

Федеральное государственное бюджетное образовательное учреждение высшего профессионального образования «Московский государственный технический университет имени Н.Э. Баумана» (МГТУ им. Н.Э. Баумана)

Лабораторная работа 4 по курсу «Технологии машинного обучения»

Выполнил студент группы ИУ5-64 XXX

Цель работы

изучение линейных моделей, SVM и деревьев решений.

Задание

- 1. Выберите набор данных (датасет) для решения задачи классификации или регрессии.
- 2. В случае необходимости проведите удаление или заполнение пропусков и кодирование категориальных признаков.
- 3. С использованием метода train_test_split разделите выборку на обучающую и тестовую.
- 4. Обучите следующие модели:
 - одну из линейных моделей;
 - SVM;
 - дерево решений.
- 5. Оцените качество моделей с помощью двух подходящих для задачи метрик. Сравните качество полученных моделей.

Дополнительные задания

- 1. Проведите эксперименты с важностью признаков в дереве решений.
- 2. Визуализируйте дерево решений.

Ход работы

```
In [1]:
          # Загрузка данных
          import pandas as pd
          data = pd.read_csv("../2/melbourne_housing.csv")
In [2]:
          display(data.dtypes), display(data.head()), display(data.isnull().sum());
         Suburb
                             object
         Address
                             object
                              int64
         Rooms
                             object
         Type
         Price
                            float64
         Method
                             object
         SellerG
                             object
         Date
                             object
         Distance
                            float64
                            float64
         Postcode
         Bedroom2
                            float64
         Bathroom
                            float64
         Car
                            float64
         Landsize
                            float64
         BuildingArea
                            float64
         YearBuilt
                            float64
         CouncilArea
                             object
                            float64
         Lattitude
         Longtitude
                            float64
                             object
         Regionname
         Propertycount
                            float64
         dtype: object
              Suburb
                                                 Price Method SellerG
                                                                          Date Distance Postcode ... Bathroom Car Landsize BuildingArea
                       Address Rooms Type
                      68 Studley
         0 Abbotsford
                                     2
                                          h
                                                 NaN
                                                           SS
                                                                 Jellis 3/09/2016
                                                                                    2.5
                                                                                           3067.0 ...
                                                                                                          1.0
                                                                                                              1.0
                                                                                                                      126.0
                                                                                                                                   NaN
                       85 Turner
         1 Abbotsford
                                     2
                                          h 1480000.0
                                                            S
                                                                Biggin 3/12/2016
                                                                                    2.5
                                                                                           3067.0 ...
                                                                                                          1.0 1.0
                                                                                                                      202.0
                                                                                                                                   NaN
                            25
         2 Abbotsford Bloomburg
                                     2
                                          h 1035000.0
                                                                                          3067.0 ...
                                                            S
                                                                Biggin 4/02/2016
                                                                                                          1.0
                                                                                                              0.0
                                                                                                                      156.0
                                                                                                                                   79.0
                                                                                    2.5
                         18/659
         3 Abbotsford
                                     3
                                                  NaN
                                                              Rounds 4/02/2016
                                                                                           3067.0 ...
                                                                                                           2.0 1.0
                                                                                                                        0.0
                                                                                                                                   NaN
                      Victoria St
                       5 Charles
         4 Abbotsford
                                     3
                                          h 1465000.0
                                                          SP
                                                               Biggin 4/03/2017
                                                                                           3067.0 ...
                                                                                                          2.0 0.0
                                                                                                                      134.0
                                                                                                                                  150.0
                                                                                    2.5
        5 rows × 21 columns
                                0
         Suburb
         Address
                                0
         Rooms
                                0
                                0
         Type
         Price
                             7610
         Method
                                0
         SellerG
                                0
         Date
                                0
         Distance
                                1
         Postcode
                                1
         Bedroom2
                             8217
         Bathroom
                             8226
         Car
                             8728
         Landsize
                            11810
         BuildingArea
                            21115
         YearBuilt
                            19306
         CouncilArea
                                3
                             7976
         Lattitude
                             7976
         Longtitude
         Regionname
                                3
         Propertycount
                                3
         dtype: int64
In [3]:
          import numpy as np
          from sklearn.preprocessing import LabelEncoder
          columns_and_types = {
            "Rooms": np.int64,
            "Type": None,
            "Price": np.int64,
```

