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**(МГТУ им. Н.Э. Баумана)**

**Факультет «Информатика и системы управления»**

**Кафедра ИУ5 «Системы обработки информации и управления»**

Курс «Технологии машинного обучения»

Лабораторная работа № 2

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2024 г.

# Задание

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.

# Датасет Melbourne Housing Snapshot

https://www.kaggle.com/datasets/dansbecker/melbourne-housing-snapshot?resource=download

In [2]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
sns.set(style="ticks")
```

In [3]:
```
from sklearn.impute import SimpleImputer
from sklearn.compose import ColumnTransformer
from sklearn.impute import MissingIndicator
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import OrdinalEncoder
```

In [4]:
```
data = pd.read_csv('/kaggle/input/melb-data/melb_data.csv', sep=",")
```

In [5]:
```
data.shape
```

Out[5]:
```
(13580, 21)
```

In [6]:
```
data.dtypes
```

Out[6]:
```
Suburb            object
Address           object
Rooms              int64
Type              object
Price            float64
Method            object
SellerG           object
Date              object
Distance         float64
Postcode         float64
Bedroom2         float64
Bathroom         float64
Car              float64
Landsize         float64
BuildingArea     float64
YearBuilt        float64
CouncilArea       object
Lattitude        float64
Longtitude       float64
Regionname        object
Propertycount    float64
dtype: object
```

In [7]:
```
data.isnull().sum()
```

Out[7]:
```
Suburb              0
Address             0
Rooms               0
Type                0
Price               0
Method              0
SellerG             0
Date                0
Distance            0
Postcode            0
Bedroom2            0
Bathroom            0
Car                62
Landsize            0
BuildingArea     6450
YearBuilt        5375
CouncilArea      1369
Lattitude           0
Longtitude          0
Regionname          0
Propertycount       0
dtype: int64
```

In [8]:
```
data.head()
```

Out[8]:

| | Suburb | Address | Rooms | Type | Price | Method | SellerG | Date | Distance | Postc |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | Abbotsford | 85 Turner St | 2 | h | 1480000.0 | S | Biggin | 3/12/2016 | 2.5 | 30 |
| **1** | Abbotsford | 25 Bloomburg St | 2 | h | 1035000.0 | S | Biggin | 4/02/2016 | 2.5 | 30 |
| **2** | Abbotsford | 5 Charles St | 3 | h | 1465000.0 | SP | Biggin | 4/03/2017 | 2.5 | 30 |
| **3** | Abbotsford | 40 Federation La | 3 | h | 850000.0 | PI | Biggin | 4/03/2017 | 2.5 | 30 |
| **4** | Abbotsford | 55a Park St | 4 | h | 1600000.0 | VB | Nelson | 4/06/2016 | 2.5 | 30 |

5 rows × 21 columns

## Обработка пропусков категориальных признаков

In [9]:
```
total_count = data.shape[0]

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
```

```
Колонка CouncilArea. Тип данных object. Количество пустых значений 1369, 10.08%.
```

In [10]:
```
data['CouncilArea'].describe()
```

Out[10]:
```
count         12211
unique           33
top        Moreland
freq           1163
Name: CouncilArea, dtype: object
```

In [11]:
```
data['CouncilArea'].unique()
```

Out[11]:
```
array(['Yarra', 'Moonee Valley', 'Port Phillip', 'Darebin', 'Hobsons Bay',
       'Stonnington', 'Boroondara', 'Monash', 'Glen Eira', 'Whitehorse',
       'Maribyrnong', 'Bayside', 'Moreland', 'Manningham', 'Banyule',
       'Melbourne', 'Kingston', 'Brimbank', 'Hume', nan, 'Knox',
       'Maroondah', 'Casey', 'Melton', 'Greater Dandenong', 'Nillumbik',
       'Whittlesea', 'Frankston', 'Macedon Ranges', 'Yarra Ranges',
       'Wyndham', 'Cardinia', 'Unavailable', 'Moorabool'], dtype=object)
```

In [12]:
```
# Проверим корреляцию региона и цены
# Для этого закодируем колонку 'CouncilArea' в зависимости от ее средней цены
df_ca_and_target = data[['Price', 'CouncilArea']].copy()
df_ca_and_target.dropna(subset=['CouncilArea'], inplace=True)

encoder_map = {}
for index, row in df_ca_and_target.groupby(by='CouncilArea').mean().sort_values(by=['
    encoder_map[row['CouncilArea']] = index
    # print(index, row)
```

```
le = LabelEncoder()
df_ca_and_target['CouncilArea'] = df_ca_and_target['CouncilArea'].map(encoder_map)
df_ca_and_target.corr()
```

Out[12]:

| | Price | CouncilArea |
|---|---|---|
| **Price** | 1.000000 | 0.423142 |
| **CouncilArea** | 0.423142 | 1.000000 |

In [13]:
```
# У нас есть небольшая корреляция между целевым признаком и ценой, поэтому просто уда
data.dropna(subset=['CouncilArea'], inplace=True)
```

In [14]:
```
data['CouncilArea'].isnull().sum()
```

Out[14]:
```
0
```

## Обработка пропусков числовых признаков

In [15]:
```
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
```

```
Колонка BuildingArea. Тип данных float64. Количество пустых значений 5765, 42.45%.
Колонка YearBuilt. Тип данных float64. Количество пустых значений 4763, 35.07%.
```

In [16]:
```
# Заполним пропуски в числовых признаков медианой, тк она меньше всего подвержена выб

def fill_missing_median(dataset, column):
    temp_data = dataset[[column]]

    imp_num = SimpleImputer(strategy='median')
    data_num_imp = imp_num.fit_transform(temp_data)


    return data_num_imp
```

In [17]:
```
cols_for_imp = ['BuildingArea', 'YearBuilt']
data[cols_for_imp].isnull().sum()
```

Out[17]:
```
BuildingArea    5765
YearBuilt       4763
dtype: int64
```

In [18]:
```
for col in cols_for_imp:
    data[col] = fill_missing_median(data, col)
    print(f'After {col} imp:')
    print(data[cols_for_imp].isnull().sum())
    print()
```

```
After BuildingArea imp:
BuildingArea      0
YearBuilt      4763
dtype: int64

After YearBuilt imp:
BuildingArea    0
YearBuilt       0
dtype: int64
```

In [19]:
```
data.isnull().sum()
```

Out[19]:
```
Suburb           0
Address          0
Rooms            0
Type             0
Price            0
Method           0
SellerG          0
Date             0
Distance         0
Postcode         0
Bedroom2         0
Bathroom         0
Car              0
Landsize         0
BuildingArea     0
YearBuilt        0
CouncilArea      0
Lattitude        0
Longtitude       0
Regionname       0
Propertycount    0
dtype: int64
```

# Преобразвание категориальных признаков в числовые

In [20]:
```
data.dtypes.loc[lambda x: x == 'object']
```

Out[20]:
```
Suburb         object
Address        object
Type           object
Method         object
SellerG        object
Date           object
CouncilArea    object
Regionname     object
dtype: object
```

### Date

In [21]:
```
data['Date'].unique()
```

Out[21]:
```
array(['3/12/2016', '4/02/2016', '4/03/2017', '4/06/2016', '7/05/2016',
       '8/10/2016', '12/11/2016', '13/08/2016', '14/05/2016',
       '15/10/2016', '16/07/2016', '17/09/2016', '18/03/2017',
       '18/06/2016', '19/11/2016', '22/08/2016', '24/09/2016',
       '25/02/2017', '26/07/2016', '27/11/2016', '28/05/2016',
       '30/07/2016', '3/09/2016', '6/08/2016', '7/11/2016', '10/09/2016',
       '10/12/2016', '11/02/2017', '16/04/2016', '22/05/2016',
       '23/04/2016', '12/06/2016', '27/06/2016', '28/08/2016',
       '11/03/2017', '28/01/2016', '6/05/2017', '8/04/2017', '29/04/2017',
       '13/05/2017', '20/05/2017', '22/04/2017', '1/07/2017', '3/06/2017',
       '17/06/2017', '24/06/2017', '27/05/2017', '8/07/2017',
       '12/08/2017', '15/07/2017', '22/07/2017', '29/07/2017'],
      dtype=object)
```

In [22]:
```python
# Разделим поле Date на day, month, year
date = pd.to_datetime(data['Date'], format='mixed')

data['Day'] = date.dt.day
data['Month'] = date.dt.month
data['Year'] = date.dt.year
data.drop(columns='Date', inplace=True)

data[['Day', 'Month', 'Year']]
```

Out[22]:

| | Day | Month | Year |
|---|---|---|---|
| **0** | 12 | 3 | 2016 |
| **1** | 2 | 4 | 2016 |
| **2** | 3 | 4 | 2017 |
| **3** | 3 | 4 | 2017 |
| **4** | 6 | 4 | 2016 |
| **...** | ... | ... | ... |
| **12208** | 29 | 7 | 2017 |
| **12209** | 29 | 7 | 2017 |
| **12210** | 29 | 7 | 2017 |
| **12211** | 29 | 7 | 2017 |
| **12212** | 29 | 7 | 2017 |

12211 rows × 3 columns

## Adress

In [23]:
```python
# Преобразуем улицу в адрес

data['Street'] = data['Address'].map(lambda addr: addr.split()[1])
data.drop(columns='Address', inplace=True)

data['Street']
```

Out[23]:
```
0              Turner
1           Bloomburg
2             Charles
3          Federation
4                Park
              ...
12208           Pasco
12209            Peel
12210        Saltlake
12211          Adeney
12212        Pentland
Name: Street, Length: 12211, dtype: object
```

In [24]:
```
data['Street'].unique().shape
```

Out[24]:
```
(3721,)
```

## Other

In [25]:
```
data.dtypes.loc[lambda x: x == 'object']
```

Out[25]:
```
Suburb         object
Type           object
Method         object
SellerG        object
CouncilArea    object
Regionname     object
Street         object
dtype: object
```

In [26]:
```
obj_cols = list(data.dtypes.loc[lambda x: x == 'object'].index)
obj_cols
```

Out[26]:
```
['Suburb', 'Type', 'Method', 'SellerG', 'CouncilArea', 'Regionname', 'Street']
```

In [27]:
```
data_obj = data[obj_cols]

oe = OrdinalEncoder()
data_obj_enc = oe.fit_transform(data_obj)
```

In [28]:
```
data[obj_cols] = data_obj_enc
data[obj_cols]
```

Out[28]:

| | Suburb | Type | Method | SellerG | CouncilArea | Regionname | Street |
|---|---|---|---|---|---|---|---|
| **0** | 0.0 | 0.0 | 1.0 | 22.0 | 31.0 | 2.0 | 3377.0 |
| **1** | 0.0 | 0.0 | 1.0 | 22.0 | 31.0 | 2.0 | 377.0 |
| **2** | 0.0 | 0.0 | 3.0 | 22.0 | 31.0 | 2.0 | 668.0 |
| **3** | 0.0 | 0.0 | 0.0 | 22.0 | 31.0 | 2.0 | 1246.0 |
| **4** | 0.0 | 0.0 | 4.0 | 146.0 | 31.0 | 2.0 | 2657.0 |
| **...** | ... | ... | ... | ... | ... | ... | ... |
| **12208** | 299.0 | 0.0 | 1.0 | 100.0 | 10.0 | 6.0 | 2670.0 |
| **12209** | 301.0 | 2.0 | 0.0 | 245.0 | 26.0 | 5.0 | 2691.0 |
| **12210** | 302.0 | 0.0 | 1.0 | 207.0 | 29.0 | 2.0 | 2995.0 |
| **12211** | 307.0 | 0.0 | 3.0 | 245.0 | 16.0 | 6.0 | 24.0 |
| **12212** | 307.0 | 0.0 | 4.0 | 224.0 | 16.0 | 6.0 | 2703.0 |

12211 rows × 7 columns

In [29]:

```
data.describe()
```

Out[29]:

| | Suburb | Rooms | Type | Price | Method | SellerG | |
|---|---|---|---|---|---|---|---|
| **count** | 12211.000000 | 12211.000000 | 12211.000000 | 1.221100e+04 | 12211.000000 | 12211.000000 | 122 |
| **mean** | 152.520514 | 2.894194 | 0.570715 | 1.063692e+06 | 1.404389 | 123.668741 | |
| **std** | 89.000246 | 0.959341 | 0.854515 | 6.388613e+05 | 1.117471 | 73.079999 | |
| **min** | 0.000000 | 1.000000 | 0.000000 | 8.500000e+04 | 0.000000 | 0.000000 | |
| **25%** | 67.000000 | 2.000000 | 0.000000 | 6.400000e+05 | 1.000000 | 70.000000 | |
| **50%** | 153.000000 | 3.000000 | 0.000000 | 8.950000e+05 | 1.000000 | 128.000000 | |
| **75%** | 229.000000 | 3.000000 | 1.000000 | 1.320000e+06 | 1.000000 | 183.000000 | |
| **max** | 307.000000 | 10.000000 | 2.000000 | 9.000000e+06 | 4.000000 | 252.000000 | |

8 rows × 23 columns

In [30]:

