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

Лабораторная работа №2-3
по дисциплине
«Технологии машинного обучения»
на тему

«Обработка пропусков в данных, кодирование категориальных признаков, масштабирование данных. Подготовка обучающей и тестовой выборки, кросс-валидация и подбор гиперпараметров на примере метода ближайших соседей»

Выполнила:
студент группы ИУ5-64б
Подопригорова С. С.

Москва — 2020 г.

1. Лабораторная №2

Обработка пропусков в данных, кодирование категориальных признаков, масштабирование данных.

Задание:

1. 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.)
2. Для выбранного датасета (датасетов) на основе материалов лекции решить следующие задачи:

   - обработку пропусков в данных;
   - кодирование категориальных признаков;
   - масштабирование данных.

2. Melbourne Housing Snapshot

- Rooms: Number of rooms
- Price: Price in dollars
- Method: S - property sold; SP - property sold prior; PI - property passed in; PN - sold prior not disclosed; SN - - sold not disclosed; NB - no bid; VB - vendor bid; W - withdrawn prior to auction; SA - sold after auction; SS - sold after auction price not disclosed. N/A - price or highest bid not available.
- Type: br - bedroom(s); h - house,cottage,villa, semi,terrace; u - unit, duplex; t - townhouse; dev site - - development site; o res - other residential.
- SellerG: Real Estate Agent
- Date: Date sold
- Distance: Distance from CBD
- Regionname: General Region (West, North West, North, North east …etc)
- Propertycount: Number of properties that exist in the suburb.
- Bedroom2 : Scraped # of Bedrooms (from different source)
- Bathroom: Number of Bathrooms
- Car: Number of carspots
- Landsize: Land Size
- BuildingArea: Building Size
- CouncilArea: Governing council for the area

[13]:
```
import sklearn
from sklearn.model_selection import train_test_split
from sklearn.impute import SimpleImputer
import pandas as pd
import numpy as np
import seaborn as sns

import matplotlib.pyplot as plt
```

[14]:
```
data = pd.read_csv('melb_data.csv')
```

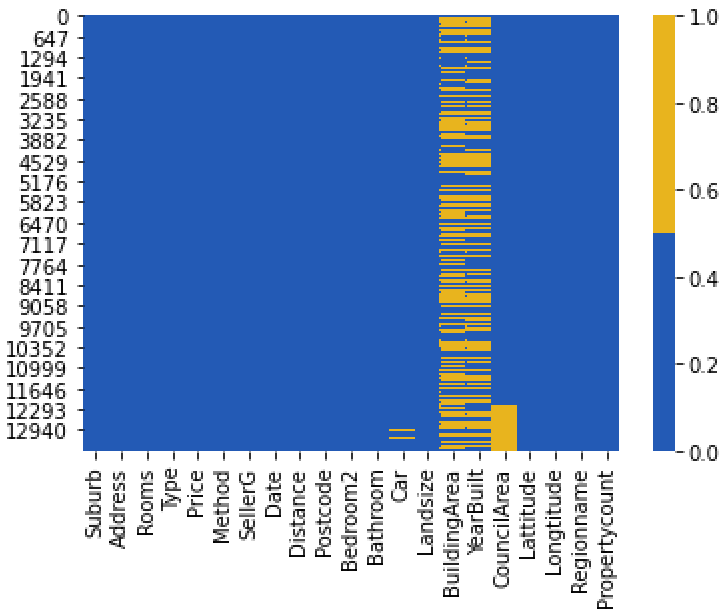
[4]:
```
data.head()
```

[4]:
```
      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]
```

2.1. Обработка пропусков в данных

[10]:
```
cols = data.columns
#
#      -            ,     -
colours = ['#235AB5', '#E8B41E']
sns.heatmap(data[cols].isnull(), cmap=sns.color_palette(colours))
```

[10]: <matplotlib.axes._subplots.AxesSubplot at 0x7fad56bcb940>



[9]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 13580 entries, 0 to 13579
Data columns (total 21 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Suburb         13580 non-null  object
 1   Address        13580 non-null  object
 2   Rooms          13580 non-null  int64
 3   Type           13580 non-null  object
 4   Price          13580 non-null  float64
 5   Method         13580 non-null  object
 6   SellerG        13580 non-null  object
 7   Date           13580 non-null  object
 8   Distance       13580 non-null  float64
 9   Postcode       13580 non-null  float64
 10  Bedroom2       13580 non-null  float64
 11  Bathroom       13580 non-null  float64
 12  Car            13518 non-null  float64
 13  Landsize       13580 non-null  float64
 14  BuildingArea   7130 non-null   float64
 15  YearBuilt      8205 non-null   float64
 16  CouncilArea    12211 non-null  object
 17  Lattitude      13580 non-null  float64
 18  Longtitude     13580 non-null  float64
 19  Regionname     13580 non-null  object
 20  Propertycount  13580 non-null  float64
dtypes: float64(12), int64(1), object(8)
memory usage: 2.2+ MB
```

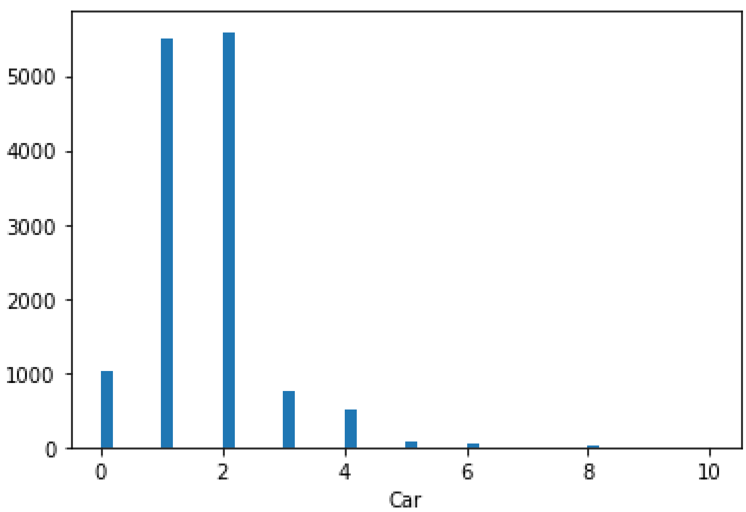
Рассмотрим числовые колонки с пропущенными значениями

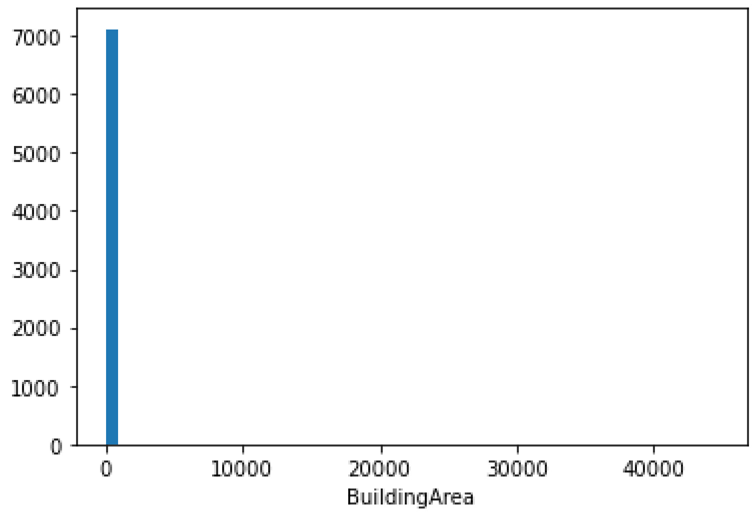
[11]:
```
total_count = data.shape[0]
num_cols = []
for col in data.columns:
    #
    temp_null_count = data[data[col].isnull()].shape[0]
    dt = str(data[col].dtype)
    if temp_null_count>0 and (dt=='float64' or dt=='int64'):
        num_cols.append(col)
        temp_perc = round((temp_null_count / total_count) * 100.0, 2)
        print('     {}.         {}.                    {}, {}%.'.format(col, dt,␣
 ↪temp_null_count, temp_perc))
```

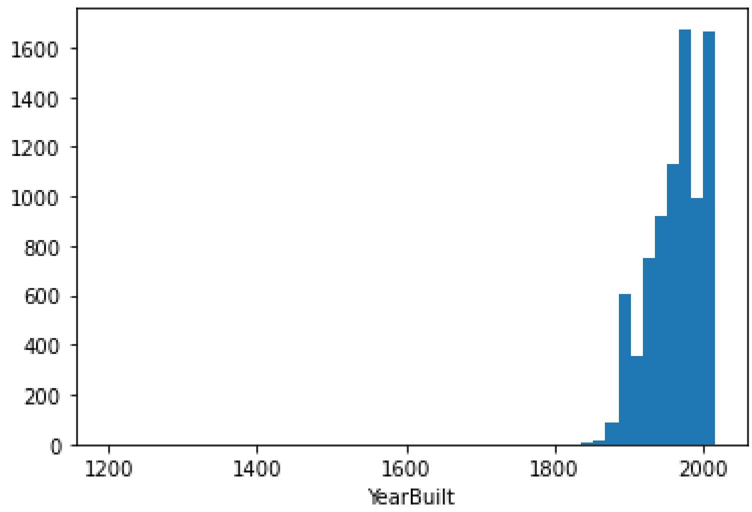
```
     Car.         float64.                   62, 0.46%.
     BuildingArea.        float64.                    6450,
47.5%.
     YearBuilt.        float64.                   5375, 39.58%.
```

[12]:
```
data_num = data[num_cols]
for col in data_num:
    plt.hist(data[col], 50)
    plt.xlabel(col)
    plt.show()
```

