Датасет Melbourne Housing Snapshot

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

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

```
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
```

```
data = pd.read_csv('/kaggle/input/melb-data/melb_data.csv', sep=",")
```

```
data.shape
```

```
(13580, 21)
```

```
data.dtypes
```

```
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
```

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

```
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
```

```
data.head()
```

```
       Suburb           Address  Rooms Type      Price Method SellerG
\
0  Abbotsford      85 Turner St      2    h  1480000.0      S  Biggin

1  Abbotsford   25 Bloomburg St      2    h  1035000.0      S  Biggin

2  Abbotsford      5 Charles St      3    h  1465000.0     SP  Biggin

3  Abbotsford  40 Federation La      3    h   850000.0     PI  Biggin

4  Abbotsford       55a Park St      4    h  1600000.0     VB  Nelson


        Date  Distance  Postcode  ...  Bathroom  Car  Landsize
BuildingArea  \
0  3/12/2016       2.5    3067.0  ...       1.0  1.0     202.0
NaN
1  4/02/2016       2.5    3067.0  ...       1.0  0.0     156.0
79.0
2  4/03/2017       2.5    3067.0  ...       2.0  0.0     134.0
150.0
3  4/03/2017       2.5    3067.0  ...       2.0  1.0      94.0
NaN
4  4/06/2016       2.5    3067.0  ...       1.0  2.0     120.0
```

```
142.0

   YearBuilt  CouncilArea Lattitude  Longtitude             Regionname  \
0        NaN        Yarra  -37.7996    144.9984  Northern Metropolitan

1     1900.0        Yarra  -37.8079    144.9934  Northern Metropolitan

2     1900.0        Yarra  -37.8093    144.9944  Northern Metropolitan

3        NaN        Yarra  -37.7969    144.9969  Northern Metropolitan

4     2014.0        Yarra  -37.8072    144.9941  Northern Metropolitan


  Propertycount
0        4019.0
1        4019.0
2        4019.0
3        4019.0
4        4019.0

[5 rows x 21 columns]
```

Обработка пропусков категориальных признаков

```
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(col, dt, temp_null_count, temp_perc))

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

data['CouncilArea'].describe()

count         12211
unique           33
top        Moreland
freq           1163
Name: CouncilArea, dtype: object

data['CouncilArea'].unique()
```

```
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)
```

```
# 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=['Pri
ce']).reset_index().iterrows():
    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()
```

	Price	CouncilArea
Price	1.000000	0.423142
CouncilArea	0.423142	1.000000

```
# У нас есть небольшая корреляция между целевым признаком и ценой,
поэтому просто удалим строки с пустыми значениями колонки
'CouncilArea'
data.dropna(subset=['CouncilArea'], inplace=True)

data['CouncilArea'].isnull().sum()
```

```
0
```

Обработка пропусков числовых признаков

```
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(col, dt, temp_null_count, temp_perc))
```

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

```
# Заполним пропуски в числовых признаков медианой, тк она меньше всего
подвержена выбросам

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

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

```
BuildingArea    5765
YearBuilt       4763
dtype: int64
```

```
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
```

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

```
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

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

```
Suburb          object
Address         object
Type            object
Method          object
SellerG         object
Date            object
CouncilArea     object
Regionname      object
dtype: object
```

Date

```
data['Date'].unique()
```

```
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)

# 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']]

       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 x 3 columns]
```

Adress

```
# Преобразуем улицу в адрес

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

data['Street']

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
```

```
data['Street'].unique().shape
```

```
(3721,)
```

Other

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

```
Suburb         object
Type           object
Method         object
SellerG        object
CouncilArea    object
Regionname     object
Street         object
dtype: object
```

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

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

```
data_obj = data[obj_cols]
```

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

```
data[obj_cols] = data_obj_enc
data[obj_cols]
```

```
       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 x 7 columns]
```

```
data.describe()
```

```
                Suburb         Rooms          Type         Price
Method  \
count  12211.000000  12211.000000  12211.000000  1.221100e+04
12211.000000
mean     152.520514      2.894194      0.570715  1.063692e+06
1.404389
std       89.000246      0.959341      0.854515  6.388613e+05
1.117471
min        0.000000      1.000000      0.000000  8.500000e+04
0.000000
25%       67.000000      2.000000      0.000000  6.400000e+05
1.000000
50%      153.000000      3.000000      0.000000  8.950000e+05
1.000000
75%      229.000000      3.000000      1.000000  1.320000e+06
1.000000
max      307.000000     10.000000      2.000000  9.000000e+06
4.000000

               SellerG      Distance      Postcode      Bedroom2
Bathroom  \
count  12211.000000  12211.000000  12211.000000  12211.000000
12211.000000
mean     123.668741      9.764368   3103.110638      2.868397
1.517402
std       73.079999      5.507993     87.359029      0.969456
0.688923
min        0.000000      0.000000   3000.000000      0.000000
0.000000
25%       70.000000      5.900000   3044.000000      2.000000
1.000000
50%      128.000000      9.200000   3083.000000      3.000000
1.000000
75%      183.000000     12.600000   3147.000000      3.000000
2.000000
max      252.000000     47.400000   3977.000000     20.000000
8.000000

       ...     YearBuilt   CouncilArea     Lattitude    Longtitude  \
count  ...  12211.000000  12211.000000  12211.000000  12211.000000
mean   ...   1966.709770     14.767668    -37.809054    144.993148
std    ...     29.382804      9.834752      0.075242      0.098867
min    ...   1196.000000      0.000000    -38.182550    144.431810
25%    ...   1960.000000      6.000000    -37.855600    144.929900
50%    ...   1970.000000     16.000000    -37.802200    144.998580
75%    ...   1975.000000     23.000000    -37.757735    145.054200
max    ...   2018.000000     32.000000    -37.457090    145.526350

         Regionname  Propertycount           Day         Month
Year  \
```

```
count   12211.000000   12211.000000  12211.000000  12211.000000
12211.000000
mean        3.800917    7452.984358     16.297682      6.586520
2016.481124
std         2.004398    4369.616618      8.212707      2.800277
0.499664
min         0.000000     249.000000      2.000000      1.000000
2016.000000
25%         2.000000    4380.000000      9.000000      5.000000
2016.000000
50%         5.000000    6567.000000     16.000000      6.000000
2016.000000
75%         5.000000   10331.000000     24.000000      8.000000
2017.000000
max         7.000000   21650.000000     30.000000     12.000000
2017.000000

             Street
count  12211.000000
mean    1895.106953
std     1083.324225
min        0.000000
25%      962.000000
50%     1909.000000
75%     2821.000000
max     3720.000000

[8 rows x 23 columns]
```

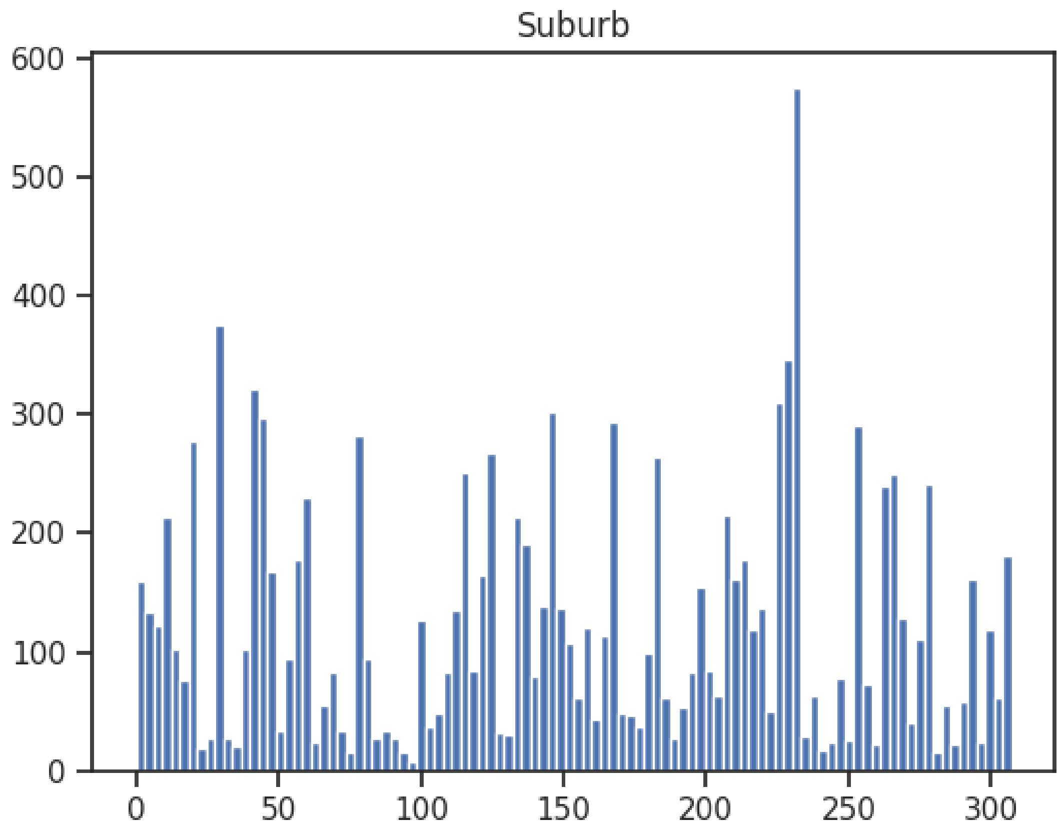
```
data.dtypes.loc[lambda x: x == 'object'].size
```