```
data.dtypes.loc[lambda x: x == 'object'].size
```

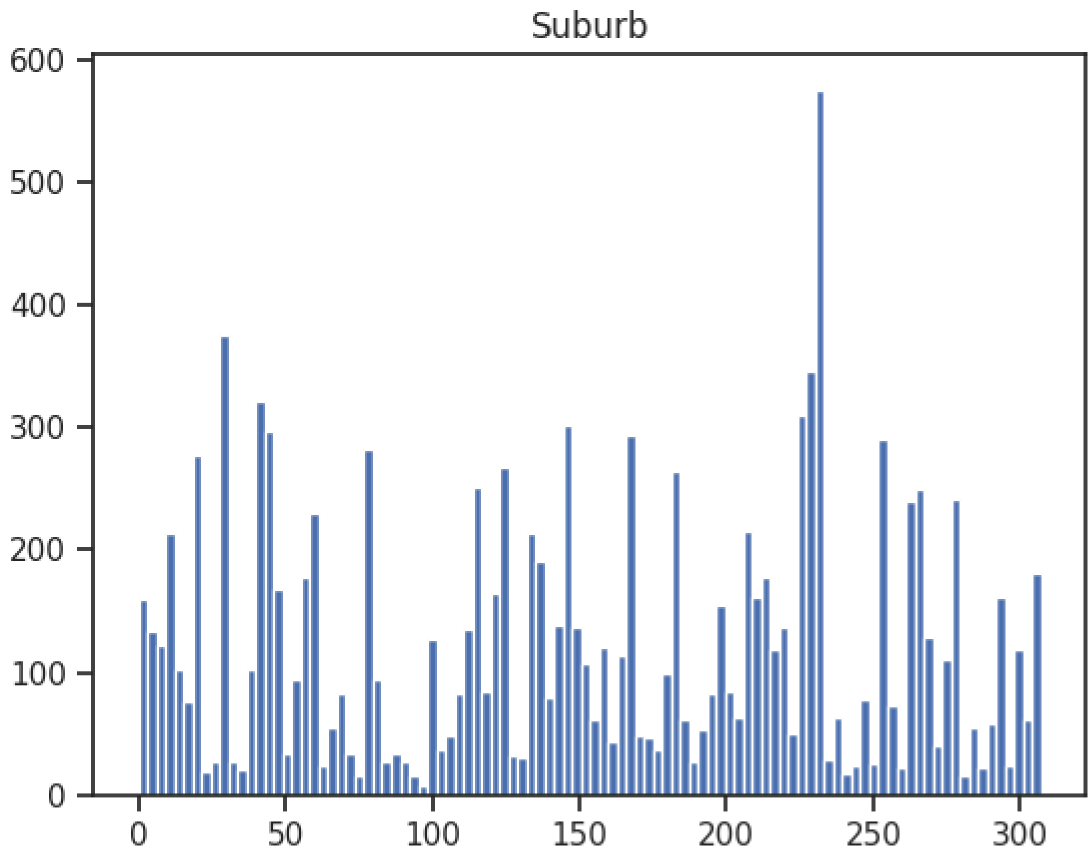
Out[30]: 0

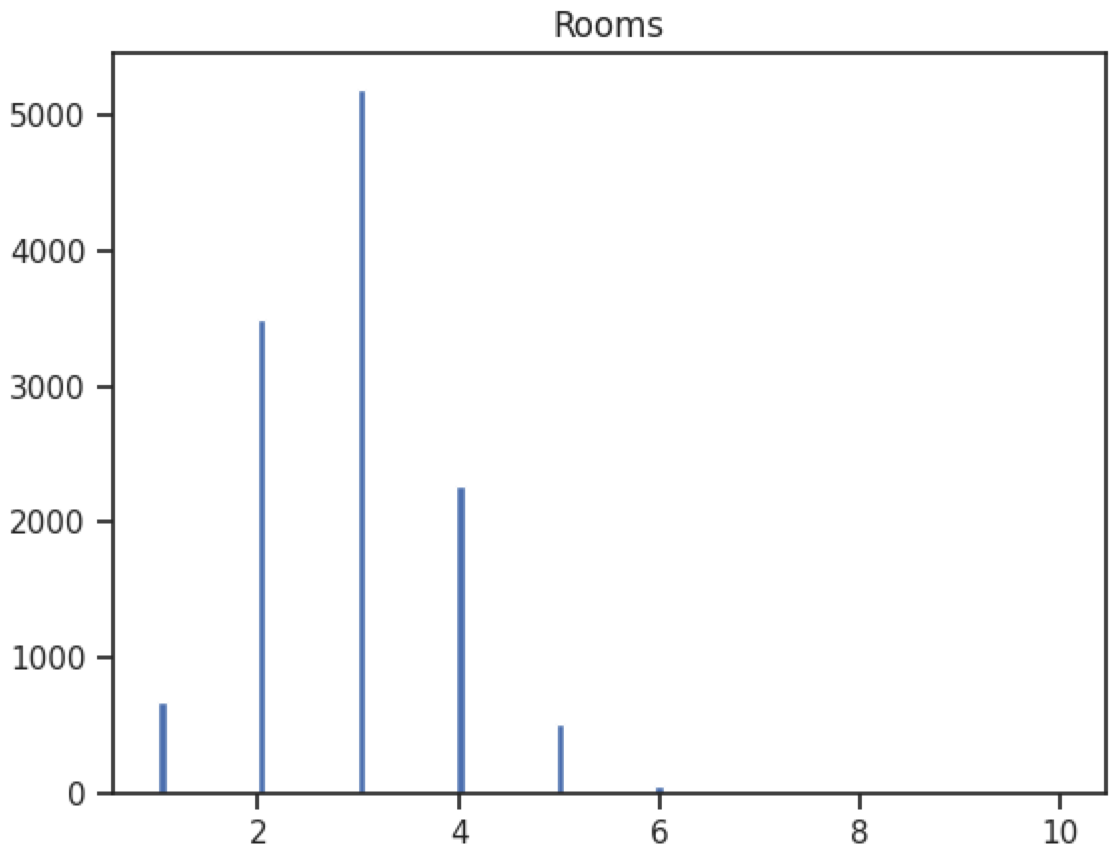
## Масштабирование данных

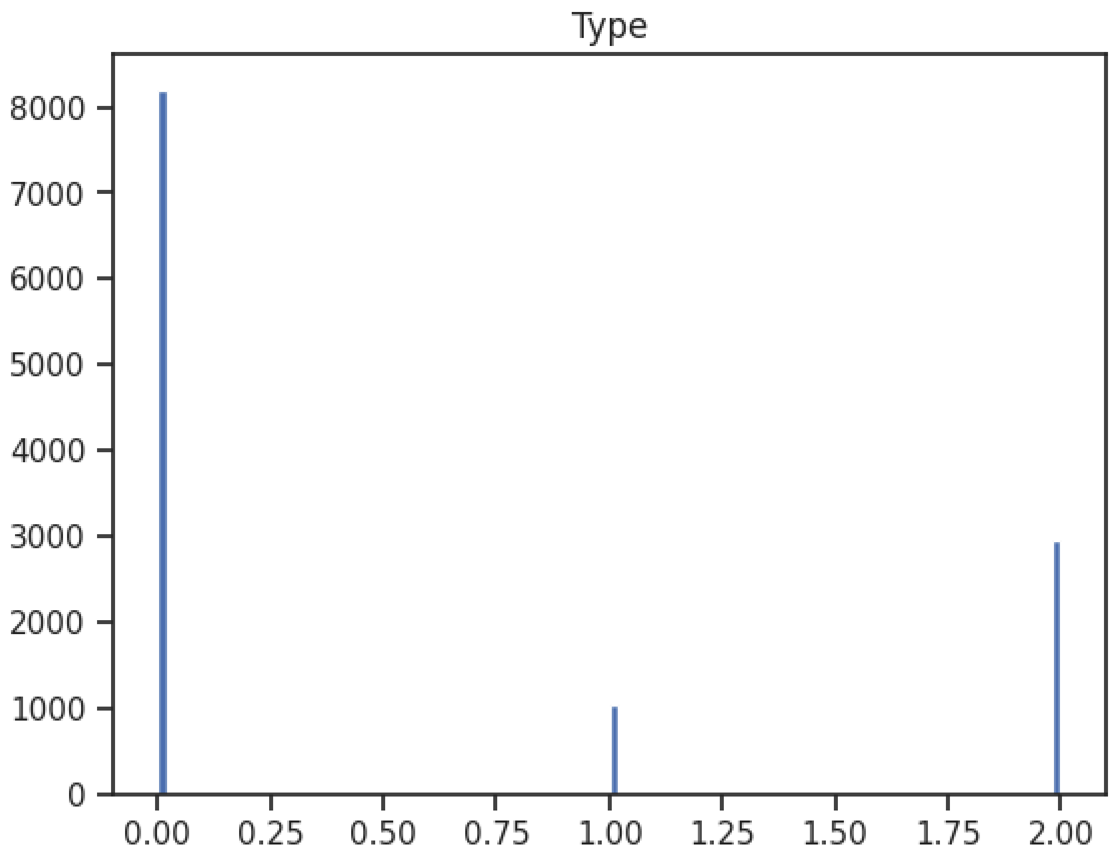
### До применения Z скеллинга

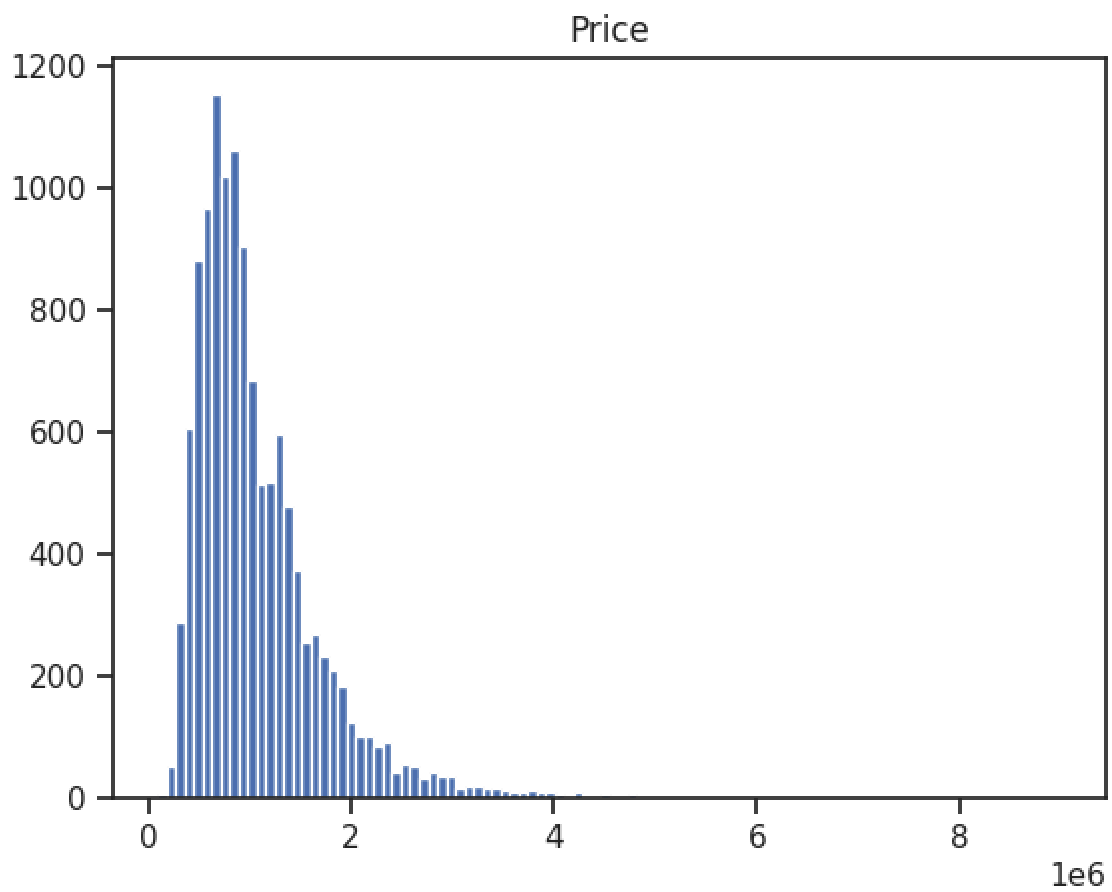
In [31]:

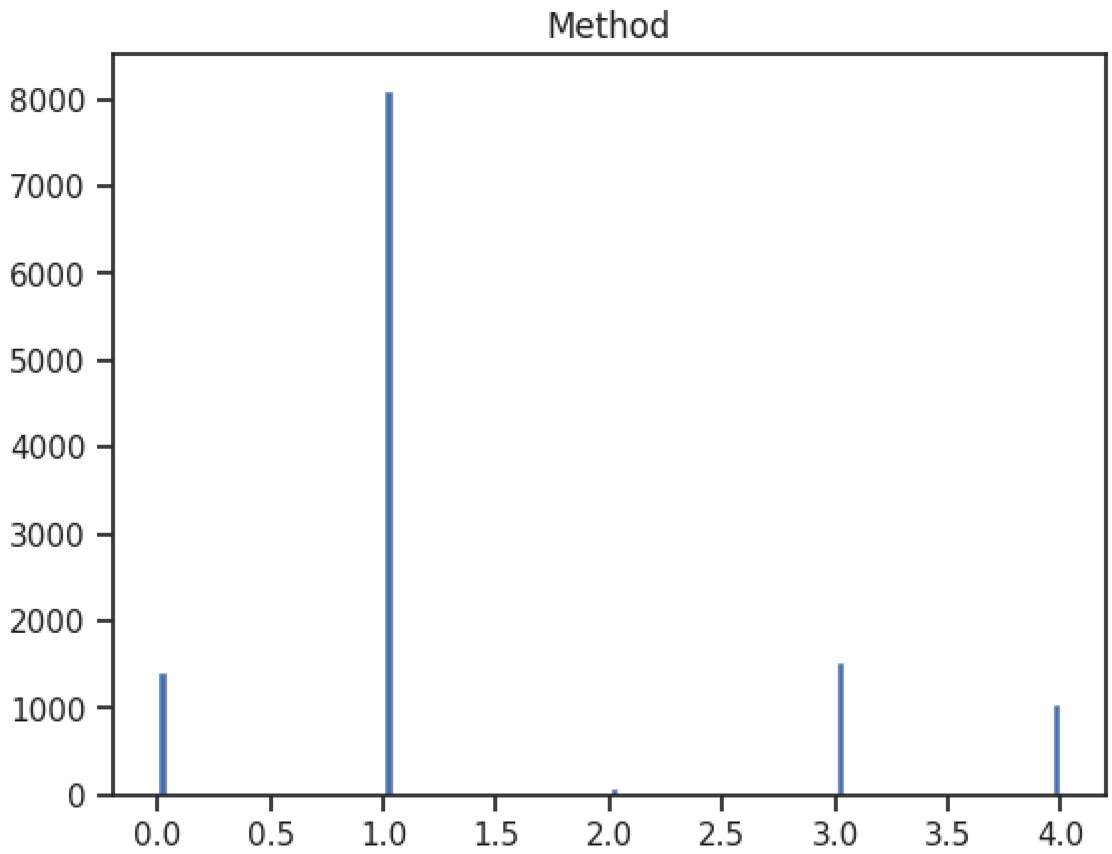
```
for col in data.columns:
    plt.hist(data[col], 100)
    plt.title(col)
    plt.show()
```

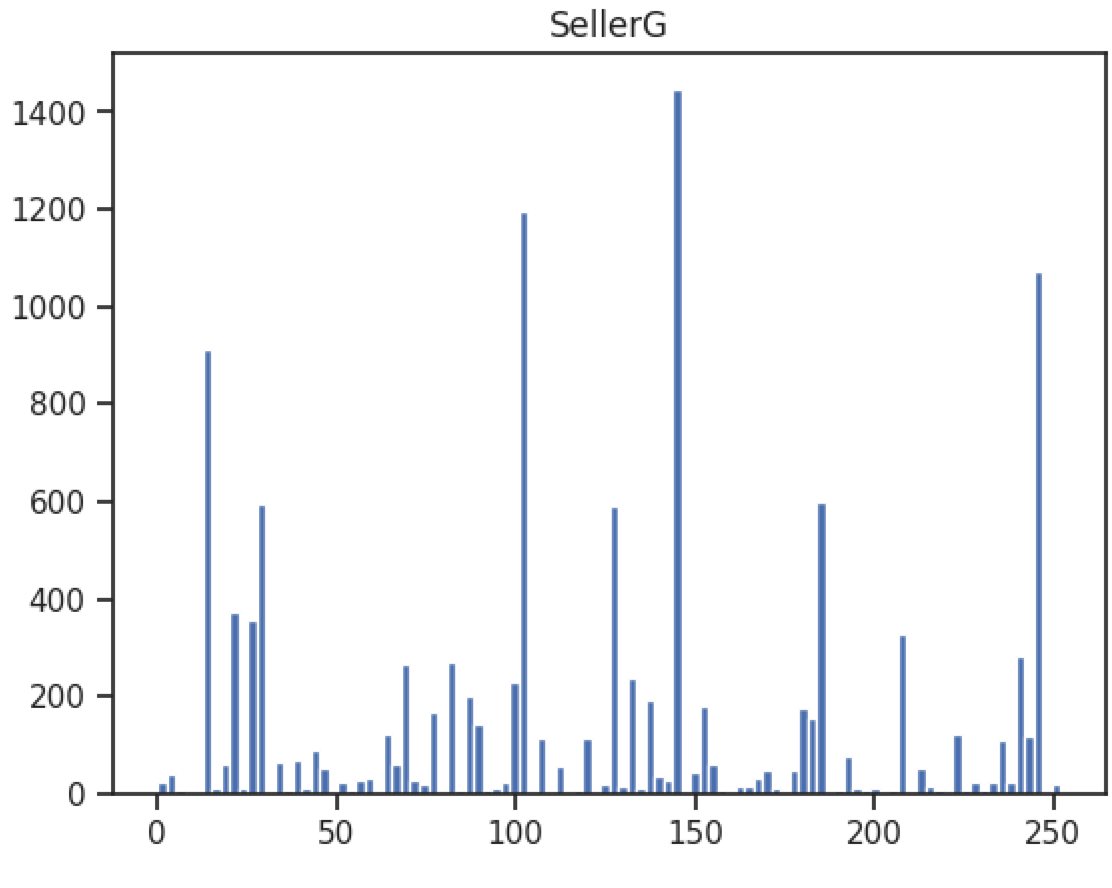

Suburb
600
500
400
300
200
100
0
0
50
100
150
200
250
300

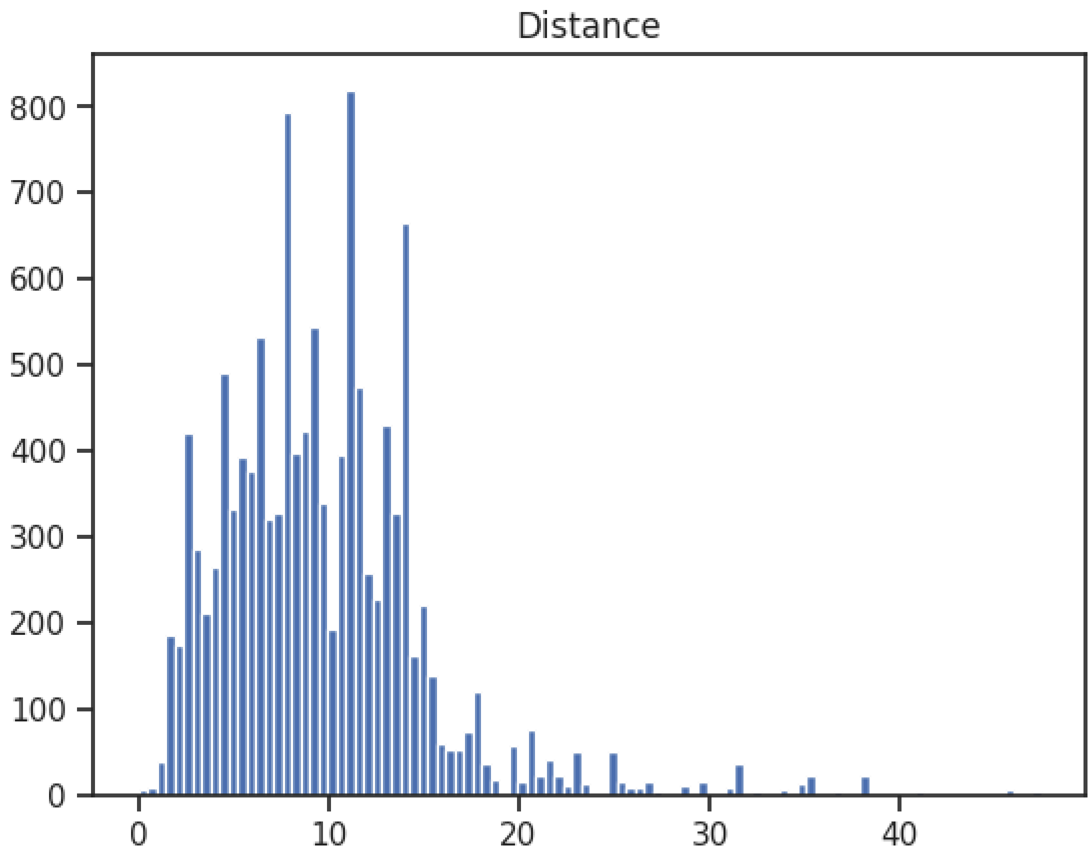

Rooms
5000
4000
3000
2000
1000
0
2
4
6
8
10

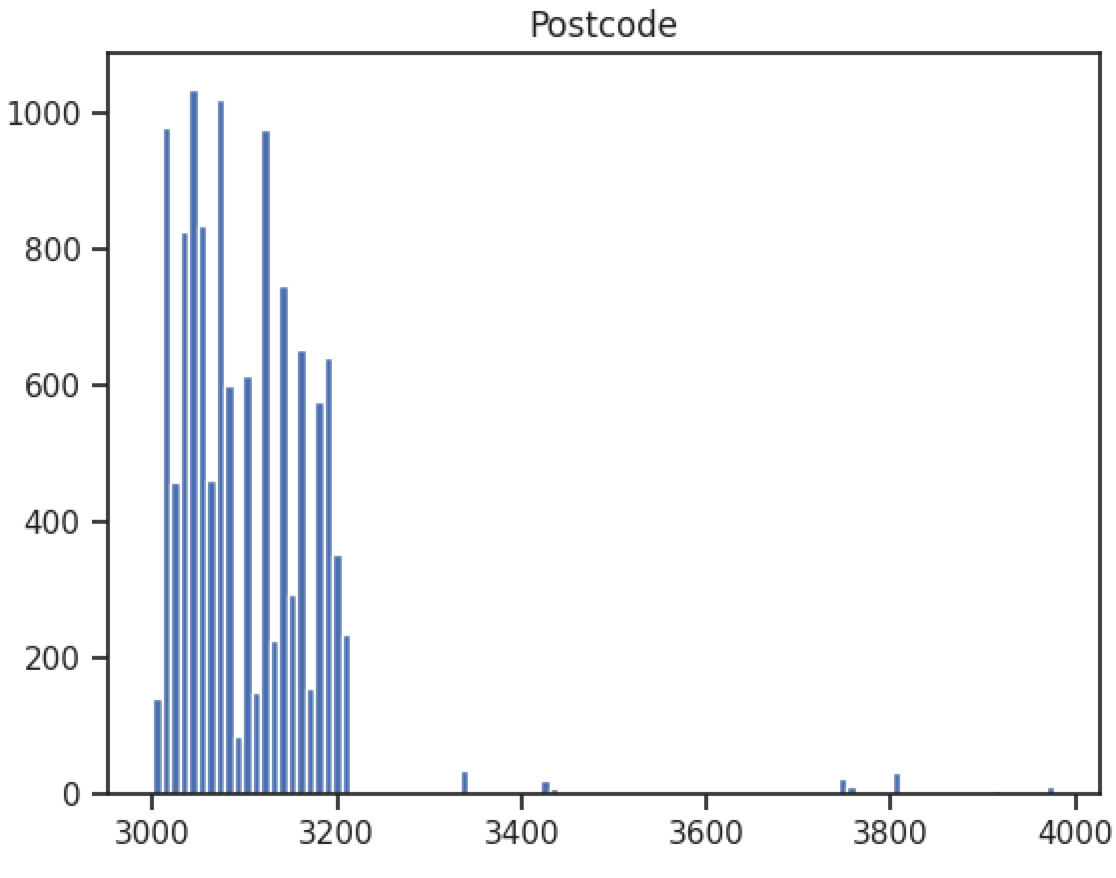

Type
8000
7000
6000
5000
4000
3000
2000
1000
0
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00

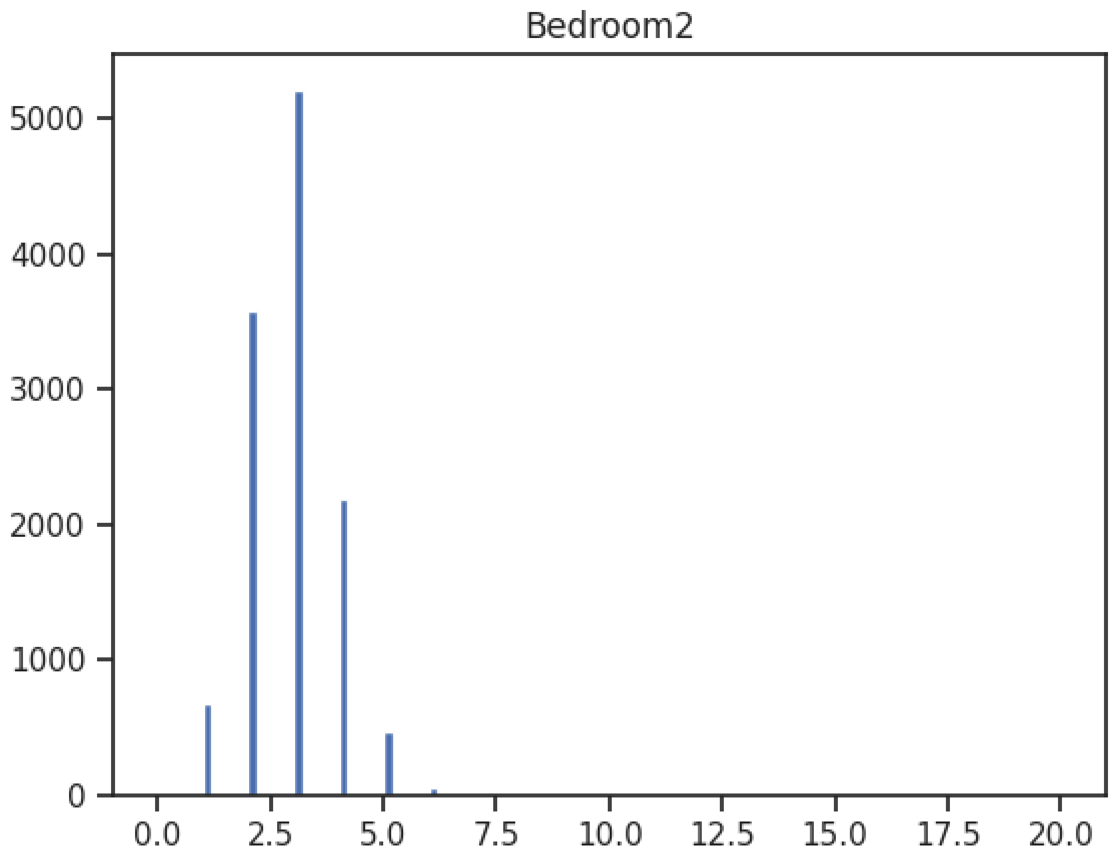

Price
1200
1000
800
600
400
200
0
0
2
4
6
8
1e6

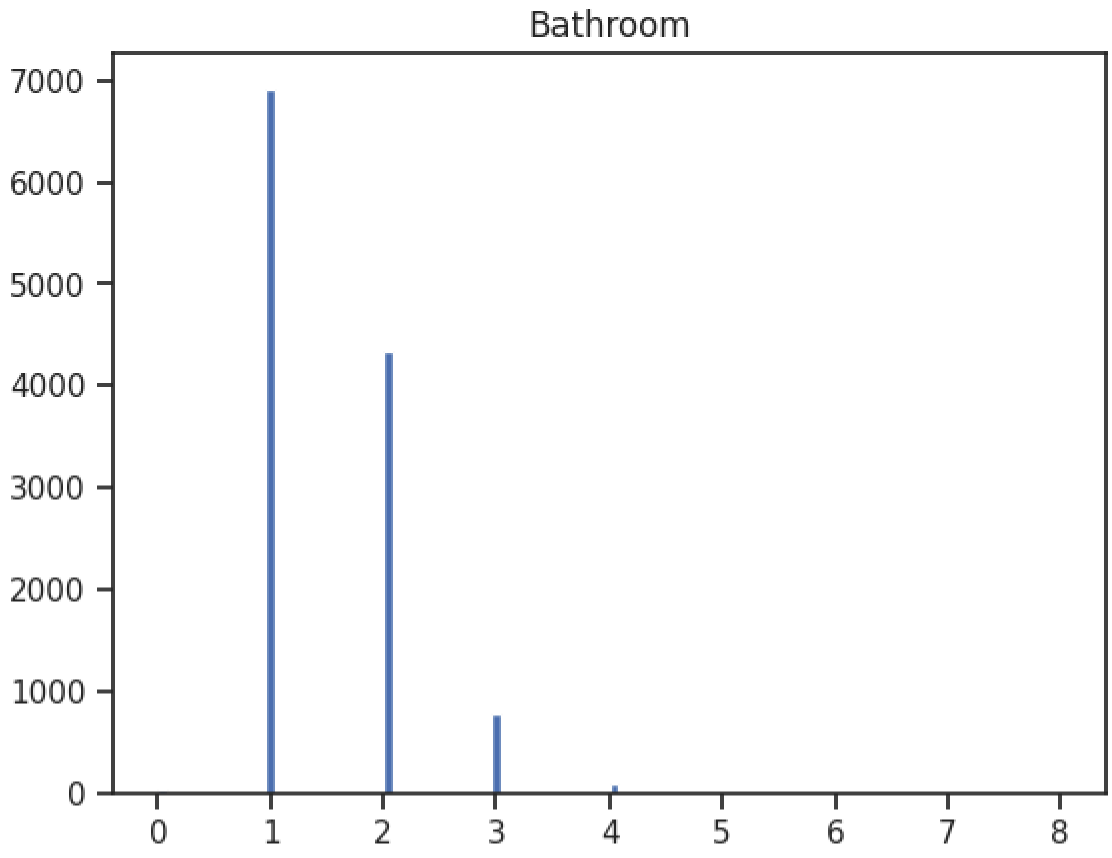

Method
0
1000
2000
3000
4000
5000
6000
7000
8000
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0

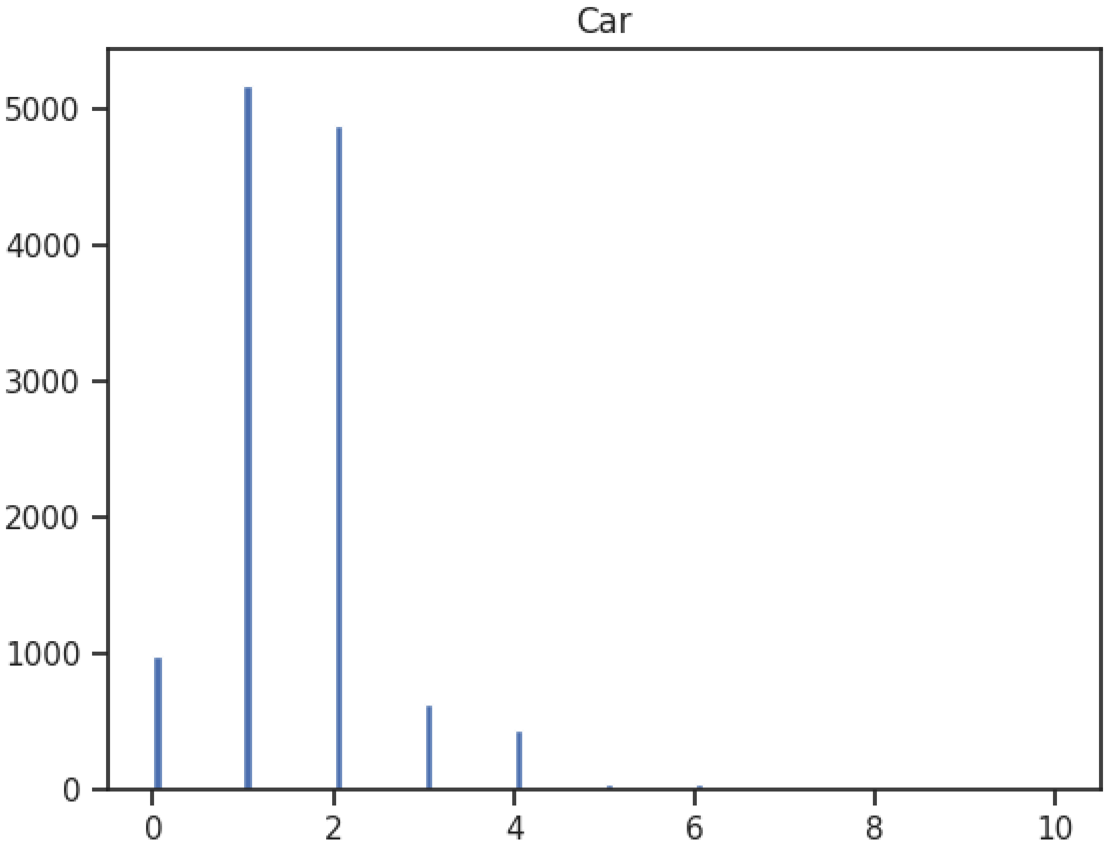

SellerG
0
200
400
600
800
1000
1200
1400
0
50
100
150
200
250

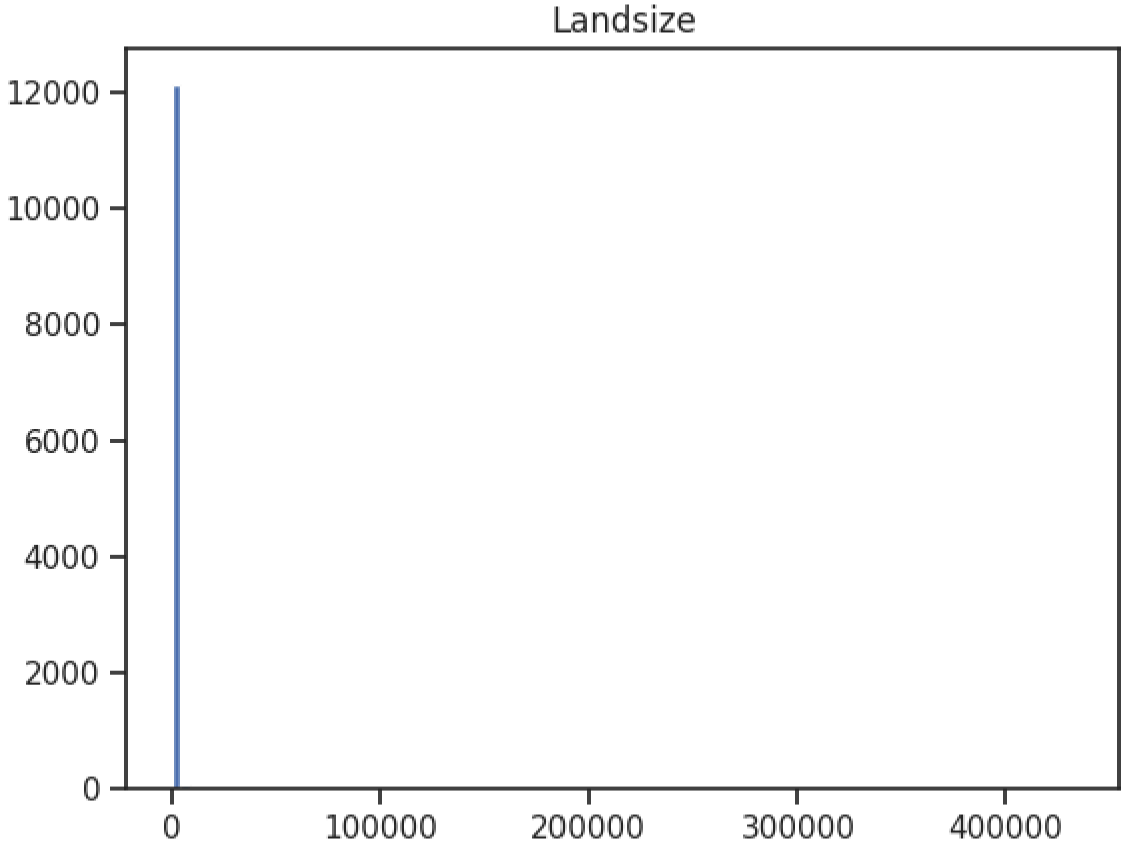

Distance
0
100
200
300
400
500
600
700
800
0
10
20
30
40

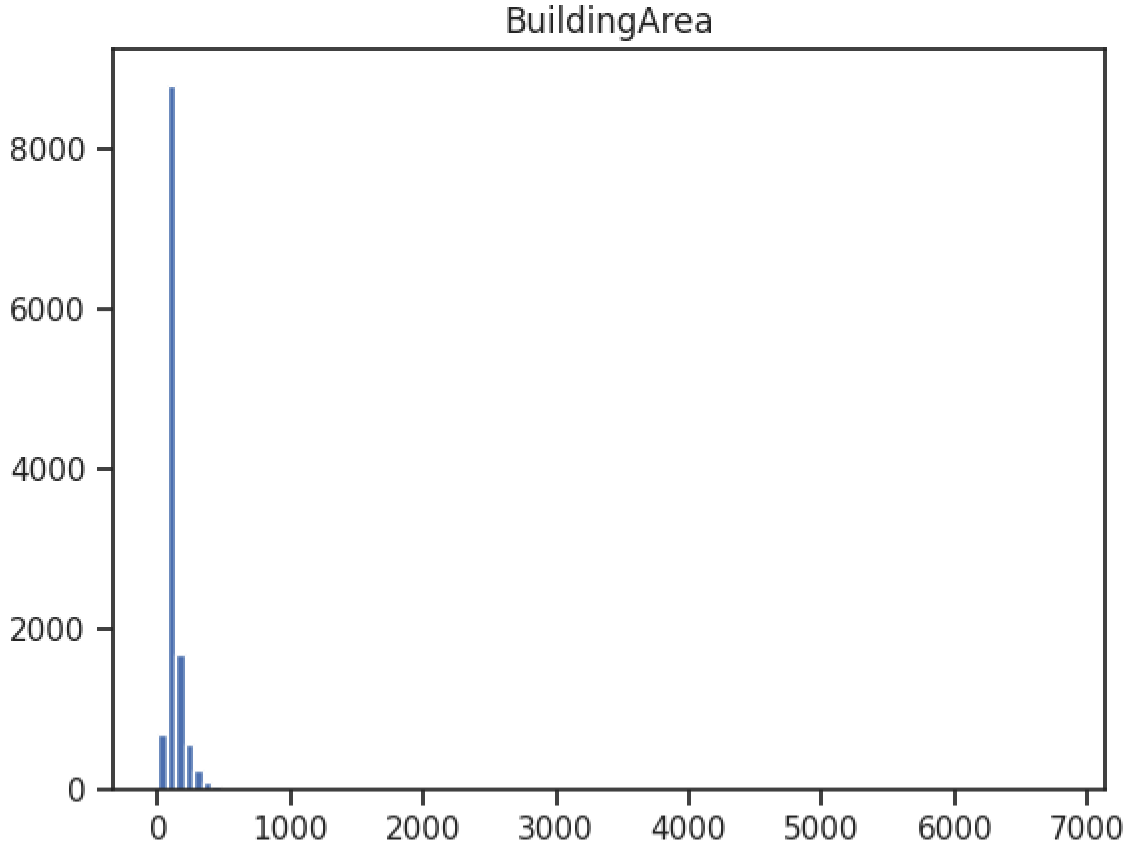

Postcode
0
200
400
600
800
1000
3000
3200
3400
3600
3800
4000

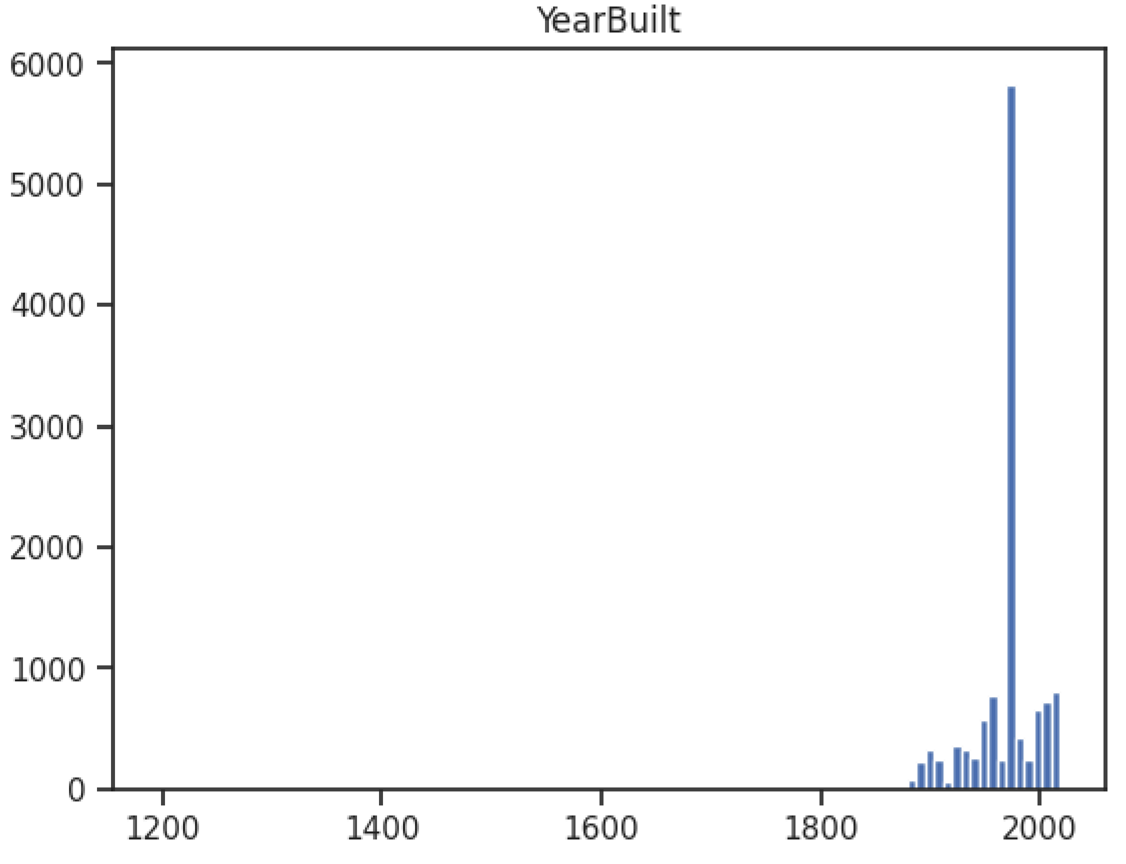

Bedroom2
5000
4000
3000
2000
1000
0
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0

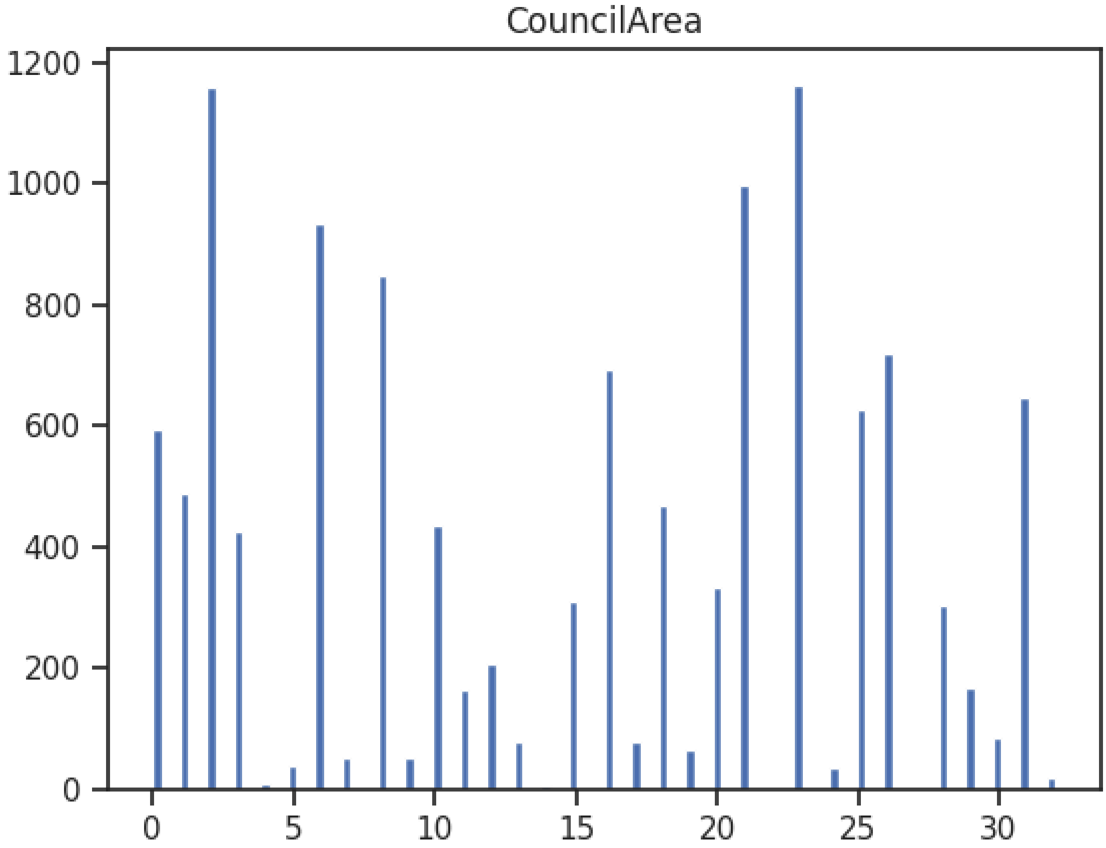