```
/Users/nonpenguin/anaconda3/lib/python3.8/site-
packages/numpy/lib/histograms.py:839: RuntimeWarning: invalid value␣
 ↪encountered
in greater_equal
  keep = (tmp_a >= first_edge)
/Users/nonpenguin/anaconda3/lib/python3.8/site-
packages/numpy/lib/histograms.py:840: RuntimeWarning: invalid value␣
 ↪encountered
in less_equal
  keep &= (tmp_a <= last_edge)
```







Выбросов нет, распределения одномодальные

[15]:
```
data = data.fillna(data.mode())
```

Рассмотрим пропуски в категориальных данных

[13]:
```
cat_cols = []
for col in data.columns:
    #
    temp_null_count = data[data[col].isnull()].shape[0]
    dt = str(data[col].dtype)
    if temp_null_count>0 and (dt=='object'):
        cat_cols.append(col)
        temp_perc = round((temp_null_count / total_count) * 100.0, 2)
```

```
        print('     {}.         {}.                    {}, {}%.'.format(col, dt,␣
 ↪temp_null_count, temp_perc))
```

```
    CouncilArea.       object.                  1369, 10.08%.
```

[16]:
```
data[:] = SimpleImputer(missing_values=np.nan, strategy='most_frequent').
 ↪fit_transform(data)
```

[17]:
```
data.isnull().sum()
```

[17]:
```
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
```

Все пропуски в данных заполнены

2.2. Кодирование категориальных признаков

Рассмотрим количество категорий в признаках типа object

[25]:
```
total_count = data.shape[0]
num_cols = []
for col in data.columns:
    dt = str(data[col].dtype)
    if (dt=='object'):
        num_cols.append(col)
        print('     {}.              : {}'.format(col, data[col].unique().
 ↪shape[0]))
```

```
    Suburb.           : 314
    Address.           : 13378
    Type.           : 3
```

```
Method.             : 5
SellerG.             : 268
Date.              : 58
CouncilArea.             : 33
Regionname.             : 8
```

В признаках Suburb, Address, SellerG, CouncilArea слишком много категорий для OneHotEncoder, так что используем LabelEncoder.

```
[18]: from sklearn.preprocessing import LabelEncoder

le = LabelEncoder()
categorical1 = ['Suburb', 'Address', 'SellerG', 'CouncilArea']
for col in categorical1:
    data[col] = le.fit_transform(data[col])
```

Для остальных признаков используем OneHotEncoder

```
[19]: categorical2 = ['Type', 'Method', 'Regionname']

data = pd.concat([data, pd.get_dummies(data[categorical2],␣
 ↪columns=categorical2, drop_first=True)],axis=1)
data.drop(categorical2, axis=1, inplace=True)
```

Дату обработаем отдельно

```
[20]: import datetime as dt

data['Date'] = pd.to_datetime(data['Date'])
data['Date'] = data['Date'].map(dt.datetime.toordinal)
```

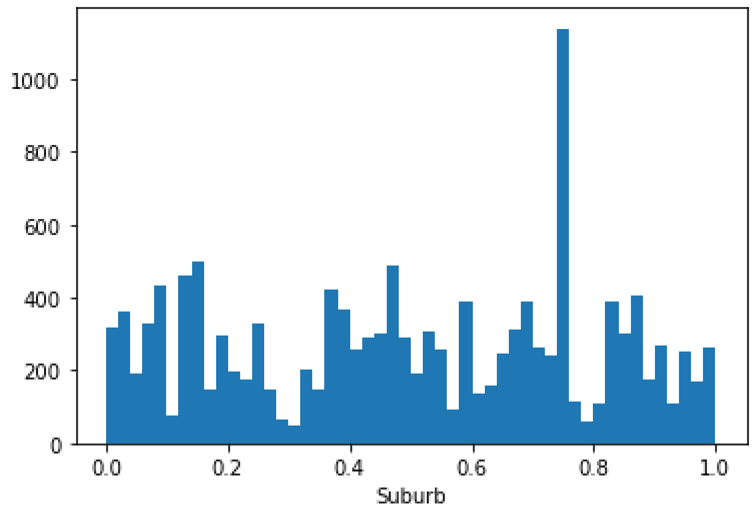
```
[35]: data.shape
```

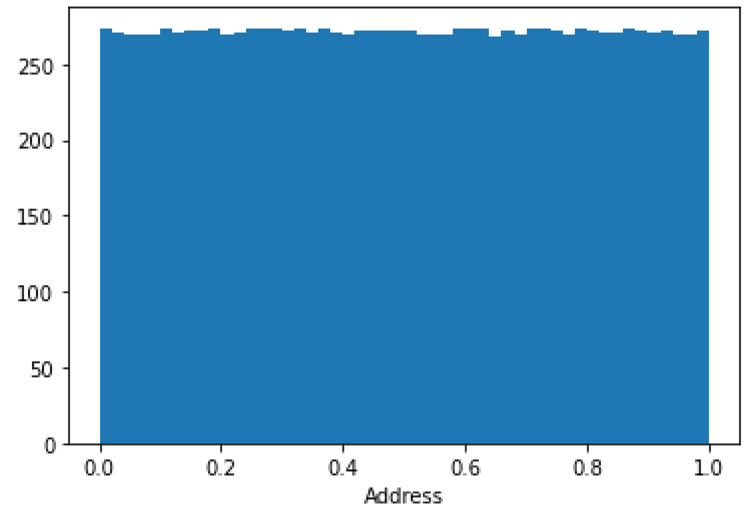
```
[35]: (13580, 31)
```

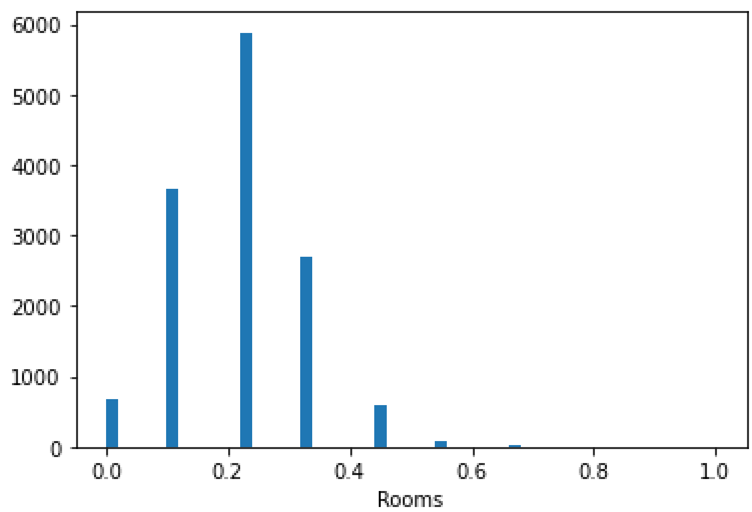
2.3. Масштабирование данных

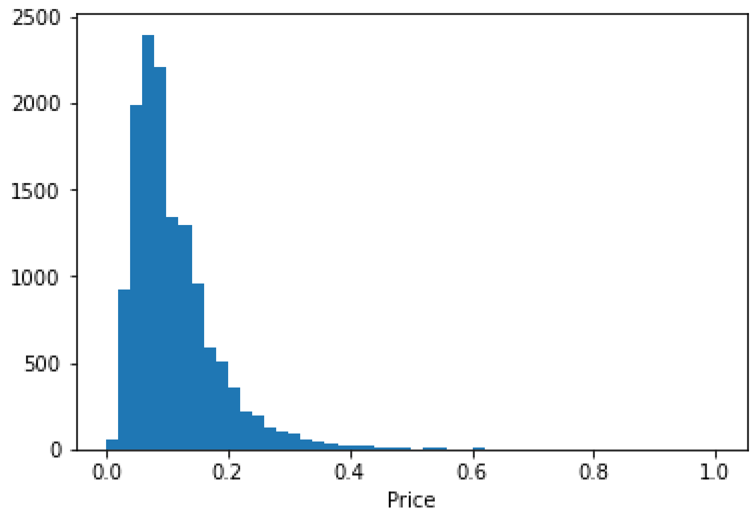
```
[21]: from sklearn.preprocessing import MinMaxScaler