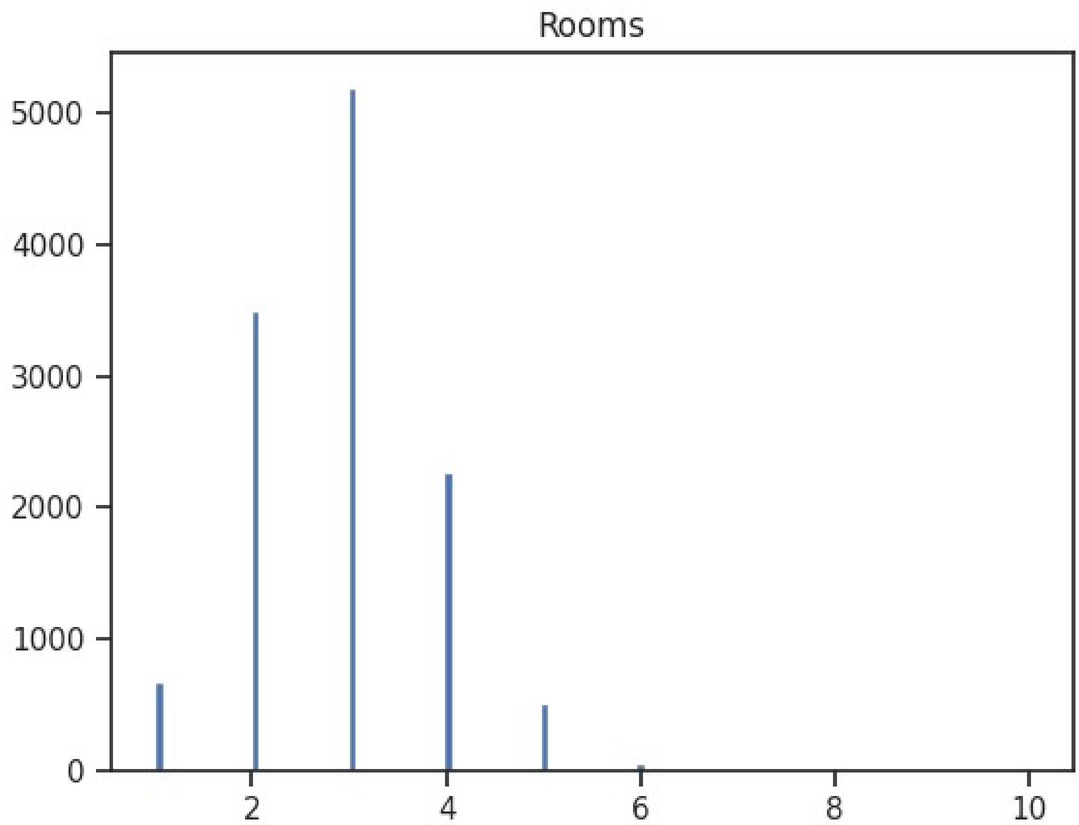
```
0
```

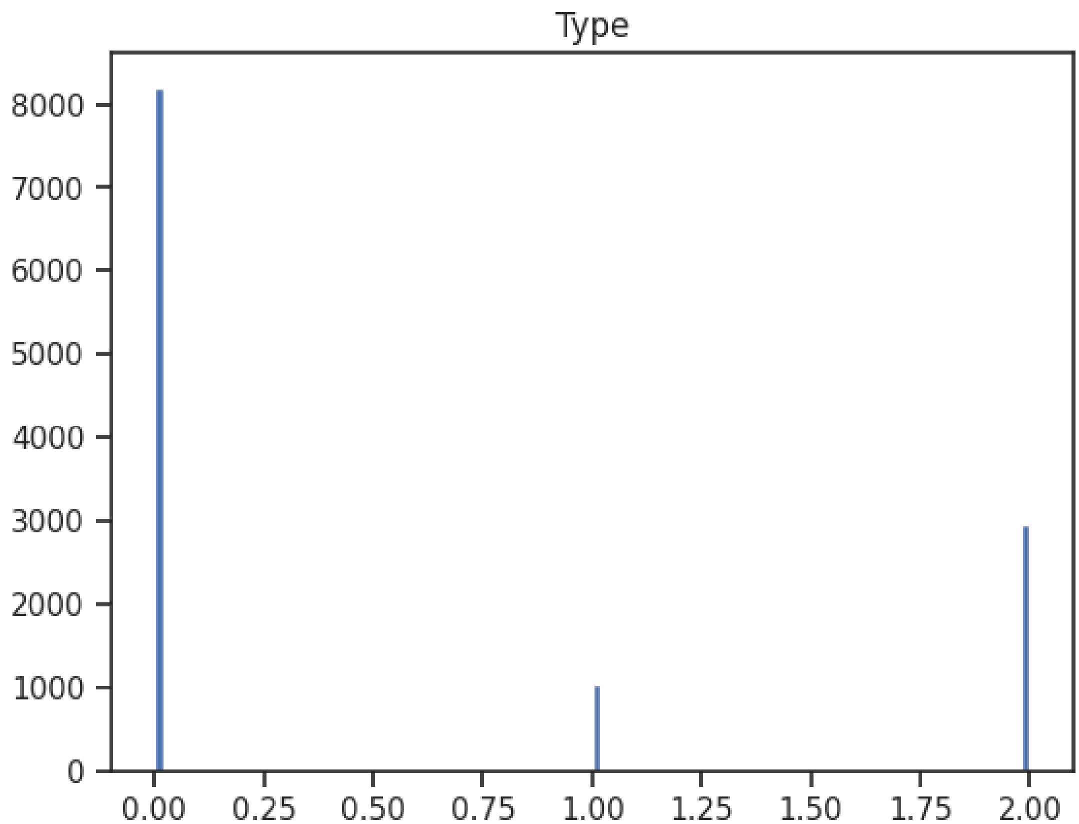
Масштабирование данных

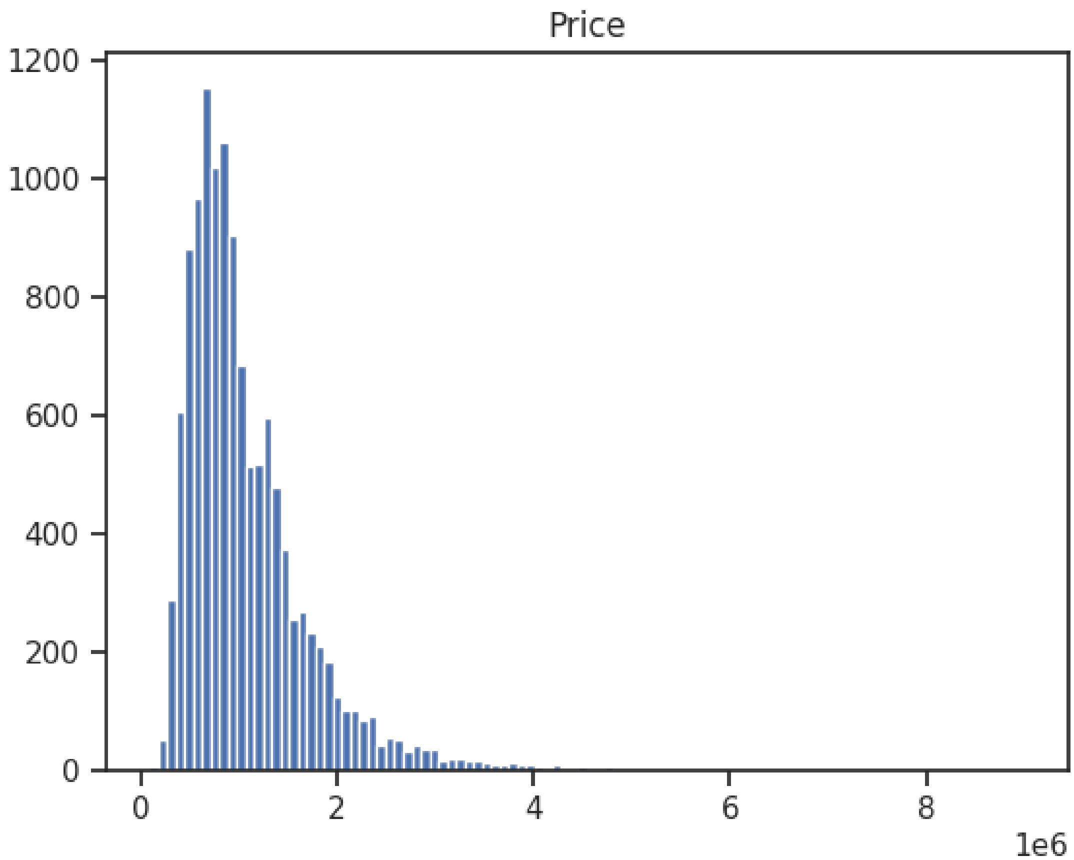
До применения Z скеллинга

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

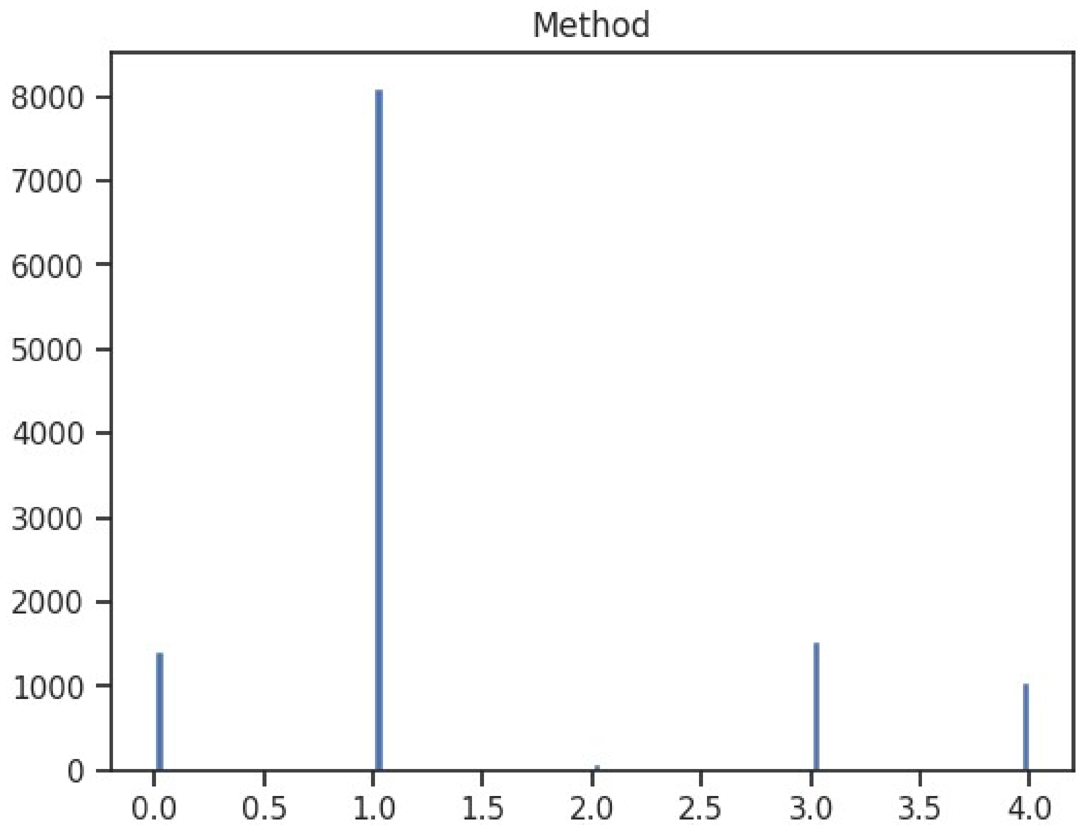

Suburb
600
500
400
300
200
100
0
0
50
100
150
200
250
300

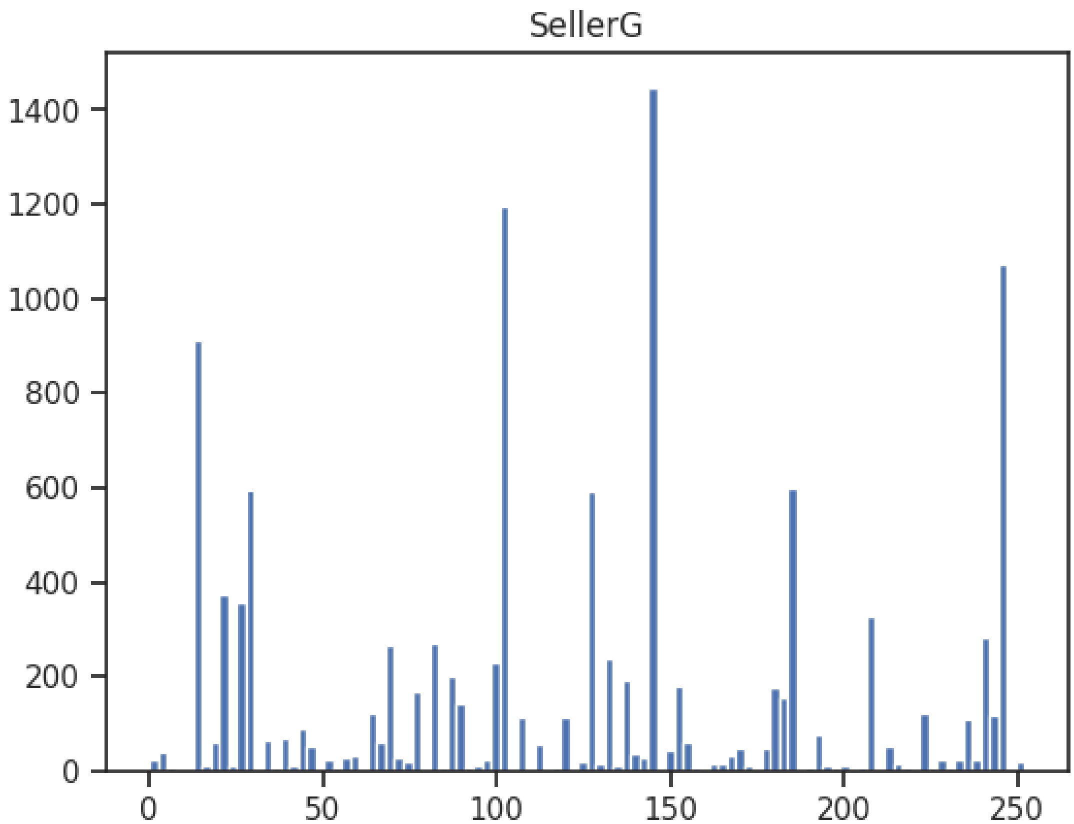

Rooms
5000
4000
3000
2000
1000
0
2
4
6
8
10

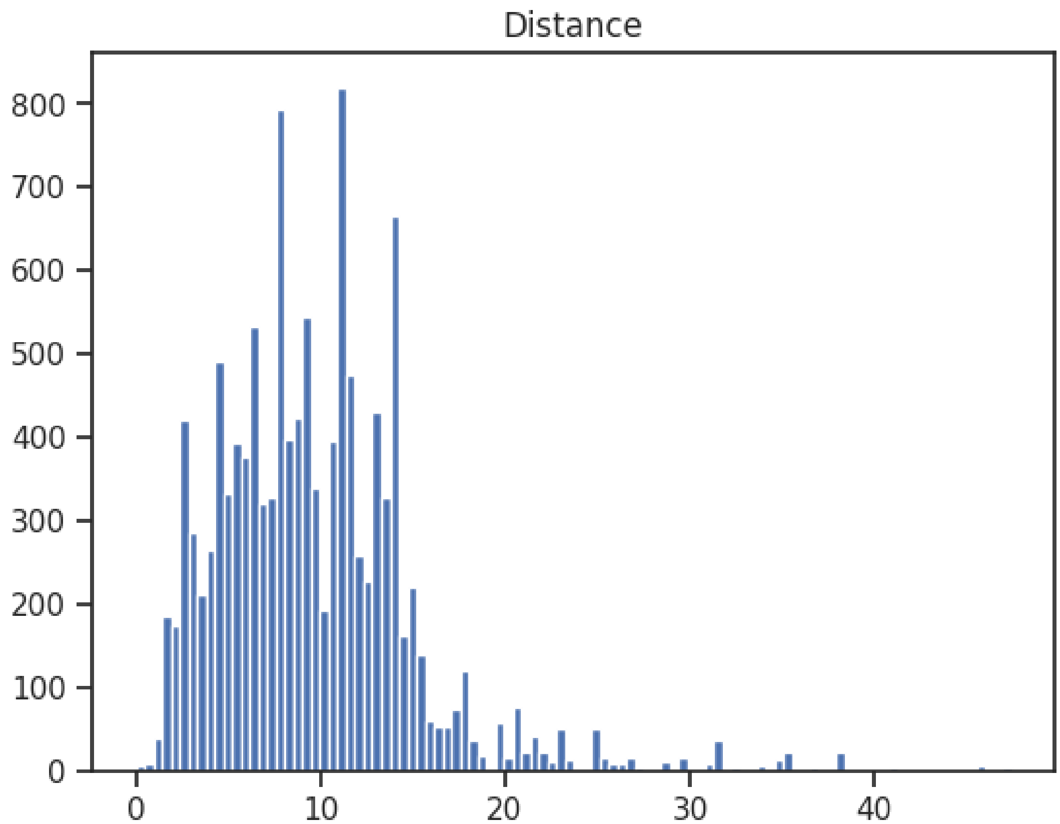

Type
8000
7000
6000
5000
4000
3000
2000
1000
0
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00

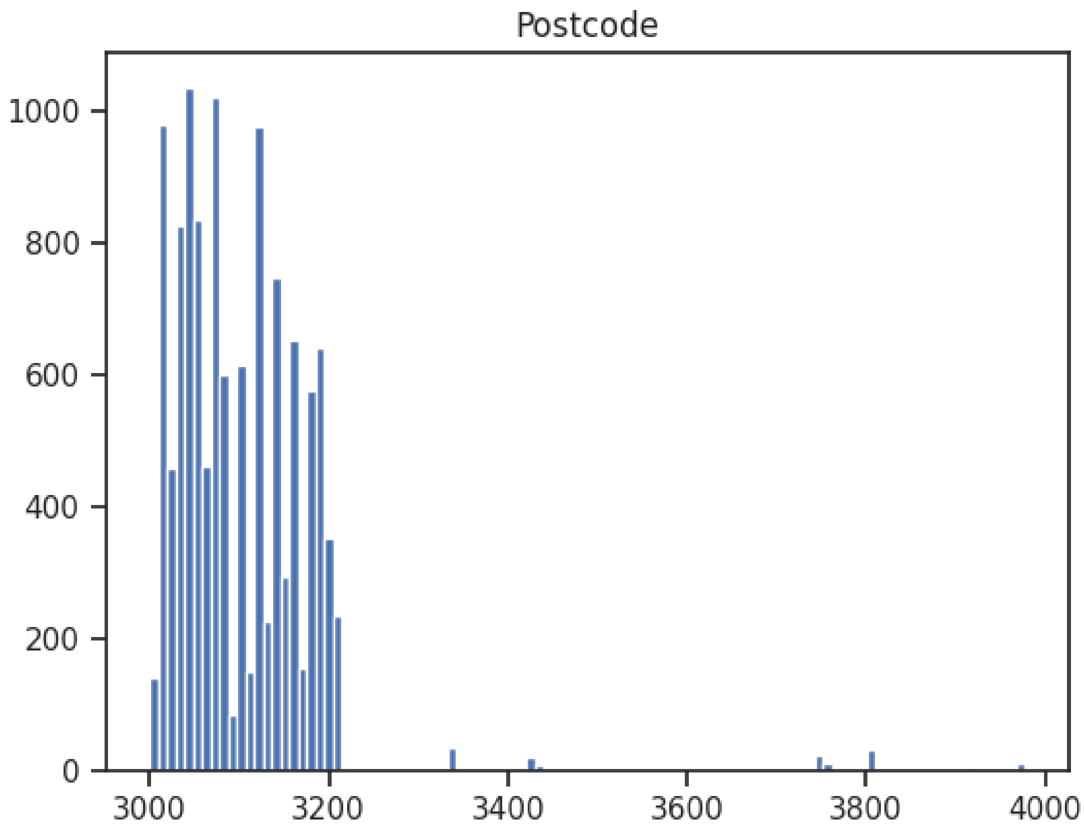


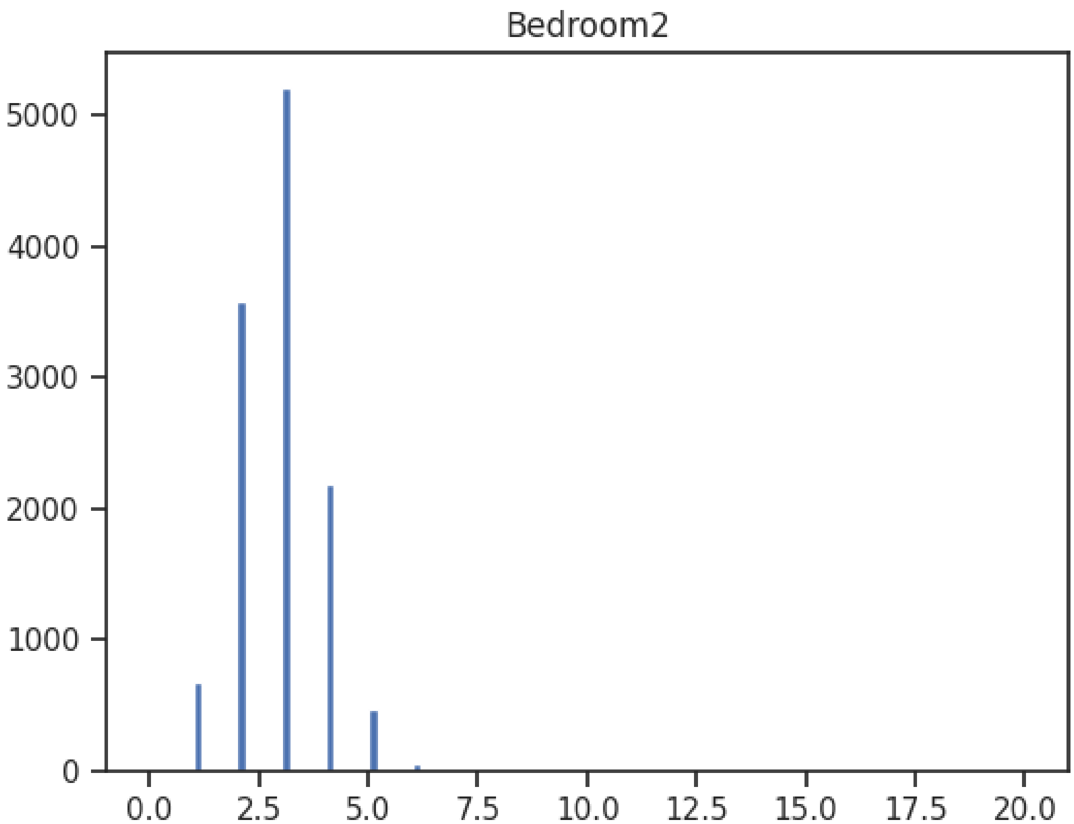
Price
1200
1000
800
600
400
200
0
0
2
4
6
8
1e6


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

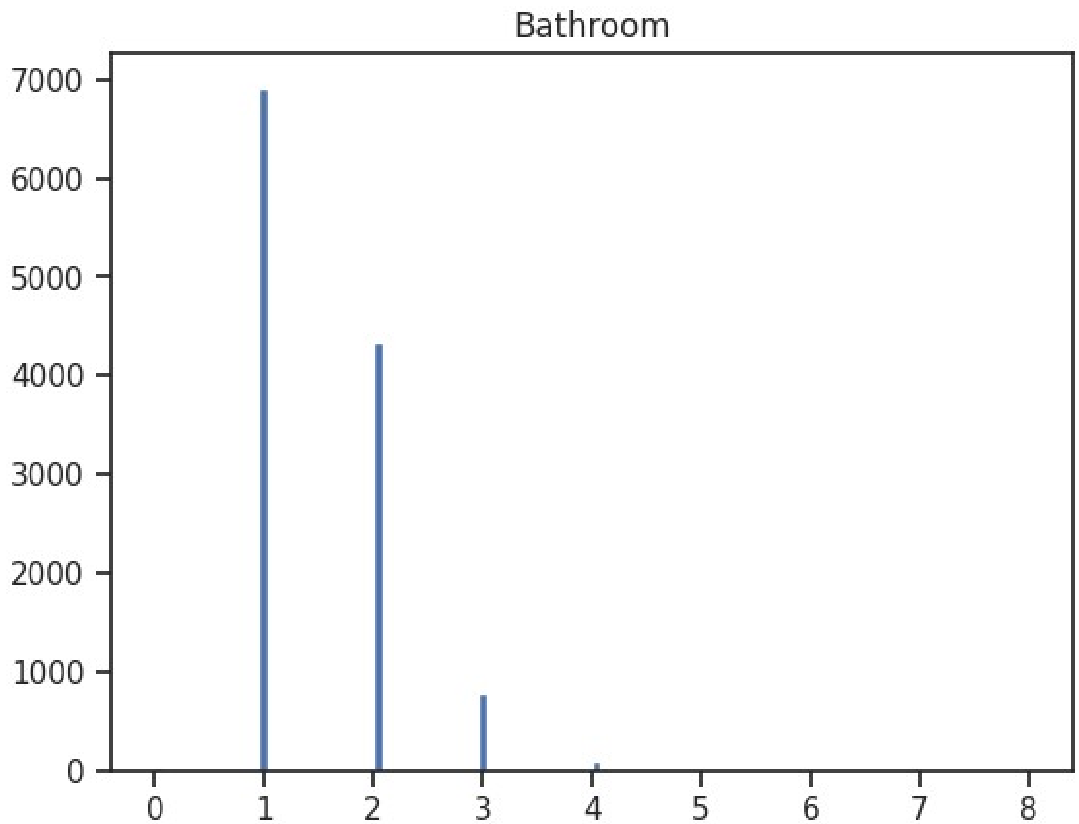

SellerG
1400
1200
1000
800
600
400
200
0
0
50
100
150
200
250


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

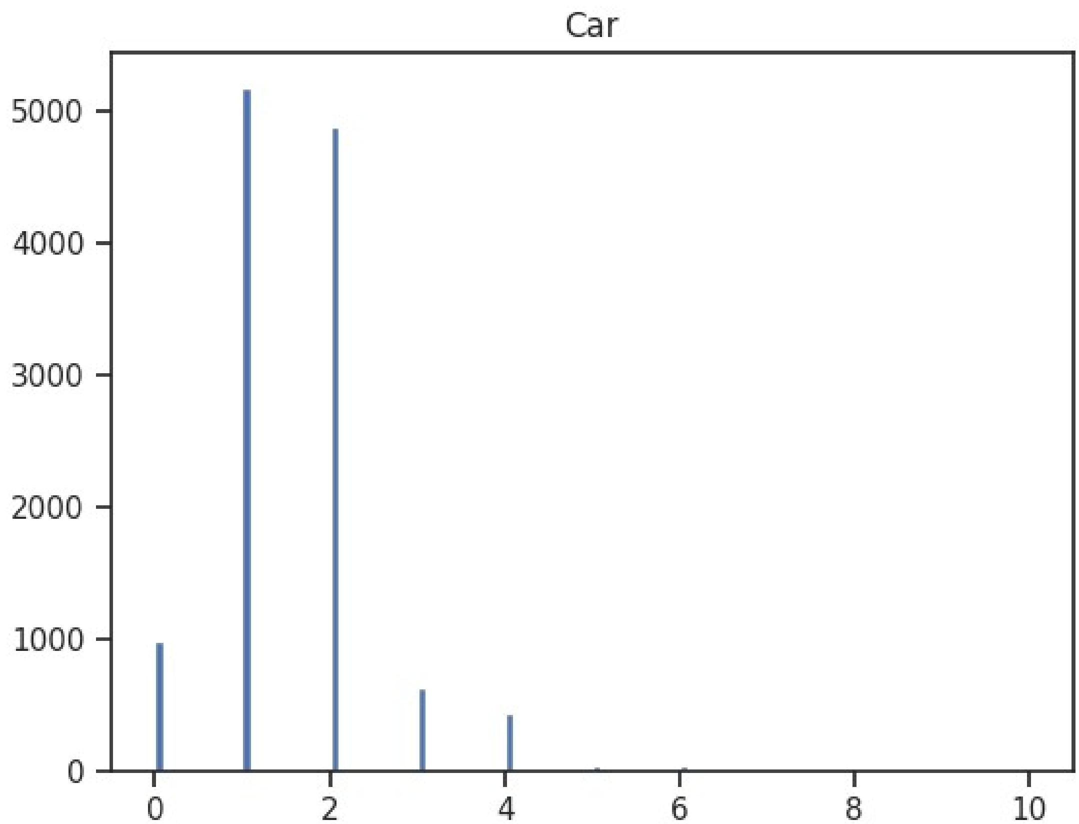

Postcode
1000
800
600
400
200
0
3000
3200
3400
3600
3800
4000



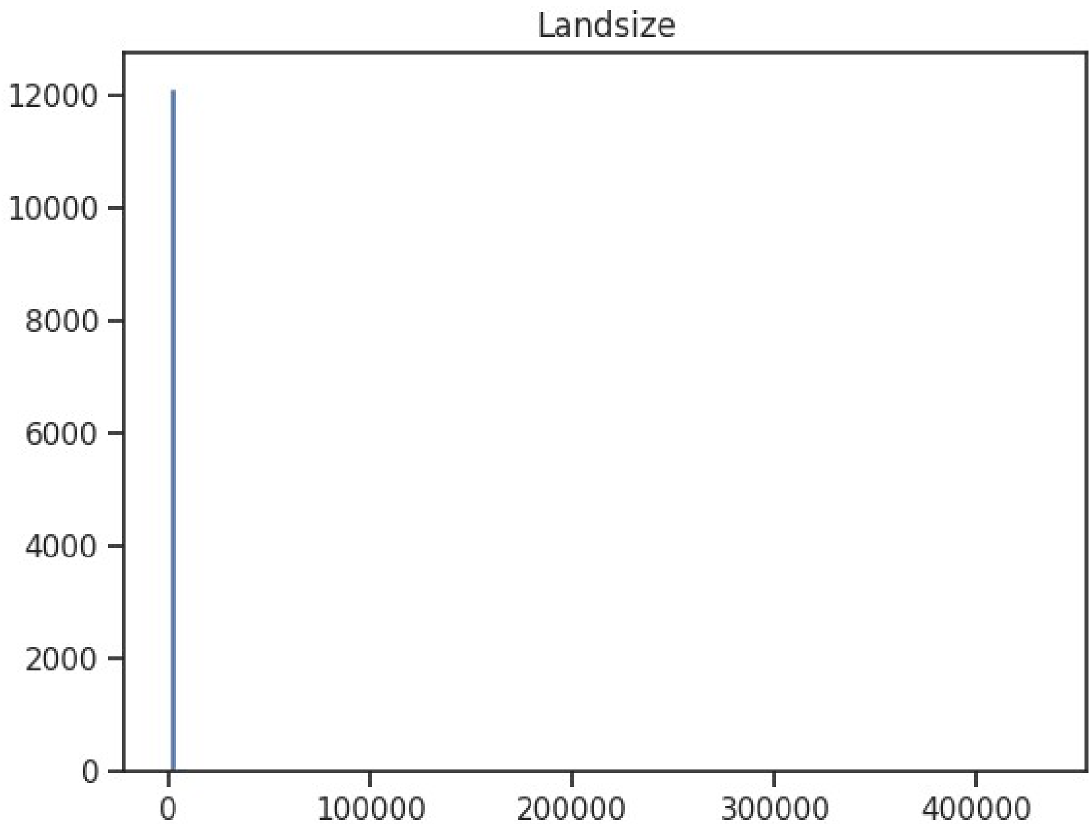
Bedroom2
5000
4000
3000
2000
1000
0
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0