Bathroom
7000
6000
5000
4000
3000
2000
1000
0
0
1
2
3
4
5
6
7
8

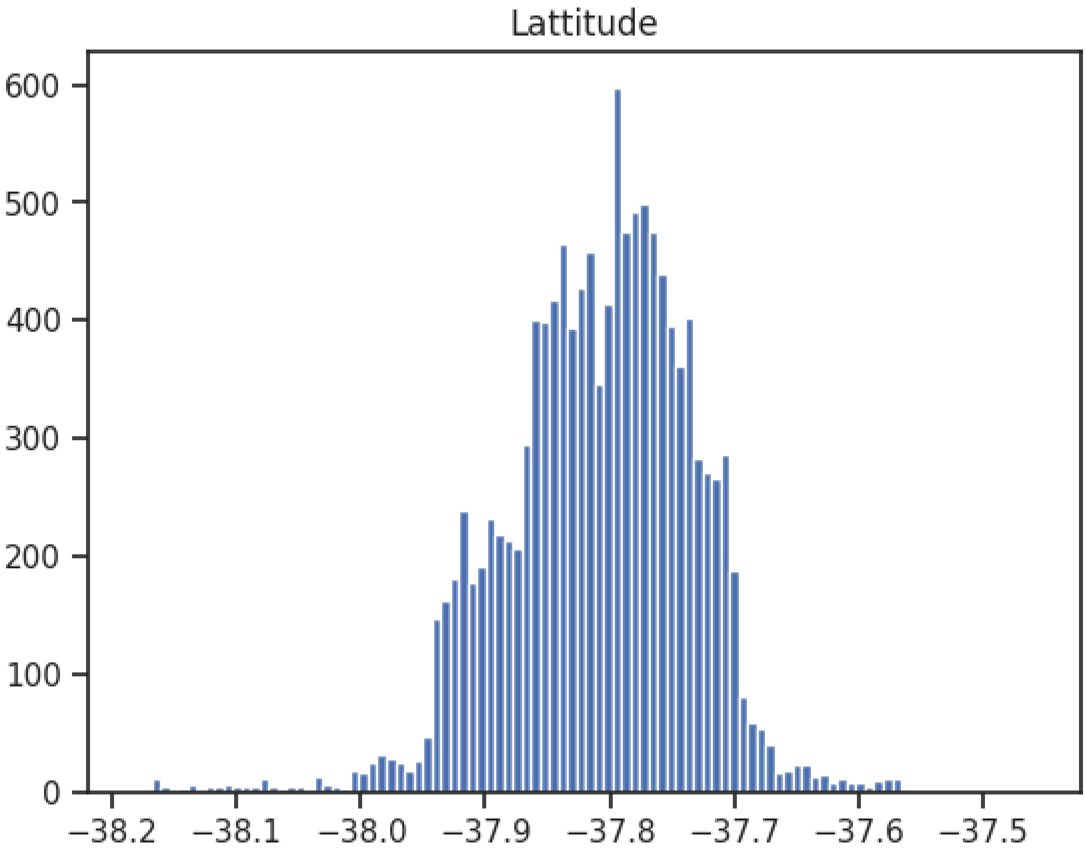

Car
5000
4000
3000
2000
1000
0
0
2
4
6
8
10

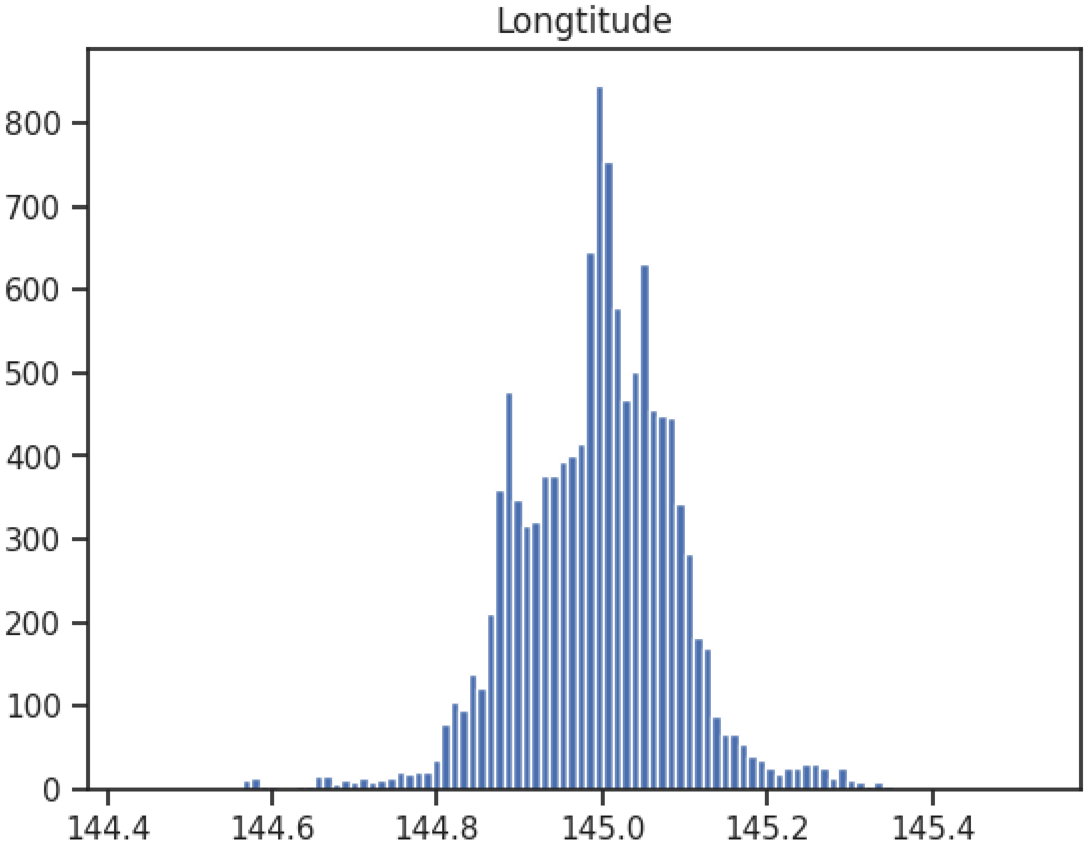

Landsize
12000
10000
8000
6000
4000
2000
0
0
100000
200000
300000
400000

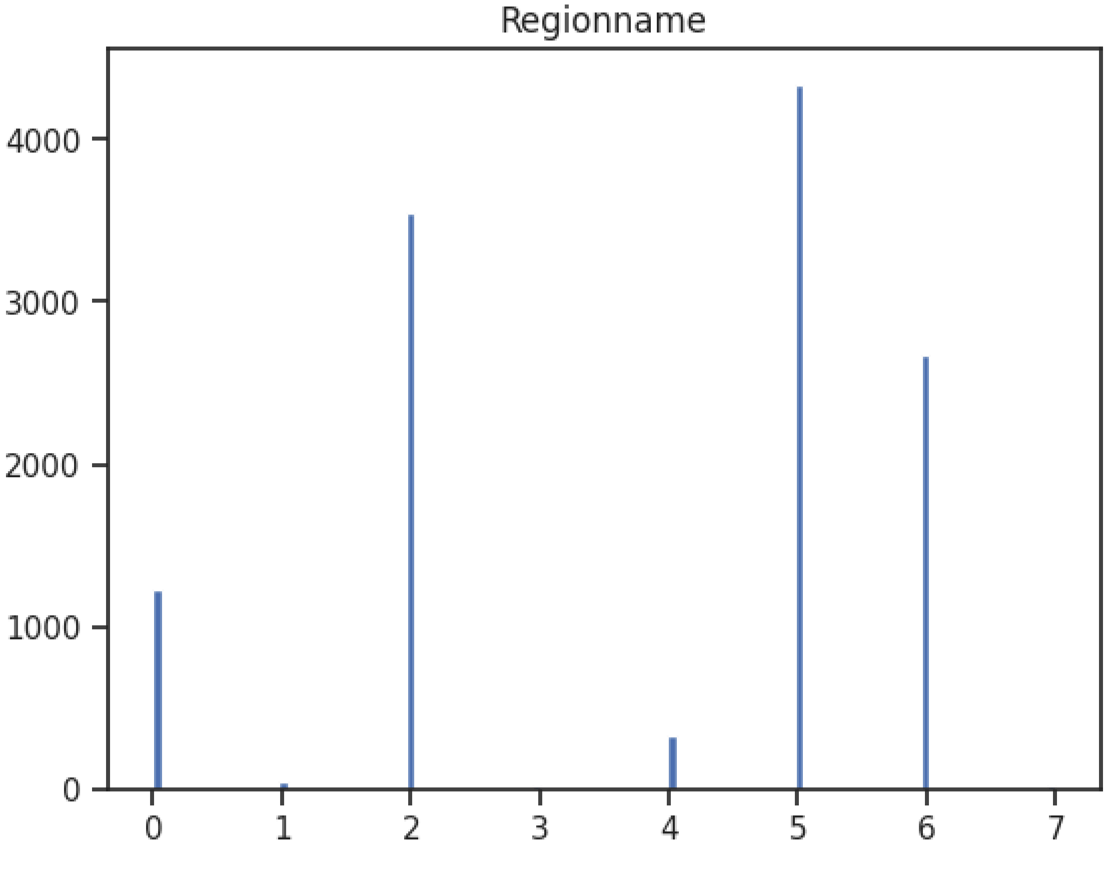

BuildingArea
8000
6000
4000
2000
0
0
1000
2000
3000
4000
5000
6000
7000

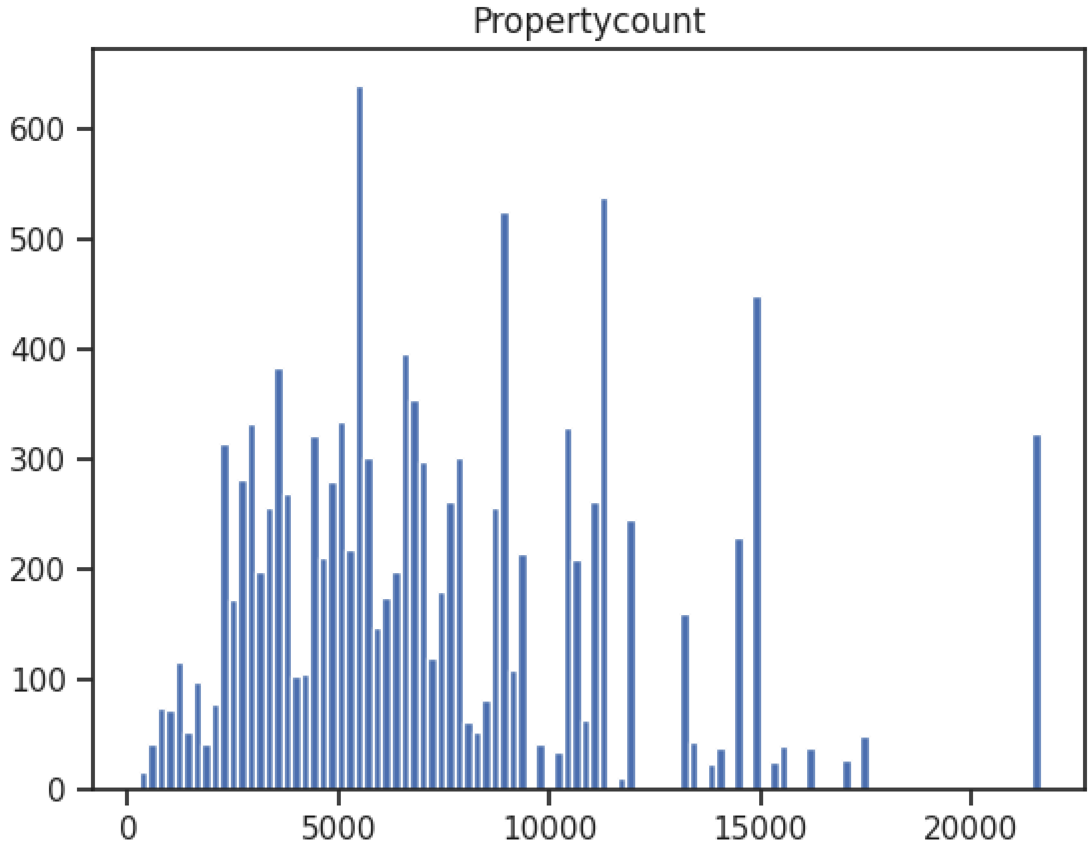

YearBuilt
6000
5000
4000
3000
2000
1000
0
1200
1400
1600
1800
2000

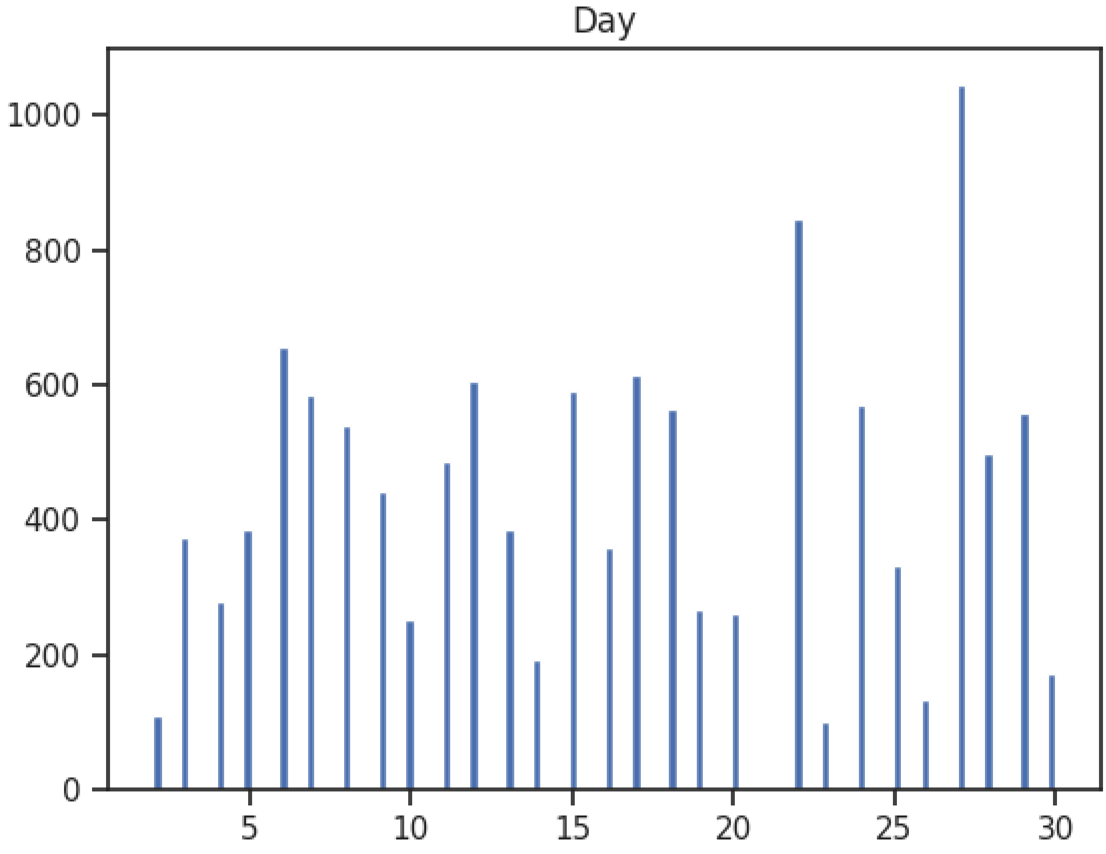

CouncilArea
1200
1000
800
600
400
200
0
0
5
10
15
20
25
30

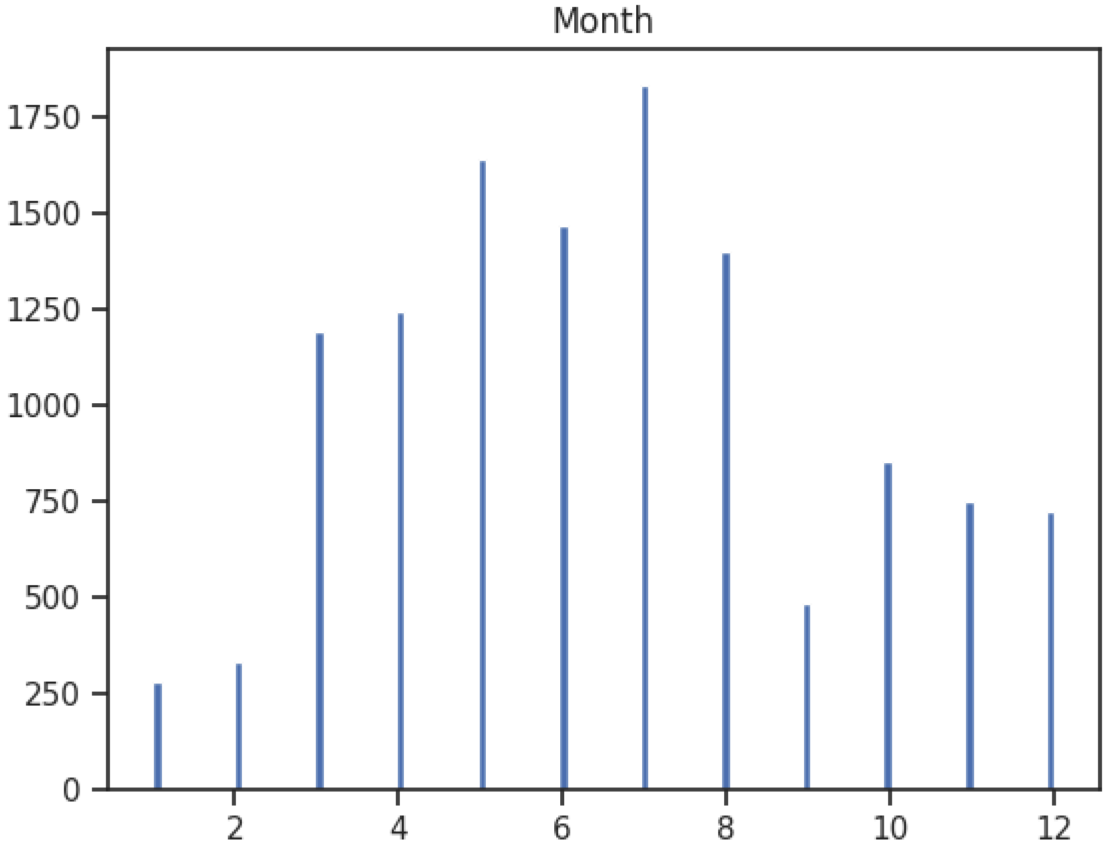

Lattitude
600
500
400
300
200
100
0
−38.2
−38.1
−38.0
−37.9
−37.8
−37.7
−37.6
−37.5

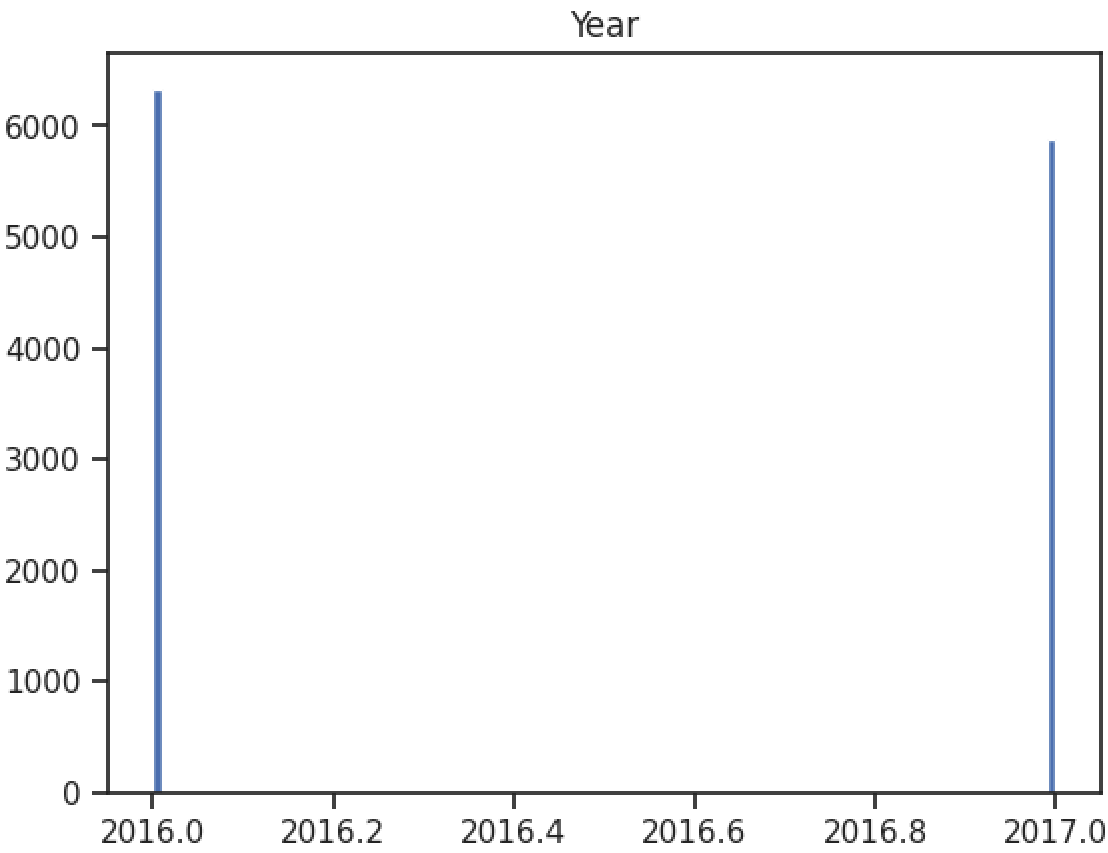

Longtitude
0
100
200
300
400
500
600
700
800
144.4
144.6
144.8
145.0
145.2
145.4

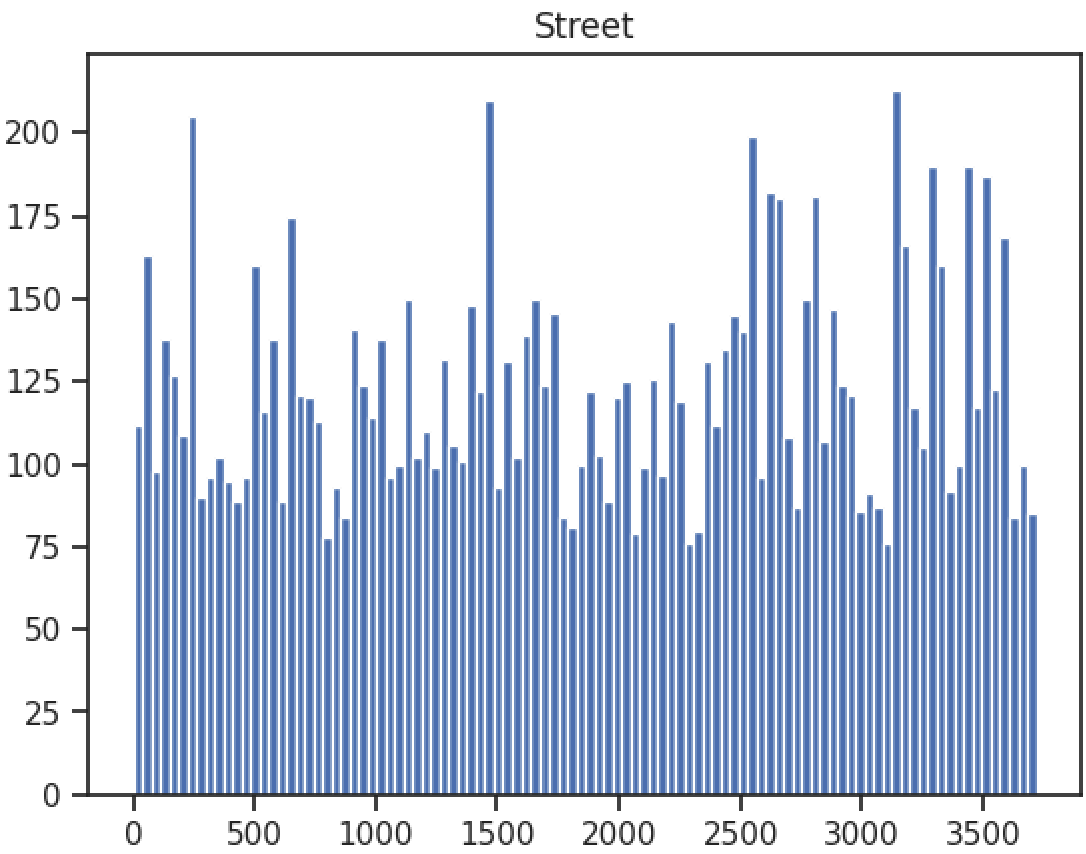

Regionname
0
1000
2000
3000
4000
0
1
2
3
4
5
6
7


Propertycount
0
100
200
300
400
500
600
0
5000
10000
15000
20000


Day
0
200
400
600
800
1000
5
10
15
20
25
30


Month
1750
1500
1250
1000
750
500
250
0
2
4
6
8
10
12


Year
6000
5000
4000
3000
2000
1000
0
2016.0
2016.2
2016.4
2016.6
2016.8
2017.0



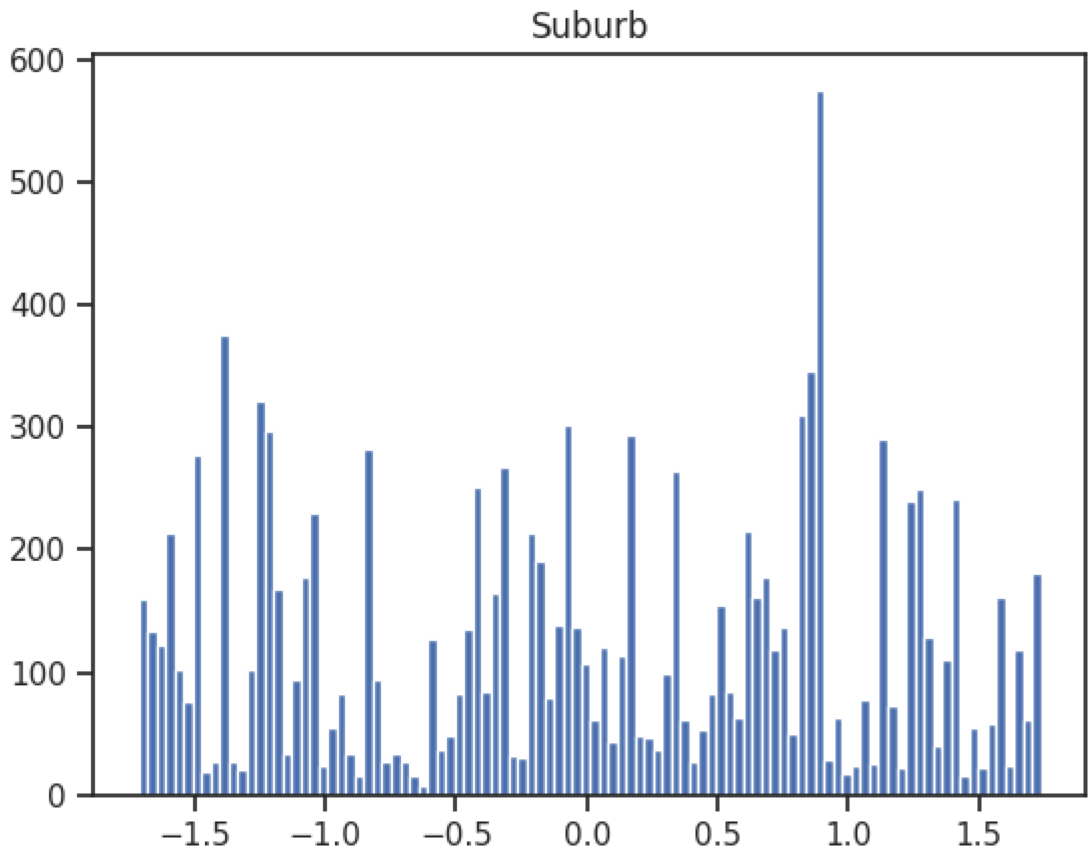

После

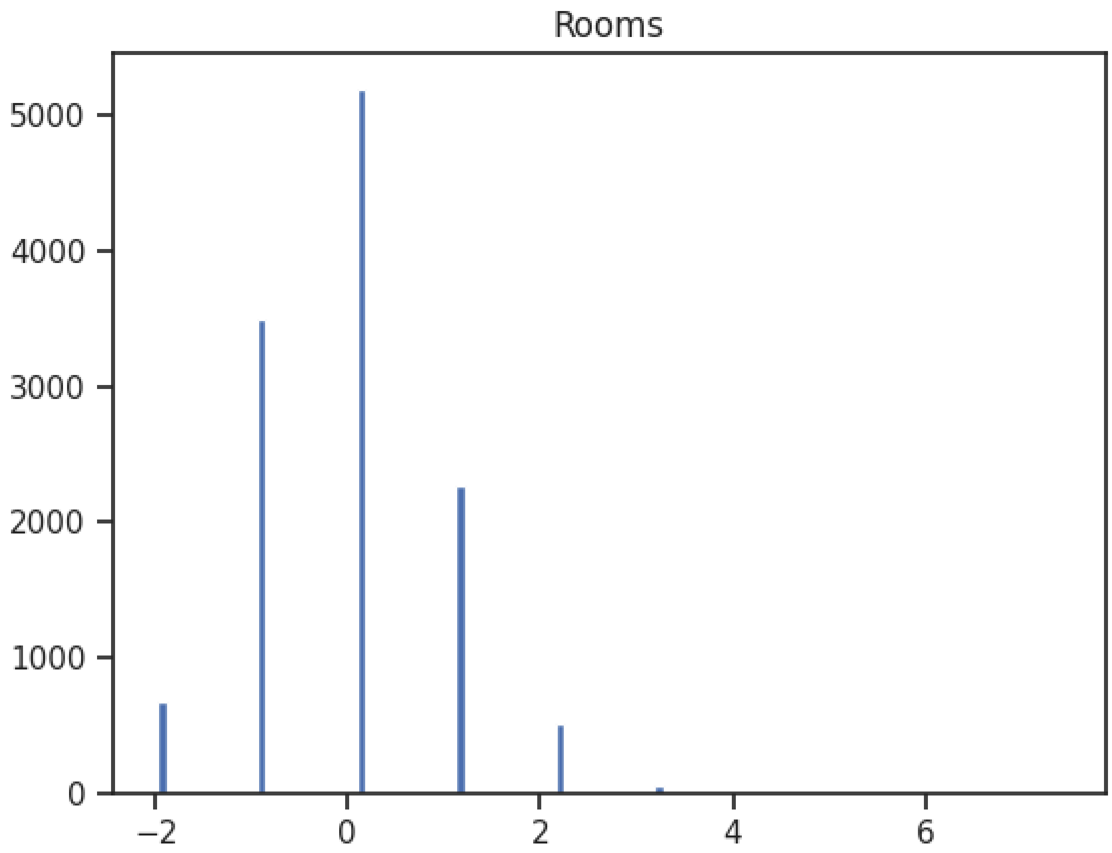
In [32]:
```
from sklearn.preprocessing import MinMaxScaler, StandardScaler, Normalizer
```

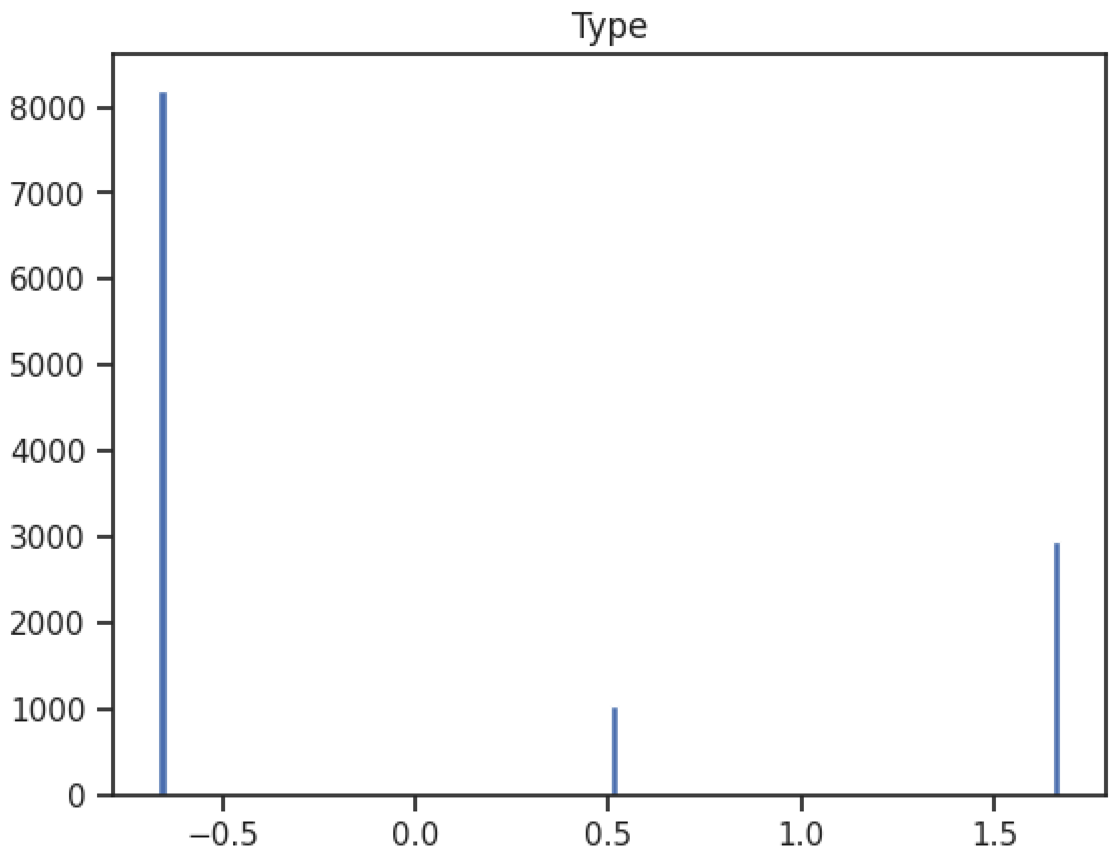
In [33]:
```
sc2 = StandardScaler()
