Practical Activity Regression analysis using SVM

1 Practical Activity

1.1 Regression Using SVM

This notebook is an exercise for developing a SVM model for regression. We apply the concepts discussed in Week 8.

Note: this activity is unmarked. It develops your skills for predictive model development using SVM.

2 The Housing dataset

For this practical activity, we will use the housing dataset (same dataset as Activity 4.1)

The Housing dataset is available online at - https://raw.githubusercontent.com/rasbt/python-machine-learning-book-3rdedition/master/ch10/housing.data.txt or - scikit-learn (https://github.com/scikit-learn/scikitlearn/blob/master/sklearn/datasets/data/boston_house_prices.csv)

Goal: our goal is to develop a SVM regerssion model to predict the value of a house given the other attributes i.e., our target is MEDV.

```
[6]: 2.1
        Data Loading
     #laoding from sklearn
     from sklearn.datasets import load boston
     data = load_boston()
[8]:
     import pandas as pd
     # Read the DataFrame, first using the feature data
     df = pd.DataFrame(data.data, columns = data.feature names)
     # Add a target column, and fill it with the target data
     df['target'] = data.target# Show the first five rows
     df.head()
CRIM
[8]:
                                        NOX
                                                RM
                                                      AGE
                    ZN
                        INDUS
                               CHAS
                                                              DIS
                                                                   RAD
                                                                           TAX
                                                                                \
       0.00632
                  18.0
                         2.31
                                0.0
                                      0.538
                                             6.575
                                                    65.2
                                                           4.0900
                                                                   1.0
                                                                         296.0
     0
        0.02731
                  0.0
                         7.07
                                0.0
                                     0.469
                                             6.421
                                                    78.9
                                                           4.9671
                                                                   2.0
                                                                         242.0
                                      0.469
                                             7.185
     2
        0.02729
                  0.0
                         7.07
                                0.0
                                                    61.1
                                                           4.9671
                                                                   2.0
                                                                         242.0
     3
        0.03237
                   0.0
                         2.18
                                0.0
                                     0.458
                                             6.998
                                                    45.8
                                                           6.0622
                                                                   3.0
                                                                         222.0
     4 0.06905
                  0.0
                         2.18
                                0.0
                                     0.458
                                             7.147
                                                    54.2
                                                          6.0622
                                                                        222.0
```

```
B LSTAT target
  PTRATIO
                          24.0
0
     15.3 396.90
                   4.98
                          21.6
     17.8 396.90
                   9.14
1
     17.8 392.83
                  4.03
                          34.7
                   2.94
                          33.4
3
     18.7 394.63
     18.7 396.90
                   5.33
                          36.2
```

2.2 Create train and test set

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

train, test = train_test_split(df, test_size = 0.3)

X_train = train.drop('target', axis=1)
y_train = train['target']

X_test = test.drop('target', axis = 1)
y_test = test['target']
```

```
[10]: from sklearn.preprocessing import MinMaxScaler
    scaler = MinMaxScaler(feature_range=(0, 1))

x_train_scaled = scaler.fit_transform(X_train)
    #reverting back to df
X_train = pd.DataFrame(x_train_scaled)

x_test_scaled = scaler.fit_transform(X_test)
X_test = pd.DataFrame(x_test_scaled)
```

2.3 Building the SVM Regression Model

```
[11]: from sklearn.svm import SVR
from sklearn.metrics import r2_score, mean_squared_error

svm_reg = SVR(kernel = 'rbf')
svm_reg.fit(X_train, y_train)
```

[11]: SVR()

2.4 Evaluation

```
[12]: import numpy as np
    predictions = svm_reg.predict(X_test)
```

```
mse = mean_squared_error(y_test, predictions)
      rmse = np.sqrt(mse)
      print(f'RMSE value is: {rmse}')
     RMSE value is: 5.56797557589552
[15]: svm_reg.n_support_
[15]: array([346])
[17]:
      svm_reg.support_vectors_
[17]: array([[4.15264132e-03, 0.00000000e+00, 3.71334311e-01, ...,
              6.38297872e-01, 9.95814212e-01, 6.11280911e-01],
             [2.33528471e-03, 2.20000000e-01, 1.97947214e-01, ...,
              6.91489362e-01, 9.49997478e-01, 4.47346485e-02],
             [4.37788609e-04, 0.00000000e+00, 4.20454545e-01, ...,
              8.93617021e-01, 1.00000000e+00, 1.97277021e-01],
             [2.92795719e-04, 0.00000000e+00, 6.30498534e-02, ...,
              6.48936170e-01, 9.94276060e-01, 2.66740761e-02],
             [3.22013248e-01, 0.00000000e+00, 6.46627566e-01, ...,
              8.08510638e-01, 5.31166473e-01, 5.02917477e-01],
             [8.29719002e-04, 0.00000000e+00, 2.01612903e-01, ...,
              7.02127660e-01, 1.00000000e+00, 1.88663518e-01]])
```