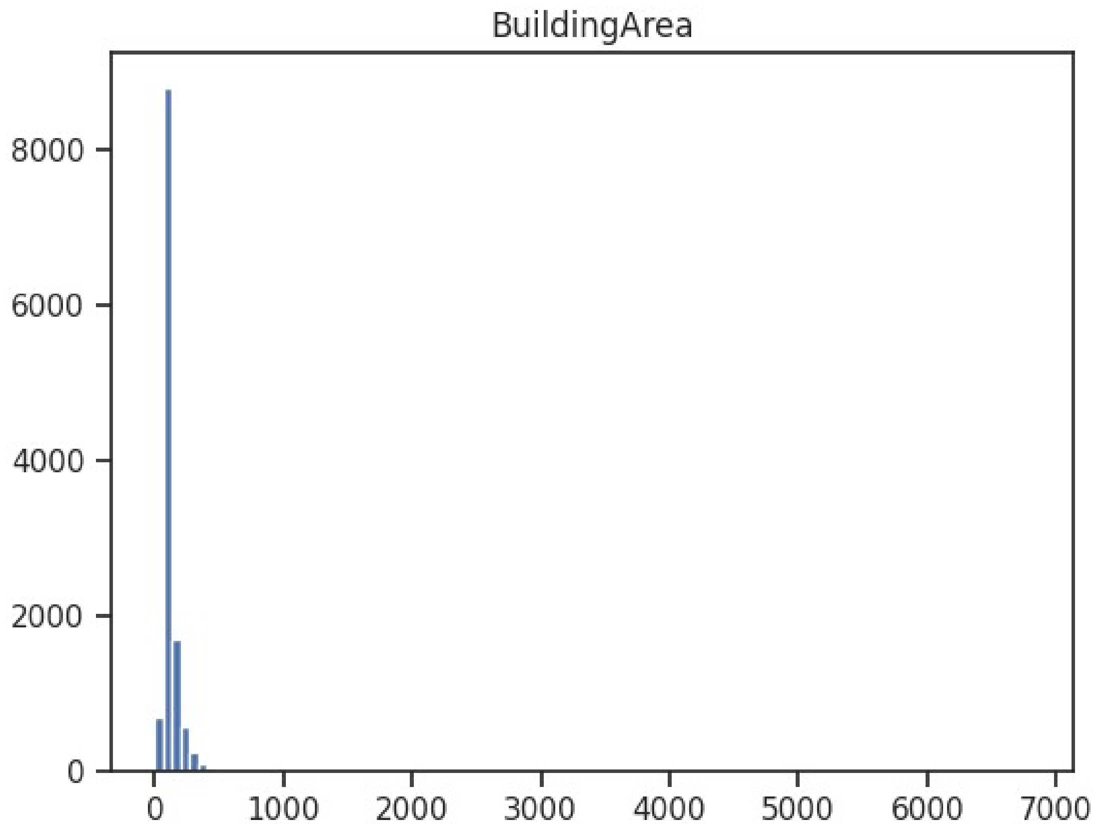


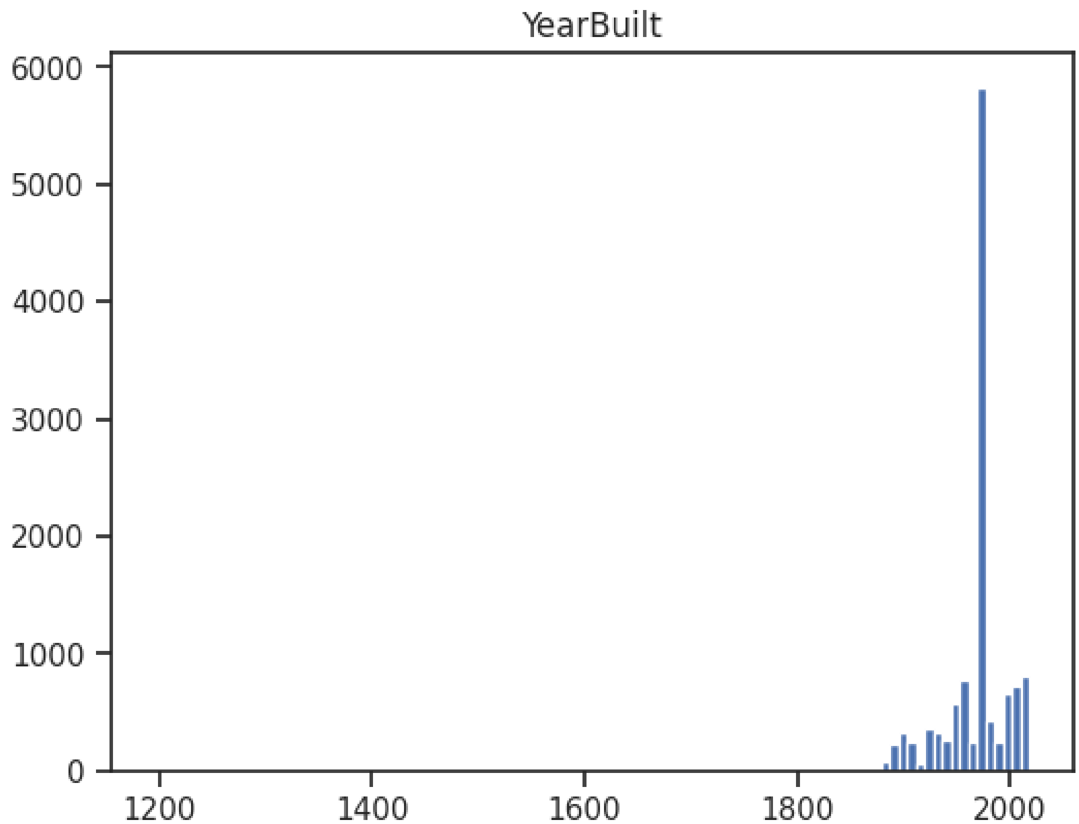
Bathroom
7000
6000
5000
4000
3000
2000
1000
0
0
1
2
3
4
5
6
7
8



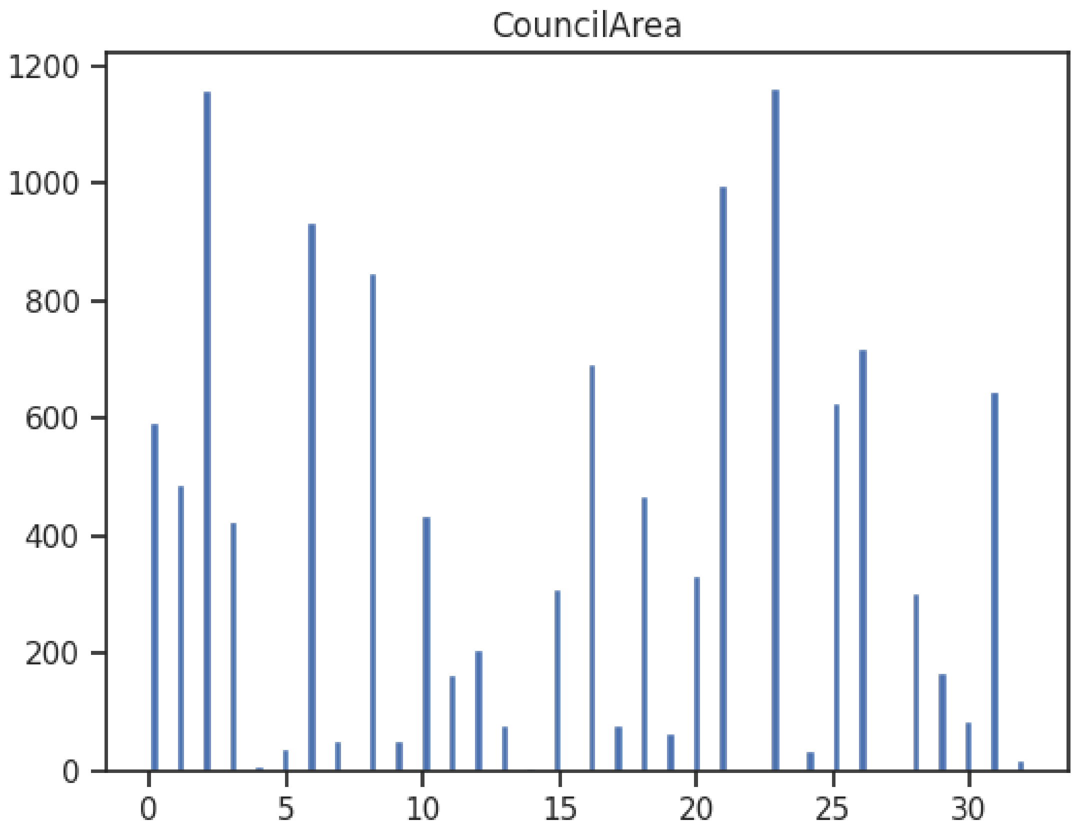
Car
5000
4000
3000
2000
1000
0
0
2
4
6
8
10

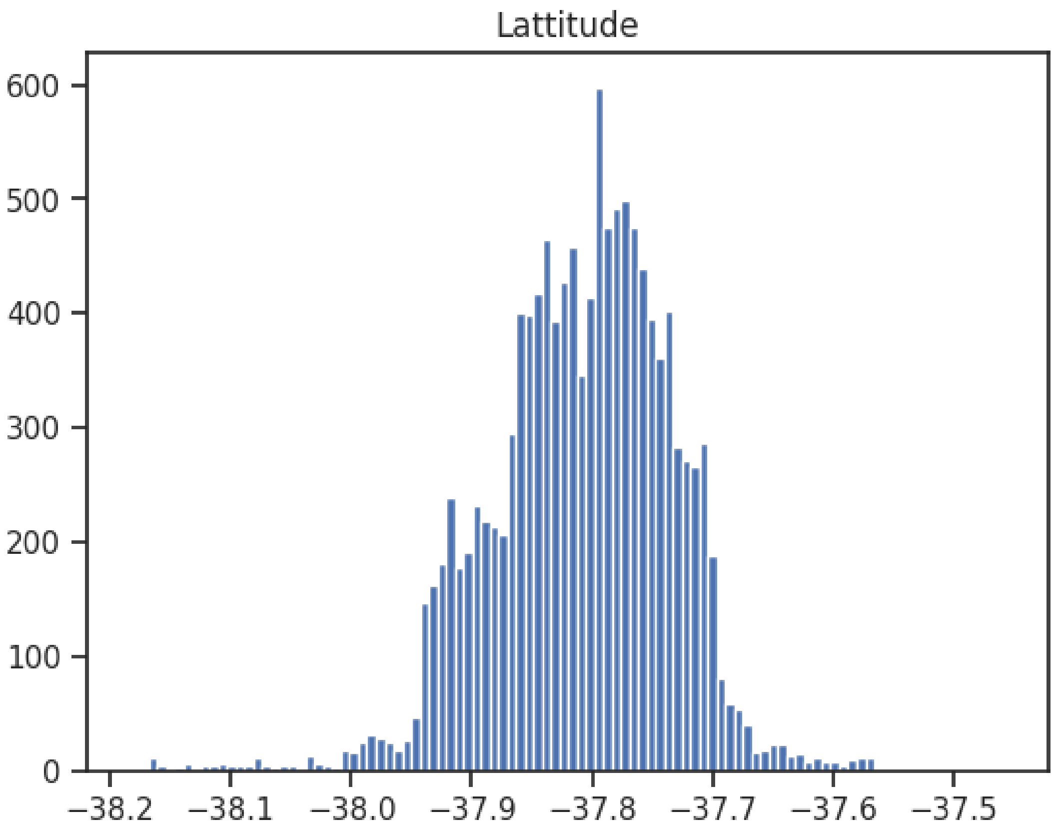

Landsize
12000
10000
8000
6000
4000
2000
0
0
100000
200000
300000
400000

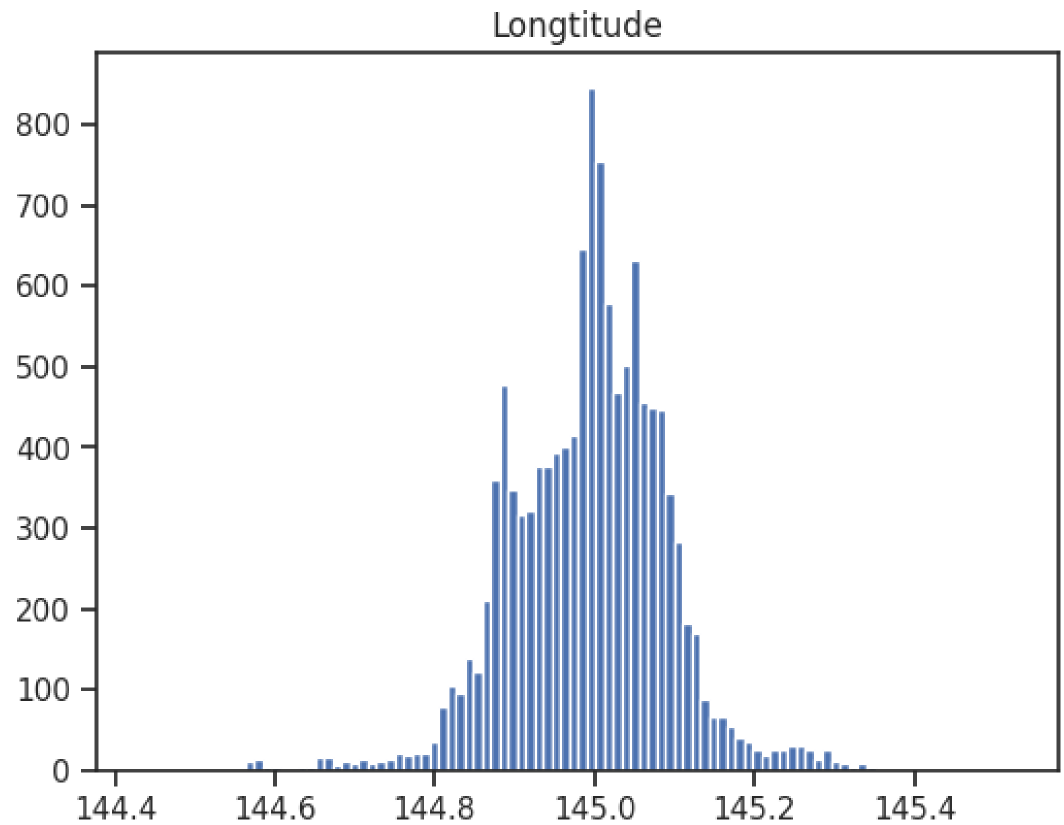

BuildingArea
8000
6000
4000
2000
0
0
1000
2000
3000
4000
5000
6000
7000

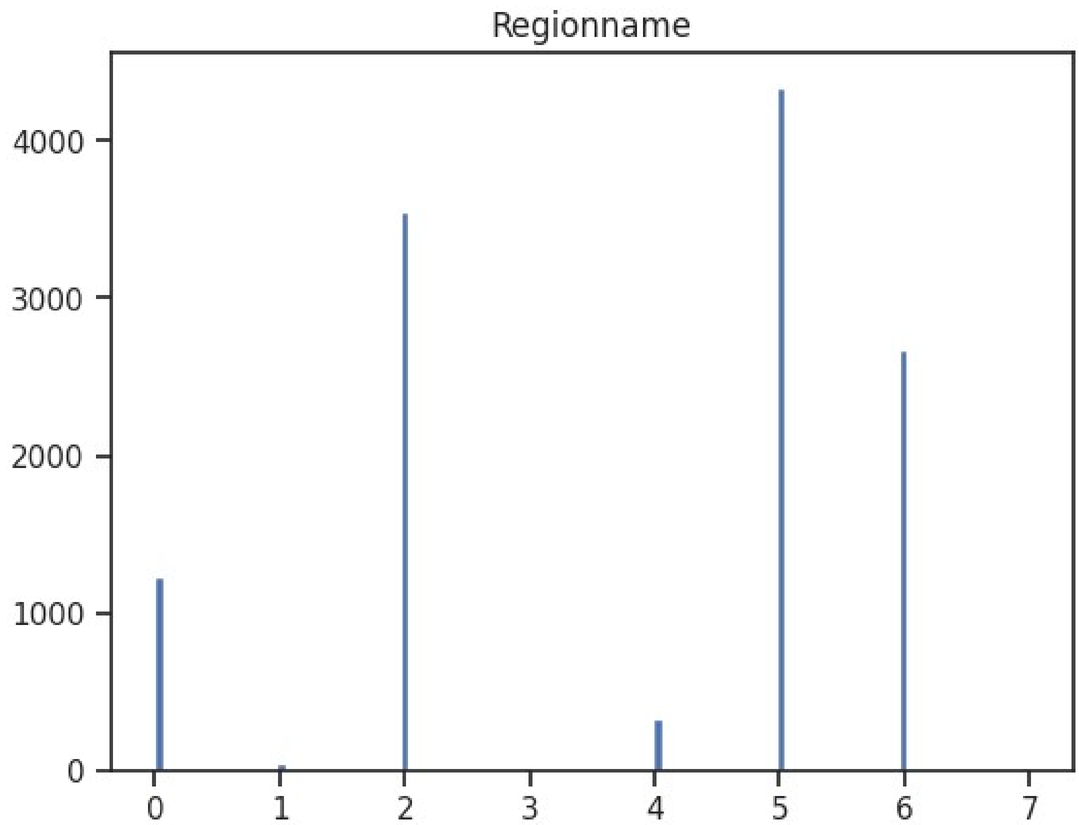


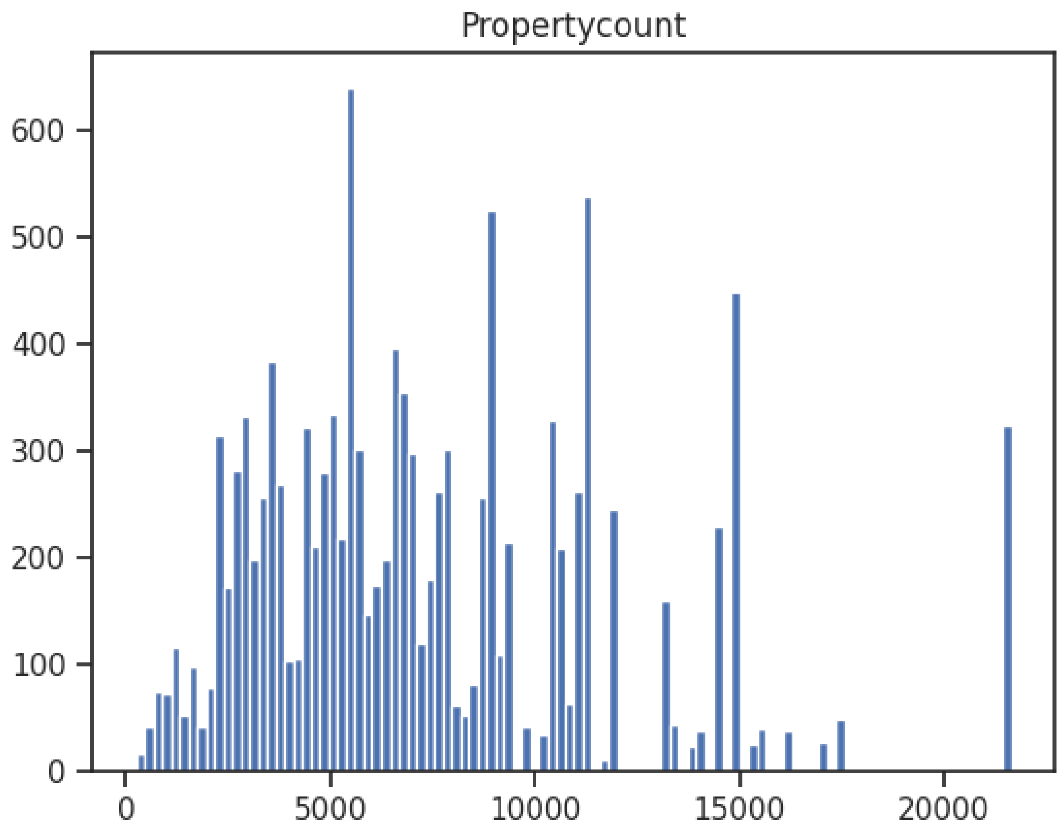
YearBuilt
6000
5000
4000
3000
2000
1000
0
1200
1400
1600
1800
2000


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

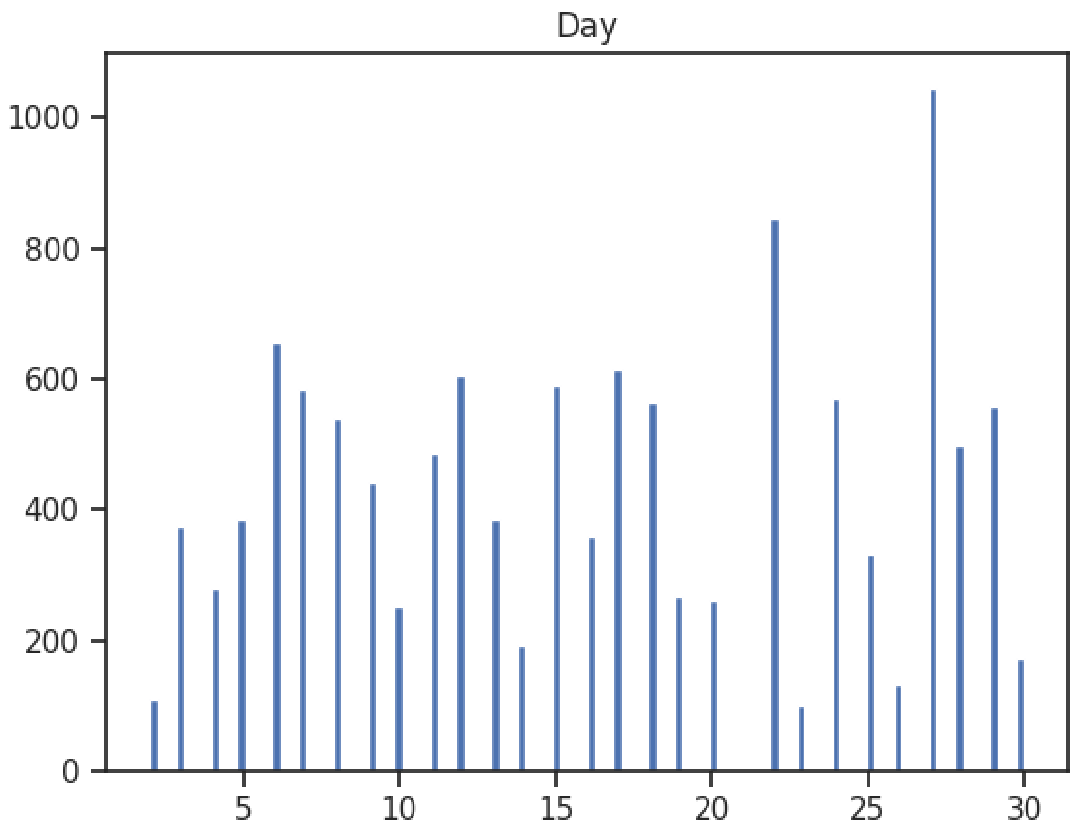

Lattitude
600
500
400
300
200
100
0
−38.2
−38.1
−38.0
−37.9
−37.8
−37.7
−37.6
−37.5