min_max_scaler = MinMaxScaler()
data[:] = min_max_scaler.fit_transform(data)
```

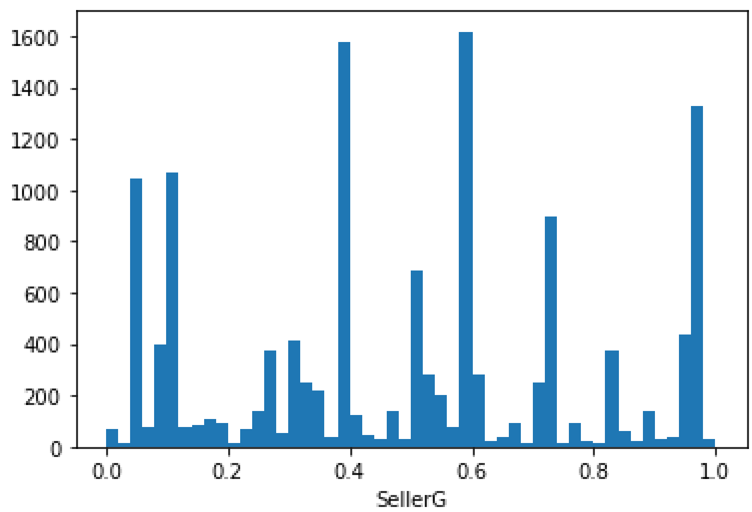
```
[38]: for col in data.columns:
    plt.hist(data[col], 50)
    plt.xlabel(col)
    plt.show()
```

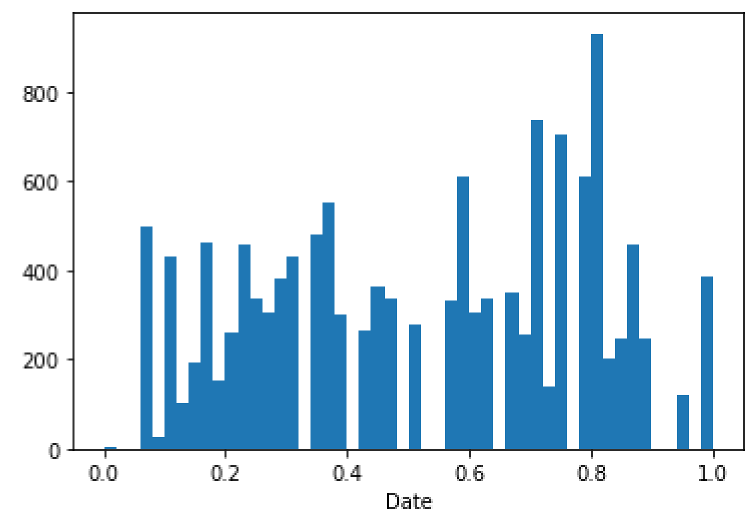

1000
800
600
400
200
0
0.0
0.2
0.4
0.6
0.8
1.0
Suburb

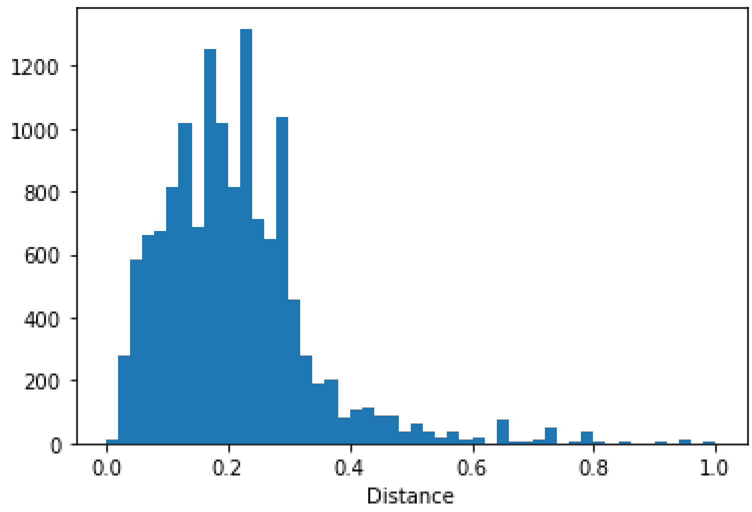

250
200
150
100
50
0
0.0
0.2
0.4
0.6
0.8
1.0
Address

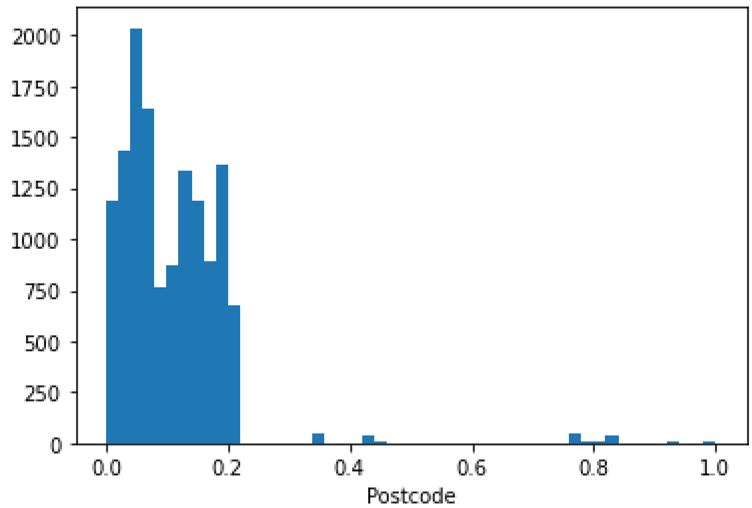

6000
5000
4000
3000
2000
1000
0
0.0
0.2
0.4
0.6
0.8
1.0
Rooms

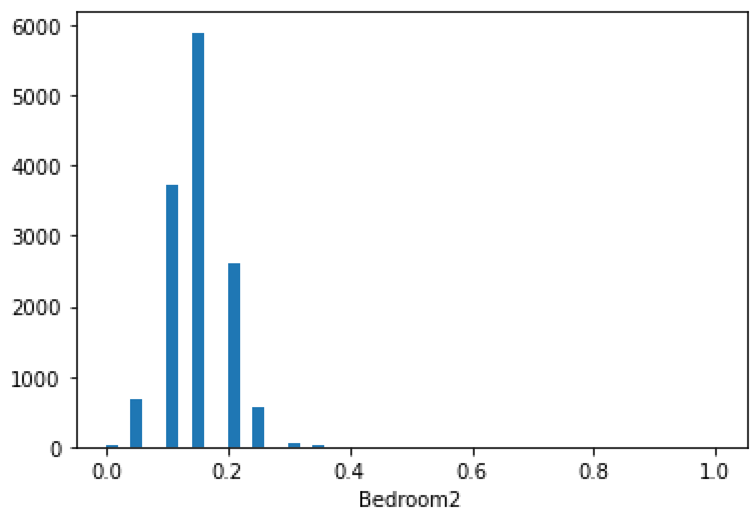

2500
2000
1500
1000
500
0
0.0
0.2
0.4
0.6
0.8
1.0
Price

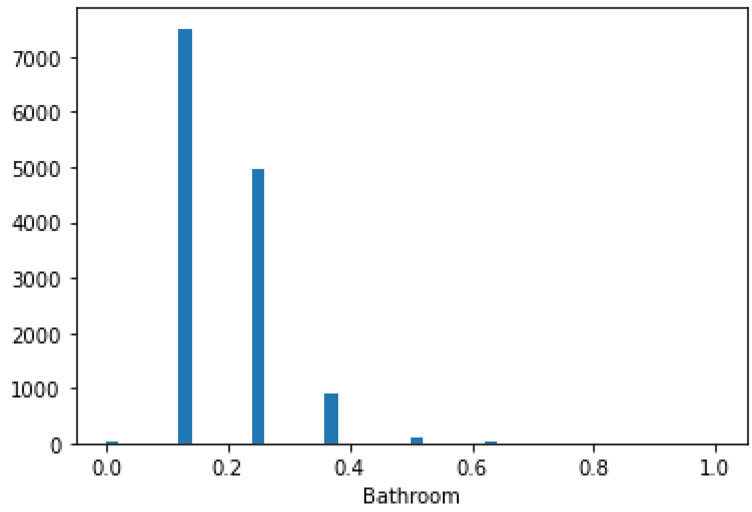

1600
1400
1200
1000
800
600
400
200
0
0.0
0.2
0.4
0.6
0.8
1.0
SellerG

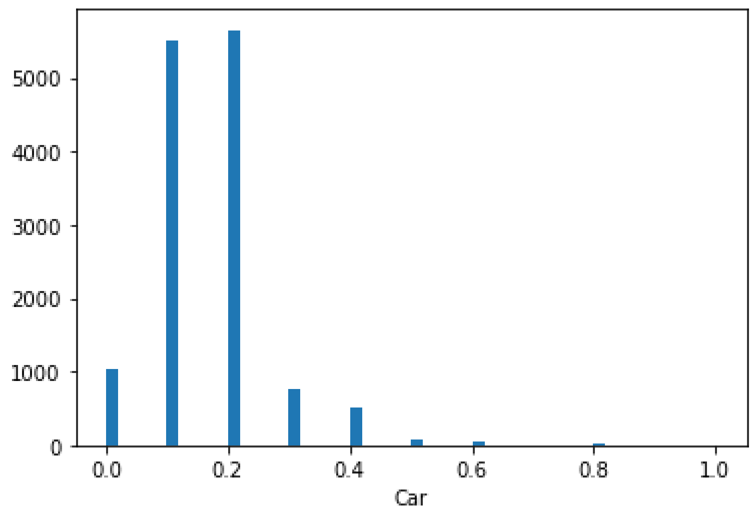

800
600
400
200
0
0.0
0.2
0.4
0.6
0.8
1.0
Date

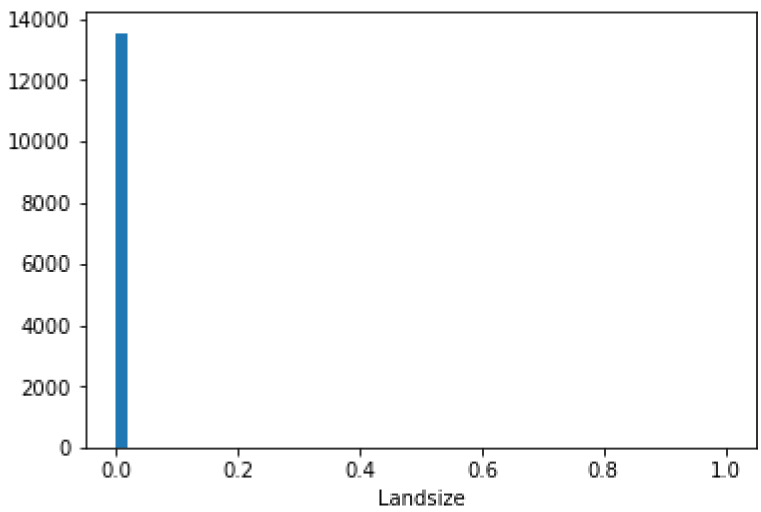

1200
1000
800
600
400
200
0