sc2_data = sc2.fit_transform(data)
```

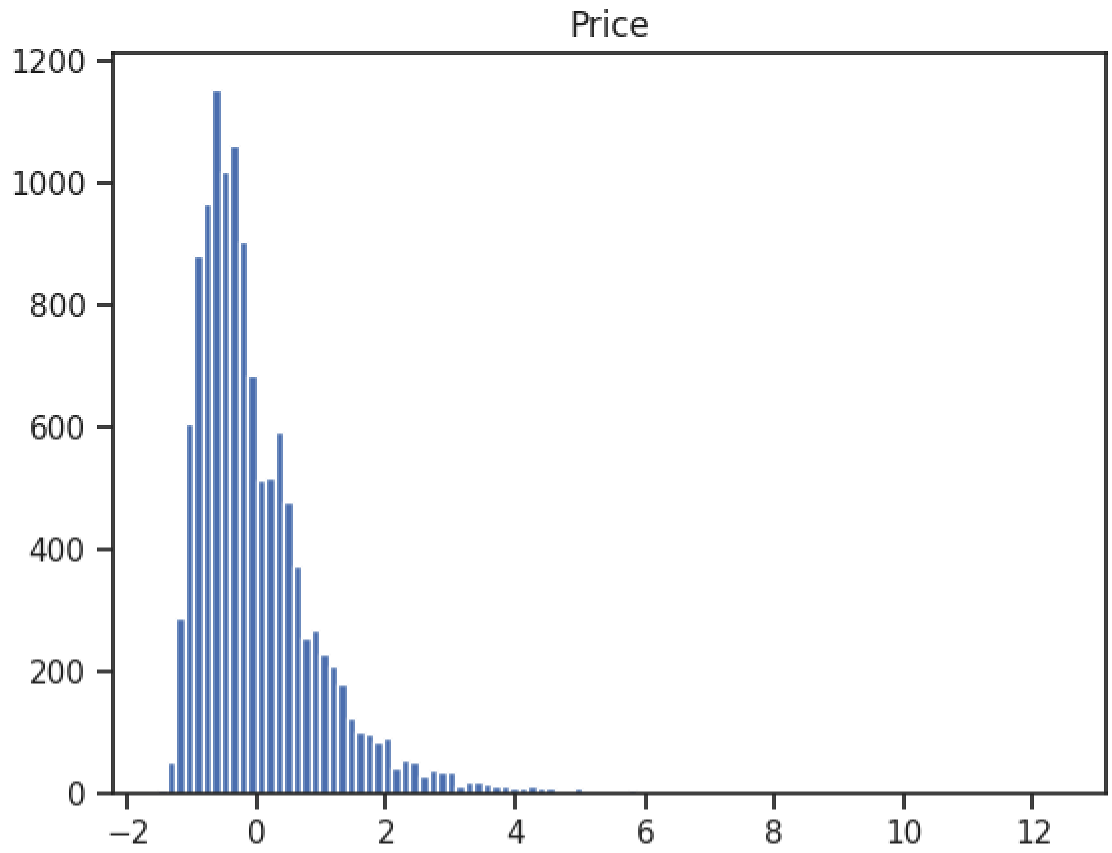
In [34]:
```
sc2_data = pd.DataFrame(sc2_data, columns=data.columns)
```

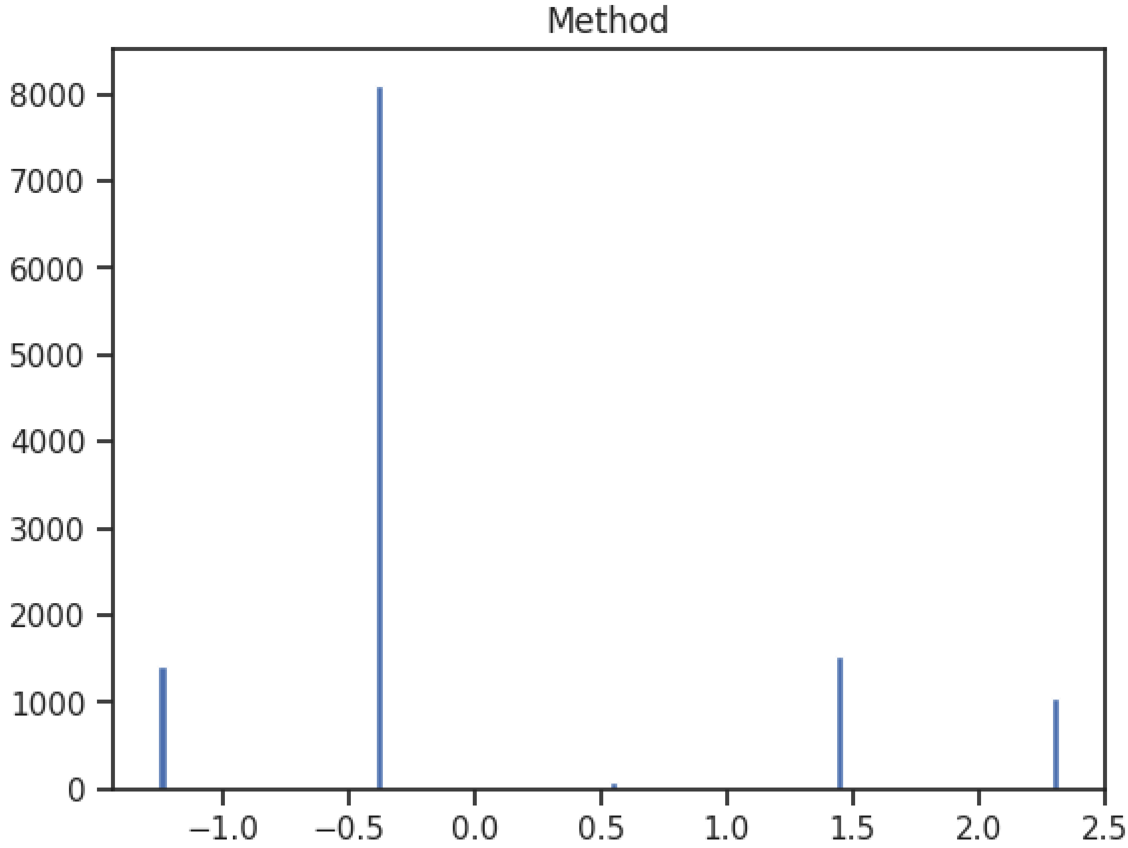
In [35]:
```
# После
for col in data.columns:
    plt.hist(sc2_data[col], 100)
    plt.title(col)
    plt.show()
```

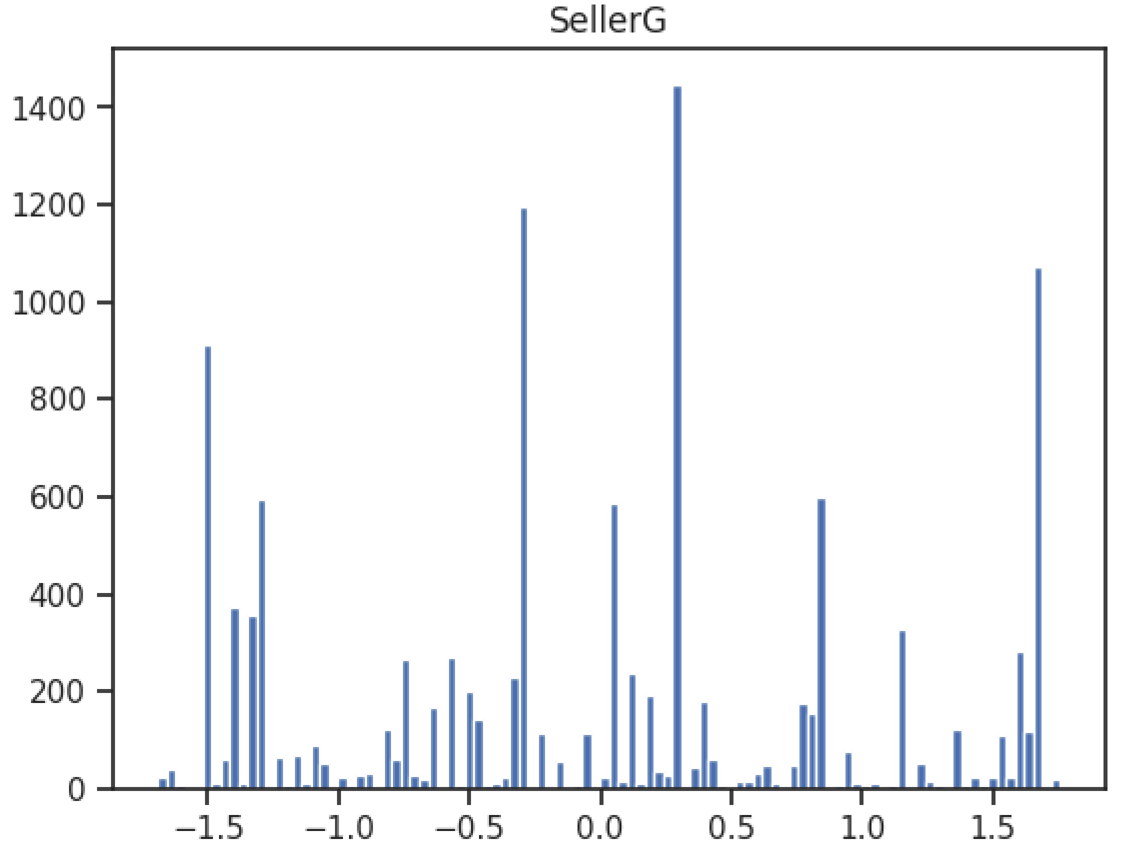

Suburb
600
500
400
300
200
100
0
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5

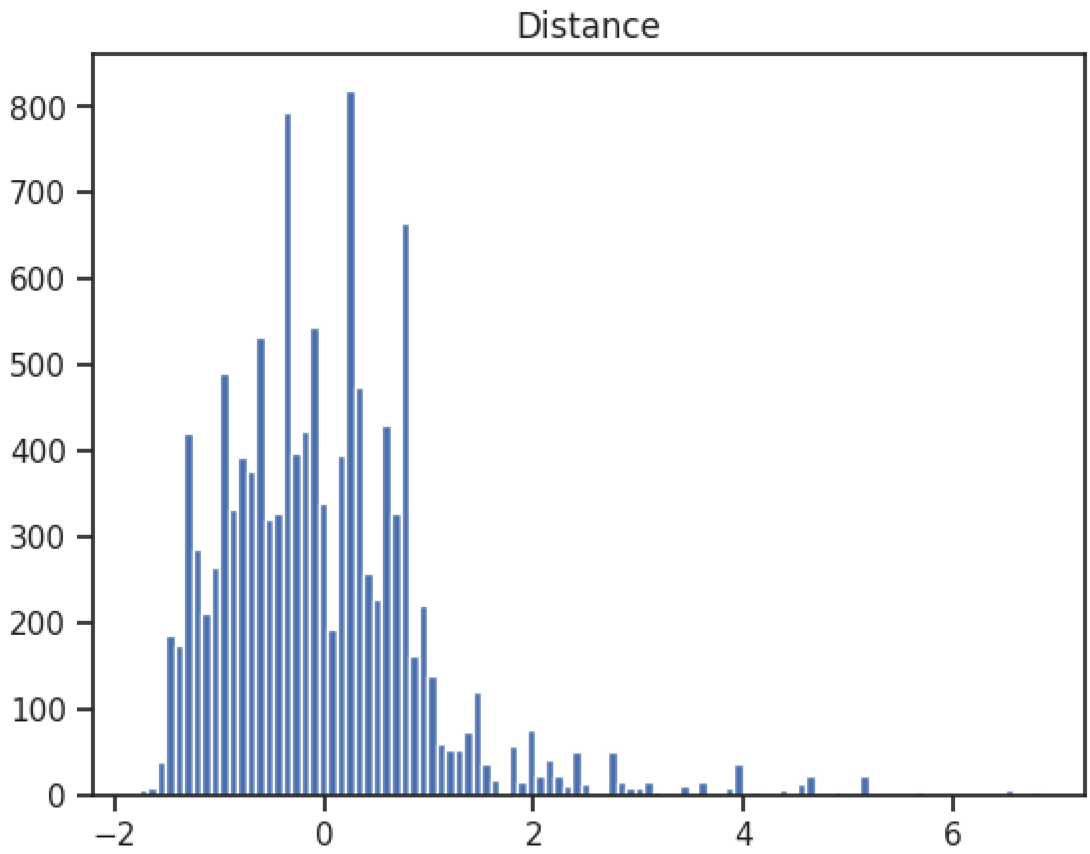

Rooms
5000
4000
3000
2000
1000
0
−2
0
2
4
6

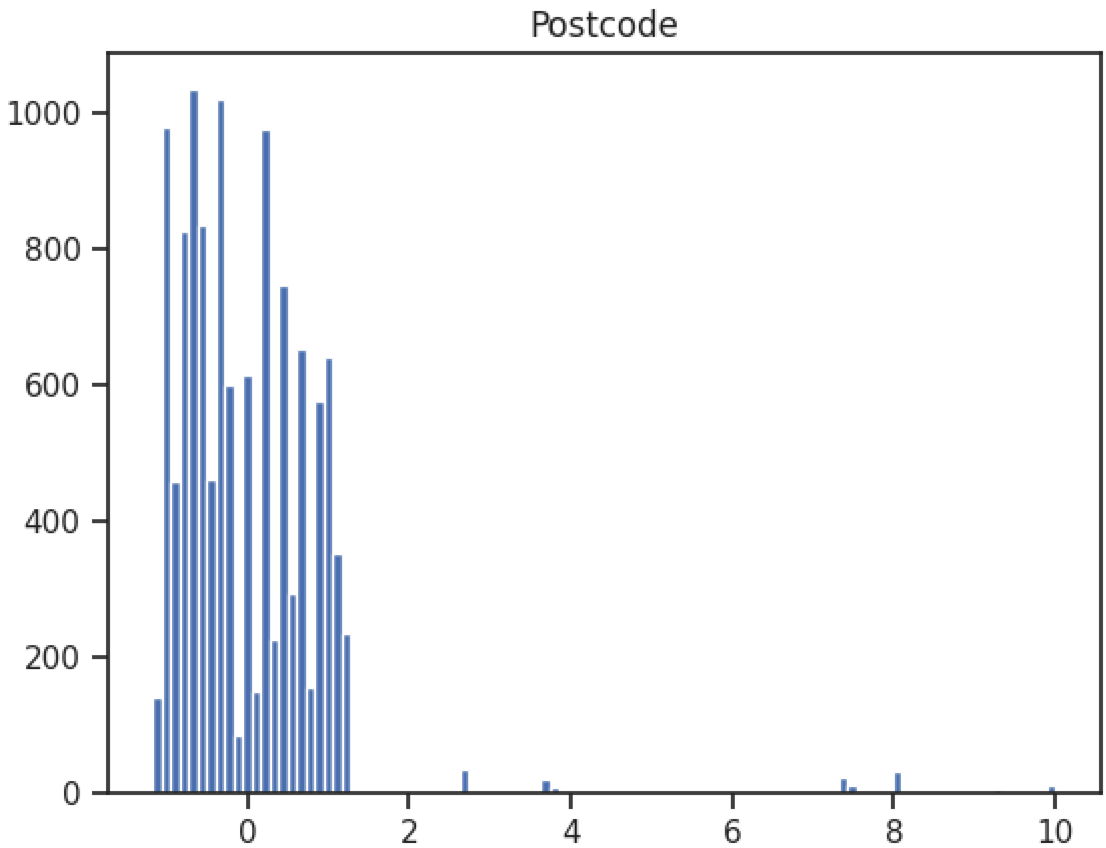

Type
0
1000
2000
3000
4000
5000
6000
7000
8000
−0.5
0.0
0.5
1.0
1.5

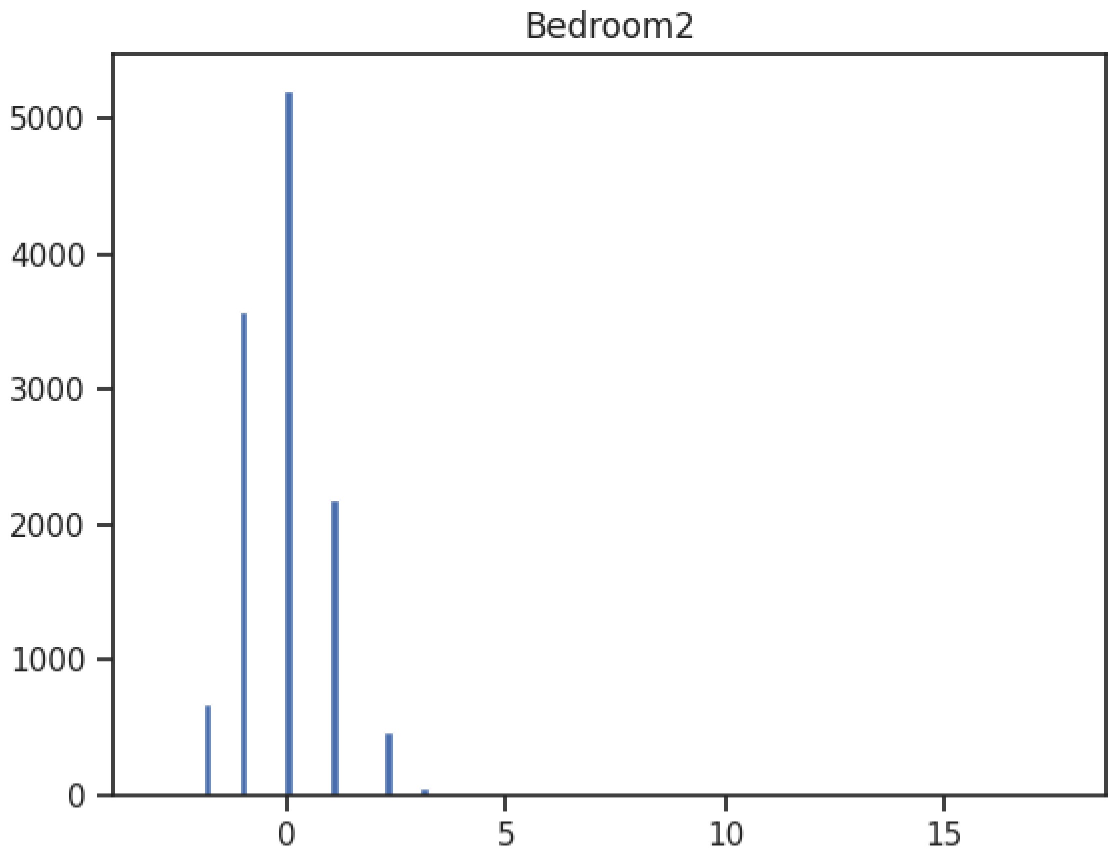

Price
0
200
400
600
800
1000
1200
−2
0
2
4
6
8
10
12


Method
8000
7000
6000
5000
4000
3000
2000
1000
0
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0
2.5

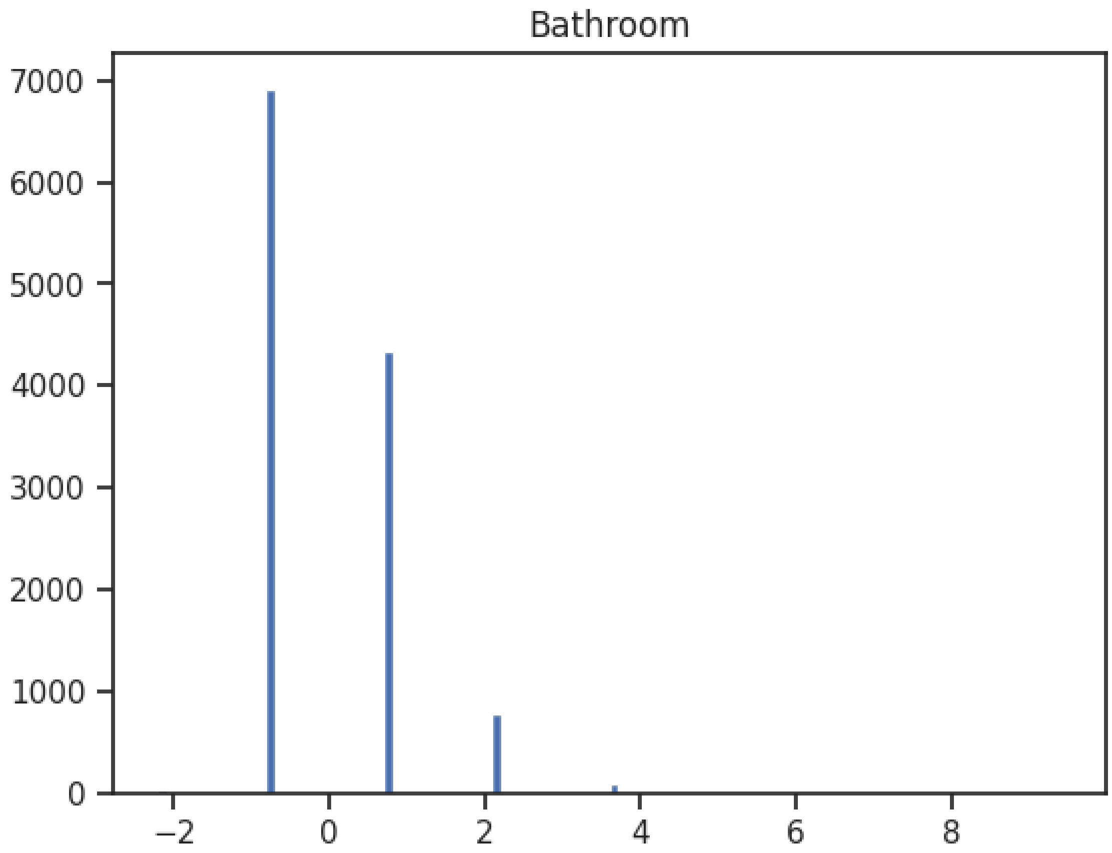

SellerG
1400
1200
1000
800
600
400
200
0
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5


Distance
800
700
600
500
400
300
200
100
0
−2
0
2
4
6

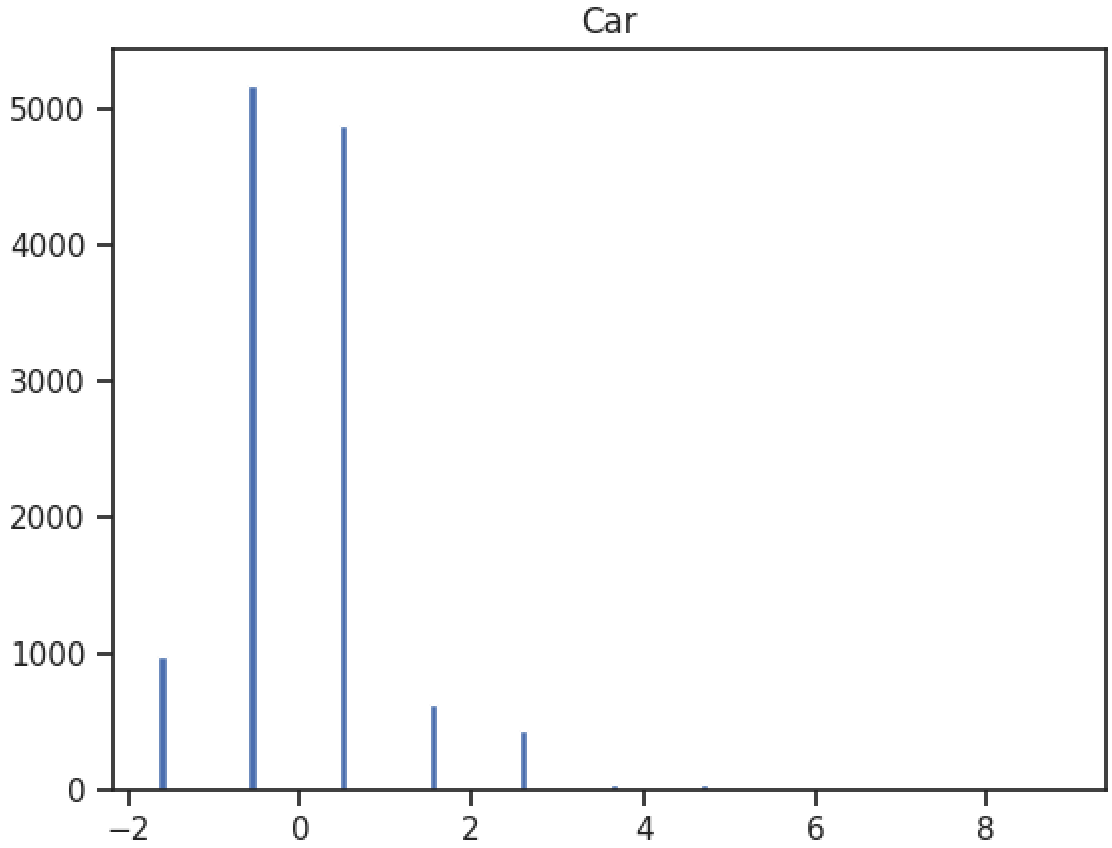

Postcode
1000
800
600
400
200
0
0
2
4
6
8
10



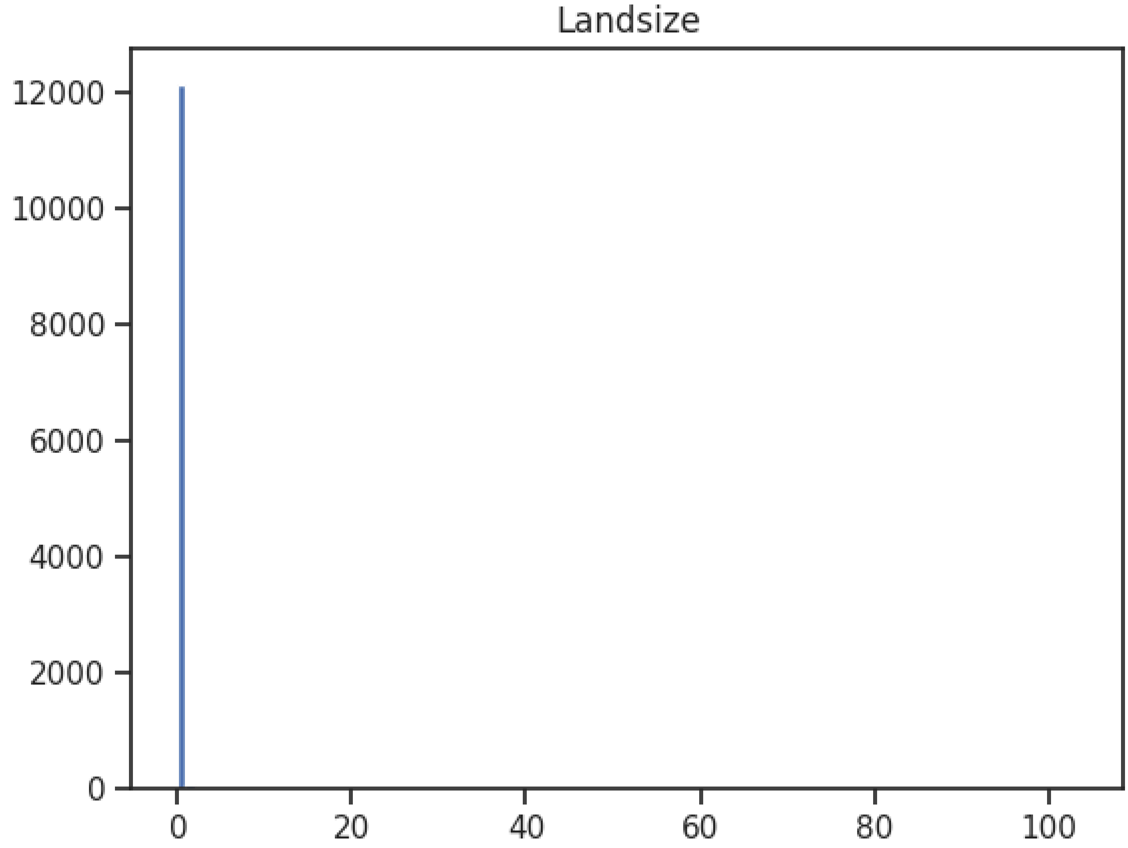
Bedroom2
5000
4000
3000
2000
1000
0
0
5
10
15

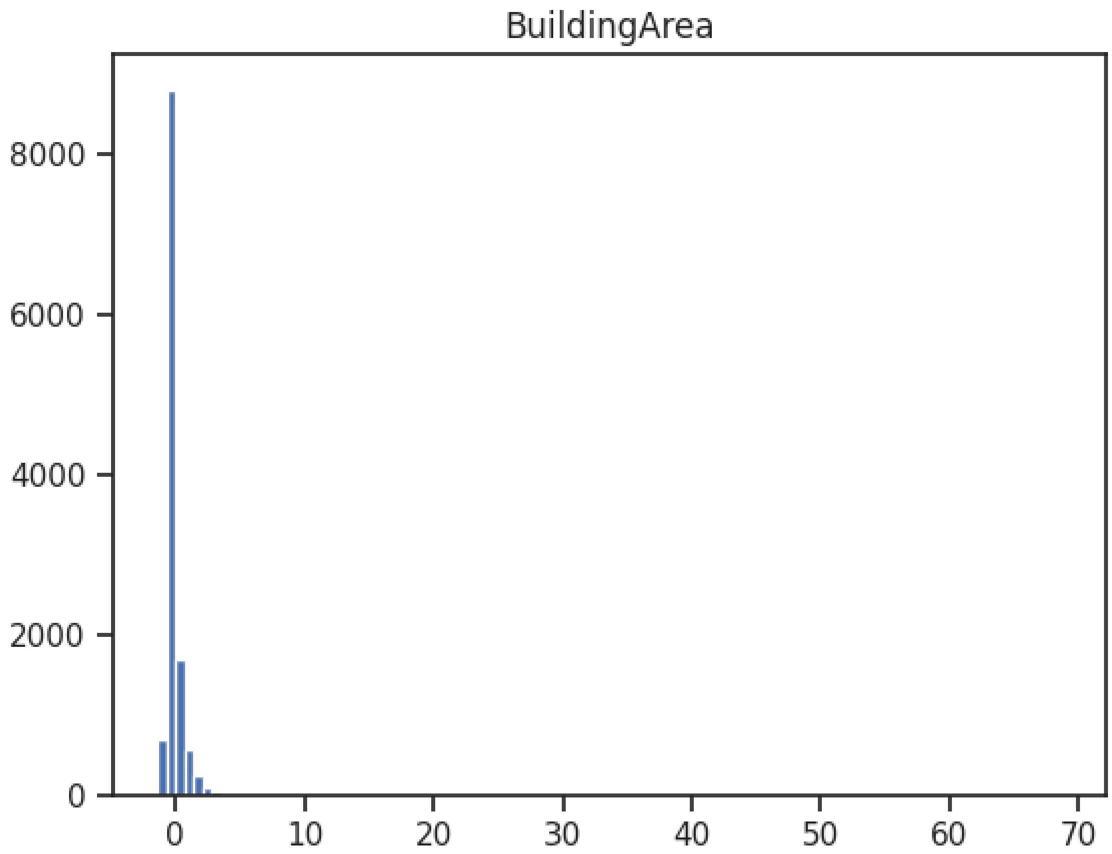
Bathroom
7000
6000
5000
4000
3000
2000
1000
0
−2
0
2
4
6
8

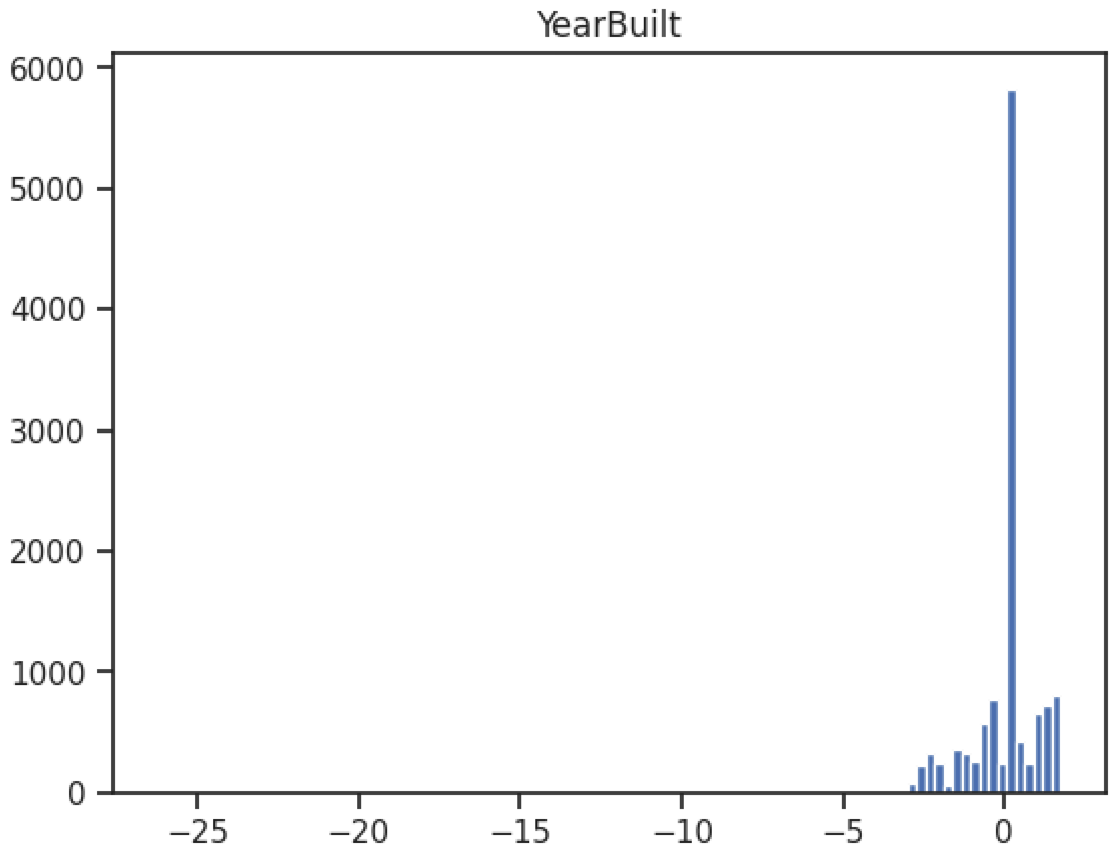


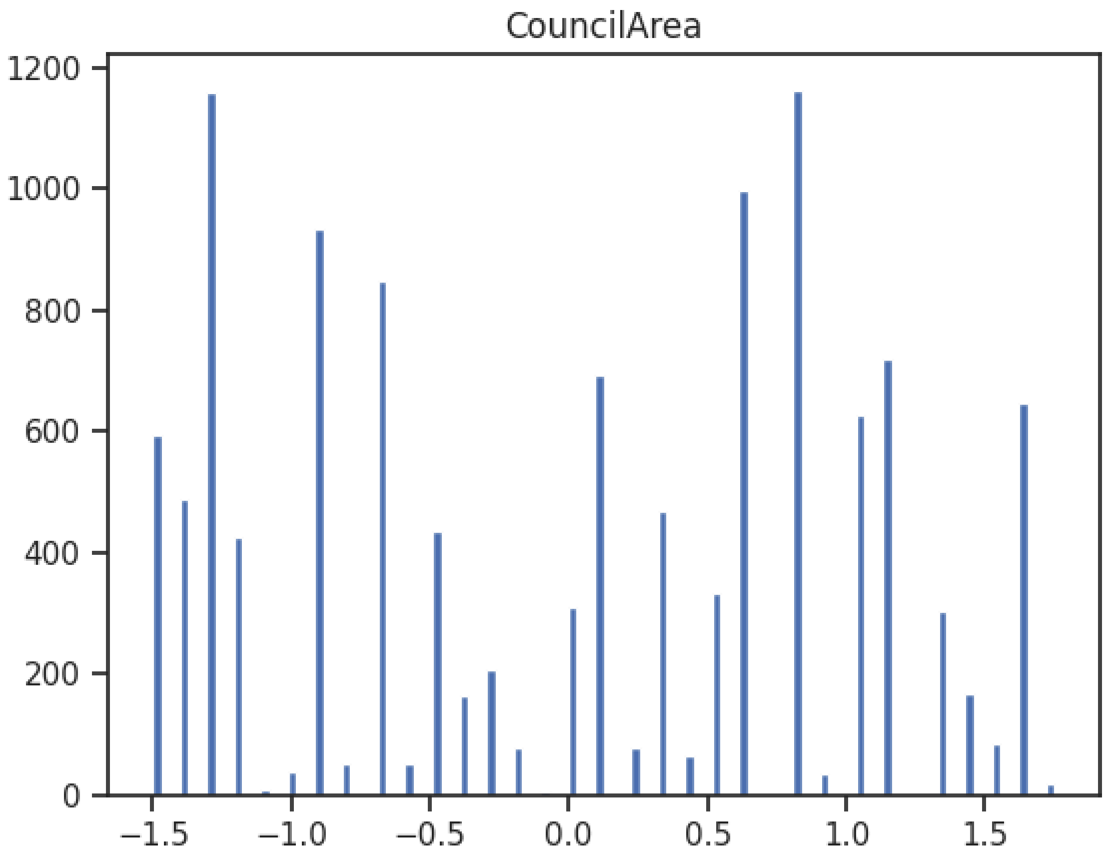
Car
5000
4000
3000
2000
1000
0
−2
0
2
4
6
8

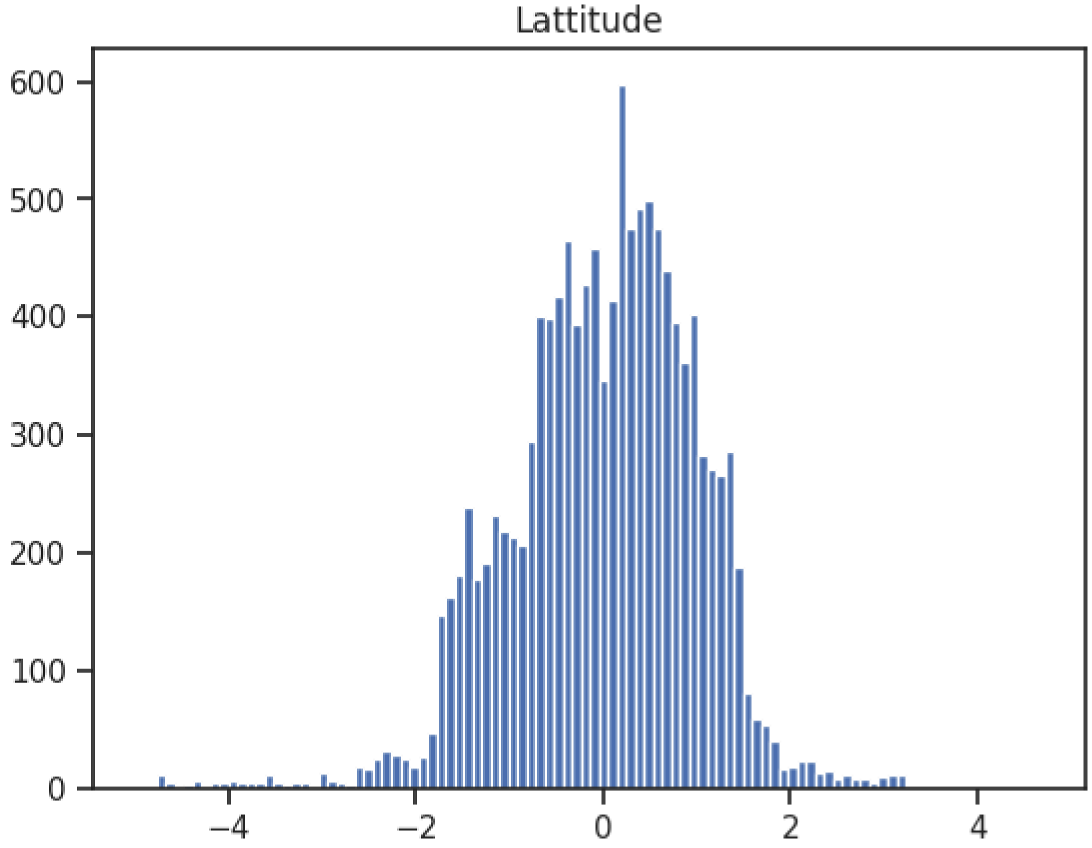