"Distance": np.float64,

```
"Postcode": np.int64,
             "Bedroom2": np.int64,
             "Bathroom": np.int64,
             "Car": np.int64,
             "Landsize": np.float64,
             "BuildingArea": np.float64,
             "YearBuilt": np.int64,
             "Lattitude": np.float64,
             "Longtitude": np.float64
             "Propertycount": np.int64,
          data = data[list(columns_and_types.keys())]
          data.dropna(axis=0, how='any', inplace=True)
data = data.astype({k: v for k,v in columns_and_types.items() if v is not None})
           type_encoder = LabelEncoder()
           data["Type"] = type_encoder.fit_transform(data["Type"])
In [4]:
          display(data.shape), display(data.dtypes)
          (8887, 14)
          Rooms
                                int64
                                int64
          Type
          Price
                                int64
                              float64
         Distance
         Postcode
                                int64
          Bedroom2
                                int64
         Bathroom
                                int64
                                int64
          Car
          Landsize
                              float64
          BuildingArea
                              float64
          YearBuilt
                                int64
                              float64
          Lattitude
          Longtitude
                              float64
          Propertycount
                                int64
          dtype: object
Out[4]: (None, None)
In [5]:
           data.head()
             Rooms Type
                              Price Distance Postcode Bedroom2 Bathroom Car Landsize BuildingArea YearBuilt Lattitude Longtitude Propertyce
Out[5]:
           2
                   2
                         0 1035000
                                          25
                                                  3067
                                                                2
                                                                          1
                                                                               0
                                                                                     156.0
                                                                                                   79.0
                                                                                                             1900
                                                                                                                   -37 8079
                                                                                                                             144.9934
           4
                   3
                           1465000
                                          2.5
                                                  3067
                                                                3
                                                                          2
                                                                               0
                                                                                     134.0
                                                                                                  150.0
                                                                                                             1900
                                                                                                                   -37.8093
                                                                                                                             144.9944
           6
                   4
                                                                3
                                                                               2
                         0
                           1600000
                                          2.5
                                                  3067
                                                                          1
                                                                                     120.0
                                                                                                  142.0
                                                                                                            2014
                                                                                                                   -37.8072
                                                                                                                             144.9941
          11
                   3
                         0
                           1876000
                                          2.5
                                                  3067
                                                                          2
                                                                               0
                                                                                     245.0
                                                                                                  210.0
                                                                                                            1910
                                                                                                                   -37.8024
                                                                                                                             144.9993
          14
                   2
                           1636000
                                          2.5
                                                  3067
                                                                2
                                                                          1
                                                                                     256.0
                                                                                                  107.0
                                                                                                             1890
                                                                                                                   -37.8060
                                                                                                                             144.9954
In [6]:
          from sklearn.preprocessing import StandardScaler
           scaler = StandardScaler()
           for col in data.columns:
             if col != "Price":
               data[col] = scaler.fit_transform(data[[col]])
In [7]:
           data.head()
Out[7]:
               Rooms
                           Type
                                    Price Distance Postcode Bedroom2 Bathroom
                                                                                        Car
                                                                                             Landsize BuildingArea YearBuilt
                                                                                                                              Lattitude Longtitud
           2 -1.140264
                       -0.556327
                                 1035000
                                           -1.27695
                                                    -0.396621
                                                              -1.115905
                                                                         -0.895892
                                                                                  -1.734910
                                                                                            -0.346267
                                                                                                          -0.799693 -1.775256
                                                                                                                              -0.037540
                                                                                                                                          0.0168
                                                                                                                              -0.053003
             -0.102631
                       -0.556327
                                  1465000
                                           -1.27695
                                                    -0.396621
                                                               -0.080939
                                                                         0.489973
                                                                                   -1.734910
                                                                                             -0.366997
                                                                                                           0.007854
                                                                                                                    -1.775256
                                                                                                                                          0.02528
              0.935002
                       -0.556327
                                                                                            -0.380188
                                                                                                          -0.083137
                                                                                                                              -0.029809
                                                                                                                                          0.02276
                                 1600000
                                           -1.27695
                                                   -0.396621
                                                               -0.080939
                                                                         -0.895892
                                                                                    0.315512
                                                                                                                    1.302598
             -0.102631
                       -0.556327
                                 1876000
                                           -1.27695
                                                   -0.396621
                                                               0.954028
                                                                         0.489973
                                                                                  -1.734910
                                                                                            -0.262404
                                                                                                           0.690288 -1.505269
                                                                                                                              0.023204
                                                                                                                                          0.06649
          14
             -1.140264 -0.556327 1636000
                                           -1.27695
                                                   -0.396621
                                                              -1.115905
                                                                         -0.895892
                                                                                   0.315512 -0.252039
                                                                                                          -0.481224 -2.045243
                                                                                                                              -0.016556
                                                                                                                                          0.03369
```

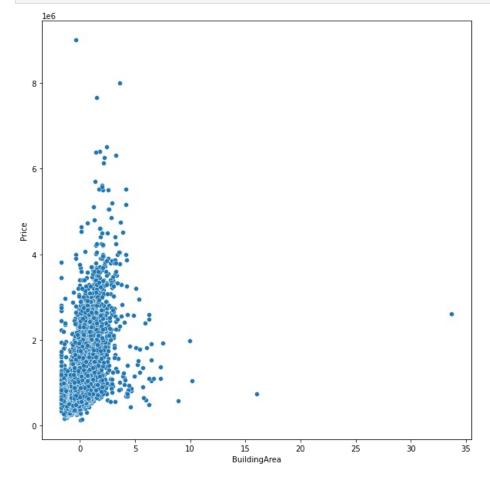
Tn [8]+

```
import seaborn as sns
import matplotlib.pyplot as plt

fig, ax = plt.subplots(figsize=(15,7))
sns.heatmap(data.corr(method="pearson"), ax=ax, annot=True, fmt='.2f');
```



```
fig, ax = plt.subplots(figsize=(10,10))
sns.scatterplot(ax=ax, x="BuildingArea", y="Price", data=data);
```