0.0
0.2
0.4
0.6
0.8
1.0
Distance

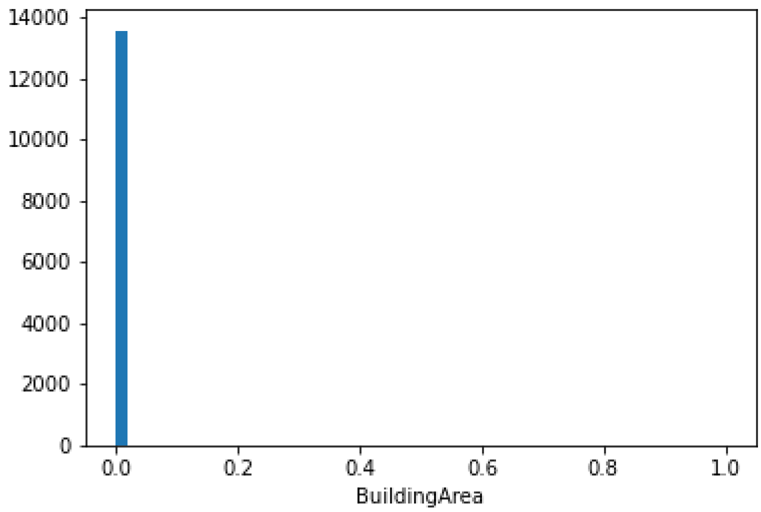

2000
1750
1500
1250
1000
750
500
250
0
0.0
0.2
0.4
0.6
0.8
1.0
Postcode

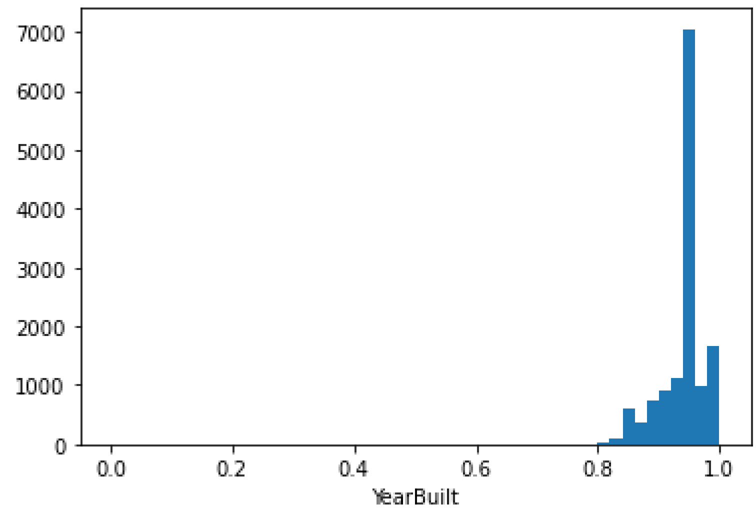

6000
5000
4000
3000
2000
1000
0
0.0
0.2
0.4
0.6
0.8
1.0
Bedroom2

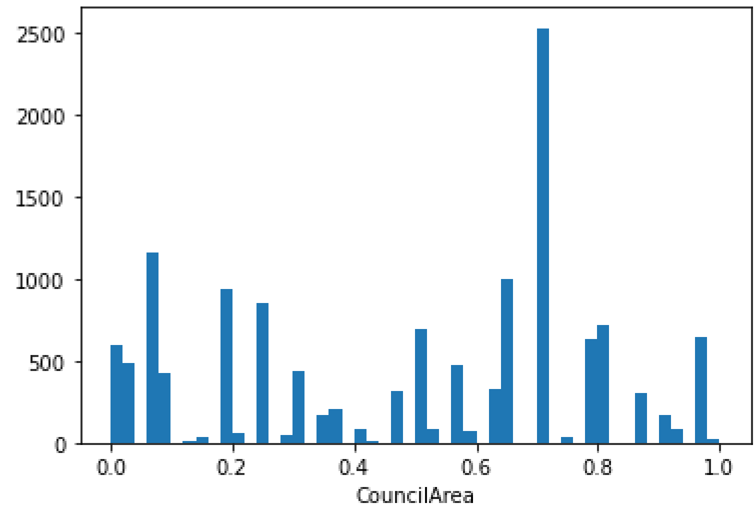

7000
6000
5000
4000
3000
2000
1000
0
0.0
0.2
0.4
0.6
0.8
1.0
Bathroom

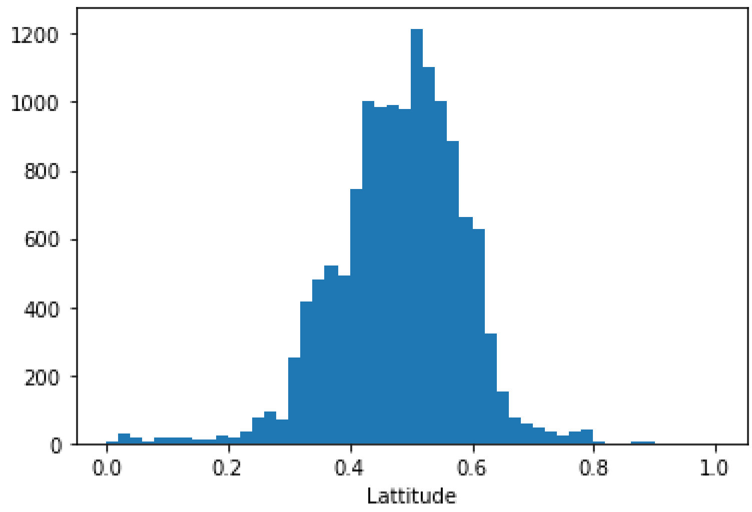

5000
4000
3000
2000
1000
0
0.0
0.2
0.4
0.6
0.8
1.0
Car


14000
12000
10000
8000
6000
4000
2000
0
0.0
0.2
0.4
0.6
0.8
1.0
Landsize

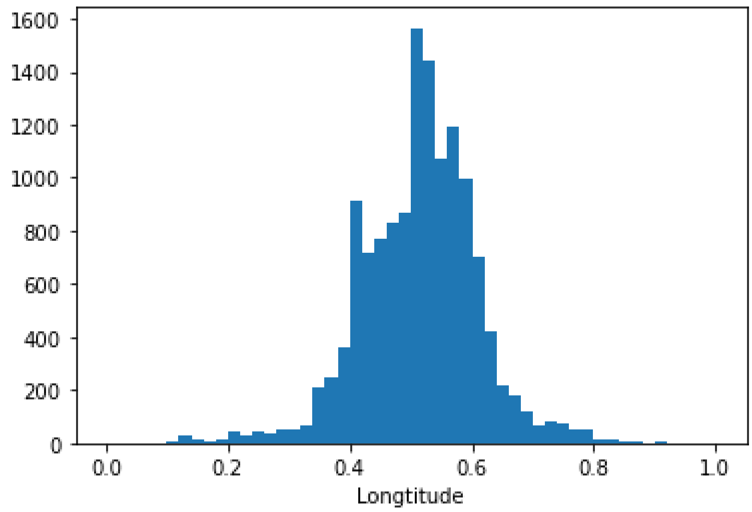

14000
12000
10000
8000
6000
4000
2000
0
0.0
0.2
0.4
0.6
0.8
1.0
BuildingArea


7000
6000
5000
4000
3000
2000
1000
0
0.0
0.2
0.4
0.6
0.8
1.0
YearBuilt

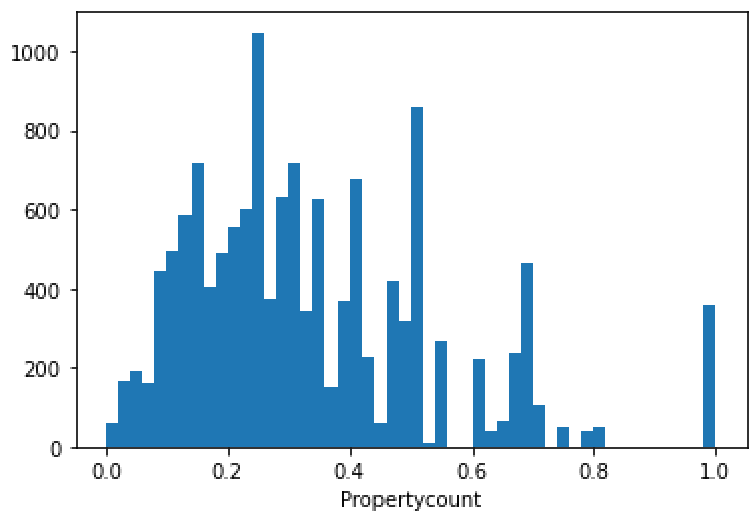

2500
2000
1500
1000
500
0
0.0
0.2
0.4
0.6
0.8
1.0
CouncilArea



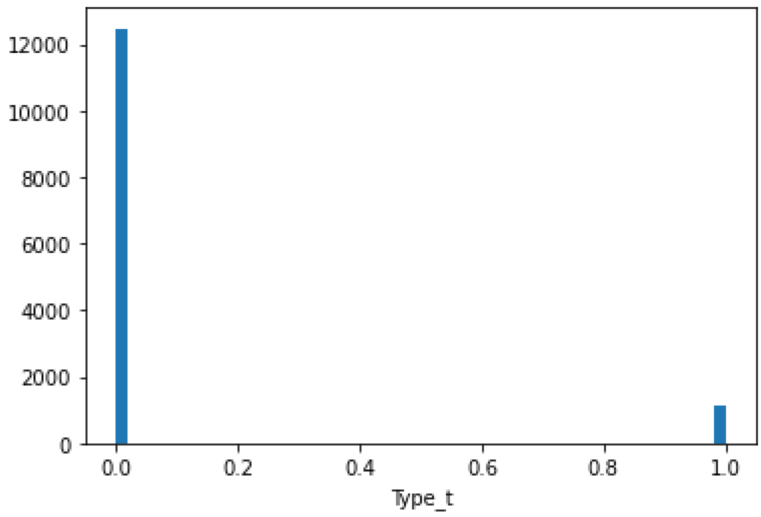
1200
1000
800
