1442	NaN	Fu
198881	M893407	8	otc alterations permit	02/23/2018	0018	004	2300	NaN	Stc
198883	M893427	8	otc alterations permit	02/23/2018	0315	021	377	NaN	(
198884	M893447	8	otc alterations permit	02/23/2018	3504	030	1699	NaN	M
198895	M862628	8	otc alterations permit	12/05/2017	0113	017A	1228	NaN	Montgc
198897	M863507	8	otc alterations permit	12/06/2017	4318	019	1568	NaN	In
198898	M863747	8	otc alterations permit	12/06/2017	0298	029	795	NaN	;
198899	M864287	8	otc alterations permit	12/07/2017	0160	006	838	NaN	F

38066 rows × 43 columns

In [16]:

```
# Запоминаем индексы строк с пустыми значениями
flt_index = data[data['Estimated Cost'].isnull()].index
flt_index
```

Out[16]:

```
Int64Index([     7,      8,      9,     10,     11,     12,     14,     1
5,
               16,     17,
            ...
            198871, 198876, 198880, 198881, 198883, 198884, 198895, 19889
7,
            198898, 198899],
           dtype='int64', length=38066)
```

In [17]:

```
# Проверяем что выводятся нужные строки
data[data.index.isin(flt_index)]
```

Out[17]:

	Permit Number	Permit Type	Permit Type Definition	Permit Creation Date	Block	Lot	Street Number	Street Number Suffix	S I
7	M803667	8	otc alterations permit	06/30/2017	4789	014	1465	NaN	R
8	M804227	8	otc alterations permit	07/05/2017	1212	054	2094	NaN	
9	M804767	8	otc alterations permit	07/06/2017	1259	016	89	NaN	/
10	M805287	8	otc alterations permit	07/06/2017	3541	001	106	NaN	Sa
11	M805907	8	otc alterations permit	07/07/2017	0829	021	675	NaN	
12	M806447	8	otc alterations permit	07/10/2017	6537	023	4082	NaN	
14	M813729	8	otc alterations permit	07/26/2017	1049	027	2761	NaN	
15	M813907	8	otc alterations permit	07/27/2017	0243	043	840	NaN	F
16	M813967	8	otc alterations permit	07/27/2017	0268	008	220	NaN	Montg
17	M814148	8	otc alterations permit	07/27/2017	3621	097	3707	NaN	
19	M814368	8	otc alterations permit	07/28/2017	2659	001	263	NaN	C
20	M814967	8	otc alterations permit	07/31/2017	1176	068	1624	NaN	F
23	M816927	8	otc alterations permit	08/07/2017	0941	012	2824	NaN	F
26	M820728	8	otc alterations permit	08/18/2017	1449	006	331	NaN	
27	M821207	8	otc alterations permit	08/21/2017	1193	024	120	NaN	Sh
28	M821268	8	otc alterations permit	08/21/2017	1851	012	1512	NaN	
29	M821847	8	otc alterations permit	08/22/2017	0326	001	165	NaN	F

	Permit Number	Permit Type	Permit Type Definition	Permit Creation Date	Block	Lot	Street Number	Street Number Suffix	S
30	M822307	8	otc alterations permit	08/23/2017	0182	004	1441	NaN	
31	M822487	8	otc alterations permit	08/23/2017	3580	017	3830	NaN	
32	M822707	8	otc alterations permit	08/23/2017	3610	041	563	NaN	
34	M823847	8	otc alterations permit	08/25/2017	3545	018A	1810	NaN	
35	M824007	8	otc alterations permit	08/25/2017	0749	006A	1445	NaN	
36	M824127	8	otc alterations permit	08/28/2017	6551	023	1383	NaN	C
37	M824927	8	otc alterations permit	08/29/2017	6597	024	681	NaN	Sar
38	M825267	8	otc alterations permit	08/29/2017	1572	017	606	NaN	
39	M828787	8	otc alterations permit	09/07/2017	0177	022	655	NaN	F
40	M829567	8	otc alterations permit	09/08/2017	0490	002	3325	NaN	S
41	M832207	8	otc alterations permit	09/15/2017	1609	021F	700	NaN	
43	M833229	8	otc alterations permit	09/19/2017	0605	028	2379	NaN	Ja
44	M834107	8	otc alterations permit	09/21/2017	7151	014	247	NaN	Cl
...	...	...	...	...	...	...	...	...	
198822	M892988	8	otc alterations permit	02/23/2018	5811	042	815	NaN	M
198824	M893007	8	otc alterations permit	02/23/2018	5880	007	36	NaN	
198830	M893027	8	otc alterations permit	02/23/2018	6474	014	680	NaN	Brun
198831	M893047	8	otc alterations permit	02/23/2018	4343	029	2587	NaN	