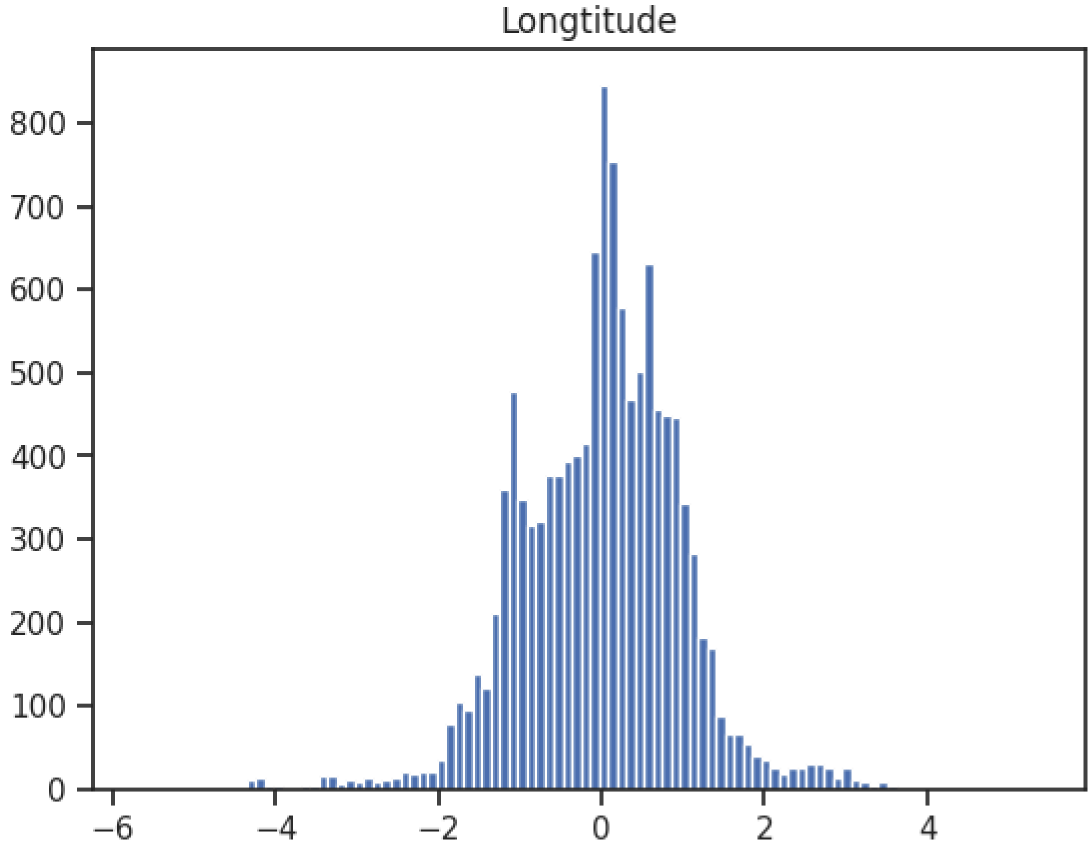
Landsize
12000
10000
8000
6000
4000
2000
0
0
20
40
60
80
100

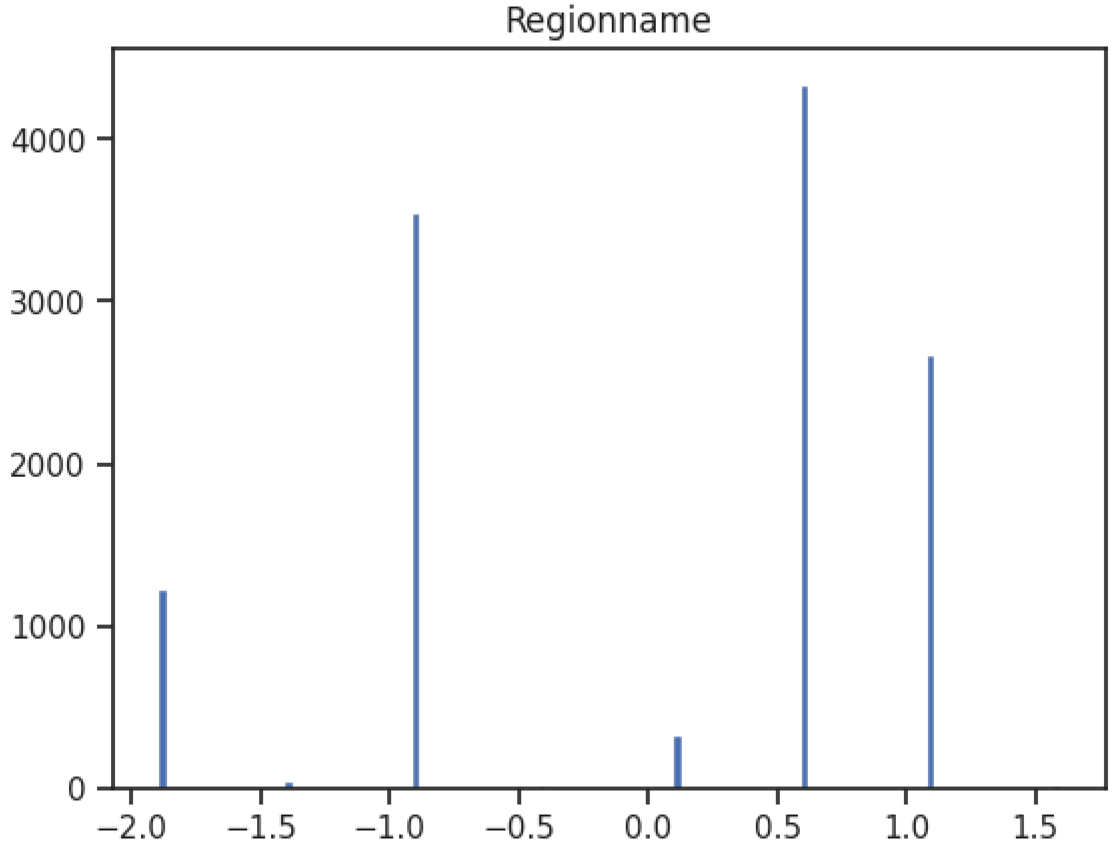

BuildingArea
8000
6000
4000
2000
0
0
10
20
30
40
50
60
70

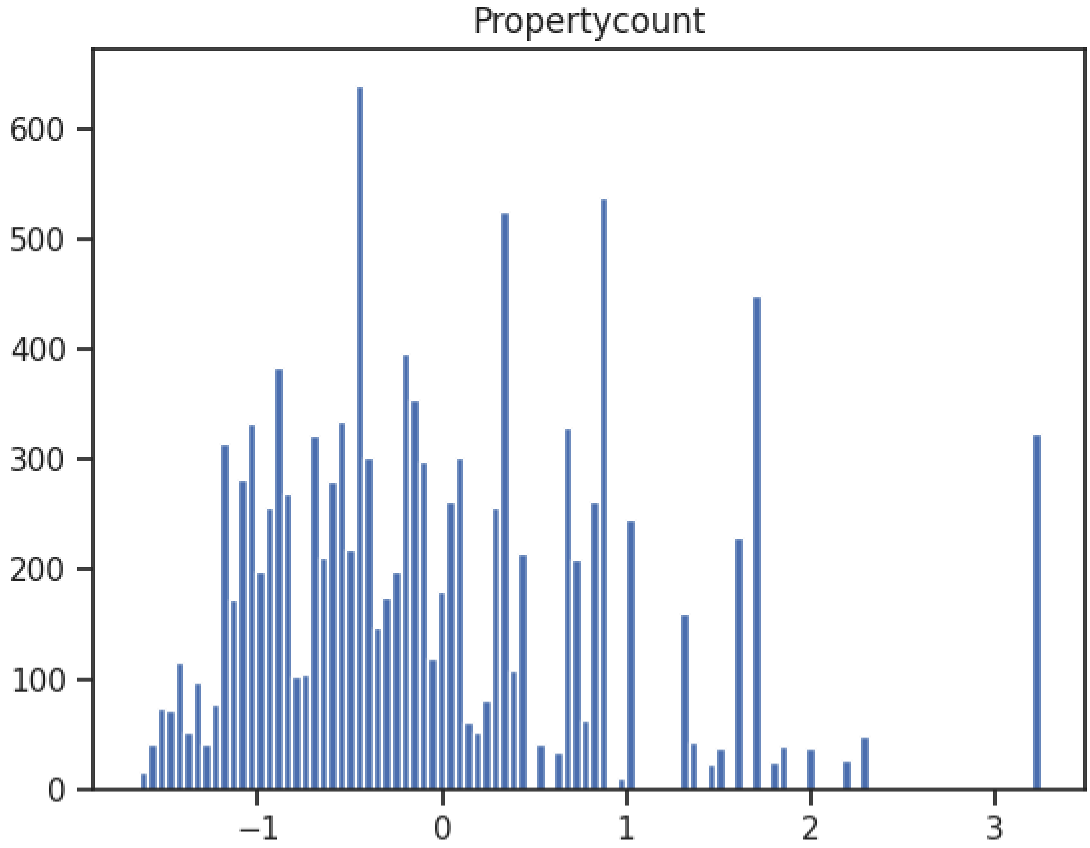

YearBuilt
6000
5000
4000
3000
2000
1000
0
−25
−20
−15
−10
−5
0

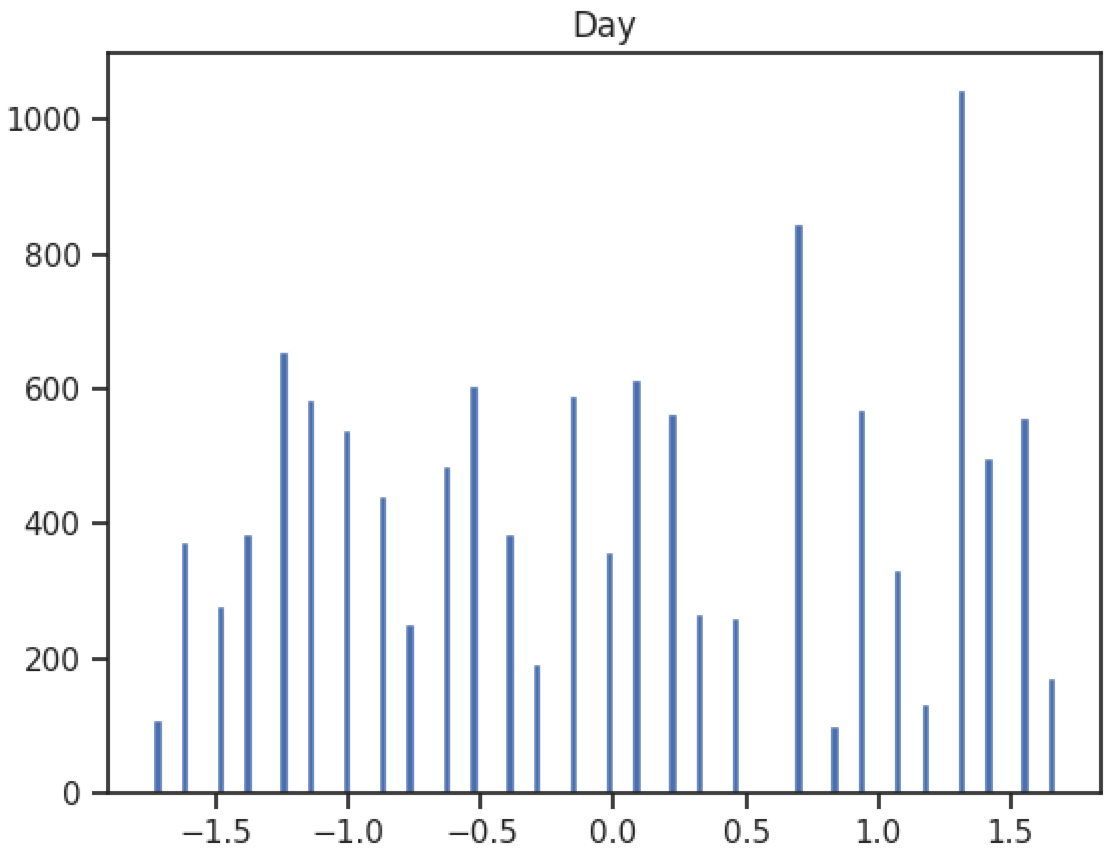

CouncilArea
1200
1000
800
600
400
200
0
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5

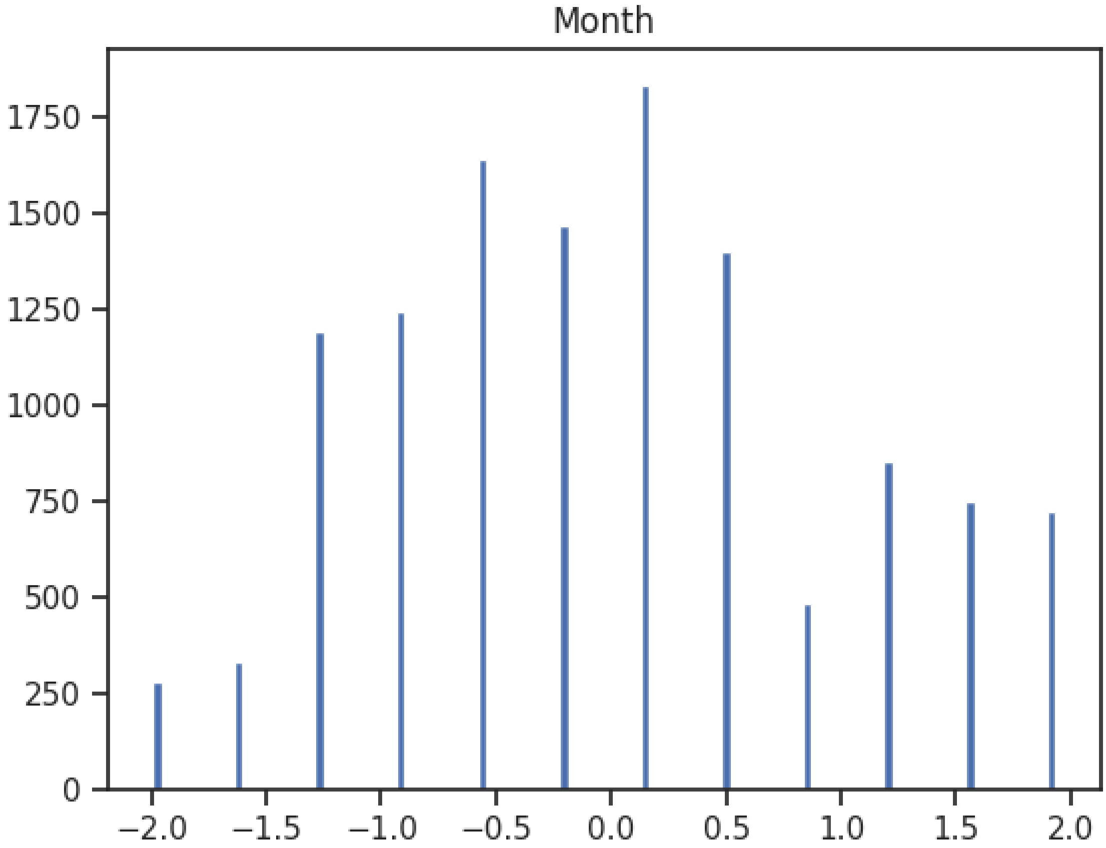

Lattitude
600
500
400
300
200
100
0
−4
−2
0
2
4

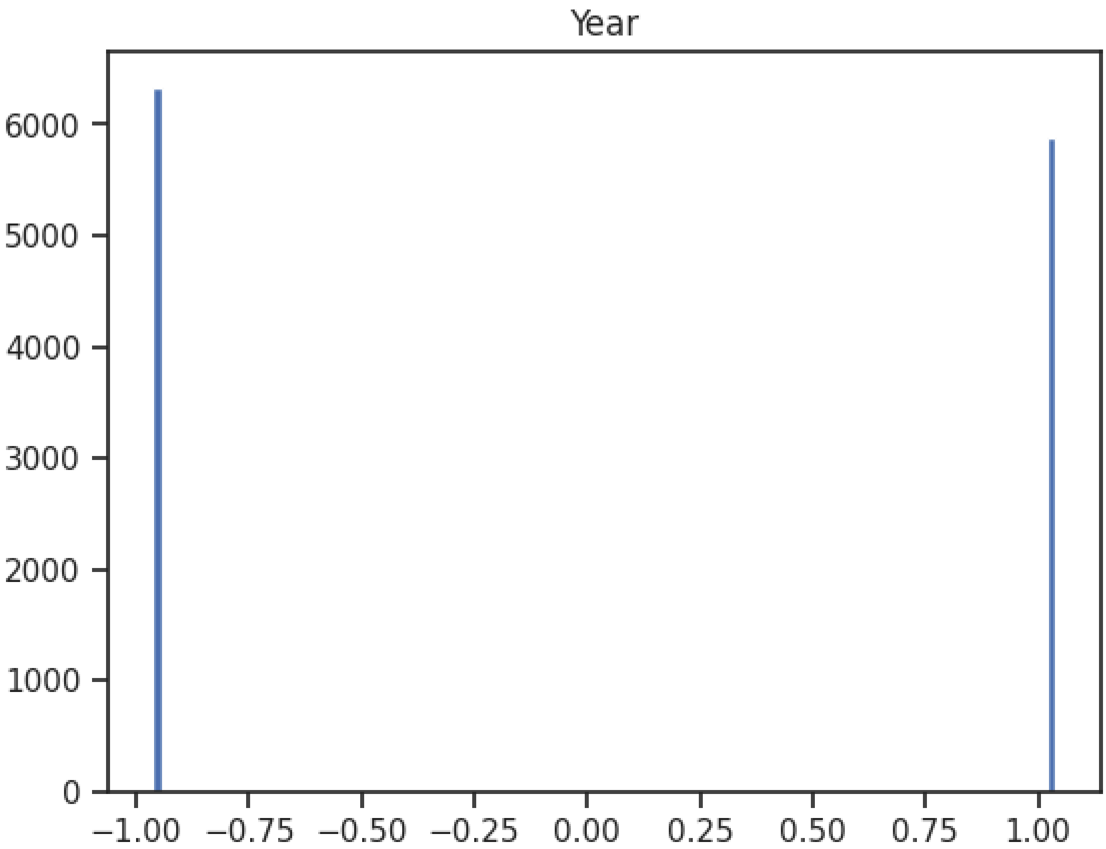

Longtitude
800
700
600
500
400
300
200
100
0
−6
−4
−2
0
2
4

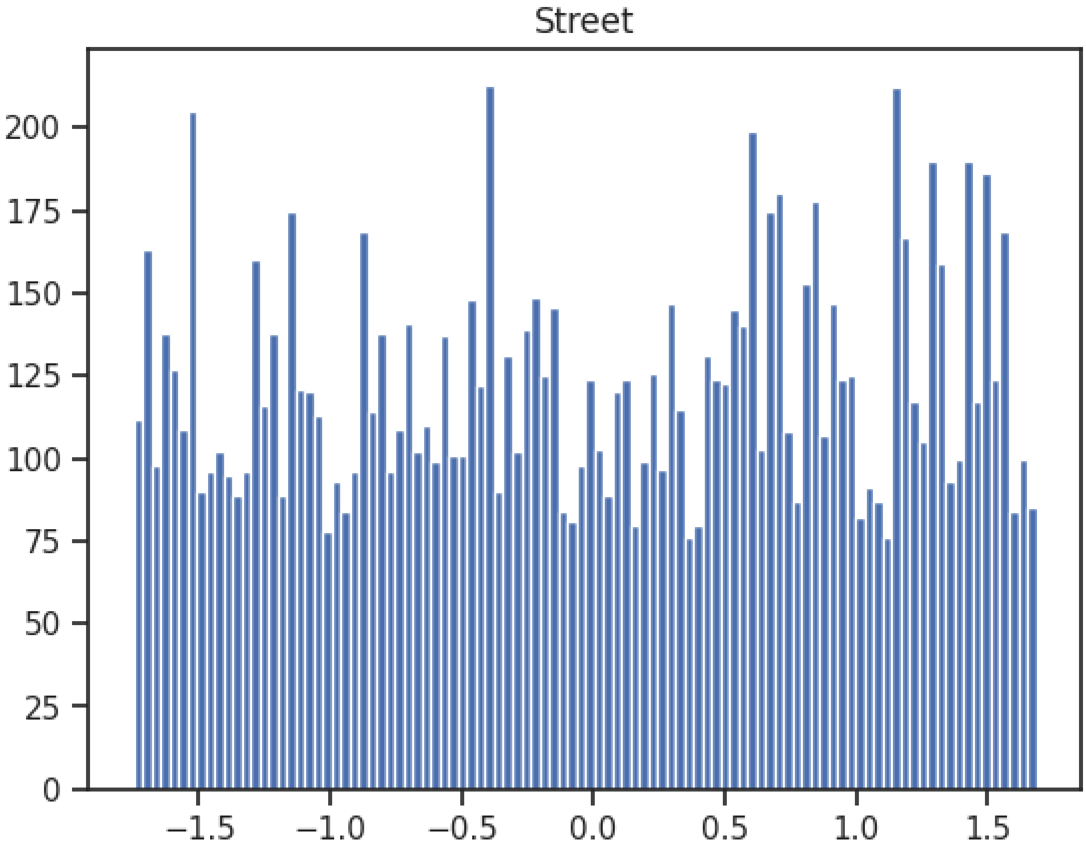

Regionname
4000
3000
2000
1000
0
−2.0
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5


Propertycount
600
500
400
300
200
100
0
−1
0
1
2
3


Day
1000
800
600
400
200
0
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5


Month
0
250
500
750
1000
1250
1500
1750
−2.0
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0


Year
0
1000
2000
3000
4000
5000
6000
−1.00
−0.75
−0.50
−0.25
0.00
0.25
0.50
0.75
1.00




In [ ]:

## Обучение с фиксированным гиперапараметром

In [36]:
```
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsRegressor, KNeighborsClassifier
from sklearn.model_selection import learning_curve, validation_curve
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score, explai
```

In [37]:
```
data = sc2_data
target = sc2_data['Price']