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

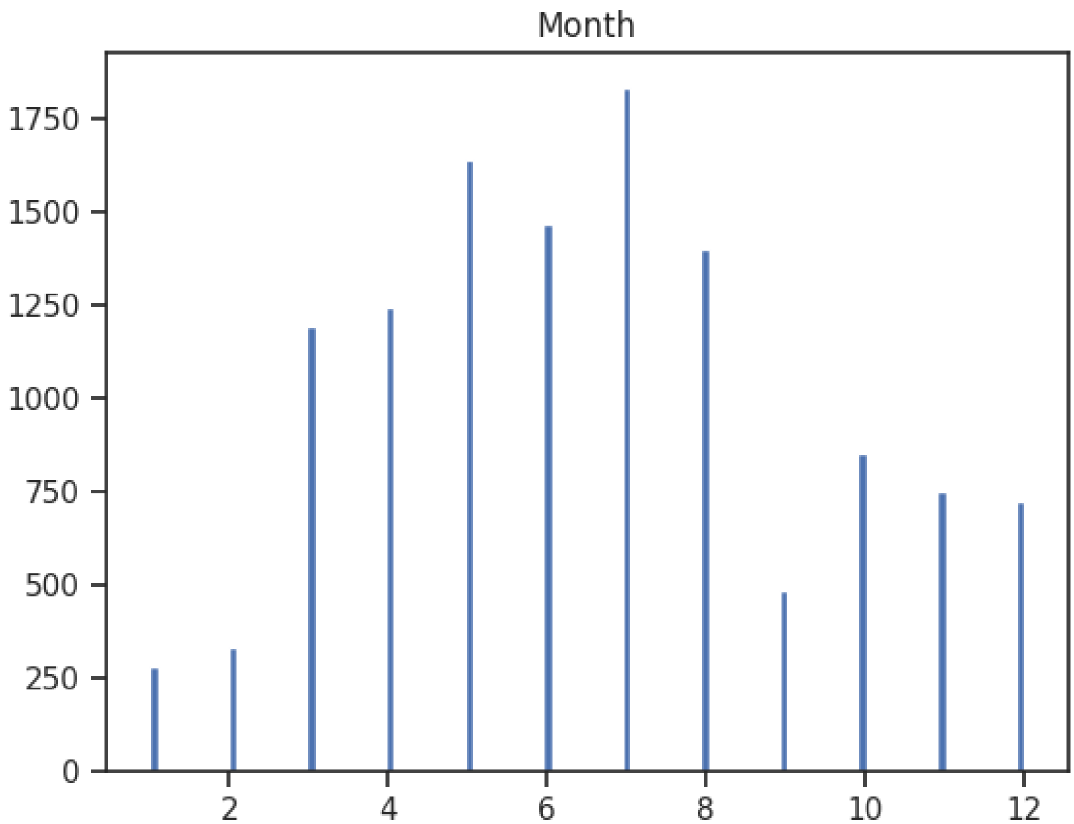

Regionname
4000
3000
2000
1000
0
0
1
2
3
4
5
6
7

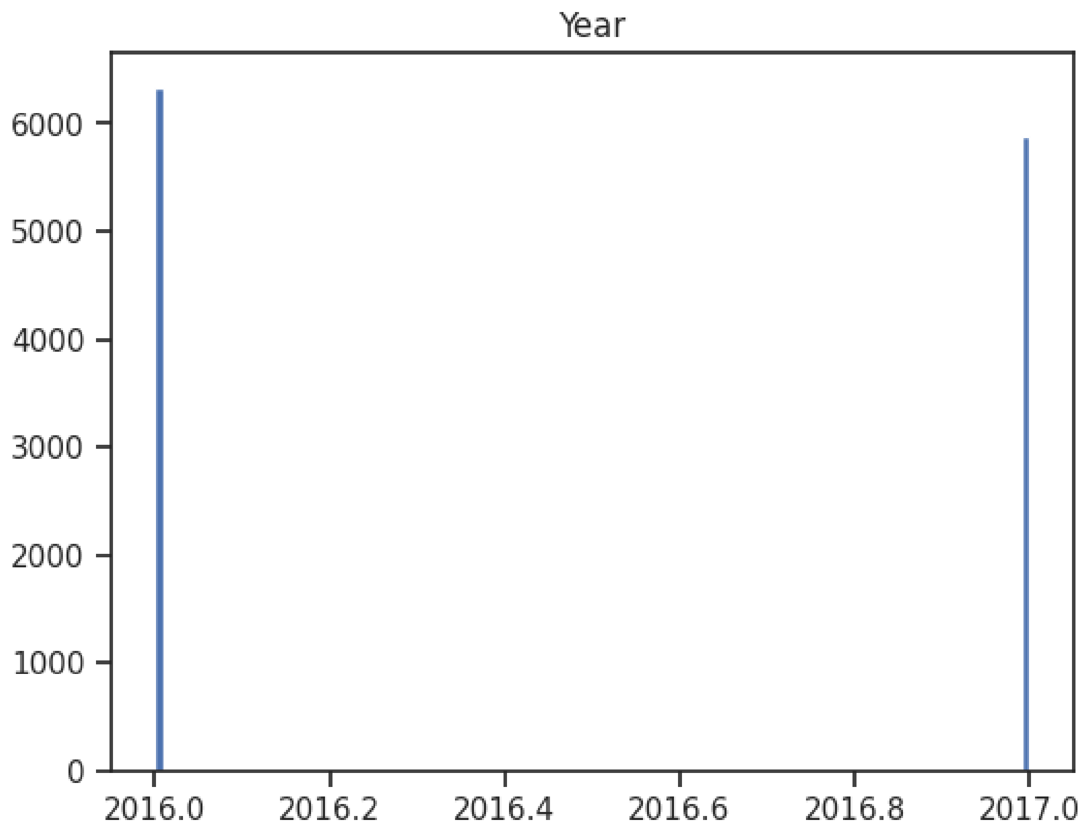


Propertycount
600
500
400
300
200
100
0
0
5000
10000
15000
20000

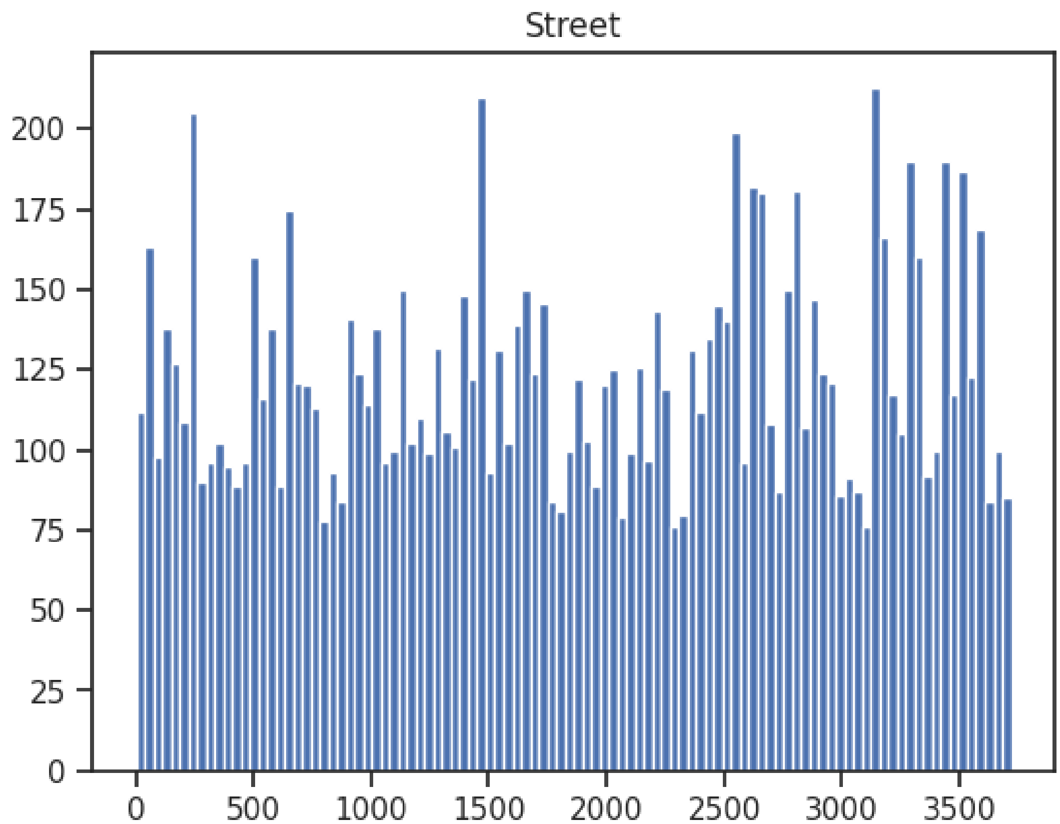


Day
0
200
400
600
800
1000
5
10
15
20
25
30


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

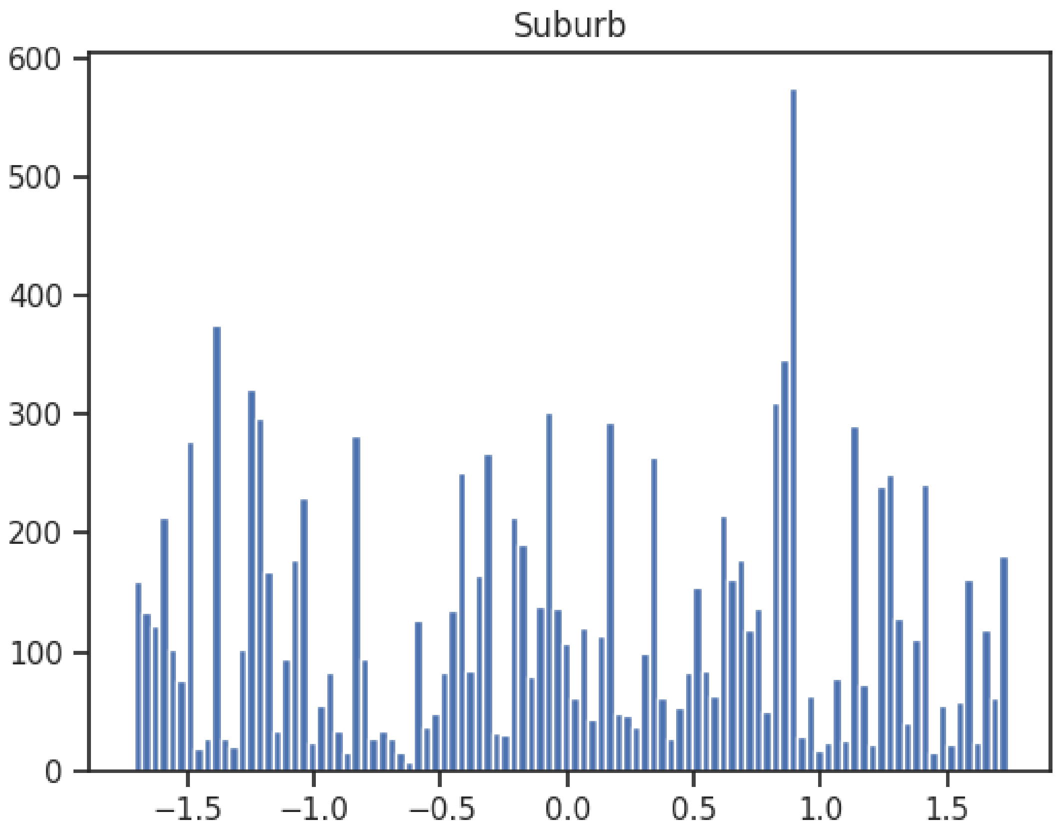


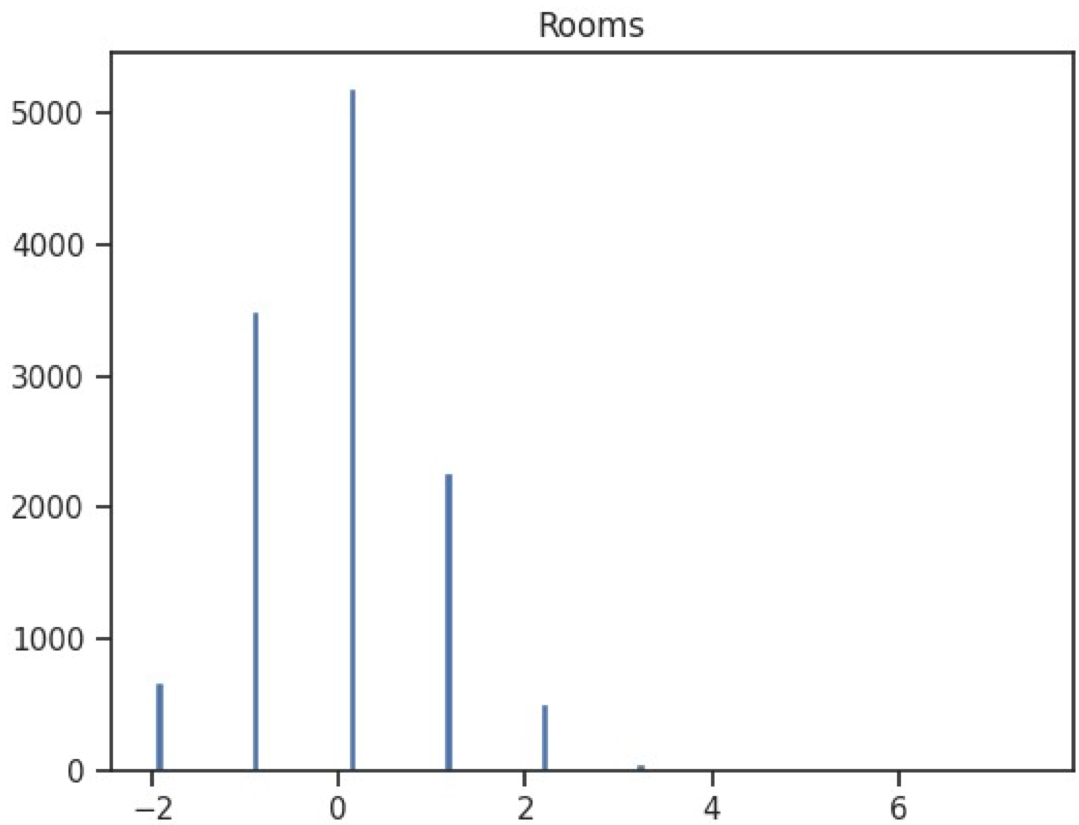
Year
6000
5000
4000
3000
2000
1000
0
2016.0
2016.2
2016.4
2016.6
2016.8
2017.0