	Permit Number	Permit Type	Permit Type Definition	Permit Creation Date	Block	Lot	Street Number	Street Number Suffix	S I
198833	M893067	8	otc alterations permit	02/23/2018	1523	031	462	NaN	
198837	M893087	8	otc alterations permit	02/23/2018	1144	001B	222	NaN	St
198840	M893107	8	otc alterations permit	02/23/2018	0576	011	1856	NaN	F
198841	M893127	8	otc alterations permit	02/23/2018	0652	032	2215	NaN	Cali
198842	M893147	8	otc alterations permit	02/23/2018	0191	018	1242	NaN	N
198843	M893167	8	otc alterations permit	02/23/2018	0852	042	221	NaN	
198847	M893187	8	otc alterations permit	02/23/2018	1205	035	403	NaN	Bro
198850	M893207	8	otc alterations permit	02/23/2018	3644	015	143	NaN	Sar
198858	M893227	8	otc alterations permit	02/23/2018	0652	005	2007	NaN	Buch
198859	M893247	8	otc alterations permit	02/23/2018	3504	030	1699	NaN	N
198861	M893267	8	otc alterations permit	02/23/2018	0309	009	156	NaN	
198862	201802232161	8	otc alterations permit	02/23/2018	0670	004	1233	NaN	
198865	M893307	8	otc alterations permit	02/23/2018	1070	001A	2750	NaN	
198868	M893327	8	otc alterations permit	02/23/2018	5744	021	311	NaN	Cre
198869	M893328	8	otc alterations permit	02/23/2018	0025	024	884	NaN	North
198870	M893328	8	otc alterations permit	02/23/2018	0025	024	888	NaN	North
198871	M893347	8	otc alterations permit	02/23/2018	1253	001	701	NaN	Cl
198876	M893367	8	otc alterations permit	02/23/2018	1213	013	500	NaN	St

	Permit Number	Permit Type	Permit Type Definition	Permit Creation Date	Block	Lot	Street Number	Street Number Suffix	S
198880	M893387	8	otc alterations permit	02/23/2018	1841	025D	1442	NaN	Fu
198881	M893407	8	otc alterations permit	02/23/2018	0018	004	2300	NaN	Sto
198883	M893427	8	otc alterations permit	02/23/2018	0315	021	377	NaN	(
198884	M893447	8	otc alterations permit	02/23/2018	3504	030	1699	NaN	M
198895	M862628	8	otc alterations permit	12/05/2017	0113	017A	1228	NaN	Montgo
198897	M863507	8	otc alterations permit	12/06/2017	4318	019	1568	NaN	In
198898	M863747	8	otc alterations permit	12/06/2017	0298	029	795	NaN	S
198899	M864287	8	otc alterations permit	12/07/2017	0160	006	838	NaN	F

38066 rows × 43 columns

In [18]:

```
# фильтр по колонке
data_num[data_num.index.isin(flt_index)]['Estimated Cost']
```

Out[18]:

```
7         NaN
8         NaN
9         NaN
10        NaN
11        NaN
12        NaN
14        NaN
15        NaN
16        NaN
17        NaN
19        NaN
20        NaN
23        NaN
26        NaN
27        NaN
28        NaN
29        NaN
30        NaN
31        NaN
32        NaN
34        NaN
35        NaN
36        NaN
37        NaN
38        NaN
39        NaN
40        NaN
41        NaN
43        NaN
44        NaN
          ..
198822    NaN
198824    NaN
198830    NaN
198831    NaN
198833    NaN
198837    NaN
198840    NaN
198841    NaN
198842    NaN
198843    NaN
198847    NaN
198850    NaN
198858    NaN
198859    NaN
198861    NaN
198862    NaN
198865    NaN
198868    NaN
198869    NaN
198870    NaN
198871    NaN
198876    NaN
198880    NaN
198881    NaN
198883    NaN
198884    NaN
198895    NaN
198897    NaN
```

```
198898    NaN
198899    NaN
Name: Estimated Cost, Length: 38066, dtype: float64
```