600
400
200
0
0.0
0.2
0.4
0.6
0.8
1.0
Lattitude

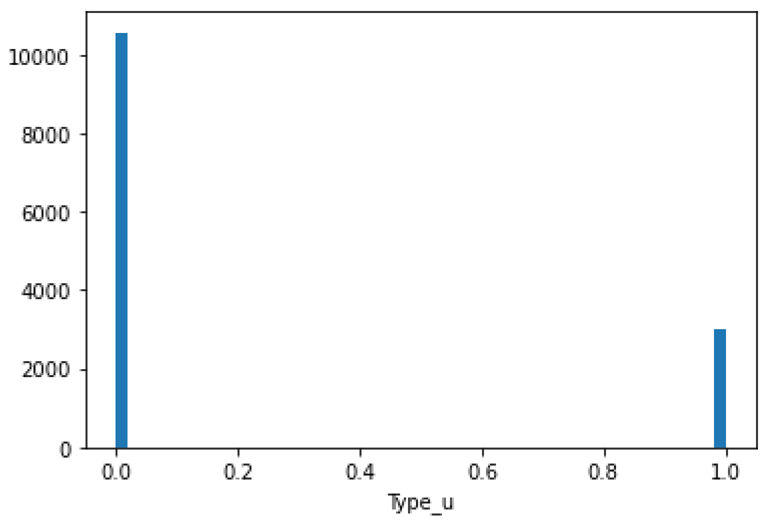


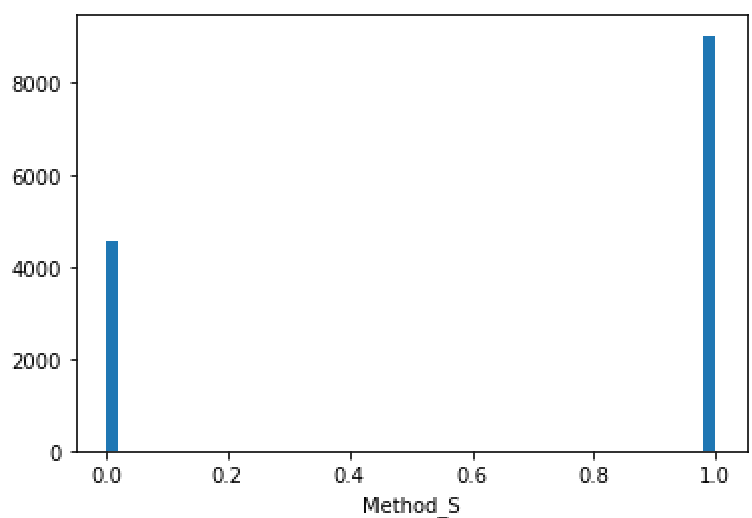
1600
1400
1200
1000
800
600
400
200
0
0.0
0.2
0.4
0.6
0.8
1.0
Longtitude

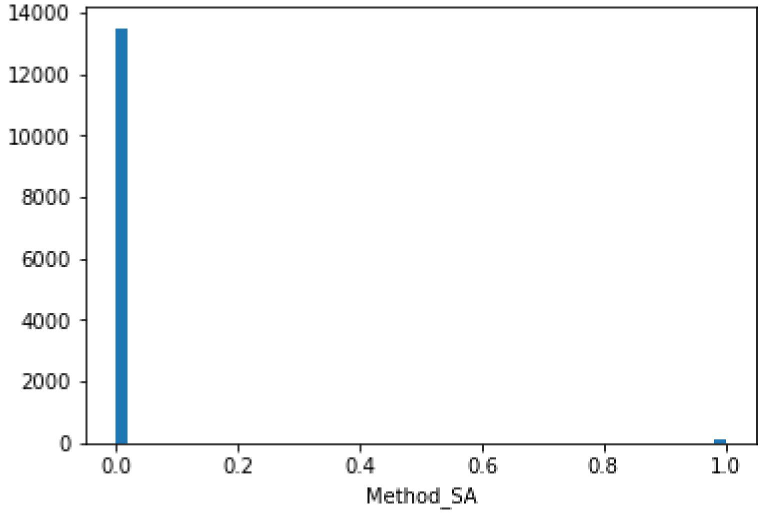


1000
800
600
400
200
0
0.0
0.2
0.4
0.6
0.8
1.0
Propertycount

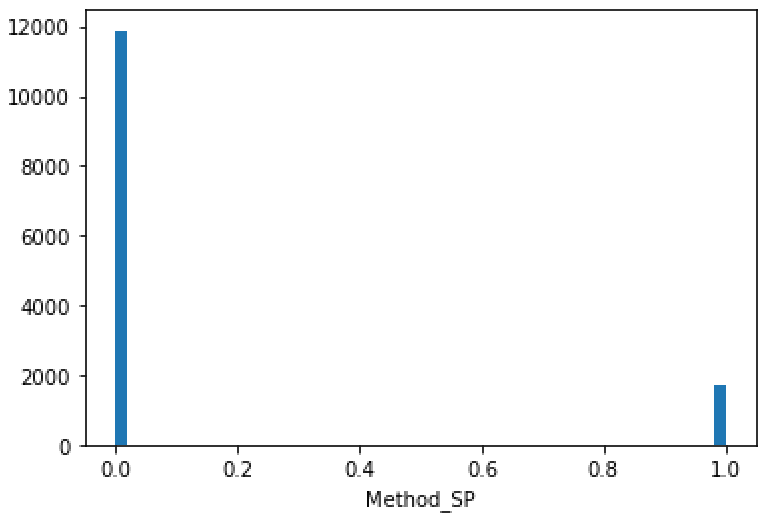

12000
10000
8000
6000
4000
2000
0
0.0
0.2
0.4
0.6
0.8
1.0
Type_t


10000
8000
6000
4000
2000
0
0.0
0.2
0.4
0.6
0.8
1.0
Type_u

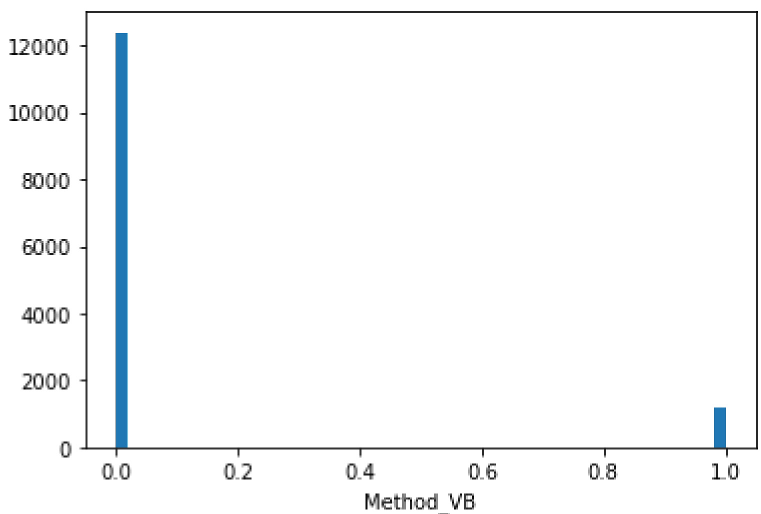

8000
6000
4000
2000
0
0.0
0.2
0.4
0.6
0.8
1.0
Method_S



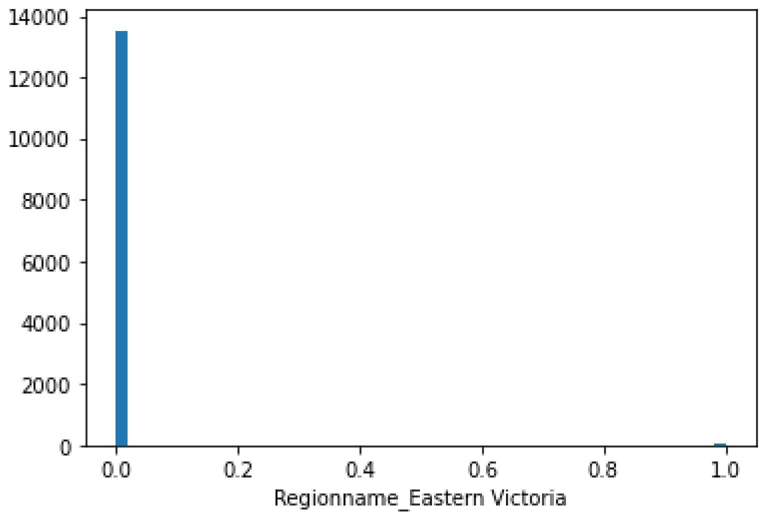
14000
12000
10000
8000
6000
4000
2000
0
0.0
0.2
0.4
0.6
0.8
1.0
Method_SA

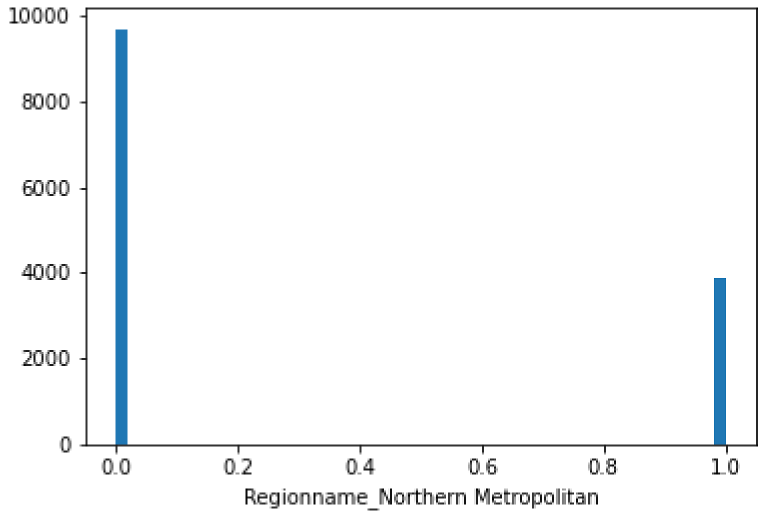


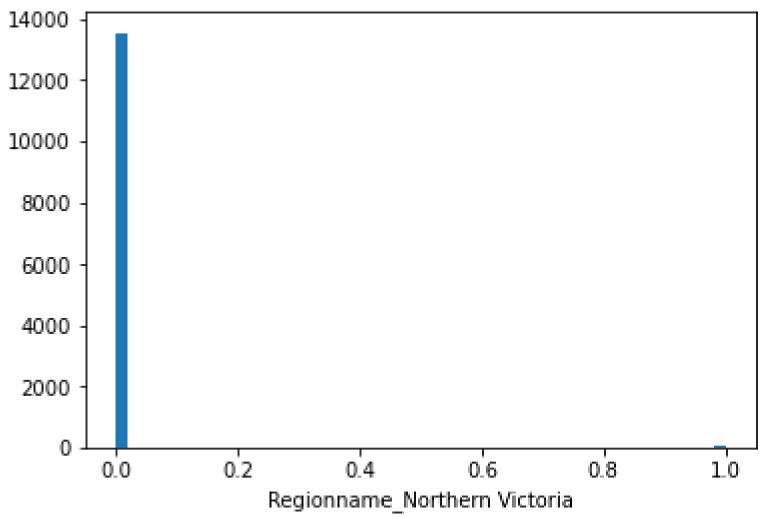
12000
10000
8000
6000
4000
2000
0
0.0
0.2
0.4
0.6
0.8
1.0
Method_SP

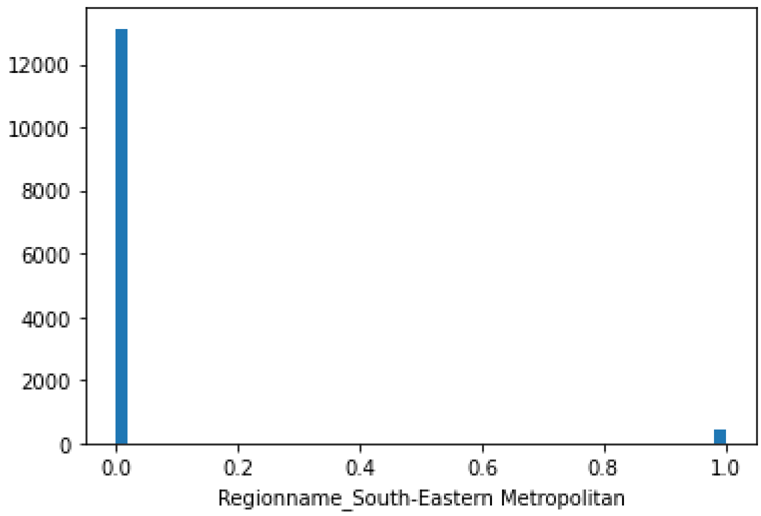