data.drop(columns=['Price'], inplace=True)
```

In [38]:
```
data.shape
```

Out[38]: (12211, 22)

In [39]:
```
data.describe()
```

Out[39]:

| | Suburb | Rooms | Type | Method | SellerG | Distanc |
|---|---|---|---|---|---|---|
| **count** | 1.221100e+04 | 1.221100e+04 | 1.221100e+04 | 1.221100e+04 | 1.221100e+04 | 1.221100e+0 |
| **mean** | -1.675836e-16 | 9.775709e-17 | -5.586119e-17 | -8.728311e-17 | 6.749894e-17 | 4.096487e-1 |
| **std** | 1.000041e+00 | 1.000041e+00 | 1.000041e+00 | 1.000041e+00 | 1.000041e+00 | 1.000041e+0 |
| **min** | -1.713779e+00 | -1.974554e+00 | -6.679092e-01 | -1.256809e+00 | -1.692307e+00 | -1.772836e+0 |
| **25%** | -9.609414e-01 | -9.321296e-01 | -6.679092e-01 | -3.618941e-01 | -7.344135e-01 | -7.016215e-0 |
| **50%** | 5.387686e-03 | 1.102950e-01 | -6.679092e-01 | -3.618941e-01 | 5.926979e-02 | -1.024677e-0 |
| **75%** | 8.593529e-01 | 1.102950e-01 | 5.023935e-01 | -3.618941e-01 | 8.119005e-01 | 5.148423e-0 |
| **max** | 1.735791e+00 | 7.407267e+00 | 1.672696e+00 | 2.322850e+00 | 1.756110e+00 | 6.833191e+0 |

8 rows × 22 columns

In [40]:

```
target.describe()
```

Out[40]:

```
count    1.221100e+04
mean    -1.629285e-16
std      1.000041e+00
min     -1.531994e+00
25%     -6.632256e-01
50%     -2.640617e-01
75%      4.012117e-01
max      1.242309e+01
Name: Price, dtype: float64
```

In [41]:

```
X_train, X_test, y_train, y_test = train_test_split(
    data, target, test_size=0.5, random_state=1)
```

In [42]:

```
K = 70

cl = KNeighborsRegressor(n_neighbors=K)
cl.fit(X_train, y_train)
target_train = cl.predict(X_train)
target_test = cl.predict(X_test)
```

In [43]:

```
def scorer(y_true, y_pred):
    scores = {
        'r2': r2_score,
        'mean_squared_error': mean_squared_error,
        'mean_absolute_error': mean_absolute_error,
        'r2_score': r2_score,
        'explained_variance_score': explained_variance_score,
        'mean_pinball_loss': mean_pinball_loss,
        'd2_pinball_score': d2_pinball_score,
        'd2_absolute_error_score': d2_absolute_error_score
    }

    for score, score_func in scores.items():
        scores[score] = score_func(y_true, y_pred)
    return scores
```

In [44]:

```
print('Train: ', scorer(y_train, target_train))
print()
print('Test :', scorer(y_test, target_test))
```

```
Train:  {'r2': 0.6074478363288117, 'mean_squared_error': 0.4054128638342073, 'mean_abs
olute_error': 0.38465733025879834, 'r2_score': 0.6074478363288117, 'explained_variance
_score': 0.6080485130705291, 'mean_pinball_loss': 0.19232866512939917, 'd2_pinball_sco
re': 0.4454301531494722, 'd2_absolute_error_score': 0.4454301531494722}

Test : {'r2': 0.6358064659388151, 'mean_squared_error': 0.3521518459937633, 'mean_abso
lute_error': 0.3775204179759272, 'r2_score': 0.6358064659388151, 'explained_variance_s
core': 0.6359862432962011, 'mean_pinball_loss': 0.1887602089879636, 'd2_pinball_scor
e': 0.4426146306868046, 'd2_absolute_error_score': 0.4426146306868046}
```

# Поиск лучших гиперпараметров

In [45]:
```python
from sklearn.model_selection import KFold, RepeatedKFold, LeaveOneOut, LeavePOut, Shu
from sklearn.model_selection import GridSearchCV, RandomizedSearchCV
```

## Вспомогательные функции

In [46]:
```python
def plot_validation_curve(estimator, title, X, y,
                          param_name, param_range, cv,
                          scoring='accuracy'):

    train_scores, test_scores = validation_curve(
        estimator, X, y, param_name=param_name, param_range=param_range,
        cv=cv, scoring=scoring, n_jobs=1)
    train_scores_mean = np.mean(train_scores, axis=1)
    train_scores_std = np.std(train_scores, axis=1)
    test_scores_mean = np.mean(test_scores, axis=1)
    test_scores_std = np.std(test_scores, axis=1)

    plt.title(title)
    plt.xlabel(param_name)
    plt.ylabel(str(scoring))
    # plt.ylim(0.0, 1.1)
    lw = 2
    plt.plot(param_range, train_scores_mean, label="Training score",
                 color="darkorange", lw=lw)
    plt.fill_between(param_range, train_scores_mean - train_scores_std,
                     train_scores_mean + train_scores_std, alpha=0.4,
                     color="darkorange", lw=lw)
    plt.plot(param_range, test_scores_mean, label="Cross-validation score",
                 color="navy", lw=lw)
    plt.fill_between(param_range, test_scores_mean - test_scores_std,
                     test_scores_mean + test_scores_std, alpha=0.2,
                     color="navy", lw=lw)
    plt.legend(loc="best")
    return plt
```

In [47]:
```python
def plot_learning_curve(estimator, title, X, y, ylim=None, cv=None,
                        n_jobs=None, train_sizes=np.linspace(.1, 1.0, 5), scoring='ac
    """
    Generate a simple plot of the test and training learning curve.

    Parameters
    ----------
    estimator : object type that implements the "fit" and "predict" methods
        An object of that type which is cloned for each validation.

    title : string
        Title for the chart.

    X : array-like, shape (n_samples, n_features)
        Training vector, where n_samples is the number of samples and
        n_features is the number of features.
```

```
    y : array-like, shape (n_samples) or (n_samples, n_features), optional
        Target relative to X for classification or regression;
        None for unsupervised learning.

    ylim : tuple, shape (ymin, ymax), optional
        Defines minimum and maximum yvalues plotted.

    cv : int, cross-validation generator or an iterable, optional
        Determines the cross-validation splitting strategy.
        Possible inputs for cv are:
          - None, to use the default 3-fold cross-validation,
          - integer, to specify the number of folds.
          - :term:`CV splitter`,
          - An iterable yielding (train, test) splits as arrays of indices.

        For integer/None inputs, if ``y`` is binary or multiclass,
        :class:`StratifiedKFold` used. If the estimator is not a classifier
        or if ``y`` is neither binary nor multiclass, :class:`KFold` is used.

        Refer :ref:`User Guide <cross_validation>` for the various
        cross-validators that can be used here.

    n_jobs : int or None, optional (default=None)
        Number of jobs to run in parallel.
        ``None`` means 1 unless in a :obj:`joblib.parallel_backend` context.
        ``-1`` means using all processors. See :term:`Glossary <n_jobs>`
        for more details.

    train_sizes : array-like, shape (n_ticks,), dtype float or int
        Relative or absolute numbers of training examples that will be used to
        generate the learning curve. If the dtype is float, it is regarded as a
        fraction of the maximum size of the training set (that is determined
        by the selected validation method), i.e. it has to be within (0, 1].
        Otherwise it is interpreted as absolute sizes of the training sets.
        Note that for classification the number of samples usually have to
        be big enough to contain at least one sample from each class.
        (default: np.linspace(0.1, 1.0, 5))
    """
    plt.figure()
    plt.title(title)
    if ylim is not None:
        plt.ylim(*ylim)
    plt.xlabel("Training examples")
    plt.ylabel(scoring)
    train_sizes, train_scores, test_scores = learning_curve(
        estimator, X, y, cv=cv, scoring=scoring, n_jobs=n_jobs, train_sizes=train_siz
    train_scores_mean = np.mean(train_scores, axis=1)
    train_scores_std = np.std(train_scores, axis=1)
    test_scores_mean = np.mean(test_scores, axis=1)
    test_scores_std = np.std(test_scores, axis=1)
    plt.grid()

    plt.fill_between(train_sizes, train_scores_mean - train_scores_std,
                     train_scores_mean + train_scores_std, alpha=0.3,
                     color="r")
    plt.fill_between(train_sizes, test_scores_mean - test_scores_std,
                     test_scores_mean + test_scores_std, alpha=0.1, color="g")
    plt.plot(train_sizes, train_scores_mean, 'o-', color="r",
             label="Training score")
    plt.plot(train_sizes, test_scores_mean, 'o-', color="g",
             label="Cross-validation score")

    plt.legend(loc="best")
    return plt
```

In [48]:
```
def get_best_param_for_score(results, score):
    return results['params'][np.where(results[f"rank_test_{score}"] == 1)[0][0]]