In [19]:

```
data_num_EstCost = data_num[['Estimated Cost']]
data_num_EstCost.head()
```

Out[19]:

	Estimated Cost
0	4000.0
1	1.0
2	20000.0
3	2000.0
4	100000.0

In [20]:

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

In [21]:

```
# Фильтр для проверки заполнения пустых значений
indicator = MissingIndicator()
mask_missing_values_only = indicator.fit_transform(data_num_EstCost)
mask_missing_values_only
```

Out[21]:

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

In [22]:

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

In [23]:

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

In [24]:

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

Out[24]:

```
('mean',
 array([168955.44329682, 168955.44329682, 168955.44329682, ...,
        168955.44329682, 168955.44329682, 168955.44329682]))
```

In [25]:

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

Out[25]:

```
('median', array([11000., 11000., 11000., ..., 11000., 11000., 11000.]))
```

In [26]:

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

Out[26]:

```
('most_frequent', array([1., 1., 1., ..., 1., 1., 1.]))
```

In [27]:

```
# Более сложная функция, которая позволяет задавать колонку и вид импьютации
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]
```

In [28]:

```
data[['Revised Cost']].describe()
```

Out[28]:

	Revised Cost
count	1.928340e+05
mean	1.328562e+05
std	3.584903e+06
min	0.000000e+00
25%	1.000000e+00
50%	7.000000e+03
75%	2.870750e+04
max	7.805000e+08

In [29]:

```
test_num_impute_col(data, 'Revised Cost', strategies[0])
```

Out[29]:

```
('Revised Cost', 'mean', 6066, 132856.1864917494, 132856.1864917494)
```

In [30]:

```
test_num_impute_col(data, 'Revised Cost', strategies[1])
```

Out[30]:

```
('Revised Cost', 'median', 6066, 7000.0, 7000.0)
```

In [31]:

```
test_num_impute_col(data, 'Revised Cost', strategies[2])
```

Out[31]:

```
('Revised Cost', 'most_frequent', 6066, 1.0, 1.0)
```

2. Обработка пропусков в категориальных данных

In [32]:

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

In [33]:

```
# Выберем категориальные колонки с пропущенными значениями
# Цикл по колонкам датасета
cat_cols = []
for col in data.columns:
    # Количество пустых значений
    temp_null_count = data[data[col].isnull()].shape[0]
    dt = str(data[col].dtype)
    if temp_null_count>0 and (dt=='object'):
        cat_cols.append(col)
        temp_perc = round((temp_null_count / total_count) * 100.0, 2)
        print('Колонка {}. Тип данных {}. Количество пустых значений {}, {}%.'.format(c
ol, dt, temp_null_count, temp_perc))
```

```
Колонка manufacturer. Тип данных object. Количество пустых значений 22764,
11.44%.
Колонка model. Тип данных object. Количество пустых значений 7989, 4.02%.
Колонка condition. Тип данных object. Количество пустых значений 231934, 1
16.61%.
Колонка cylinders. Тип данных object. Количество пустых значений 199683, 1
00.39%.
Колонка fuel. Тип данных object. Количество пустых значений 3985, 2.0%.
Колонка title_status. Тип данных object. Количество пустых значений 3062,
1.54%.
Колонка transmission. Тип данных object. Количество пустых значений 3719,
1.87%.
Колонка vin. Тип данных object. Количество пустых значений 207425, 104.2
9%.
Колонка drive. Тип данных object. Количество пустых значений 144143, 72.4
7%.
Колонка size. Тип данных object. Количество пустых значений 342003, 171.9
5%.
Колонка type. Тип данных object. Количество пустых значений 141531, 71.1
6%.
Колонка paint_color. Тип данных object. Количество пустых значений 164706,
82.81%.
Колонка image_url. Тип данных object. Количество пустых значений 14, 0.0
1%.
Колонка description. Тип данных object. Количество пустых значений 16, 0.0
1%.
```

In [34]:

```
cat_temp_data = data[['model']]
cat_temp_data.head()
```

Out[34]:

	model
0	golf r
1	f-150
2	sierra 1500
3	f-150
4	f-450

In [35]:

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

Out[35]:

```
array(['golf r', 'f-150', 'sierra 1500', ..., 'Camaro 2-door coupe',
       'Isuzu VehiCROSS', 'peterbilt 378'], dtype=object)
```

In [36]:

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

Out[36]:

```
(7989, 1)
```

In [37]:

```
# Импьютация наиболее частыми значениями
imp2 = SimpleImputer(missing_values=np.nan, strategy='most_frequent')
data_imp2 = imp2.fit_transform(cat_temp_data)
data_imp2
```

Out[37]:

```
array([['golf r'],
       ['f-150'],
       ['sierra 1500'],
       ...,
       ['cherokee'],
       ['Porsche Macan GTS'],
       ['f-150']], dtype=object)
```

In [38]:

```
# Пустые значения отсутствуют
np.unique(data_imp2)
```

Out[38]:

```
array(['#350', '#4', '$1500 DOWN PAYMENT', ..., 'É\x9bÌ\x83fini MS-9',
       'â\x80\x9898 Astro',
       'ð\x9d\x97\x9fð\x9d\x97¶ð\x9d\x97»ð\x9d\x97°ð\x9d\x97¼ð\x9d\x97¹ð\x
9d\x97» ð\x9d\x97\xa0ð\x9d\x97\x9eð\x9d\x97¦ ð\x9d\x9f¯.ð\x9d\x9f³ð\x9d\x9
7\x9f ð\x9d\x97\x94ð\x9d\x97ªð\x9d\x97\x97'],
      dtype=object)
```

In [39]:

```
# Импьютация константой
imp3 = SimpleImputer(missing_values=np.nan, strategy='constant', fill_value='!!!')
data_imp3 = imp3.fit_transform(cat_temp_data)
data_imp3
```

Out[39]:

```
array([['golf r'],
       ['f-150'],
       ['sierra 1500'],
       ...,
       ['cherokee'],
       ['Porsche Macan GTS'],
       ['!!!']], dtype=object)
```

In [40]:

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

Out[40]:

```
array(['!!!', '#350', '#4', ..., 'É\x9bÌ\x83fini MS-9',
       'â\x80\x9898 Astro',
       'ð\x9d\x97\x9fð\x9d\x97¶ð\x9d\x97»ð\x9d\x97°ð\x9d\x97¼ð\x9d\x97¹ð\x
9d\x97» ð\x9d\x97\xa0ð\x9d\x97\x9eð\x9d\x97¦ ð\x9d\x9f¯.ð\x9d\x9f³ð\x9d\x9
7\x9f ð\x9d\x97\x94ð\x9d\x97ªð\x9d\x97\x97'],
      dtype=object)
```

In [41]:

```
data_imp3[data_imp3=='!!!'].size
```

Out[41]:

```
7989
```

2. Преобразование категориальных признаков в числовые

In [42]:

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

Out[42]:

	c1
0	golf r
1	f-150
2	sierra 1500
3	f-150
4	f-450
5	f-150
6	f-350
7	sierra
8	f-250
9	f-150
10	f-250
11	yukon
12	tundra
13	sierra
14	f-150
15	2500
16	sierra
17	silverado
18	s-class
19	f-350
20	sierra
21	wrangler rubicon unlimited
22	excursion limited
23	olet Silverado 2500HD
24	civic
25	sierra 1500
26	ierra 1500
27	3500 hd
28	silverado 1500
29	spark ev
...	...
509547	f-150
509548	express 3500
509549	silverado 1500
509550	f-150
509551	versa note
509552	fusion

	c1
509553	mustang
509554	f-350 super duty
509555	canyon crew cab slt
509556	f-150
509557	3500
509558	wheelchair conversion van
509559	silverado 2500hd
509560	olet Silverado 2500HD
509561	gx470
509562	silverado 1500
509563	ierra 1500
509564	pathfinder platinum
509565	super duty f-250 srw
509566	silverado
509567	f-250
509568	F-150
509569	olet Silverado 1500
509570	jetta 2.0l s
509571	peterbilt 378
509572	xterra
509573	3 series 328i
509574	cherokee
509575	Porsche Macan GTS
509576	f-150