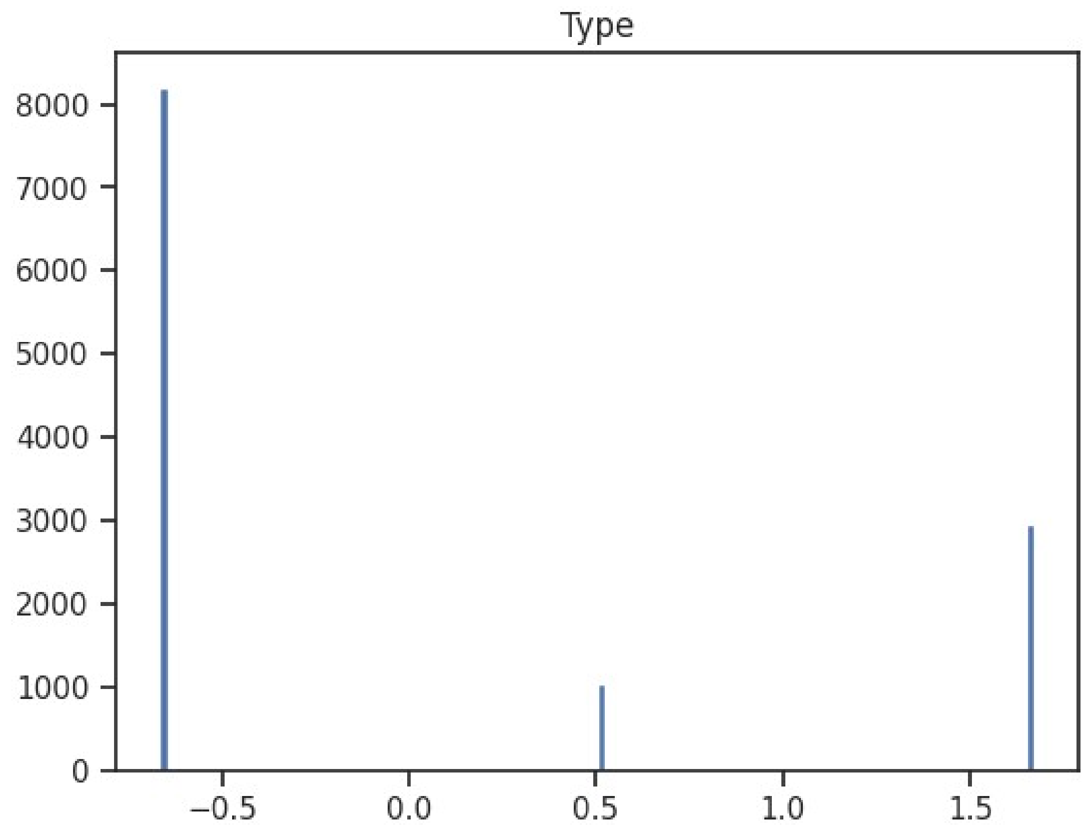
После

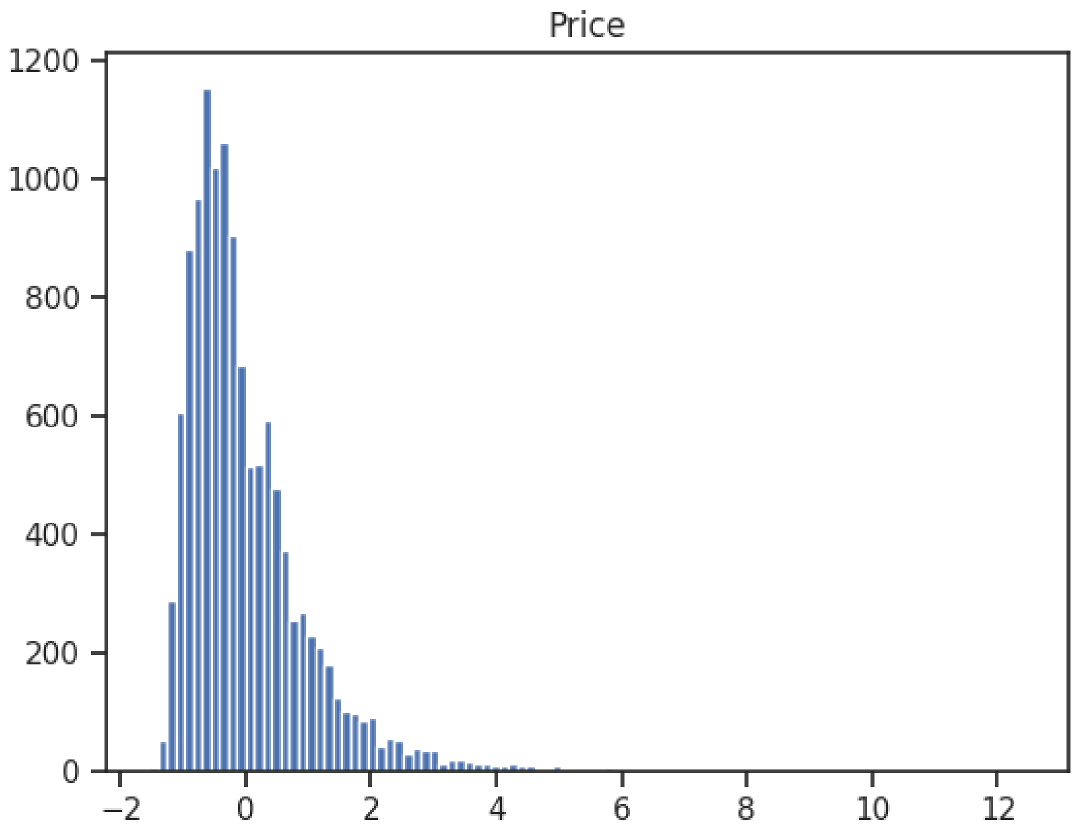
```
from sklearn.preprocessing import MinMaxScaler, StandardScaler, Normalizer

sc2 = StandardScaler()
sc2_data = sc2.fit_transform(data)

sc2_data = pd.DataFrame(sc2_data, columns=data.columns)

# 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

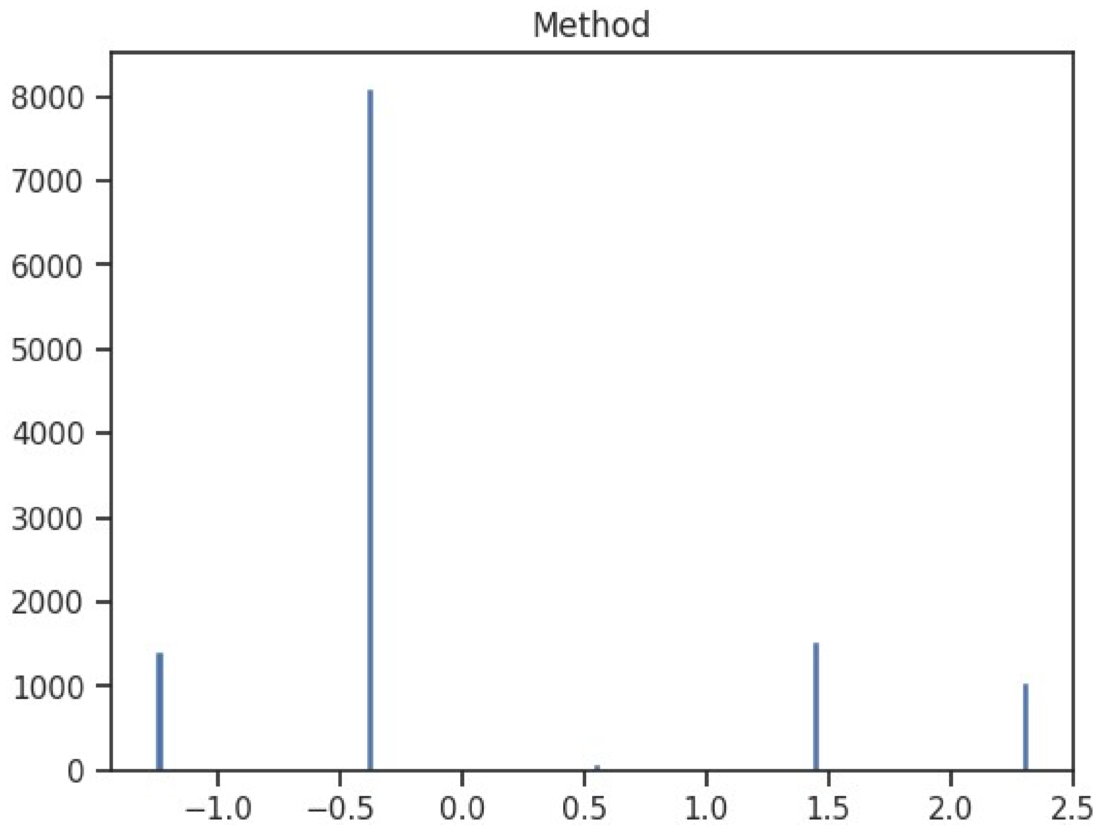


Rooms
5000
4000
3000
2000
1000
0
−2
0
2
4
6

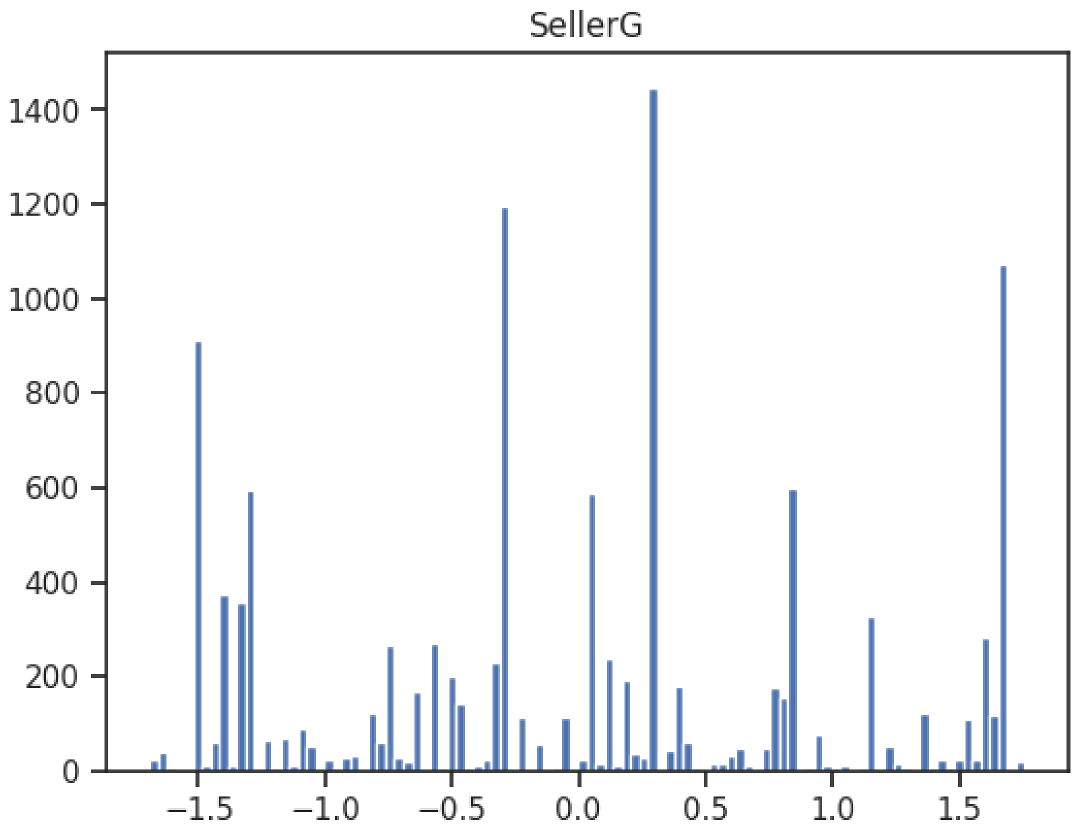

Type
8000
7000
6000
5000
4000
3000
2000
1000
0
−0.5
0.0
0.5
1.0
1.5



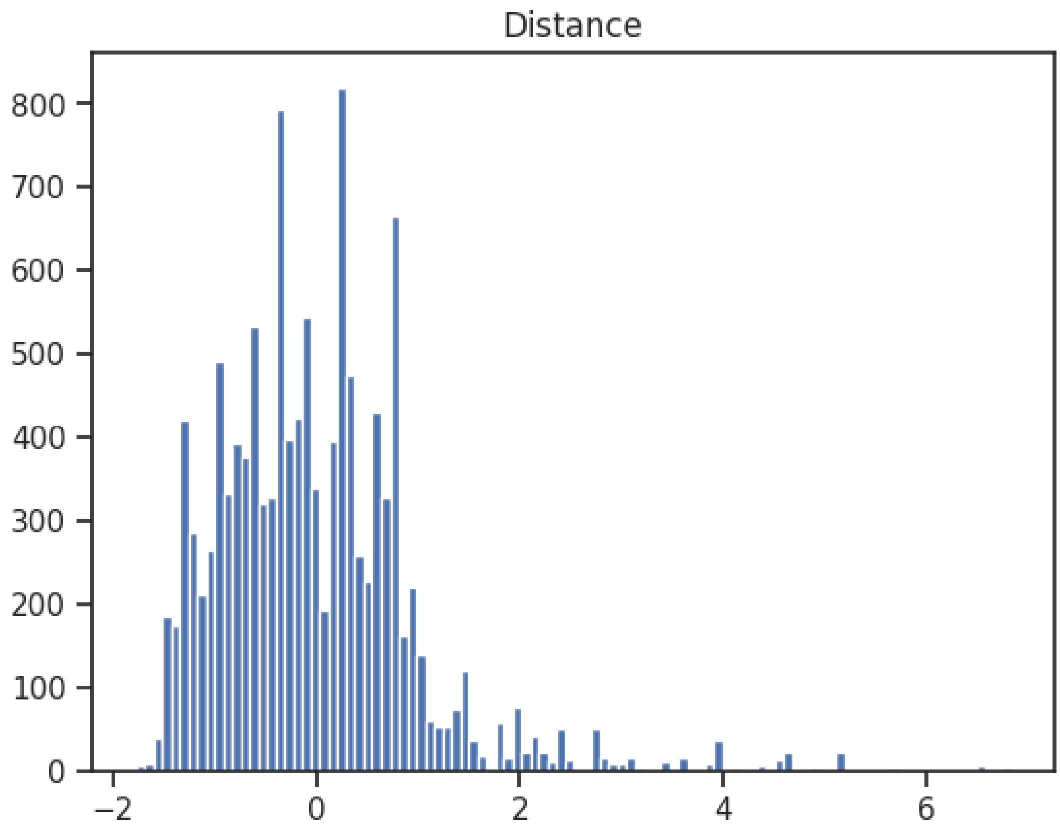
Price
1200
1000
800
600
400
200
0
−2
0
2
4
6
8
10
12

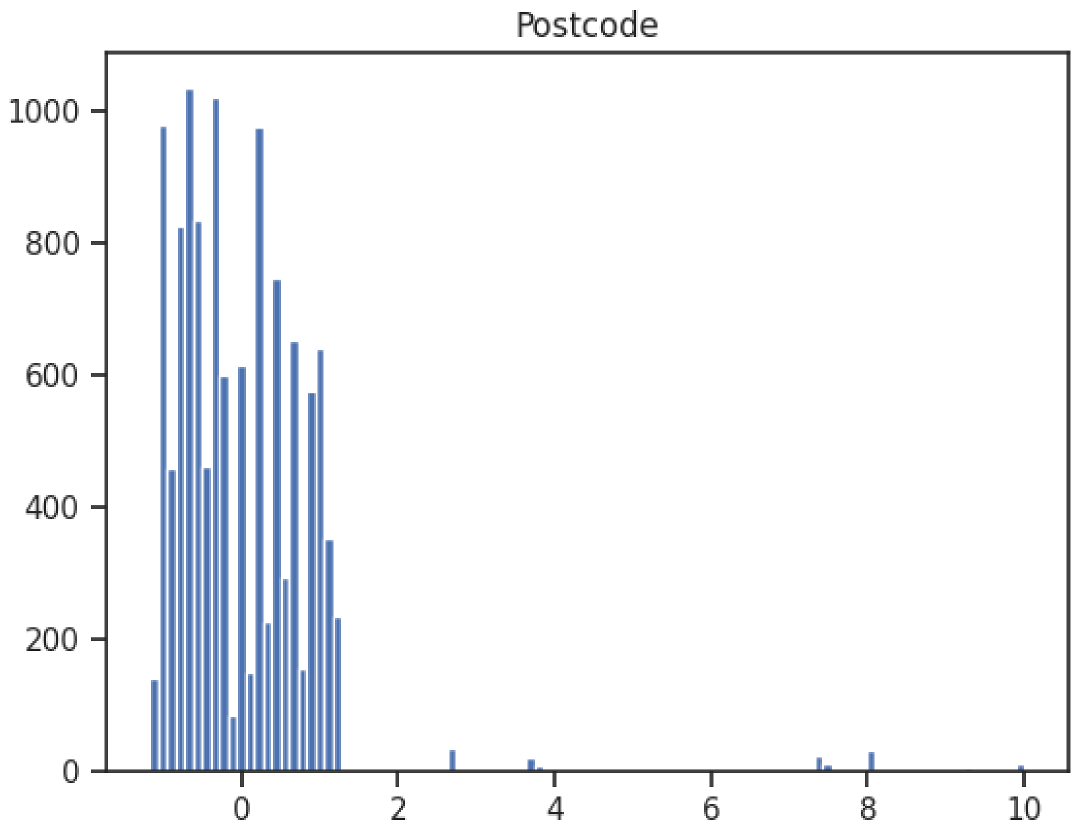


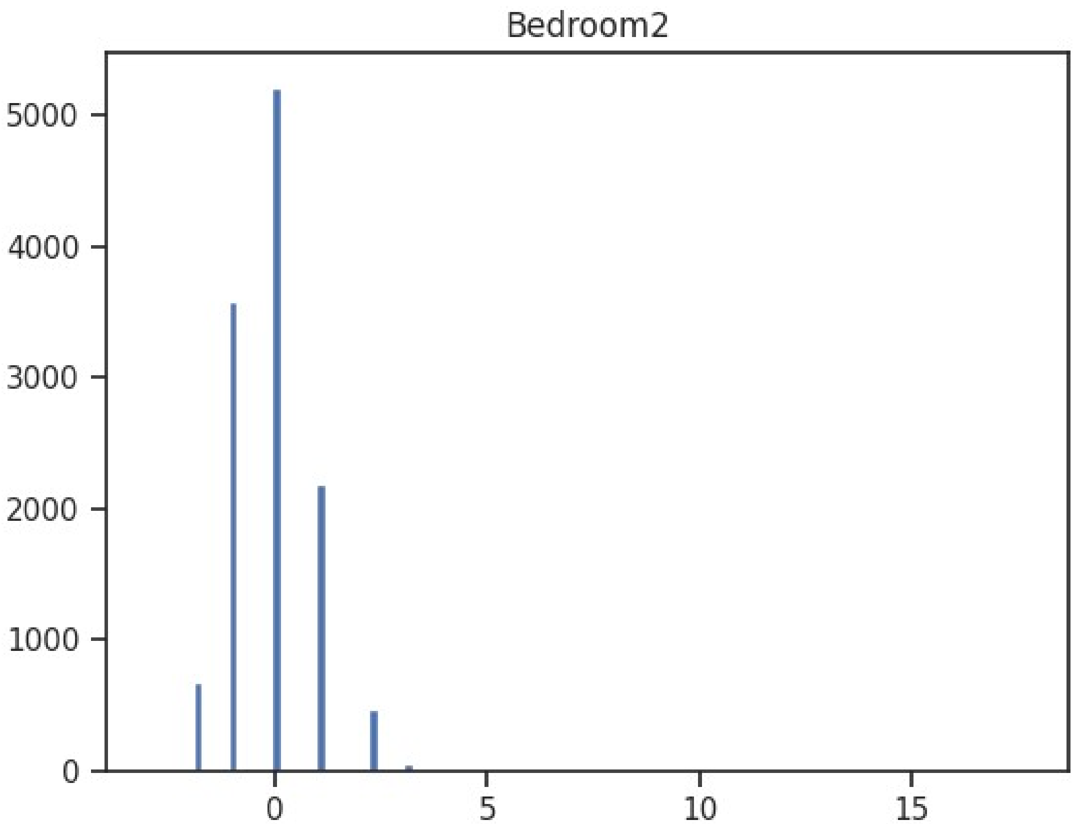
Method
8000
7000
6000
5000
4000
3000
2000
1000
0
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0
2.5

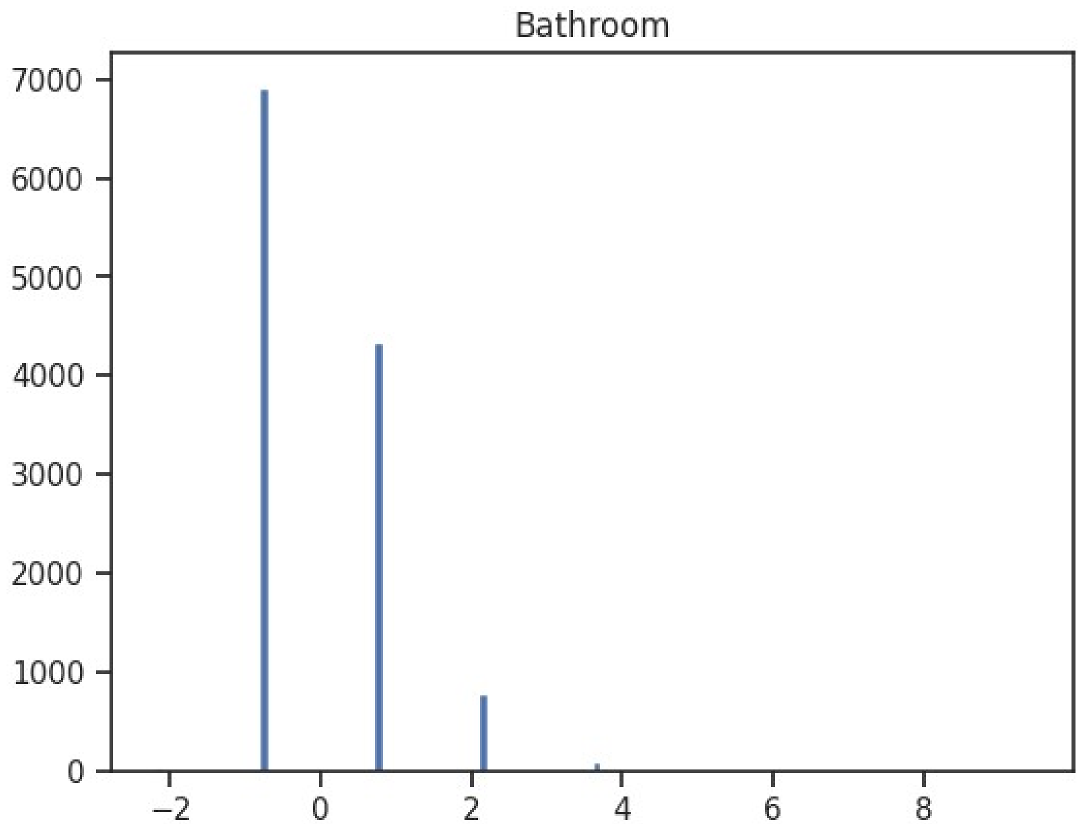


SellerG
1400
1200
1000
800
600
400
200
0
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5

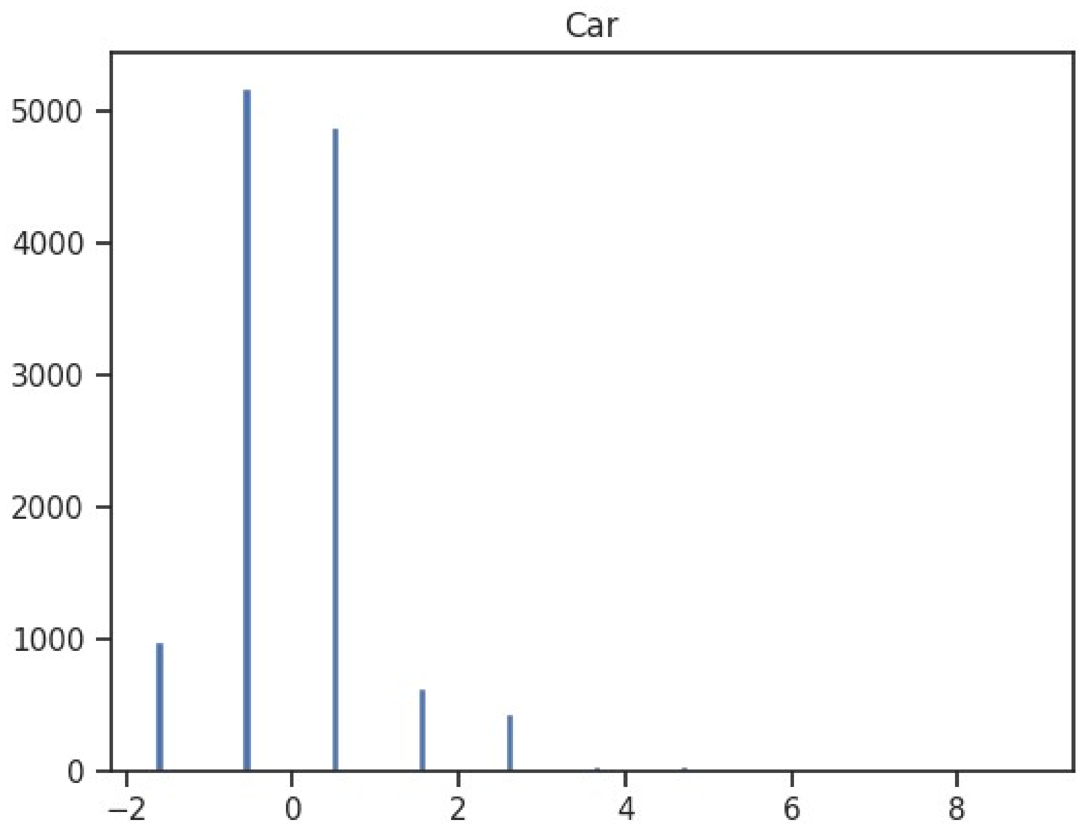

Distance
800
700
600
500
400
300
200
100
0
−2
0
2
4
6


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

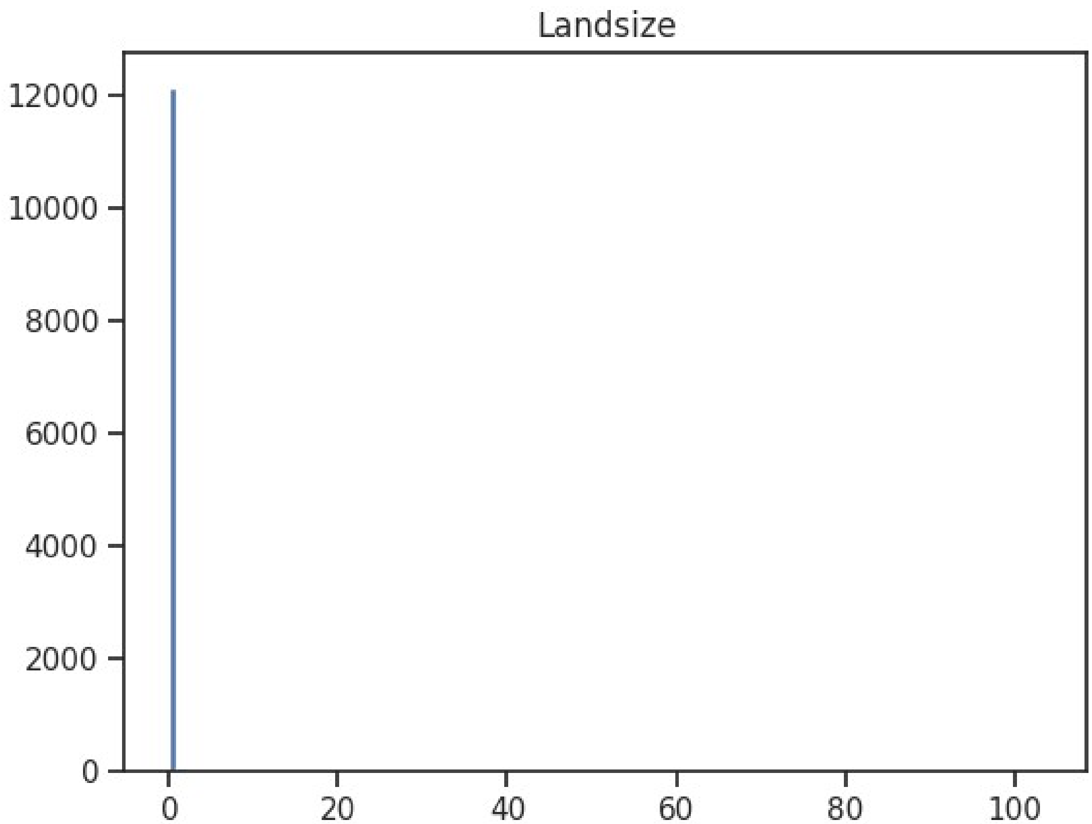

Bedroom2
5000
4000
3000
2000
1000
0
0
5
10
15



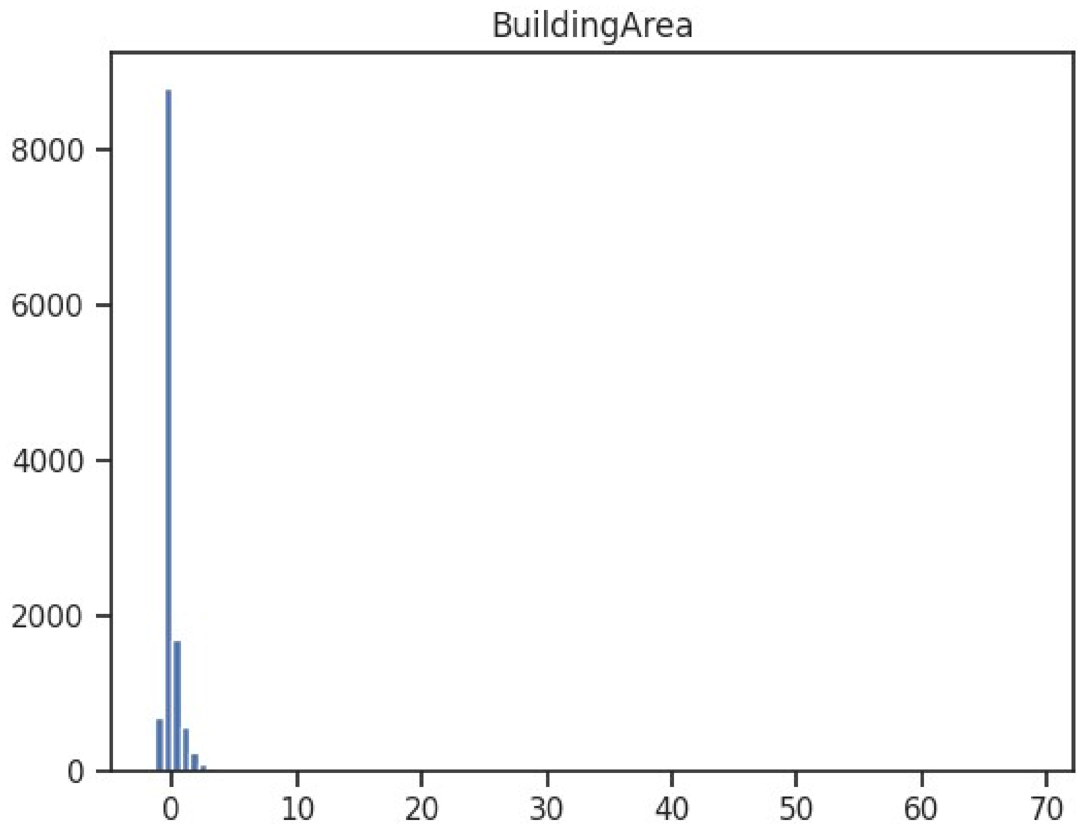
Bathroom
7000
6000
5000