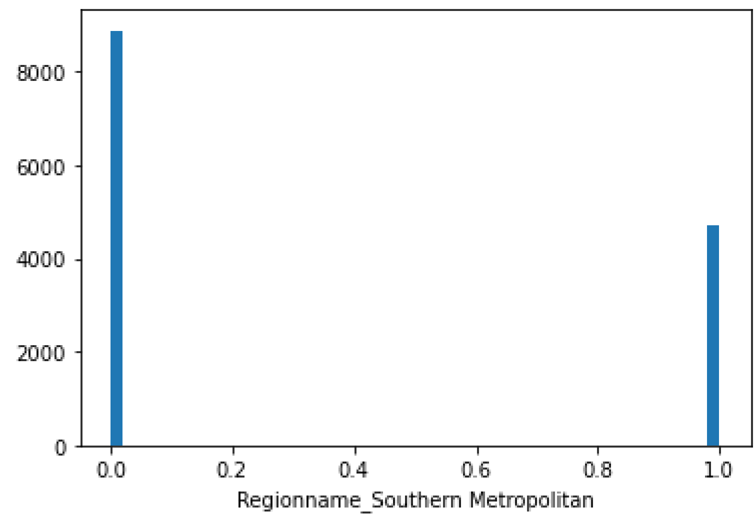
12000
10000
8000
6000
4000
2000
0
0.0
0.2
0.4
0.6
0.8
1.0
Method_VB

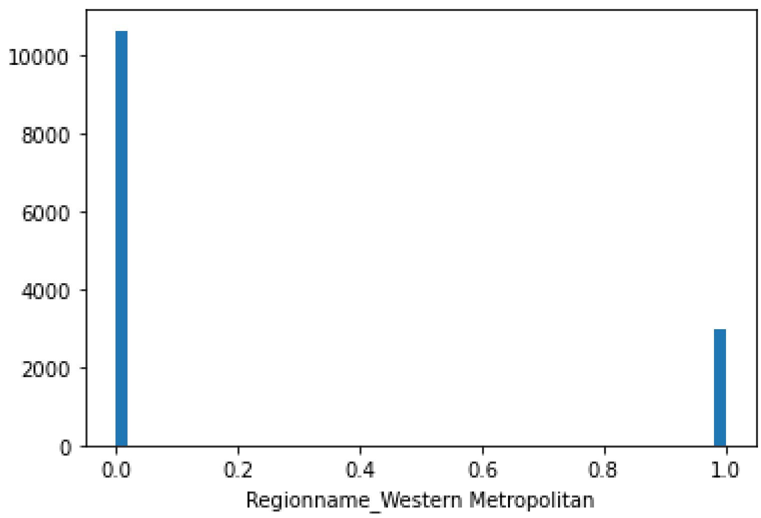

14000
12000
10000
8000
6000
4000
2000
0
0.0
0.2
0.4
0.6
0.8
1.0
Regionname_Eastern Victoria

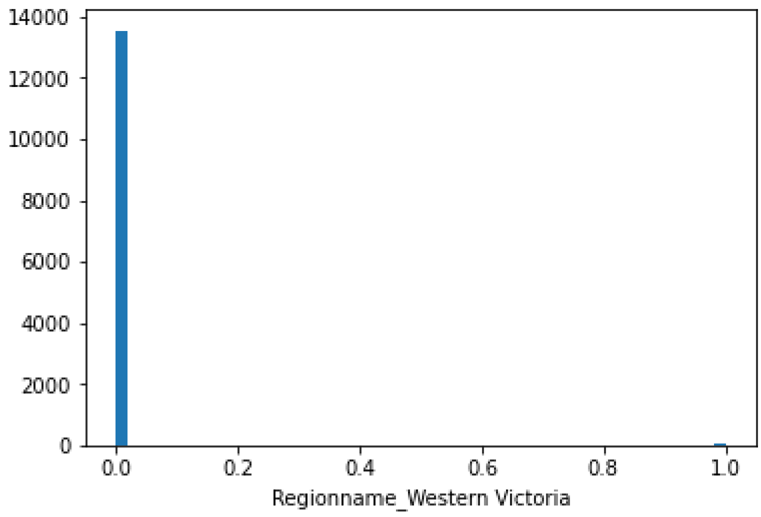

10000
8000
6000
4000
2000
0
0.0
0.2
0.4
0.6
0.8
1.0
Regionname_Northern Metropolitan


14000
12000
10000
8000
6000
4000
2000
0
0.0
0.2
0.4
0.6
0.8
1.0
Regionname_Northern Victoria


12000
10000
8000
6000
4000
2000
0
0.0
0.2
0.4
0.6
0.8
1.0
Regionname_South-Eastern Metropolitan


8000
6000
4000
2000
0
0.0
0.2
0.4
0.6
0.8
1.0
Regionname_Southern Metropolitan


10000
8000
6000
4000
2000
0
0.0
0.2
0.4
0.6
0.8
1.0
Regionname_Western Metropolitan



3. 3 лабораторная

Подготовка обучающей и тестовой выборки, кросс-валидация и подбор гиперпараметров на примере метода ближайших соседей.

Задание:

1. Выберите набор данных (датасет) для решения задачи классификации или регрессии.
2. С использованием метода train_test_split разделите выборку на обучающую и тестовую.
3. Обучите модель ближайших соседей для произвольно заданного гиперпараметра K. Оцените качество модели с помощью подходящих для задачи метрик.
4. Произведите подбор гиперпараметра K с использованием GridSearchCV и/или RandomizedSearchCV и кросс-валидации, оцените качество оптимальной модели. Желательно использование нескольких стратегий кросс-валидации.
5. Сравните метрики качества исходной и оптимальной моделей.

3.1. Разделение выборки на обучающую и тестовую

[22]:
```
%%capture
y = data['Price']
data.drop(['Price'], axis = 1)
```

[40]:
```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(data, y, test_size=0.
↪25, random_state=23)
```

3.2. Модель ближайших соседей для произвольно заданного гиперпараметра K

Выберем параметр 50