509577 rows × 1 columns

Кодирование категорий целочисленными значениями - label encoding¶

In [43]:

```
from sklearn.preprocessing import LabelEncoder, OneHotEncoder
```

In [44]:

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

In [45]:

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

Out[45]:

```
array(['golf r', 'f-150', 'sierra 1500', ..., 'Camaro 2-door coupe',
       'Isuzu VehiCROSS', 'peterbilt 378'], dtype=object)
```

In [46]:

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

Out[46]:

```
array([    0,     1,     2, ..., 35849, 35850, 35851])
```

In [47]:

```
le.inverse_transform([0, 1, 2, 3])
```

Out[47]:

```
array(['#350', '#4', '$1500 DOWN PAYMENT', '$500 DOWN PROGRAMS!'],
      dtype=object)
```

Кодирование категорий наборами бинарных значений - one-hot encoding

In [48]:

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

In [49]:

```
cat_enc.shape
```

Out[49]:

```
(509577, 1)
```

In [50]:

```
cat_enc_ohe.shape
```

Out[50]:

```
(509577, 35852)
```

In [51]:

```
cat_enc_ohe
```

Out[51]:

```
<509577x35852 sparse matrix of type '<class 'numpy.float64'>'
        with 509577 stored elements in Compressed Sparse Row format>
```

In [24]:

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

Out[24]:

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

In [52]:

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

Out[52]:

	c1
0	golf r
1	f-150
2	sierra 1500
3	f-150
4	f-450
5	f-150
6	f-350
7	sierra
8	f-250
9	f-150

Pandas get_dummies - быстрый вариант one-hot кодирования

In [57]:

```
pd.get_dummies(cat_enc[:30000]).head(2)
```

```
---------------------------------------------------------------------------
MemoryError                               Traceback (most recent call las
t)
<ipython-input-57-bc7013508324> in <module>
----> 1 pd.get_dummies(cat_enc).head(2)

c:\users\innap\miniconda3\lib\site-packages\pandas\core\reshape\reshape.py
in get_dummies(data, prefix, prefix_sep, dummy_na, columns, sparse, drop_f
irst, dtype)
    857             dummy = _get_dummies_1d(col[1], prefix=pre, prefix_sep
=sep,
    858                                     dummy_na=dummy_na, sparse=spar
se,
--> 859                                     drop_first=drop_first, dtype=d
type)
    860             with_dummies.append(dummy)
    861         result = concat(with_dummies, axis=1)

c:\users\innap\miniconda3\lib\site-packages\pandas\core\reshape\reshape.py
in _get_dummies_1d(data, prefix, prefix_sep, dummy_na, sparse, drop_first,
dtype)
    961
    962     else:
--> 963         dummy_mat = np.eye(number_of_cols, dtype=dtype).take(codes
, axis=0)
    964
    965         if not dummy_na:

MemoryError:
```

In [27]:

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

Out[27]:

	model_08 titan	model_1 series	model_117,000	model_122S Amazon	model_124 spider	model_128i	model_135i	mc co
0	0	0	0	0	0	0	0	
1	0	0	0	0	0	0	0	
2	0	0	0	0	0	0	0	
3	0	0	0	0	0	0	0	
4	0	0	0	0	0	0	0	

5 rows × 2494 columns

3 Масштабирование данных

In [28]:

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

3.1. MinMax масштабирование

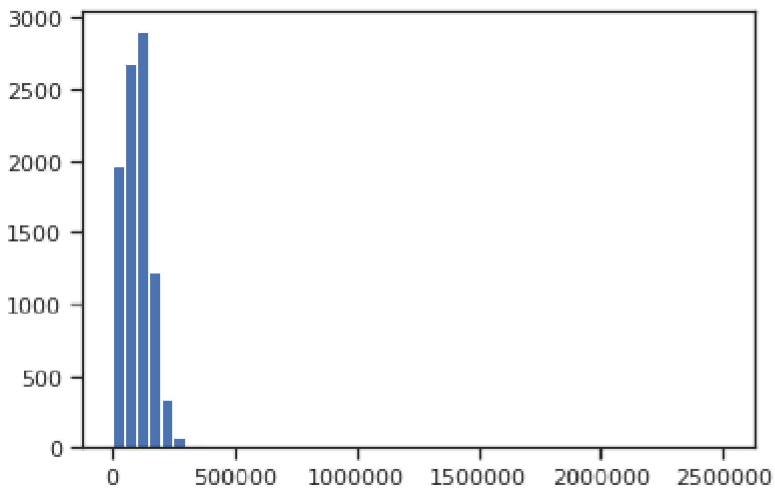
In [34]:

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

In [35]:

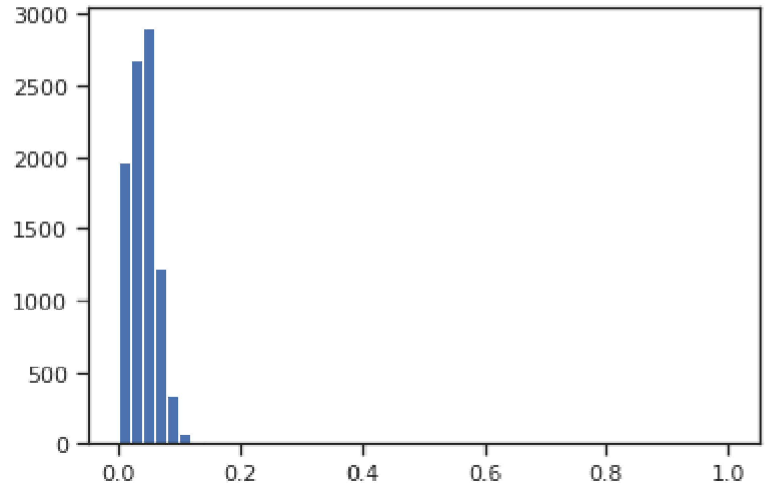
```
plt.hist(data['odometer'], 50)
plt.show()
```

```
/srv/conda/envs/notebook/lib/python3.7/site-packages/numpy/lib/histograms.
py:824: RuntimeWarning: invalid value encountered in greater_equal
  keep = (tmp_a >= first_edge)
/srv/conda/envs/notebook/lib/python3.7/site-packages/numpy/lib/histograms.
py:825: RuntimeWarning: invalid value encountered in less_equal
  keep &= (tmp_a <= last_edge)
```



In [36]:

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



3.2. Масштабирование данных на основе Z-оценки - StandardScaler

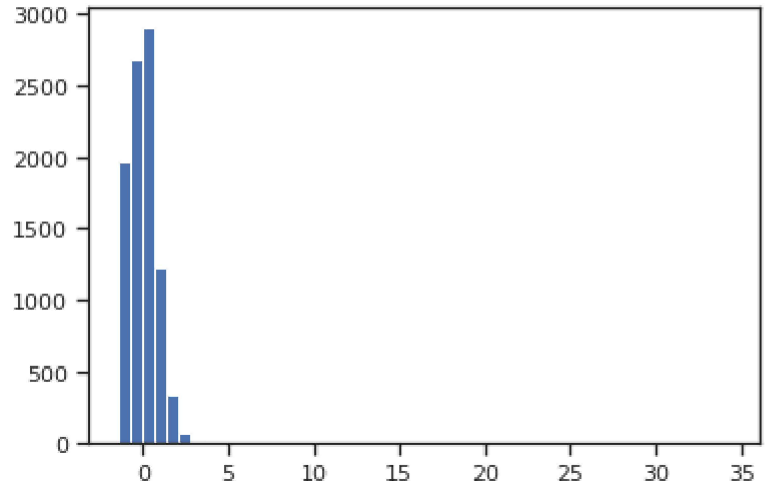
In [37]:

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

In [38]:

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

```
/srv/conda/envs/notebook/lib/python3.7/site-packages/numpy/lib/histograms.
py:824: RuntimeWarning: invalid value encountered in greater_equal
  keep = (tmp_a >= first_edge)
/srv/conda/envs/notebook/lib/python3.7/site-packages/numpy/lib/histograms.
py:825: RuntimeWarning: invalid value encountered in less_equal
  keep &= (tmp_a <= last_edge)
```



3.3. Нормализация данных

In [43]:

```
sc3 = Normalizer()
sc3_data = sc3.fit_transform(data[['odometer']])
```

In [67]:

```
dict = {'odometer': 0}
data = data.fillna(dict)
```

In [68]:

```
data[data['odometer'].isnull()]
```

Out[68]:

id	url	region	region_url	price	year	manufacturer	model	condition	cylinders	...	driv