def get_best_param_for_scores(results, scores):
    return {score: get_best_param_for_score(results, score) for score in scores}
```

In [68]:
```
def show_plots_for_scores(n_range, results, scores):
    for score in scores:
        plt.plot(n_range, results[f"mean_test_{score}"])
        plt.title(score)
        plt.show()
```

## Поиск

In [50]:
```
scores = [
        'r2',
        'neg_mean_squared_error',
        'neg_mean_absolute_error',
]
```

### RandomizedSearch + KFolds

In [51]:
```
n_range_1 = np.array(range(3,100,10))
tuned_parameters_1 = [{'n_neighbors': n_range_1}]
tuned_parameters_1
```

Out[51]:
```
[{'n_neighbors': array([ 3, 13, 23, 33, 43, 53, 63, 73, 83, 93])}]
```

In [52]:
```
data.shape
```

Out[52]:
```
(12211, 22)
```

In [53]:
```
kf = KFold(n_splits=24) # 500 samples for 1 fold
```

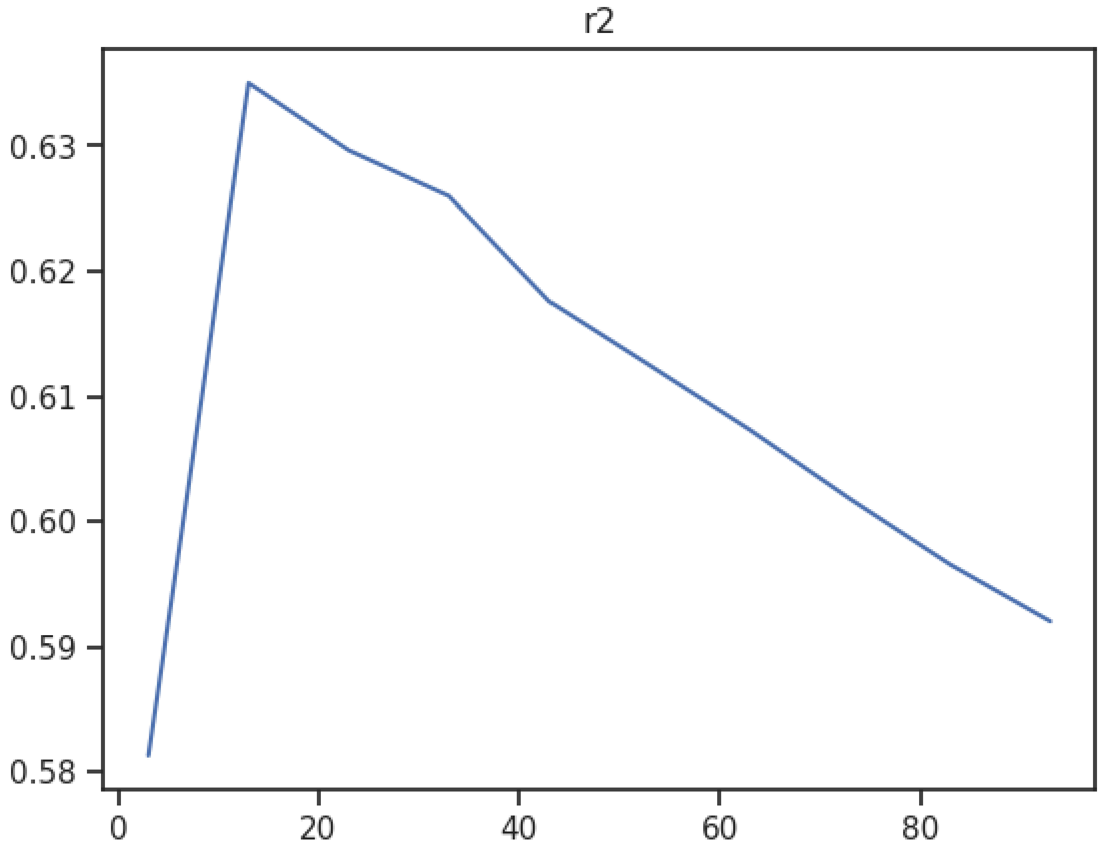
In [54]:
```
%%time
clf_rs = RandomizedSearchCV(KNeighborsRegressor(), tuned_parameters_1, cv=kf, scoring
s = clf_rs.fit(X_train, y_train)
```

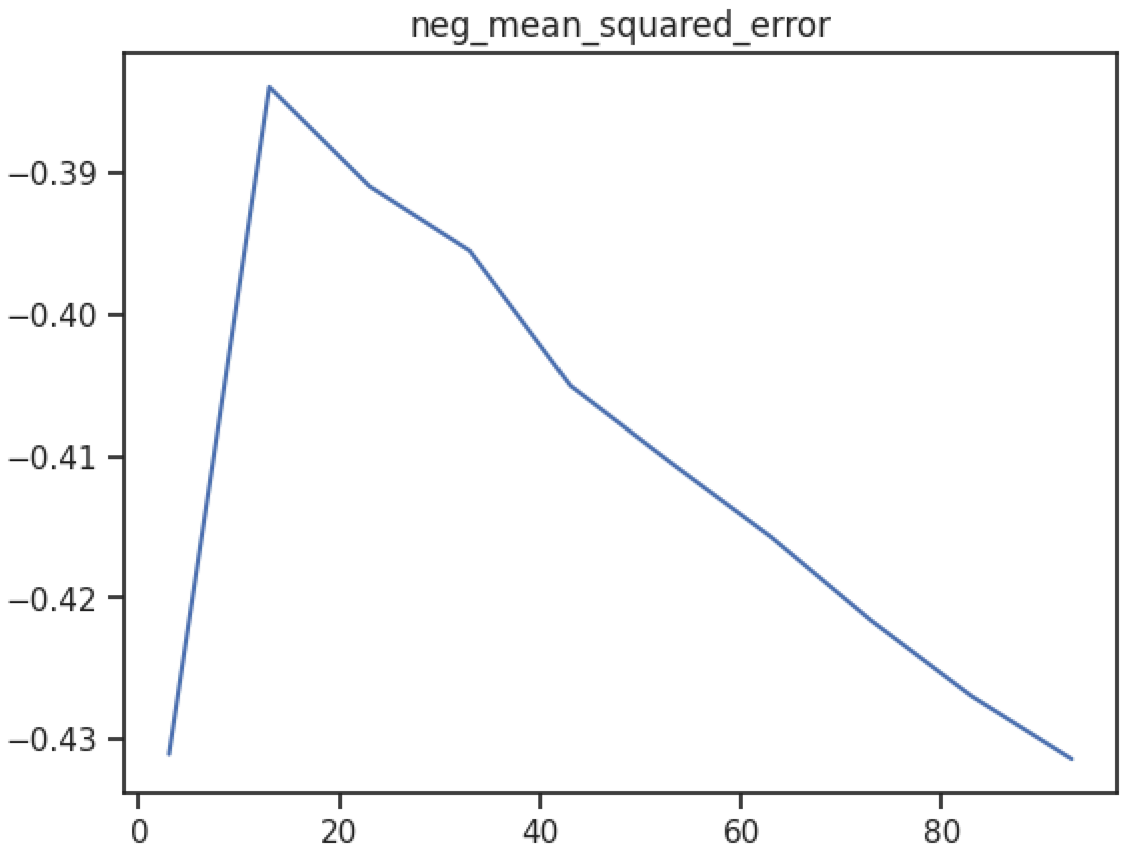
```
CPU times: user 14.7 s, sys: 39.4 ms, total: 14.8 s
Wall time: 4.12 s
```

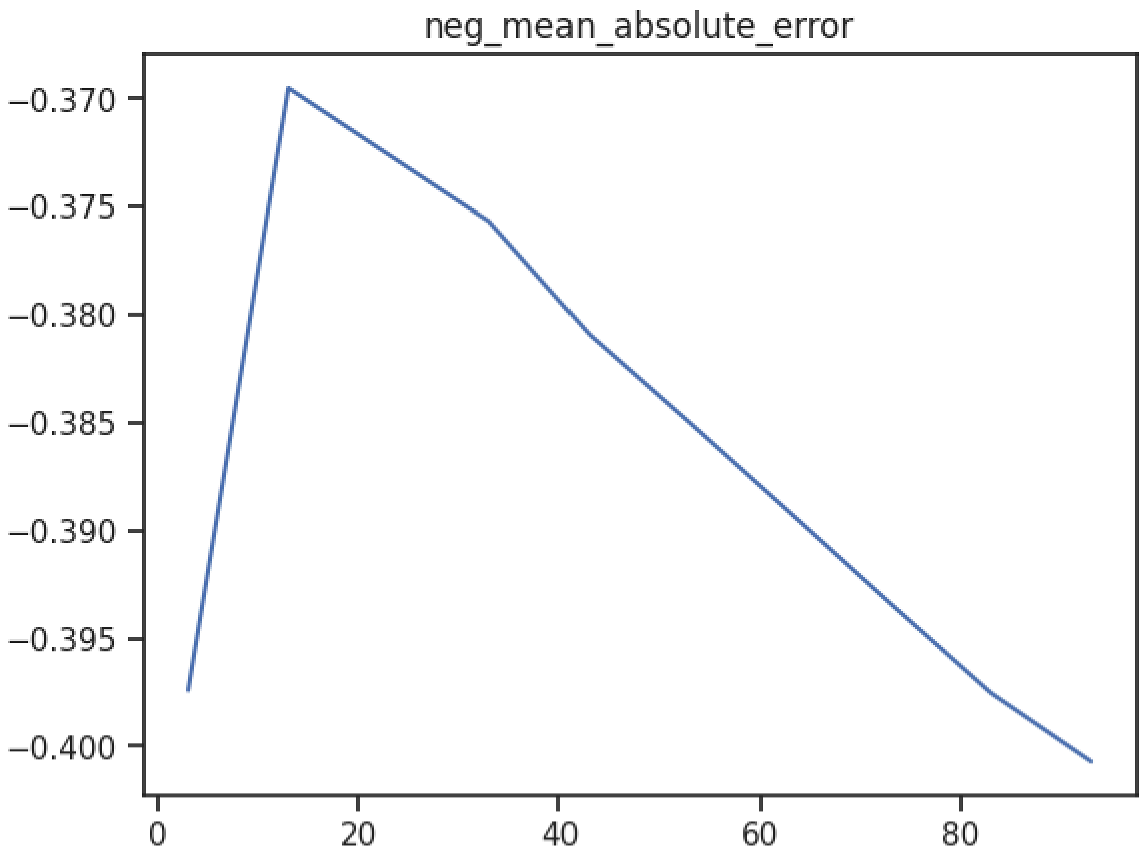
In [55]:
```
get_best_param_for_scores(clf_rs.cv_results_, scores)
```

Out[55]:
```
{'r2': {'n_neighbors': 13},
 'neg_mean_squared_error': {'n_neighbors': 13},
 'neg_mean_absolute_error': {'n_neighbors': 13}}
```

In [69]:
```
show_plots_for_scores(n_range_1, clf_rs.cv_results_, scores)
```


r2
0.63
0.62
0.61
0.60
0.59
0.58
0
20
40
60
80


neg_mean_squared_error
−0.39
−0.40
−0.41
−0.42
−0.43
0
20
40
60
80




GridSearch + LeavePOut folds

In [57]:
```
n_range_2 = np.array(range(10,20,1))
tuned_parameters_2 = [{'n_neighbors': n_range_2}]
tuned_parameters_2
```

Out[57]: `[{'n_neighbors': array([10, 11, 12, 13, 14, 15, 16, 17, 18, 19])}]`

In [58]:
```
data.shape[0] / 3
```

Out[58]: `4070.3333333333335`

In [62]:
```
rkf = RepeatedKFold(n_splits=12, n_repeats=2)
len(list(rkf.split(X_train, y_train)))
```

Out[62]: `24`

In [63]:
```
%%time
clf_gs = GridSearchCV(KNeighborsRegressor(), tuned_parameters_2, cv=rkf, scoring=scor
clf_gs.fit(X_train, y_train)
```

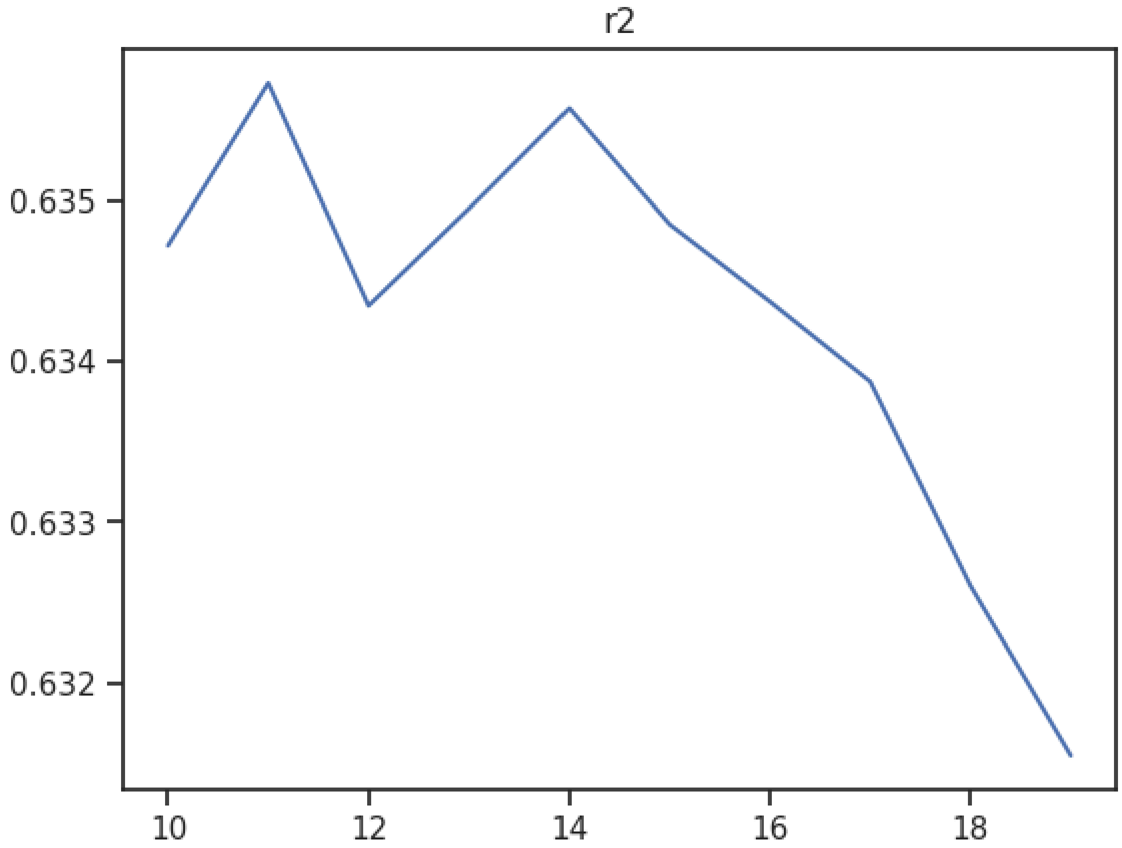
```
CPU times: user 15.6 s, sys: 23.4 ms, total: 15.6 s
Wall time: 4.46 s
```

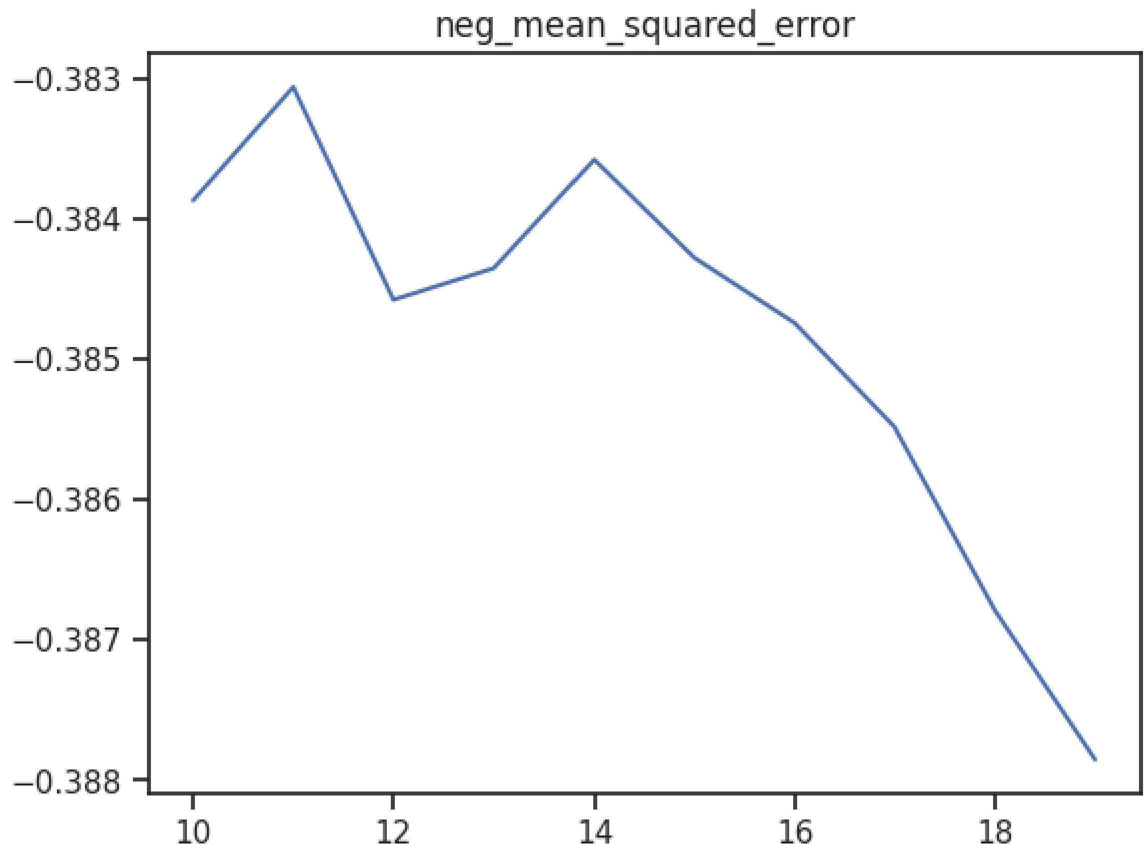
Out[63]:
```
▸ GridSearchCV
▸ estimator: KNeighborsRegressor
▸ KNeighborsRegressor
```

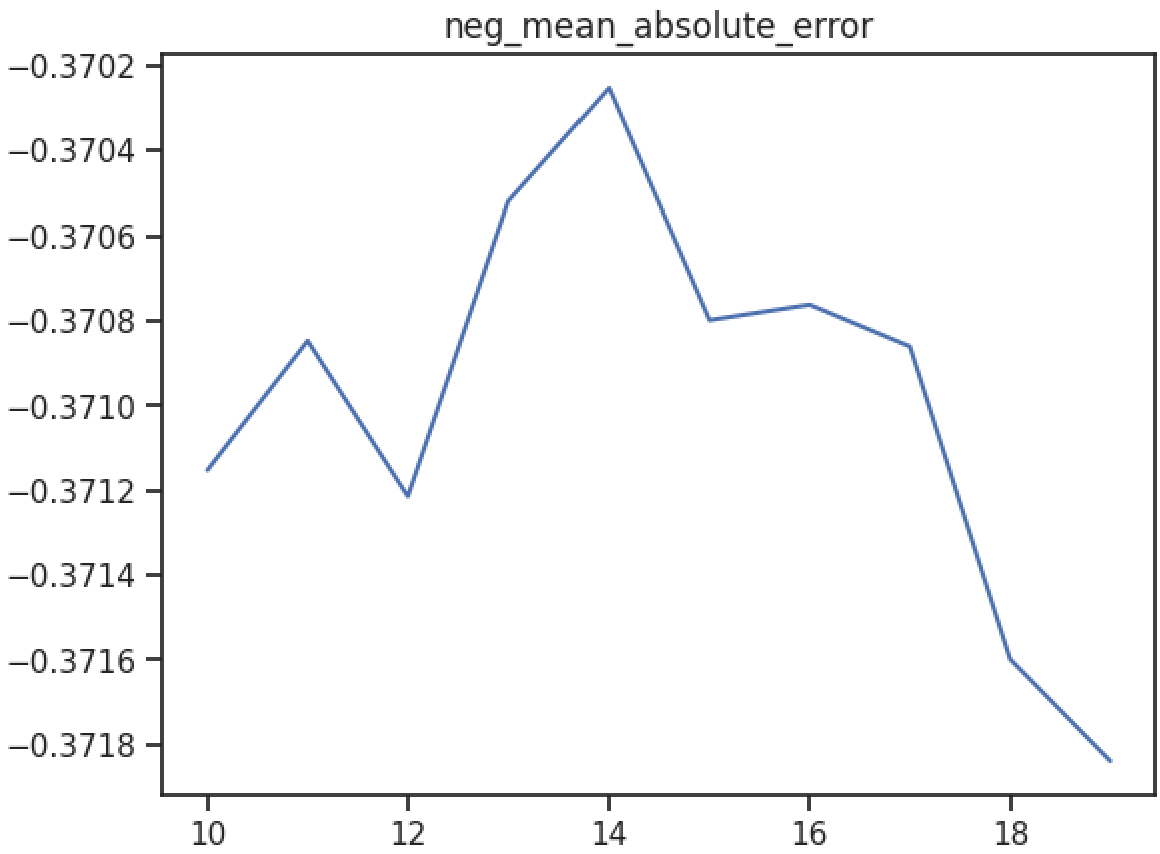
In [71]:
```
get_best_param_for_scores(clf_gs.cv_results_, scores)
```

Out[71]:
```
{'r2': {'n_neighbors': 11},
 'neg_mean_squared_error': {'n_neighbors': 11},
 'neg_mean_absolute_error': {'n_neighbors': 14}}
```

In [70]:
```
show_plots_for_scores(n_range_2, clf_gs.cv_results_, scores)
```


r2
0.635
0.634
0.633
0.632
10
12
14
16
18

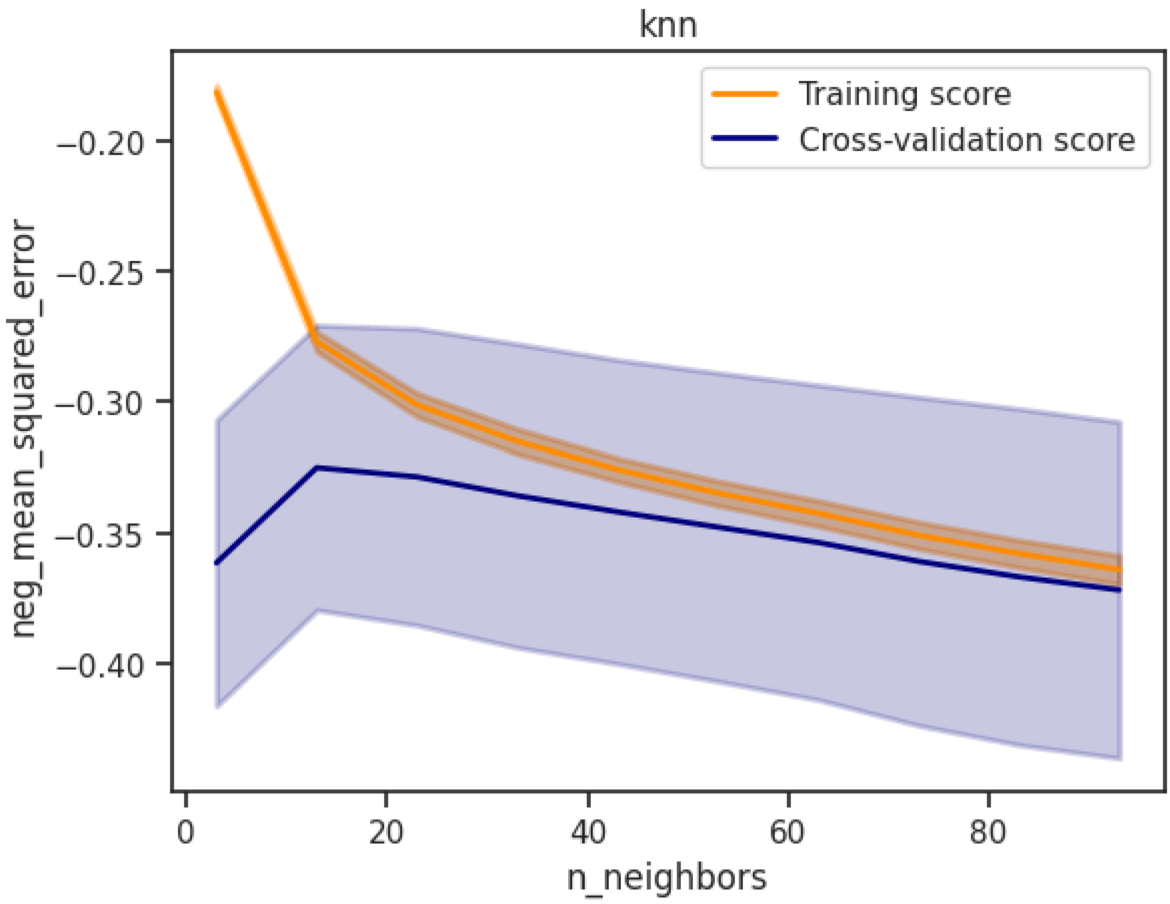

neg_mean_squared_error
−0.383
−0.384
−0.385
−0.386
−0.387
−0.388
10
12
14
16
18




Validation curve

In [76]:
```
plot_validation_curve(KNeighborsRegressor(), 'knn',
                      X_test, y_test,
                      param_name='n_neighbors', param_range=n_range_1,
                      cv=12, scoring='neg_mean_squared_error')
```

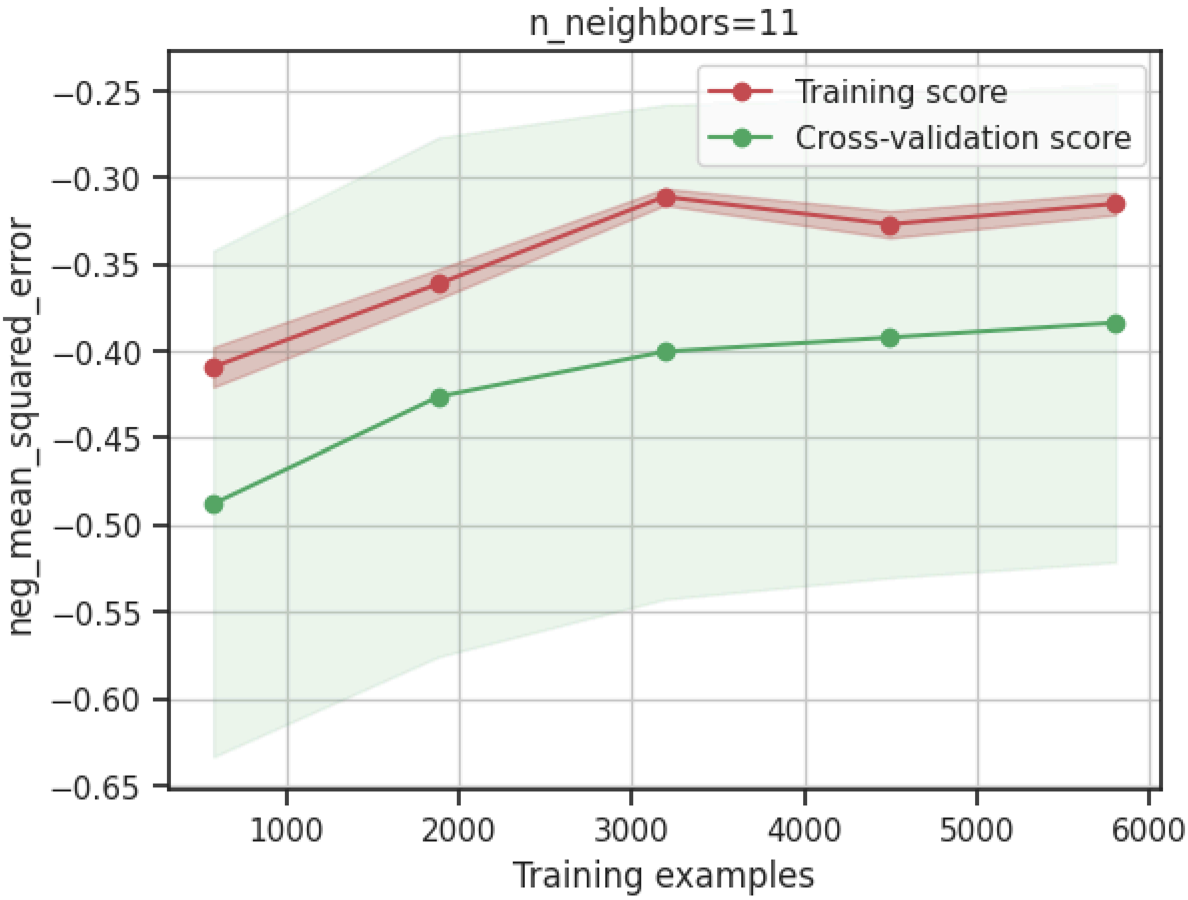
Out[76]:
```
<module 'matplotlib.pyplot' from '/opt/conda/lib/python3.10/site-packages/matplotli
b/pyplot.py'>
```




Learning Curve for best hyperparams

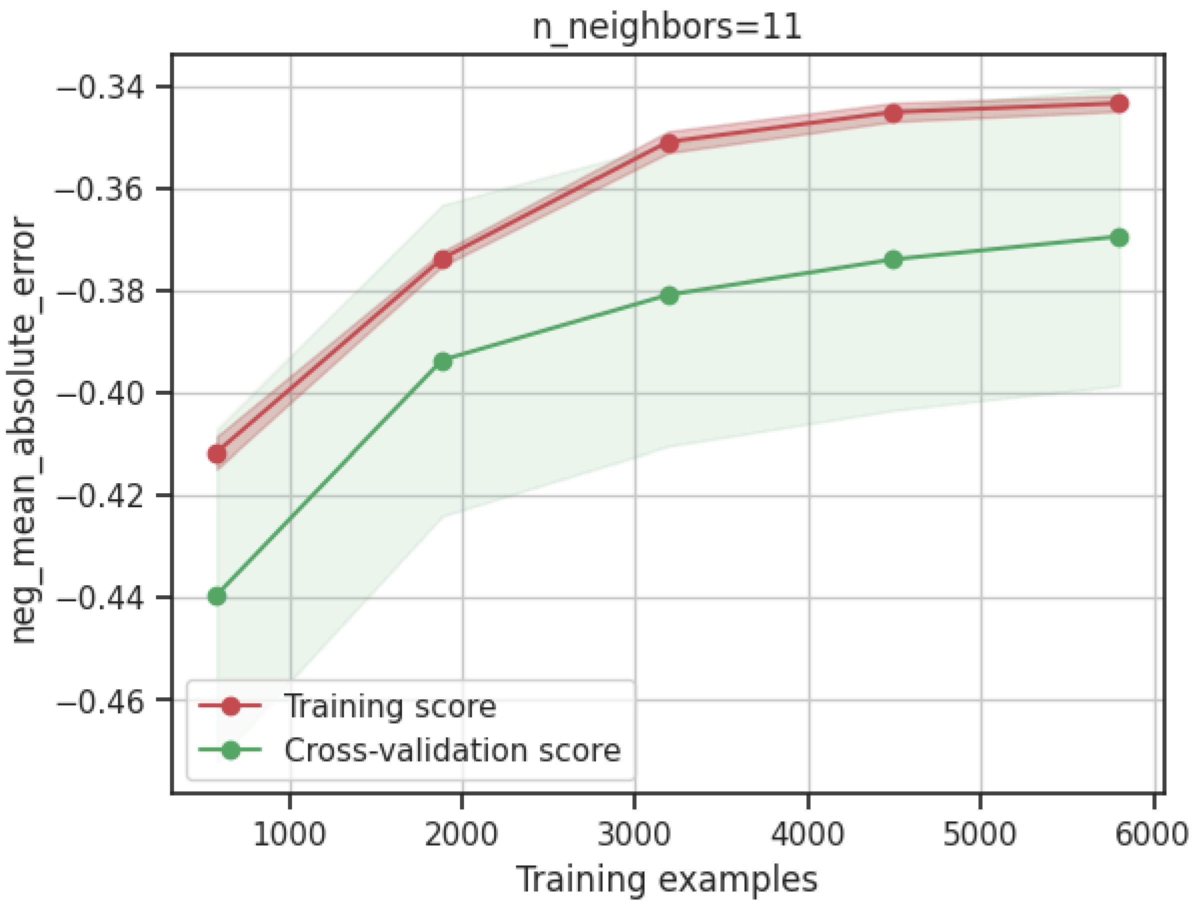
In [78]:
```
K = 11
plot_learning_curve(KNeighborsRegressor(n_neighbors=11), 'n_neighbors=11',
                    X_train, y_train, cv=20, scoring='neg_mean_squared_error')
```

Out[78]: <module 'matplotlib.pyplot' from '/opt/conda/lib/python3.10/site-packages/matplotlib/pyplot.py'>




In [79]:
```
K = 14
plot_learning_curve(KNeighborsRegressor(n_neighbors=14), 'n_neighbors=11',
                    X_train, y_train, cv=20, scoring='neg_mean_absolute_error')
```

Out[79]: <module 'matplotlib.pyplot' from '/opt/conda/lib/python3.10/site-packages/matplotlib/pyplot.py'>


n_neighbors=11
neg_mean_absolute_error
−0.34
−0.36
−0.38
−0.40
−0.42
−0.44
−0.46
1000
2000
3000
4000
5000
6000
Training examples
Training score
Cross-validation score