4000
3000
2000
1000
0
−2
0
2
4
6
8

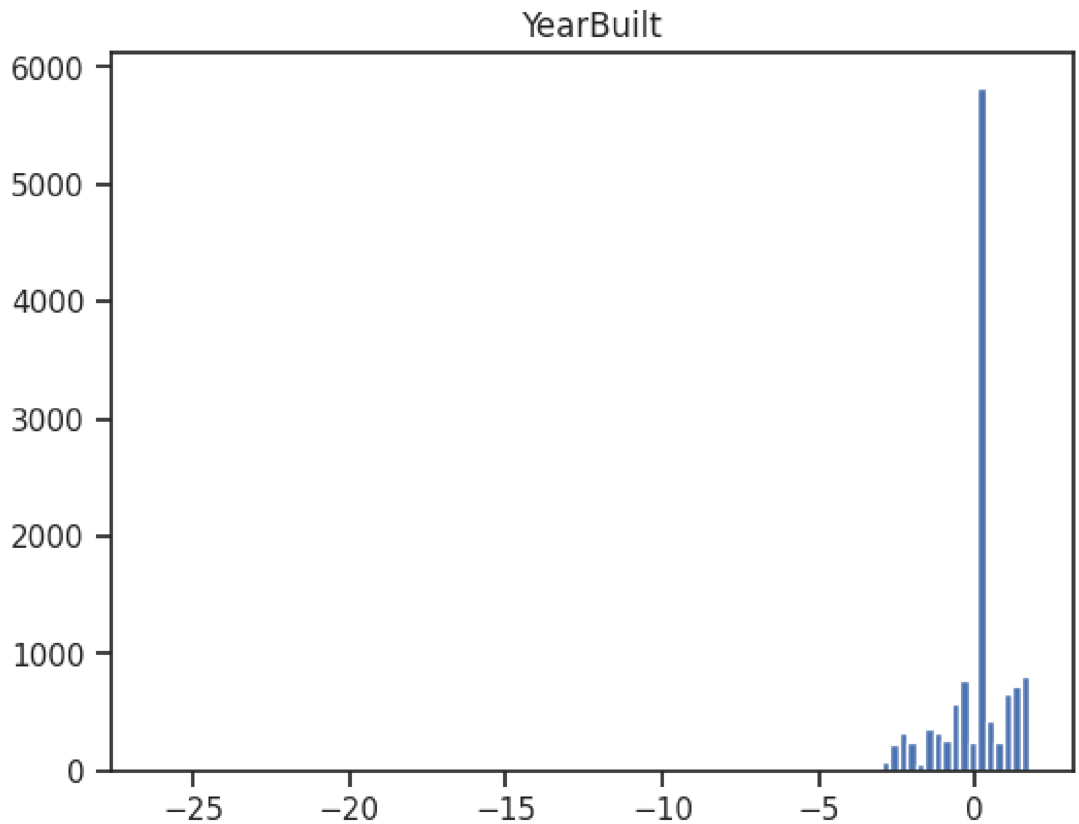


Car
5000
4000
3000
2000
1000
0
−2
0
2
4
6
8

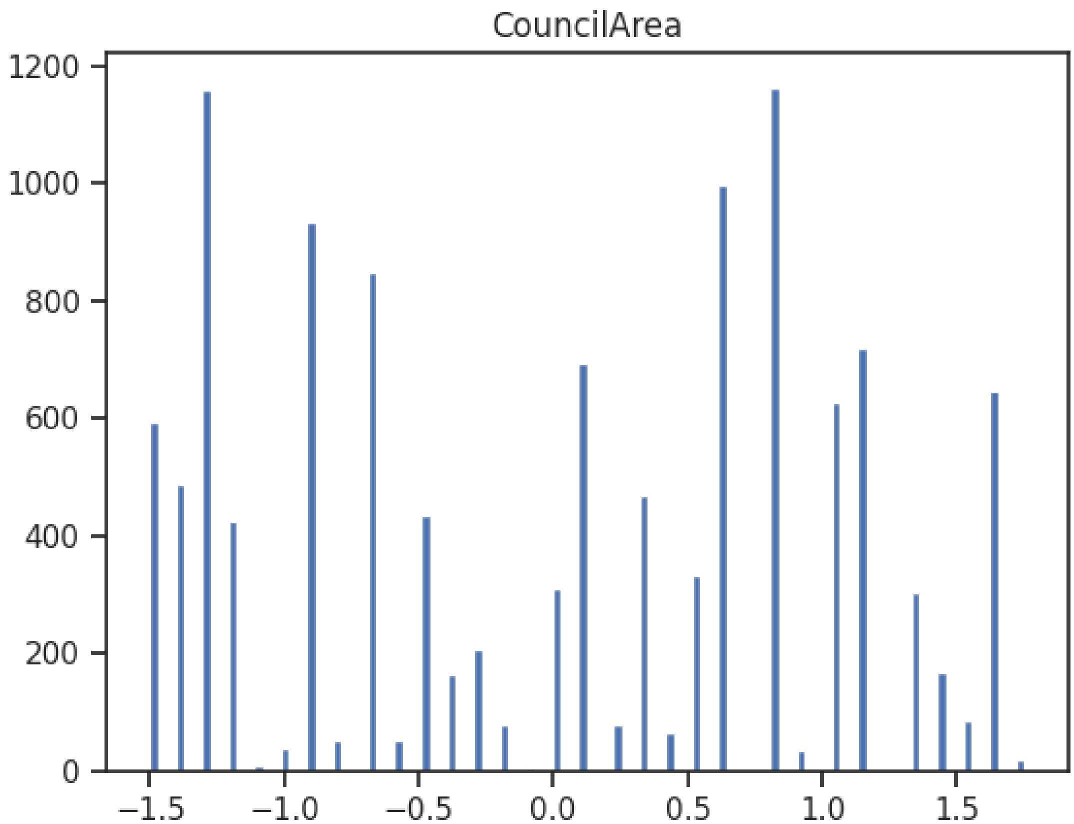


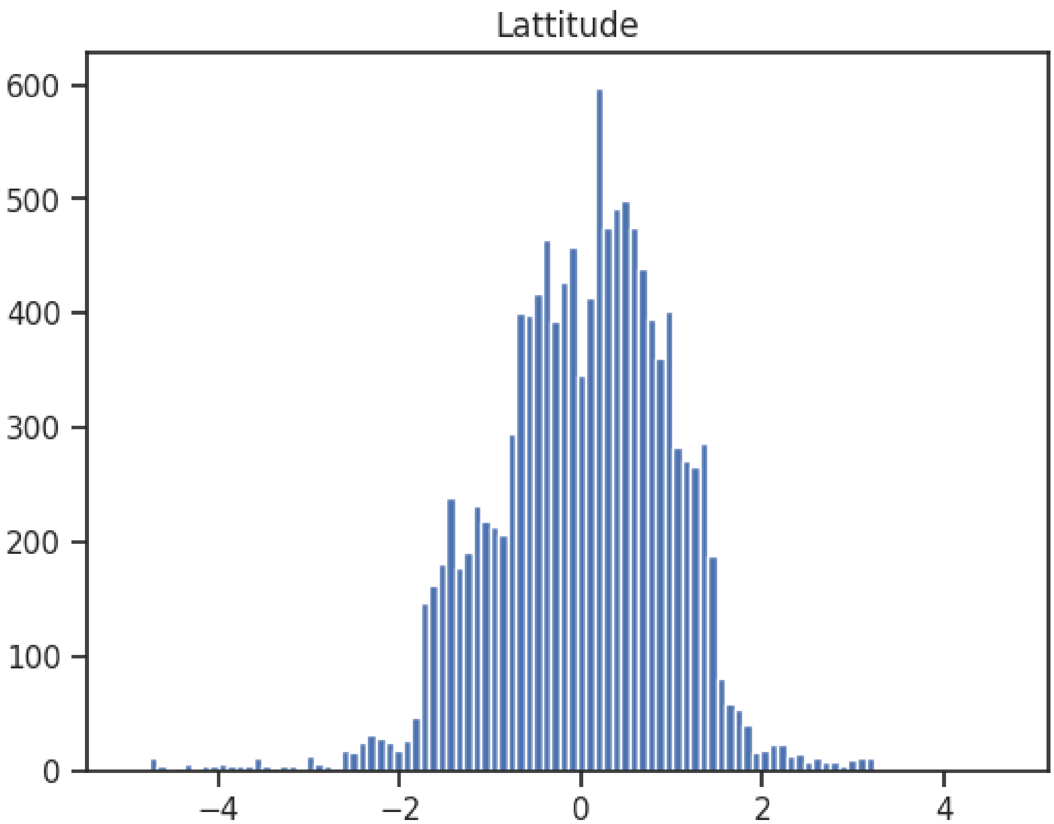
Landsize
12000
10000
8000
6000
4000
2000
0
0
20
40
60
80
100


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

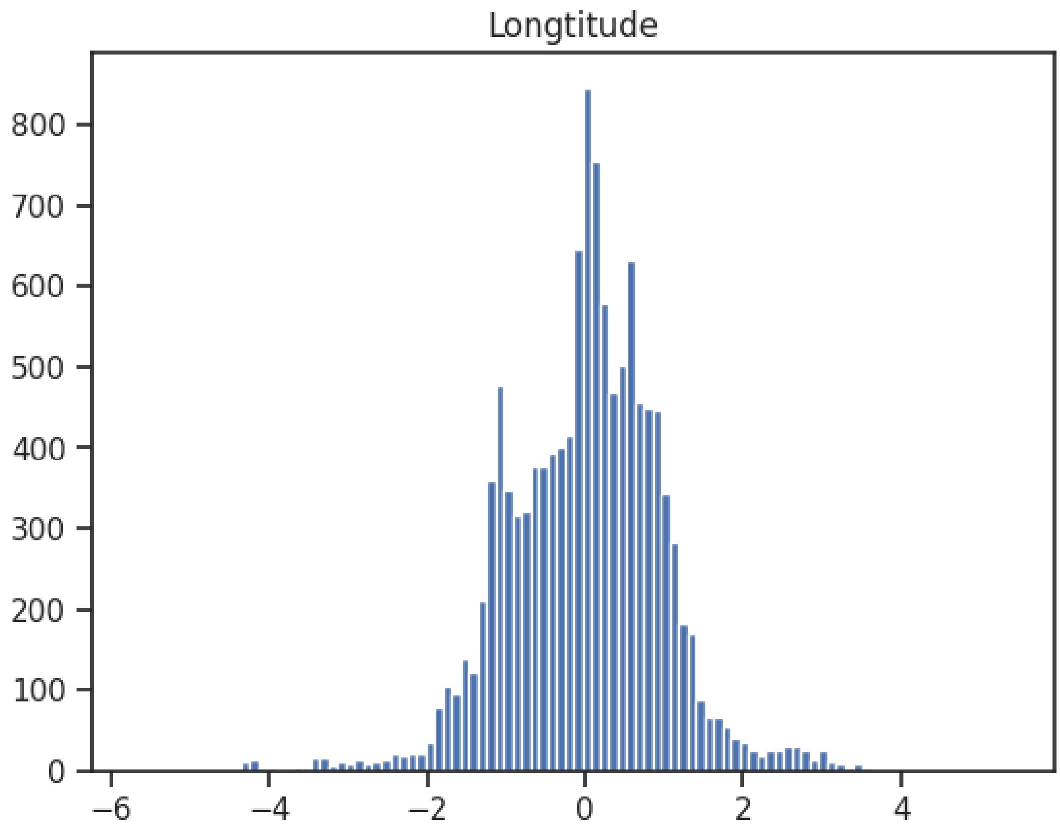


YearBuilt
6000
5000
4000
3000
2000
1000
0
−25
−20
−15
−10
−5
0

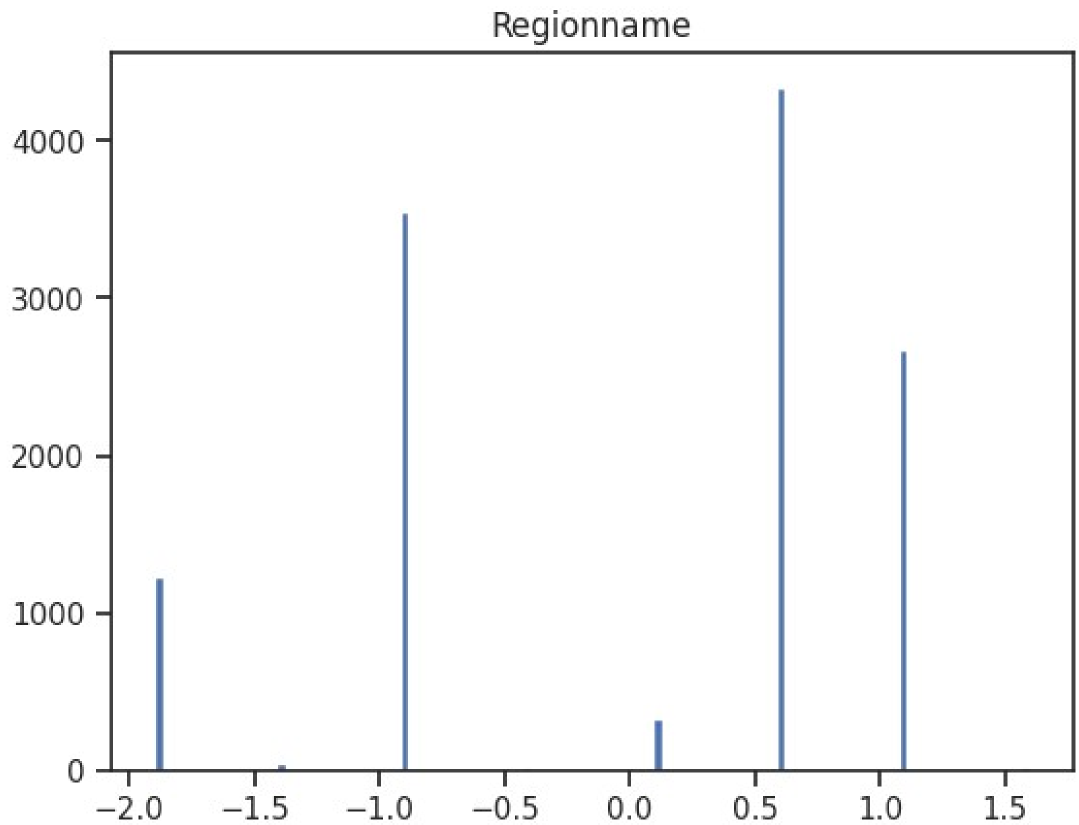

CouncilArea
1200
1000
800
600
400
200
0
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5

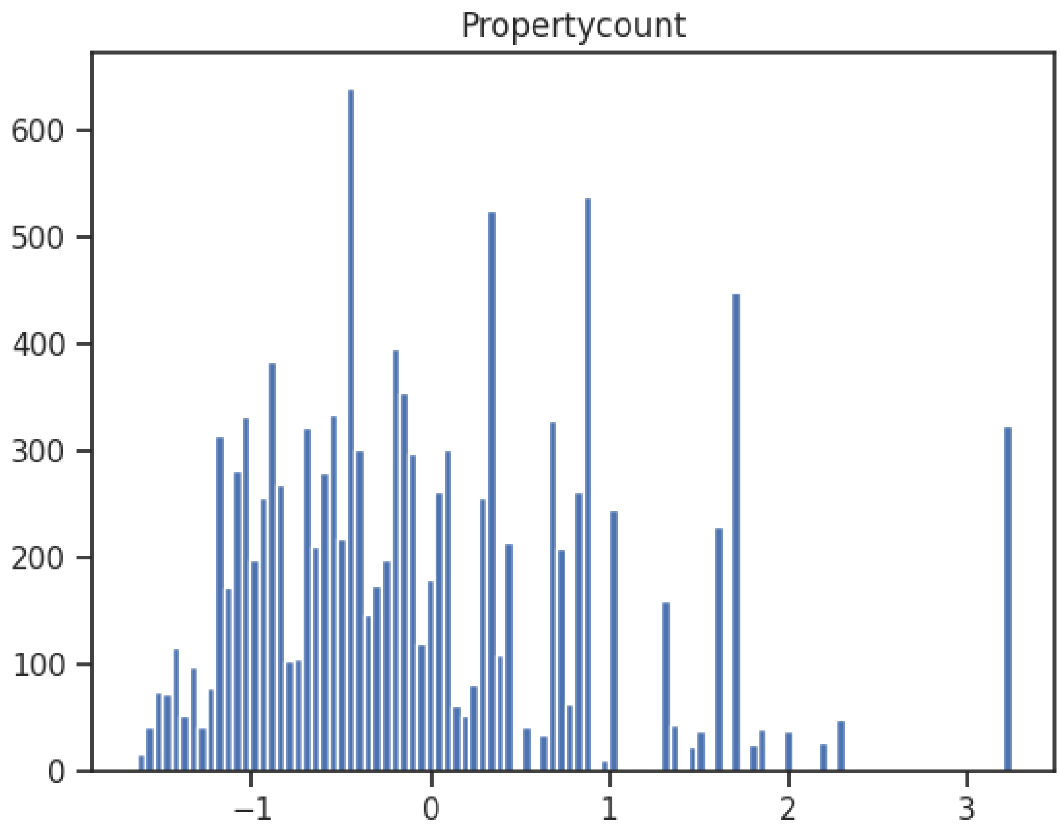


Lattitude
600
500
400
300
200
100
0
−4
−2
0
2
4

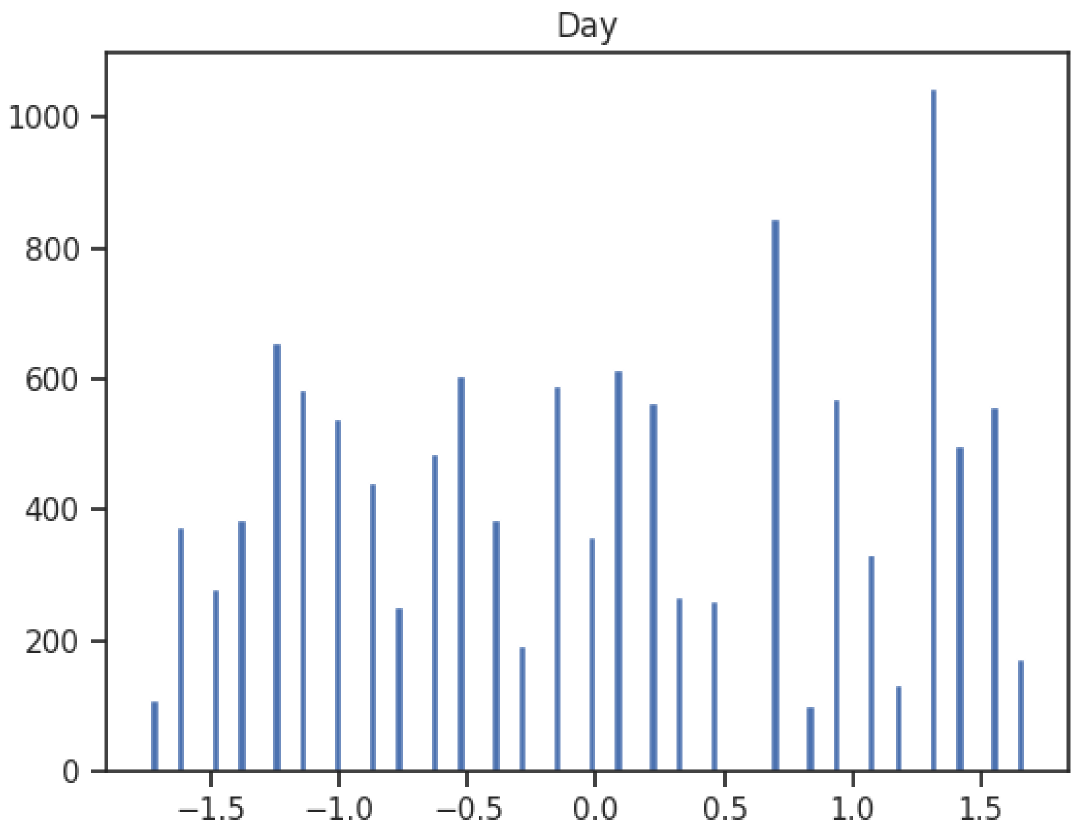


Longtitude
800
700
600
500
400
300
200
100
0
−6
−4
−2
0
2
4

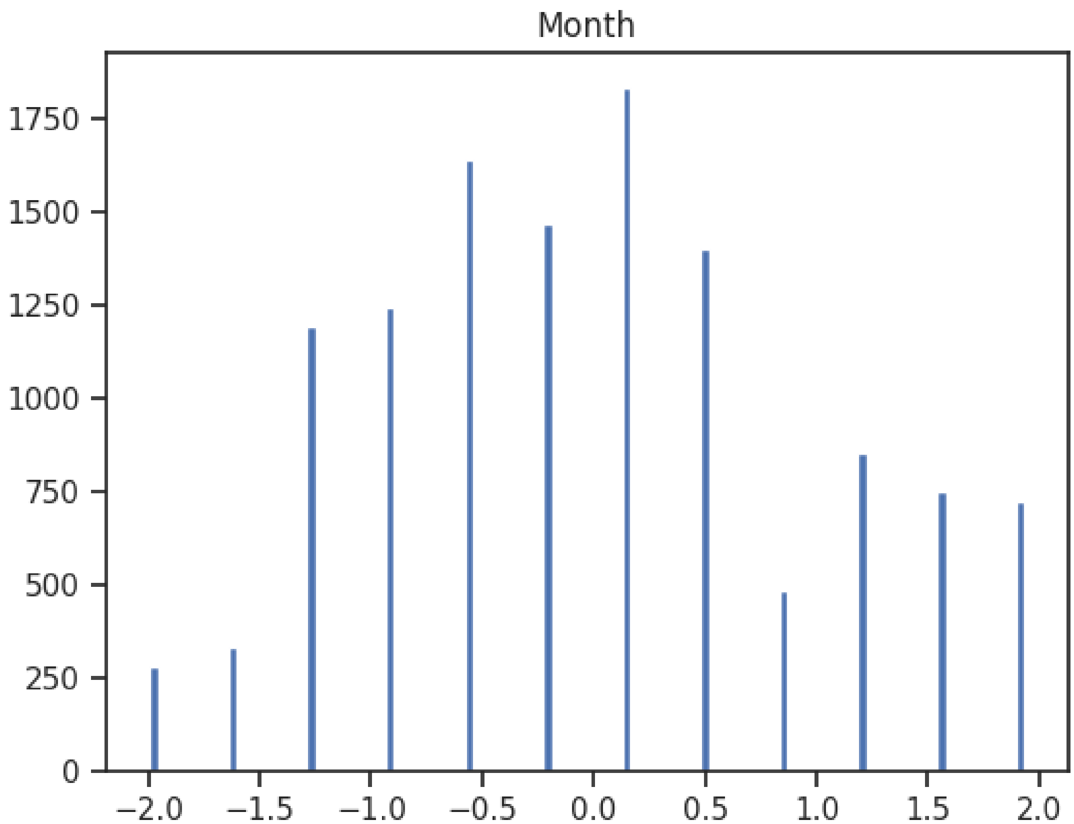

Regionname
4000
3000
2000
1000
0
−2.0
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5

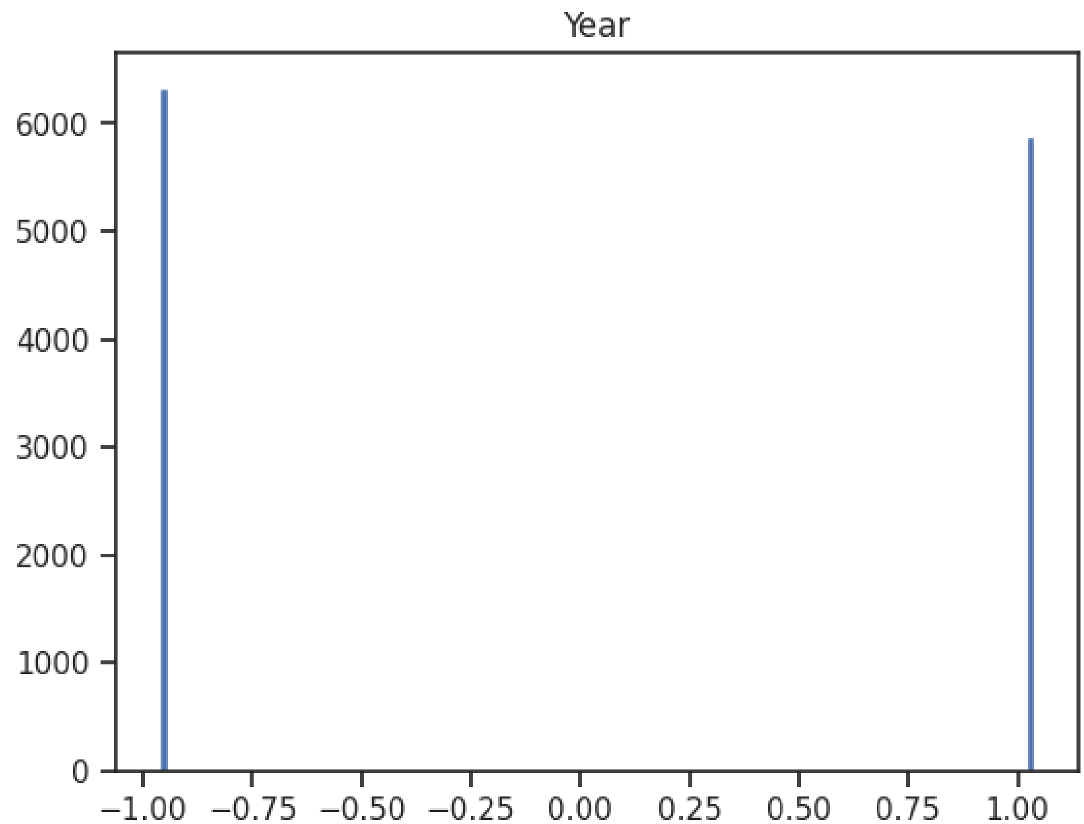


Propertycount
0
100
200
300
400
500
600
−1
0
1
2
3

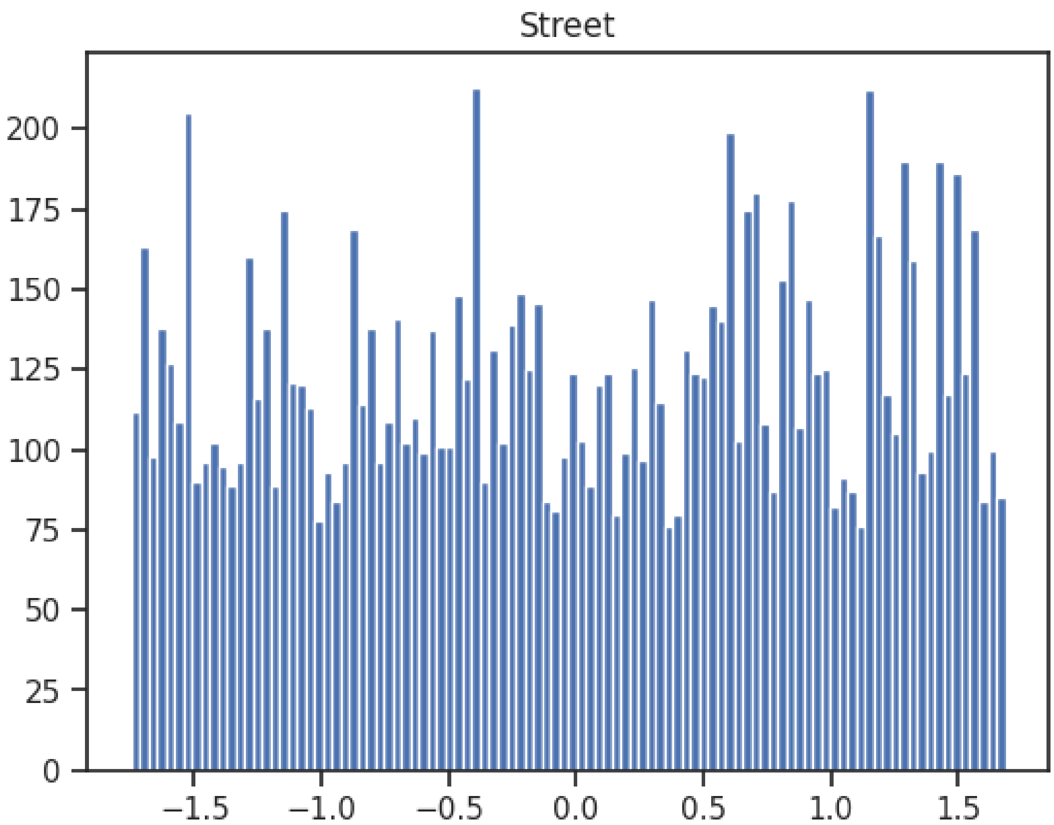


Day
1000
800
600
400
200
0
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5


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



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



Обучение с фиксированным гиперапараметром