```
[43]: from sklearn.neighbors import KNeighborsRegressor
      from sklearn.metrics import mean_absolute_error, mean_squared_error,␣
       ↪median_absolute_error, r2_score
```

```
[79]: %%time
      neigh = KNeighborsRegressor(n_neighbors=50)
      neigh.fit(X_train, y_train)

      prediction = neigh.predict(X_test)
```

```
CPU times: user 791 ms, sys: 2.94 ms, total: 794 ms
Wall time: 793 ms
```

```
[94]: print ("mean_absolute_error = {:f}".format(mean_absolute_error(y_test,␣
       ↪prediction)))
      print ("mean_squared_error = {:f}".format(mean_squared_error(y_test,␣
       ↪prediction, squared=False))) # RMSE       MAE
      print ("median_absolute_error = {:f}".format(median_absolute_error(y_test,␣
       ↪prediction))) # 0 -
      print ("r2_score = {:f}".format(r2_score(y_test, prediction))) # 1 -     ␣
       ↪
```

```
mean_absolute_error = 0.029946
mean_squared_error = 0.046587
median_absolute_error = 0.021470
r2_score = 0.575862
```

3.3. Подбор гиперпараметра K

```
[51]: from sklearn.model_selection import cross_val_score, cross_validate
      from sklearn.model_selection import KFold, RepeatedKFold, LeaveOneOut,␣
       ↪LeavePOut, ShuffleSplit, StratifiedKFold
      from sklearn.model_selection import GridSearchCV, RandomizedSearchCV
      from sklearn.model_selection import learning_curve, validation_curve
```

Оценка качества модели с использованием кросс-валидации

```
[52]: scores = cross_val_score(KNeighborsRegressor(n_neighbors=50),
                               data, y,
                               cv=5)
      scores, np.mean(scores)
```

```
[52]: (array([0.54788388, 0.58733528, 0.54792813, 0.55006166, 0.52367828]),
       0.5513774456972729)
```

Подбор гиперпараметров на основе решетчатого поиска и кросс-валидации

```
[53]: n_range = np.array(range(5,55,5))
      tuned_parameters = [{'n_neighbors': n_range}]
      tuned_parameters
```

[53]: [{'n_neighbors': array([5, 10, 15, 20, 25, 30, 35, 40, 45, 50])}]

[54]:
```
%%time
rand_search = RandomizedSearchCV(KNeighborsRegressor(), tuned_parameters,␣
 ↪cv=RepeatedKFold(n_splits=3, n_repeats=3), scoring="r2")
rand_search.fit(data, y)
```

```
CPU times: user 1min 11s, sys: 119 ms, total: 1min 11s
Wall time: 1min 11s
```

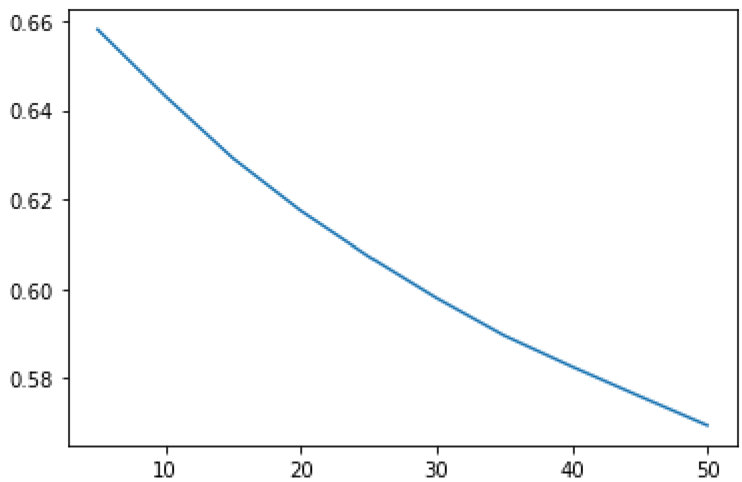
[54]:
```
RandomizedSearchCV(cv=RepeatedKFold(n_repeats=3, n_splits=3,␣
 ↪random_state=None),
                   estimator=KNeighborsRegressor(),
                   param_distributions=[{'n_neighbors': array([ 5, 10, 15,␣
 ↪20,
25, 30, 35, 40, 45, 50])}],
                   scoring='r2')
```

[56]:
```
rand_search.best_score_, rand_search.best_params_, rand_search.
 ↪best_estimator_
```

[56]: (0.6581000916606975, {'n_neighbors': 5}, KNeighborsRegressor())

[60]:
```
plt.plot(n_range, rand_search.cv_results_['mean_test_score'])
```

[60]: [<matplotlib.lines.Line2D at 0x7fad3b438f70>]



Уточним результаты с помощью GridSearchCV

[57]:
```
%%time
grid_search = GridSearchCV(KNeighborsRegressor(),␣
 ↪param_grid=[{'n_neighbors': range(1,10,1)}], cv=RepeatedKFold(n_splits=3,␣
 ↪n_repeats=3), scoring="r2")
grid_search.fit(data, y)
```

```
CPU times: user 45.3 s, sys: 52.3 ms, total: 45.4 s
Wall time: 45.4 s
```

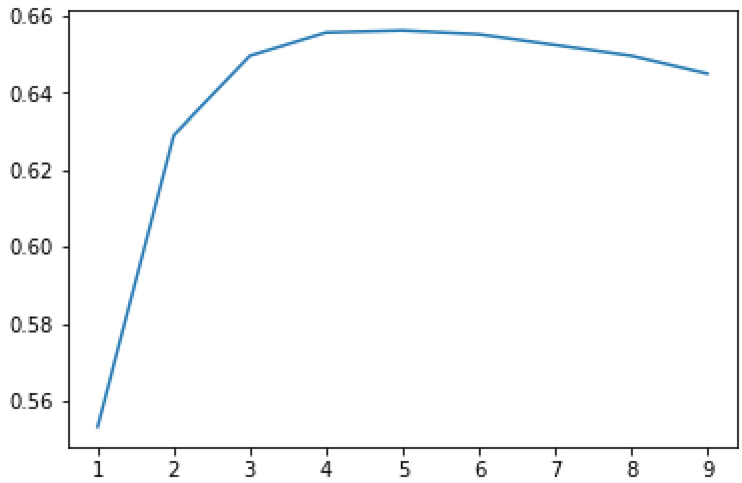
[57]:
```
GridSearchCV(cv=RepeatedKFold(n_repeats=3, n_splits=3, random_state=None),
             estimator=KNeighborsRegressor(),
             param_grid=[{'n_neighbors': range(1, 10)}], scoring='r2')
```

[59]:
```
grid_search.best_score_, grid_search.best_params_, grid_search.
 ↪best_estimator_
```

[59]:
```
(0.6562228888988018, {'n_neighbors': 5}, KNeighborsRegressor())
```

[63]:
```
plt.plot(range(1,10,1), grid_search.cv_results_['mean_test_score'])
```

[63]:
```
[<matplotlib.lines.Line2D at 0x7fad3ba92370>]
```



[70]:
```
grid_search.best_estimator_.fit(X_train, y_train)
best_prediction1 = grid_search.best_estimator_.predict(X_train)
best_prediction2 = grid_search.best_estimator_.predict(X_test)

r2_score(y_train, best_prediction1), r2_score(y_test, best_prediction2)
```

[70]:
```
(0.7857188039408536, 0.6682558405805463)
```

[67]:
```
scores = cross_val_score(grid_search.best_estimator_,
                         data, y,
                         cv=RepeatedKFold(n_splits=3, n_repeats=3))
scores, np.mean(scores)
```

[67]:
```
(array([0.6191961 , 0.68078657, 0.67071197, 0.67664658, 0.65997609,
        0.64285568, 0.68481807, 0.66114259, 0.63168748]),
 0.6586467918647686)
```

[93]:

```
print("K = 50")
print ("mean_absolute_error = {:f}".format(mean_absolute_error(y_test,␣
↪prediction)))
print ("mean_squared_error = {:f}".format(mean_squared_error(y_test,␣
↪prediction, squared=False))) # RMSE      MAE
print ("median_absolute_error = {:f}".format(median_absolute_error(y_test,␣
↪prediction))) # 0 -
print ("r2_score = {:f}".format(r2_score(y_test, prediction))) # 1 -    ␣
↪
print()
print("K = 5")
print ("mean_absolute_error = {:f}".format(mean_absolute_error(y_test,␣
↪best_prediction2)))
print ("mean_squared_error = {:f}".format(mean_squared_error(y_test,␣
↪best_prediction2, squared=False))) # RMSE      MAE
print ("median_absolute_error = {:f}".format(median_absolute_error(y_test,␣
↪best_prediction2))) # 0 -
print ("r2_score = {:f}".format(r2_score(y_test, best_prediction2))) # 1 -␣
↪
```

```
K = 50
mean_absolute_error = 0.029946
mean_squared_error = 0.046587
median_absolute_error = 0.021470
r2_score = 0.575862

K = 5
mean_absolute_error = 0.026512
mean_squared_error = 0.041201
median_absolute_error = 0.018082
r2_score = 0.668256
```