Линейная регрессия

```
data_X = data.loc[:, [x for x in data.columns if x != "Price"]]
data_Y = data.loc[:, 'Price']
          data_X_train, data_X_test, data_y_train, data_y_test = train_test_split(
            data X.
            data_Y,
            test_size=0.2,
            random_state=1
In [11]:
          from sklearn.linear_model import LinearRegression
          from sklearn.metrics import r2_score, mean_absolute_percentage_error
          # Обучим линейную регрессию и сравним коэффициенты с рассчитанными ранее
          reg1 = LinearRegression()
          reg1.fit(data_X_train, data_y_train)
          y_pred = reg1.predict(data_X_test)
          r2_score(data_y_test, y_pred), mean_absolute_percentage_error(data_y_test, y_pred)
Out[11]: (0.6175514371440386, 0.26894243290410874)
         SVR
In [12]:
          from sklearn.svm import SVR
          svr = SVR(max_iter=10000, kernel="rbf", C=1e6)
          svr.fit(data_X_train, data_y_train);
         /usr/lib/python3.9/site-packages/sklearn/svm/_base.py:255: ConvergenceWarning: Solver terminated early (max_iter=
         10000). Consider pre-processing your data with StandardScaler or MinMaxScaler.
          warnings.warn('Solver terminated early (max_iter=%i).'
In [13]:
          y_pred = svr.predict(data_X_test)
In [14]:
          r2_score(data_y_test, y_pred), mean_absolute_percentage_error(data_y_test, y_pred)
Out[14]: (0.8007830168563735, 0.15056431505942702)
        Деревья решений
In [15]:
          # Обучим дерево и предскажем результаты
          from sklearn.tree import DecisionTreeRegressor
          tree_regr = DecisionTreeRegressor(random_state=1, max_depth=7).fit(data_X_train, data_y_train)
          y_test_predict = tree_regr.predict(data_X_test)
          y_test_predict.shape
Out[15]: (1778,)
In [16]:
          r2_score(data_y_test, y_test_predict)
Out[16]: 0.6626220166750287
In [17]:
          list(
            zip(
              data_X_train.columns.values,
              tree_regr.feature_importances_
```

Out[17]: [('Rooms', 0.005024582426006323),

('Type', 0.01650526758281762),

```
('Postcode', 0.09971740359027761),
('Bedroom2', 0.0006393899010610526),
('Bathroom', 0.011851644859025727),
               ('Car', 0.0),
               ('Landsize', 0.0506516356530368),
               ('BuildingArea', 0.4239520690926708),
               ('YearBuilt', 0.129300603225875),
               ('Lattitude', 0.06167573602026102),
               ('Longtitude', 0.032645389732301903),
               ('Propertycount', 0.0012447951383578269)]
In [18]:
               # Визуализация дерева
               from sklearn.tree import export_graphviz
               from io import StringIO
               import pydot
               def get_png_tree(tree_model_param, feature_names_param):
                  dot_data = StringIO()
                  export_graphviz(
                     tree_model_param, out_file=dot_data,
                     feature_names=feature_names_param, filled=True,
                     rounded=True, special_characters=True
                  (graph,) = pydot.graph_from_dot_data(dot_data.getvalue())
                  return graph.create_png()
In [19]:
               tree_regr_depth3 = DecisionTreeRegressor(
                  random_state=1,
                  max depth=3
               ).fit(data_X_train, data_y_train)
               tree_regr_depth3
Out[19]: DecisionTreeRegressor(max_depth=3, random_state=1)
In [20]:
               from IPython.display import Image
               Image(get_png_tree(tree_regr_depth3, [x for x in data.columns if x != "Price"]))
                                                                                     BuildingArea ≤ 0.605
mse = 461233821812.648
samples = 7109
value = 1090353.469
Out[20]:
                                                                                     True
                                                                                                           Distance ≤ 0.015
ise = 88592247072.621
samples = 1276
value = 1788391.905
                                      BuildingArea ≤ -0.271
se = 270624281398.889
samples = 1451
value = 1338783.753
                                                                           BuildingArea ≤ -0.395
se = 156838382503.376
samples = 4382
value = 804828.734
                                                                                                                                                 Lattitude ≤ 0.586
ase = 341877111159.534
samples = 570
value = 1272690.321
                                                          mse = 70770938986.856
samples = 2003
value = 635530.051
                                                                               mse = 184852918211.329
samples = 2379
value = 947369.827
                                      samples = 680
value = 1603772.906
                                                                                                      samples = 290
value = 1584812.759
               value = 1105070.882
```

In []:

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('Distance', 0.16679148277830835),