```
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, explained_variance_score, mean_pinball_loss,
d2_pinball_score, d2_absolute_error_score

data = sc2_data
target = sc2_data['Price']

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

data.shape

(12211, 22)

data.describe()

                 Suburb          Rooms            Type         Method
SellerG  \
```

```
count  1.221100e+04  1.221100e+04  1.221100e+04  1.221100e+04
1.221100e+04
mean  -1.675836e-16  9.775709e-17 -5.586119e-17 -8.728311e-17
6.749894e-17
std    1.000041e+00  1.000041e+00  1.000041e+00  1.000041e+00
1.000041e+00
min   -1.713779e+00 -1.974554e+00 -6.679092e-01 -1.256809e+00 -
1.692307e+00
25%   -9.609414e-01 -9.321296e-01 -6.679092e-01 -3.618941e-01 -
7.344135e-01
50%    5.387686e-03  1.102950e-01 -6.679092e-01 -3.618941e-01
5.926979e-02
75%    8.593529e-01  1.102950e-01  5.023935e-01 -3.618941e-01
8.119005e-01
max    1.735791e+00  7.407267e+00  1.672696e+00  2.322850e+00
1.756110e+00

           Distance      Postcode      Bedroom2      Bathroom
Car  \
count  1.221100e+04  1.221100e+04  1.221100e+04  1.221100e+04
1.221100e+04
mean   4.096487e-16 -1.955142e-16  1.582734e-16 -9.542954e-17
4.655099e-17
std    1.000041e+00  1.000041e+00  1.000041e+00  1.000041e+00
1.000041e+00
min   -1.772836e+00 -1.180357e+00 -2.958890e+00 -2.202661e+00 -
1.655768e+00
25%   -7.016215e-01 -6.766680e-01 -8.957937e-01 -7.510612e-01 -
6.038672e-01
50%   -1.024677e-01 -2.302162e-01  1.357545e-01 -7.510612e-01 -
6.038672e-01
75%    5.148423e-01  5.024227e-01  1.357545e-01  7.005387e-01
4.480333e-01
max    6.833191e+00  1.000383e+01  1.767207e+01  9.410138e+00
8.863237e+00

       ...     YearBuilt   CouncilArea     Lattitude    Longtitude  \
count  ...  1.221100e+04  1.221100e+04  1.221100e+04  1.221100e+04
mean   ...  8.006771e-16  3.956834e-17  6.633168e-14  1.136496e-13
std    ...  1.000041e+00  1.000041e+00  1.000041e+00  1.000041e+00
min    ... -2.623103e+01 -1.501642e+00 -4.964142e+00 -5.677929e+00
25%    ... -2.283664e-01 -8.915352e-01 -6.186451e-01 -6.397538e-01
50%    ...  1.119827e-01  1.253089e-01  9.109507e-02  5.494373e-02
75%    ...  2.821572e-01  8.370998e-01  6.820801e-01  6.175395e-01
max    ...  1.745658e+00  1.752259e+00  4.677957e+00  5.393332e+00

         Regionname  Propertycount           Day         Month
Year  \
count  1.221100e+04   1.221100e+04  1.221100e+04  1.221100e+04
1.221100e+04
```

```
mean  -2.793060e-17  -3.491325e-18  4.073212e-18  5.586119e-17
9.682607e-15
std    1.000041e+00   1.000041e+00  1.000041e+00  1.000041e+00
1.000041e+00
min   -1.896366e+00  -1.648721e+00 -1.740993e+00 -1.995070e+00 -
9.629336e-01
25%   -8.985197e-01  -7.032906e-01 -8.886206e-01 -5.665816e-01 -
9.629336e-01
50%    5.982504e-01  -2.027685e-01 -3.624805e-02 -2.094594e-01 -
9.629336e-01
75%    5.982504e-01   6.586696e-01  9.378921e-01  5.047849e-01
1.038493e+00
max    1.596097e+00   3.249163e+00  1.668497e+00  1.933274e+00
1.038493e+00

             Street
count  1.221100e+04
mean   6.517139e-17
std    1.000041e+00
min   -1.749416e+00
25%   -8.613720e-01
50%    1.282498e-02
75%    8.547127e-01
max    1.684600e+00

[8 rows x 22 columns]
```

```
target.describe()
```

```
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
```

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

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)

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

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_absolute_error': 0.38465733025879834,
'r2_score': 0.6074478363288117, 'explained_variance_score':
0.6080485130705291, 'mean_pinball_loss': 0.19232866512939917,
'd2_pinball_score': 0.4454301531494722, 'd2_absolute_error_score':
0.4454301531494722}

Test : {'r2': 0.6358064659388151, 'mean_squared_error':
0.3521518459937633, 'mean_absolute_error': 0.3775204179759272,
'r2_score': 0.6358064659388151, 'explained_variance_score':
0.6359862432962011, 'mean_pinball_loss': 0.1887602089879636,
'd2_pinball_score': 0.4426146306868046, 'd2_absolute_error_score':
0.4426146306868046}
```

Поиск лучших гиперпараметров

```
from sklearn.model_selection import KFold, RepeatedKFold, LeaveOneOut,
LeavePOut, ShuffleSplit, StratifiedKFold
from sklearn.model_selection import GridSearchCV, RandomizedSearchCV
```

Вспомогательные функции

```
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

def plot_learning_curve(estimator, title, X, y, ylim=None, cv=None,
                        n_jobs=None, train_sizes=np.linspace(.1, 1.0,
5), scoring='accuracy'):
    """
    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_sizes)
    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

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}

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

```
scores = [
        'r2',
        'neg_mean_squared_error',
        'neg_mean_absolute_error',
]
```

RandomizedSearch + KFolds

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

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

```
data.shape
```

```
(12211, 22)
```

```
kf = KFold(n_splits=24) # 500 samples for 1 fold
```

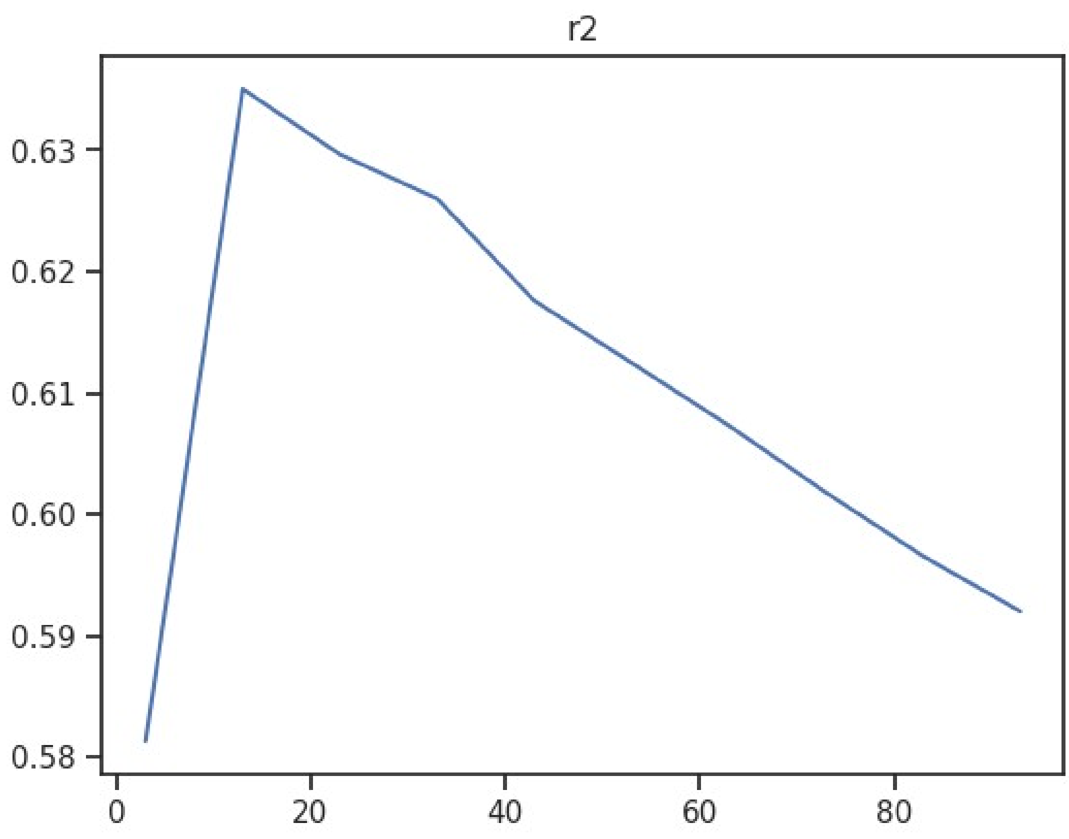
```
%%time
clf_rs = RandomizedSearchCV(KNeighborsRegressor(), tuned_parameters_1,
cv=kf, scoring=scores , n_iter=n_range_1.size, refit=False)
s = clf_rs.fit(X_train, y_train)
```

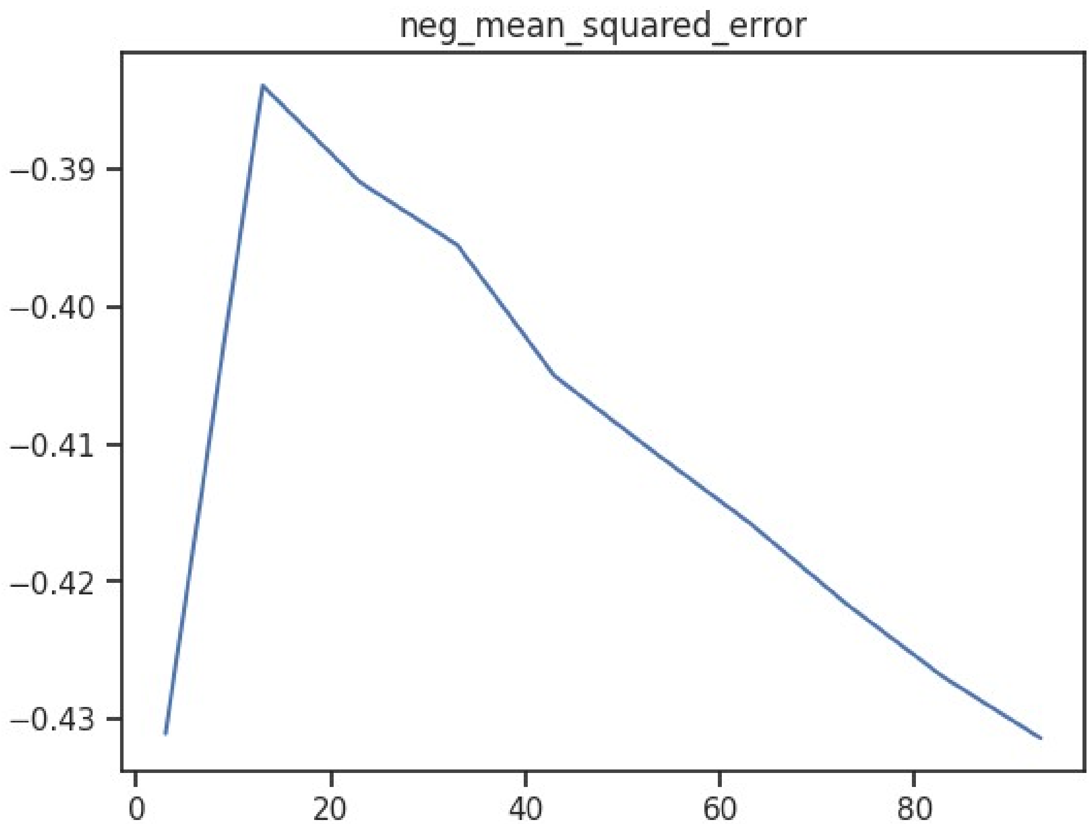
```
CPU times: user 14.7 s, sys: 39.4 ms, total: 14.8 s
Wall time: 4.12 s
```

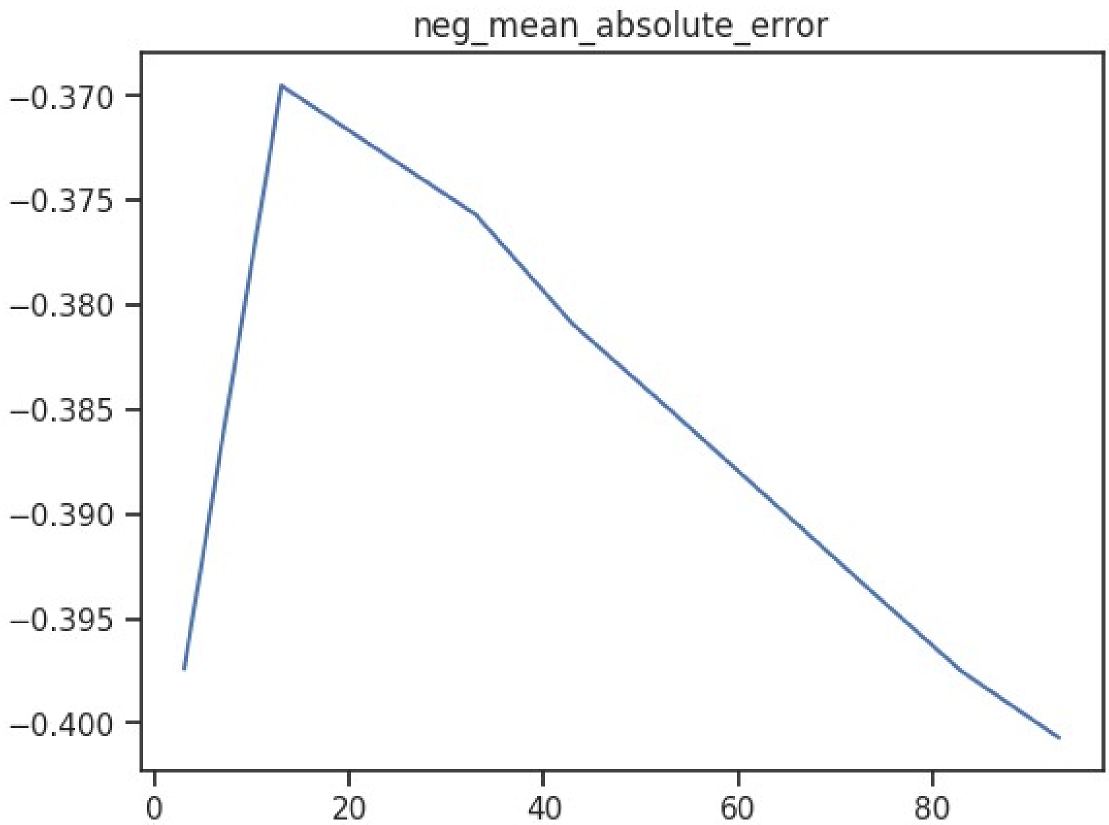
```
get_best_param_for_scores(clf_rs.cv_results_, scores)
```