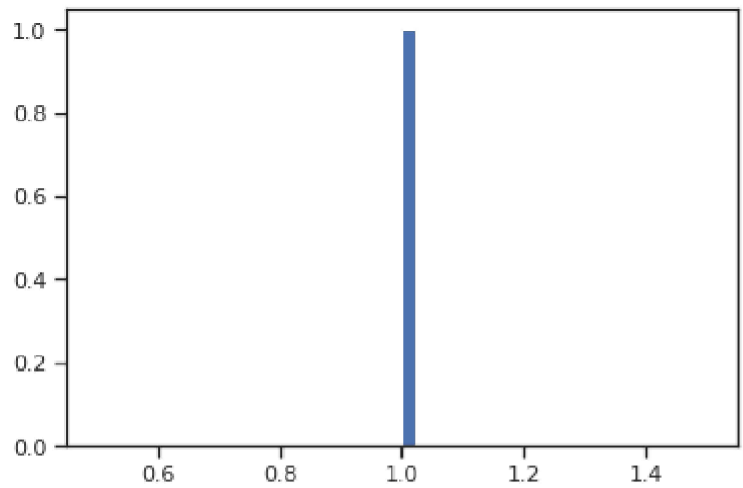
0 rows × 25 columns

In [69]:

```
sc3 = Normalizer()
sc3_data = sc3.fit_transform(data[['odometer']])
```

In [70]:

```
plt.hist(sc3_data, 50)
plt.show()
```



In [ ]:

```

```

In [ ]:

```

```

In [ ]:

Вывод: в ходе выполнения лабораторной работы были изучены способы обработки пропусков данных, выполнено кодирование категориальных признаков, произведено масштабирование данных.
Обработка пропусков данных может быть выполнена следующими способами:

- Удаление или заполнение нулями недостающих данных;
- Внедрение значений (импьюация).

С помощью импьютации можно обрабатывать числовые и категориальные данные, цель метода – заполнить пропуски в данных усредненными значениями, заданными значениями и т.д. При выполнении лабораторной работы использовался класс SimpleImputer библиотеки sklearn, использовались следующие стратегии: 'mean', 'median','most_frequent'.
Кодирование категориальных признаков выполняется при помощи целочисленных значений (label encoding) и бинарных значений (one-hot encoding). Используются классы библиотеки sklearn LabelEncoder и OneHotEncoder соответственно. Также был рассмотрен Pandas get_dummies - быстрый вариант one-hot кодирования.
Масштабирование данных - изменение диапазона измерения величины.
Если признаки лежат в различных диапазонах, то необходимо их нормализовать.
Как правило, применяют два подхода:

- MinMax масштабирование;
- Масштабирование данных на основе Z-оценки.

MinMax масштабирование реализовано при помощи класса MinMaxScaler библиотеки sklearn, а масштабирование данных на основе Z-оценки - StandardScaler. Нормализация данных предполагает изменение распределения данных. Доступна в sklearn при помощи класса Normalizer.

Список литературы

[1] Гапанюк Ю. Е. Лабораторная работа «Обработка пропусков в данных, кодирование категориальных признаков, масштабирование данных» [Электронный ресурс] // GitHub. – 2020. – Режим доступа: `https://github.com/ugapanyuk/ml_course/wiki/LAB_MISSING` (дата обращения: 25.03.2020).

[2] Team The IPython Development. IPython 7.3.0 Documentation [Electronic resource] // Read the Docs. — 2019. — Access mode: `https://ipython.readthedocs.io/en/stable/` (online; accessed: 20.02.2019).

[3] Waskom M. seaborn 0.9.0 documentation [Electronic resource] // PyData. — 2018. — Access mode: `https://seaborn.pydata.org/` (online; accessed: 20.02.2019).

[4] pandas 0.24.1 documentation [Electronic resource] // PyData. — 2019. — Access mode: `http://pandas.pydata.org/pandas-docs/stable/` (online; accessed: 20.02.2019).

[5] Gupta L. Google Play Store Apps [Electronic resource] // Kaggle. — 2019. — Access mode: `https://www.kaggle.com/lava18/google-play-store-apps` (online; accessed: 05.04.2019).