```
{'r2': {'n_neighbors': 13},
 'neg_mean_squared_error': {'n_neighbors': 13},
 'neg_mean_absolute_error': {'n_neighbors': 13}}
```

```
show_plots_for_scores(n_range_1, clf_rs.cv_results_, scores)
```




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



GridSearch + LeavePOut folds

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

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

```
data.shape[0] / 3
```

```
4070.3333333333335
```

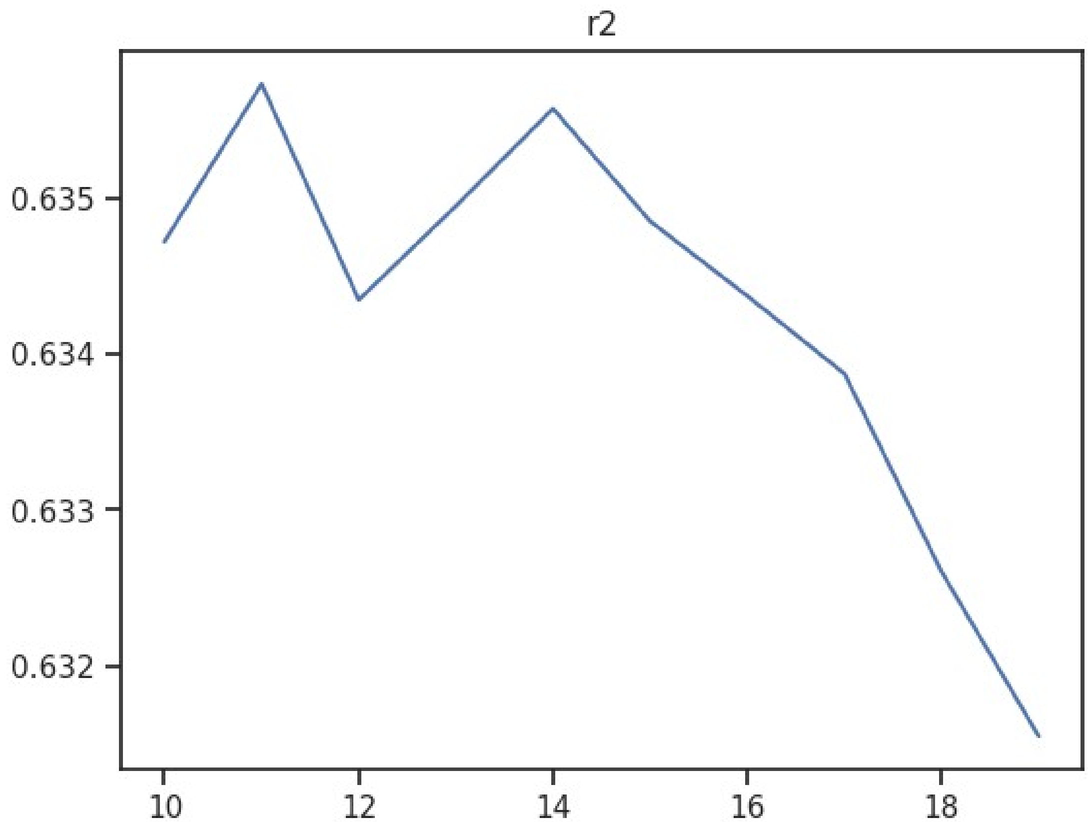
```
rkf = RepeatedKFold(n_splits=12, n_repeats=2)
len(list(rkf.split(X_train, y_train)))
```

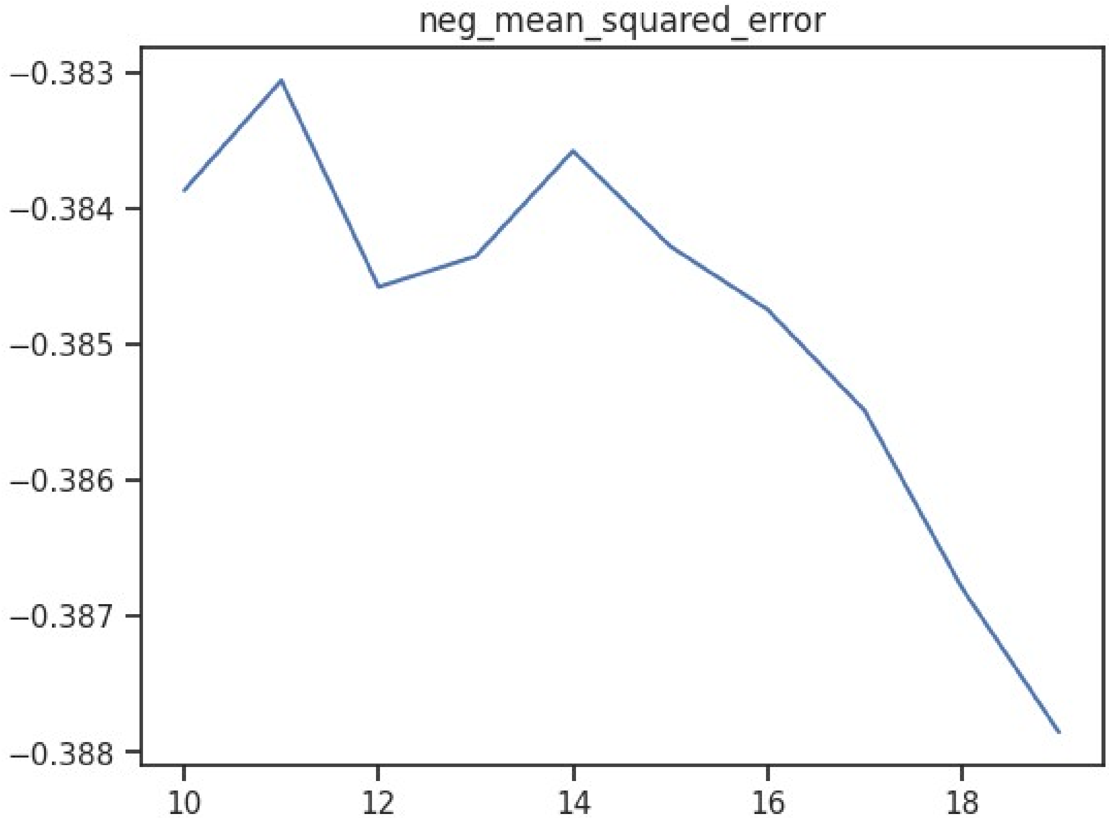
```
24
```

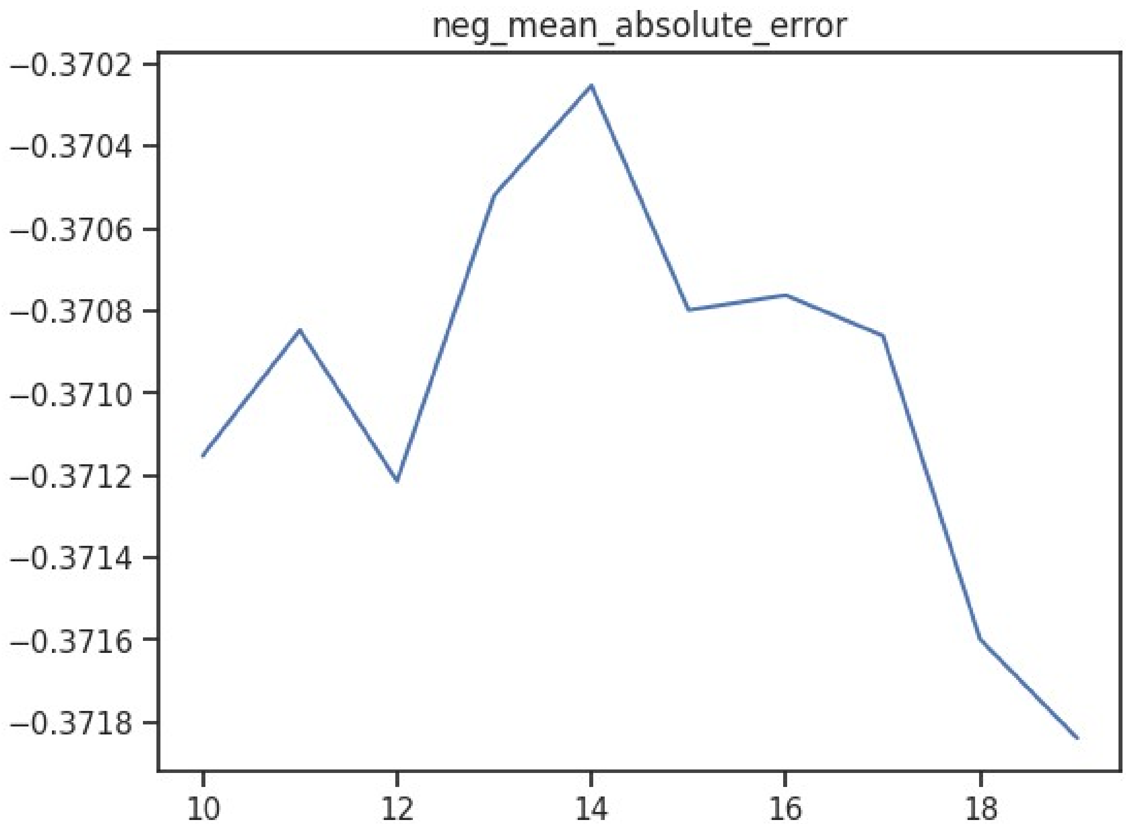
```
%%time
clf_gs = GridSearchCV(KNeighborsRegressor(), tuned_parameters_2,
cv=rkf, scoring=scores, refit=False)
clf_gs.fit(X_train, y_train)
```

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

```
GridSearchCV(cv=RepeatedKFold(n_repeats=2, n_splits=12,
random_state=None),
             estimator=KNeighborsRegressor(),
             param_grid=[{'n_neighbors': array([10, 11, 12, 13, 14,
15, 16, 17, 18, 19])}],
             refit=False,
             scoring=['r2', 'neg_mean_squared_error',
                      'neg_mean_absolute_error'])

get_best_param_for_scores(clf_gs.cv_results_, scores)

{'r2': {'n_neighbors': 11},
 'neg_mean_squared_error': {'n_neighbors': 11},
 'neg_mean_absolute_error': {'n_neighbors': 14}}

show_plots_for_scores(n_range_2, clf_gs.cv_results_, scores)
```



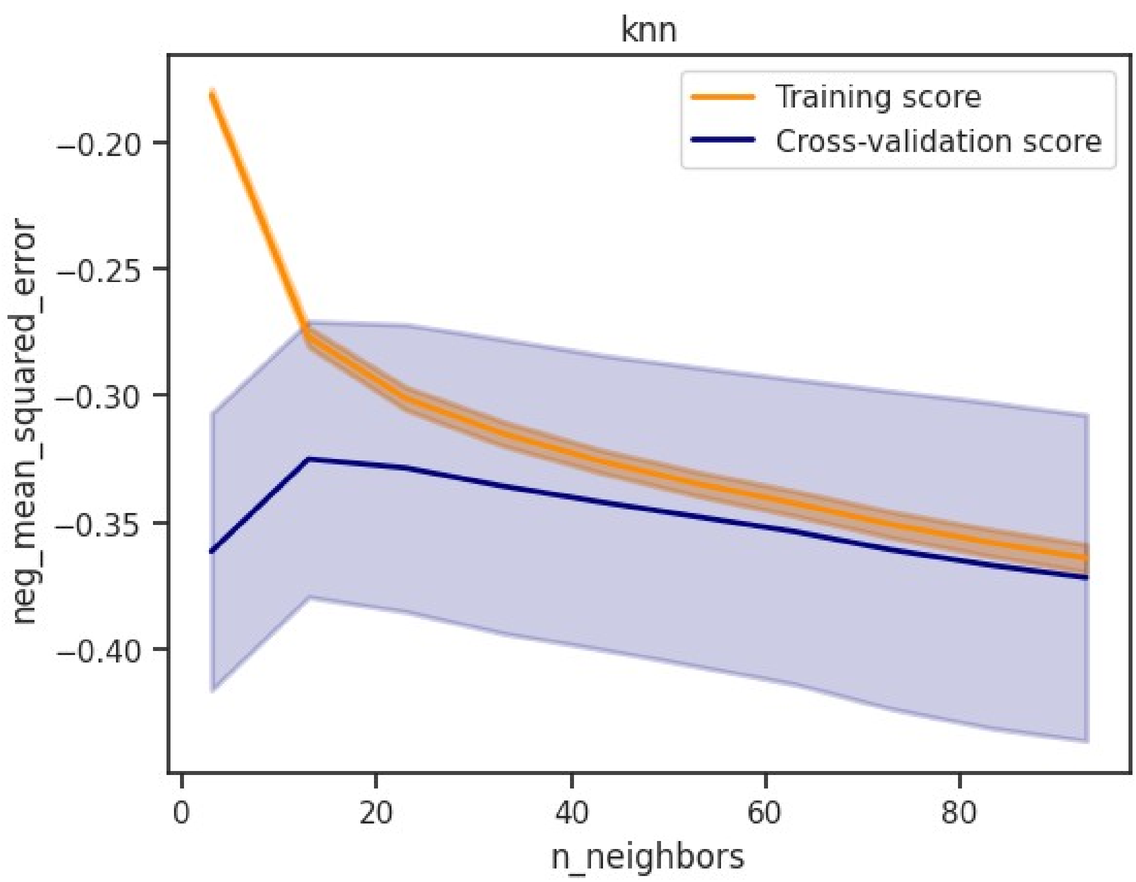

neg_mean_squared_error
−0.383
−0.384
−0.385
−0.386
−0.387
−0.388
10
12
14
16
18



Validation curve

```
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')
```

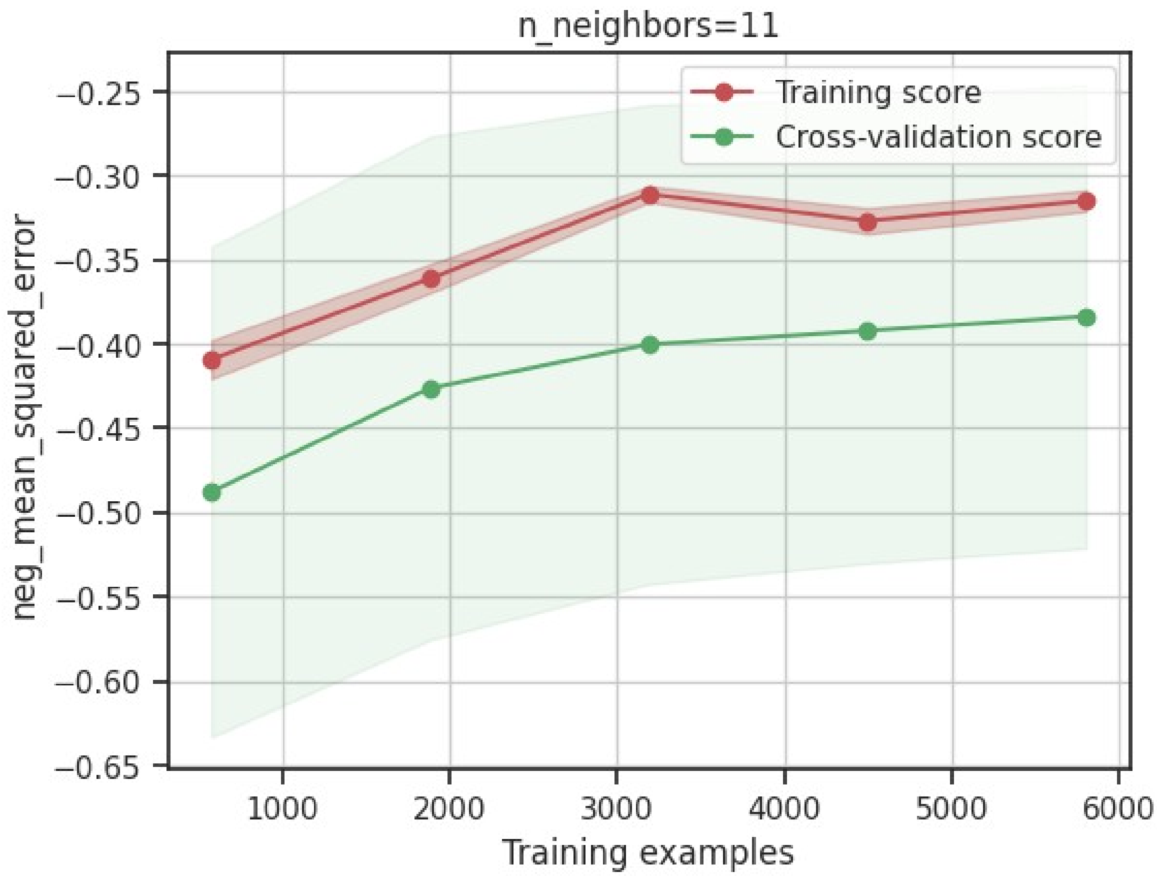
```
<module 'matplotlib.pyplot' from '/opt/conda/lib/python3.10/site-packages/matplotlib/pyplot.py'>
```



Learning Curve for best hyperparams

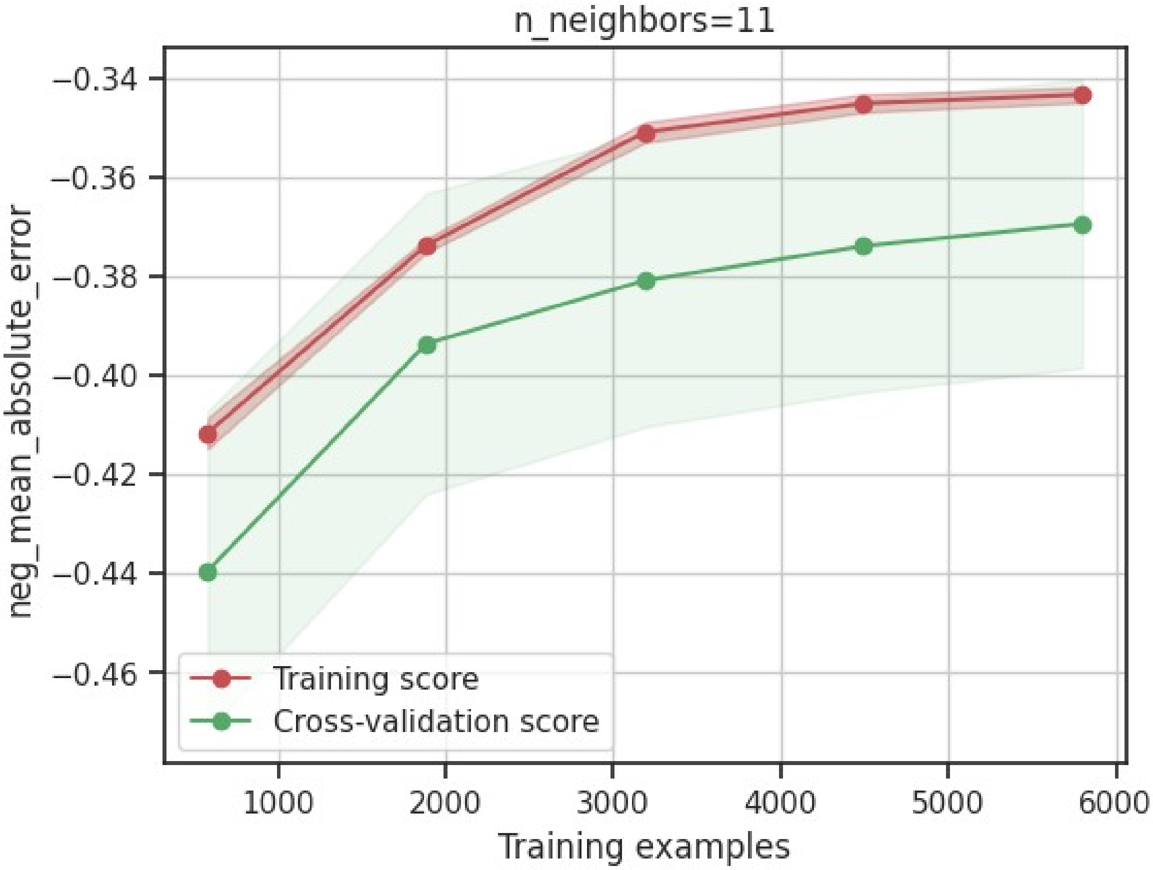
```
K = 11
plot_learning_curve(KNeighborsRegressor(n_neighbors=11),
'n_neighbors=11',
                    X_train, y_train, cv=20,
scoring='neg_mean_squared_error')
```

```
<module 'matplotlib.pyplot' from '/opt/conda/lib/python3.10/site-
packages/matplotlib/pyplot.py'>
```




```
K = 14
plot_learning_curve(KNeighborsRegressor(n_neighbors=14),
'n_neighbors=11',
                    X_train, y_train, cv=20,
scoring='neg_mean_absolute_error')
```

```
<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