VIT UNIVERSITY, ANDHRA PRADESH School of CSE

CSE3008 - Introduction to Machine Learning Lab Experiment-1

(Implementation FIND-S algorithm) Faculty-Dr. B. SRINIVASA RAO

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```
FIND-S Algorithm

[10] import csv
    num_attributes = 6
    a = []
    print("\n The Given Training Data Set \n")
    with open('EnjoySport.csv', 'r') as csvfile:
        reader = csv.reader(csvfile)
        for row in reader:
            a.append (row)
            print(row)

The Given Training Data Set

['Sunny', 'Warm', 'Normal', 'Strong', 'Warm', 'Same', 'Yes']
    ['Sunny', 'Warm', 'High', 'Strong', 'Warm', 'Same', 'Yes']
    ['Rainy', 'Cold', 'High', 'Strong', 'Warm', 'Change', 'No']
    ['Sunny', 'Warm', 'High', 'Strong', 'Cool', 'Change', 'Yes']
```

```
[11] print("\n The initial value of hypothesis: ")
        hypothesis = ['0'] * num attributes
        print(hypothesis)
        for j in range(0,num_attributes):
                      hypothesis[j] = a[0][j];
          The initial value of hypothesis:
        ['0', '0', '0', '0', '0', '0']
[12] print("\n Find S: Finding a Maximally Specific Hypothesis\n")
      for i in range(0,len(a)):
            if a[i][num_attributes]=='yes':
                      for j in range(0,num_attributes):
                            if a[i][j]!=hypothesis[j]:
                                hypothesis[j]='?'
                                hypothesis[j]= a[i][j]
           print(" For Training instance No:{0} the hypothesis is".format(i),hypothesis)
       Find S: Finding a Maximally Specific Hypothesis
       For Training instance No:0 the hypothesis is ['Sunny', 'Warm', 'Normal', 'Strong', 'Warm', 'Same']
For Training instance No:1 the hypothesis is ['Sunny', 'Warm', 'Normal', 'Strong', 'Warm', 'Same']
For Training instance No:2 the hypothesis is ['Sunny', 'Warm', 'Normal', 'Strong', 'Warm', 'Same']
For Training instance No:3 the hypothesis is ['Sunny', 'Warm', 'Normal', 'Strong', 'Warm', 'Same']
```

[13] print("\n The Maximally Specific Hypothesis for a given Training Examples :\n")

The Maximally Specific Hypothesis for a given Training Examples :

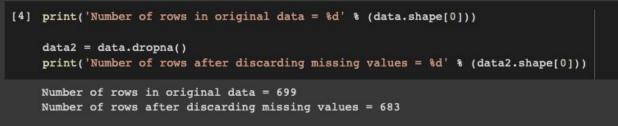
['Sunny', 'Warm', 'Normal', 'Strong', 'Warm', 'Same']

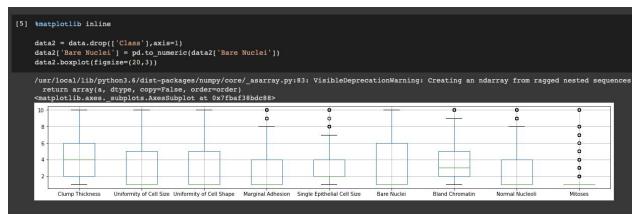
print(hypothesis)

ML Data Preprocessing

```
import numpy as np
[2]
    data = data.replace('?',np.NaN)
    print('Number of instances = %d' % (data.shape[0]))
    print('Number of attributes = %d' % (data.shape[1]))
    print('Number of missing values:')
    for col in data.columns:
        print('\t%s: %d' % (col,data[col].isna().sum()))
    Number of instances = 699
    Number of attributes = 10
    Number of missing values:
            Clump Thickness: 0
            Uniformity of Cell Size: 0
            Uniformity of Cell Shape: 0
            Marginal Adhesion: 0
            Single Epithelial Cell Size: 0
            Bare Nuclei: 16
            Bland Chromatin: 0
            Normal Nucleoli: 0
            Mitoses: 0
            Class: 0
```

```
[3] data2 = data['Bare Nuclei']
    print('Before replacing missing values:')
    print(data2[20:25])
    data2 = data2.fillna(data2.median())
    print('\nAfter replacing missing values:')
    print(data2[20:25])
    Before replacing missing values:
            10
    20
    21
    22
             1
    23
           NaN
    24
    Name: Bare Nuclei, dtype: object
    After replacing missing values:
    20
           10
    21
    22
            1
    23
            1
    24
            1
    Name: Bare Nuclei, dtype: object
[4] print('Number of rows in original data = %d' % (data.shape[0]))
    data2 = data.dropna()
    print('Number of rows after discarding missing values = %d' % (data2.shape[0]))
    Number of rows in original data = 699
    Number of rows after discarding missing values = 683
```





```
[6] Z = (data2-data2.mean())/data2.std()
    Z[20:25]
              Clump Uniformity of Cell
Thickness Size
                                                     Uniformity of Cell
                                                                                  Marginal Single Epithelial Cell
                                                                                                                            Bare
Nuclei
                                                                                                                                                            Normal
Nucleoli Mitoses
                                                                                                                                          Chromatin
               0.917080
                                       -0.044070
                                                                -0.406284
                                                                                   2.519152
                                                                                                              0.805662
                                                                                                                           1.771569
                                                                                                                                           0.640688
                                                                                                                                                            0.371049 1.405526
     21
               1.982519
                                       0.611354
                                                                0.603167
                                                                                   0.067638
                                                                                                             1.257272
                                                                                                                           0.948266
                                                                                                                                            1.460910
                                                                                                                                                            2.335921 -0.343666
     22
               -0.503505
                                       -0.699494
                                                                -0.742767
                                                                                   -0.632794
                                                                                                              -0.549168
                                                                                                                           -0.698341
                                                                                                                                            -0.589645
                                                                                                                                                             -0.611387 -0.343666
                                                                                                                                                            0.043570 -0.343666
               1.272227
                                       0.283642
                                                                                                              -0.549168
                                                                                                                               NaN
                                                                                                                                            1.460910
     23
                                                                0.603167
                                                                                   -0.632794
                                                                                                                           -0.698341
                                                                                                                                                            -0.611387 -0.343666
               -1.213798
                                       -0.699494
                                                                -0.742767
                                                                                   -0.632794
                                                                                                              -0.549168
```

```
[7] print('Number of rows before discarding outliers = %d' % (Z.shape[0]))

Z2 = Z.loc[((Z > -3).sum(axis=1)==9) & ((Z <= 3).sum(axis=1)==9),:]
print('Number of rows after discarding missing values = %d' % (Z2.shape[0]))

Number of rows before discarding outliers = 699
Number of rows after discarding missing values = 632</pre>
```

```
[9] print('Number of rows before discarding duplicates = %d' % (data.shape[0]))
    data2 = data.drop_duplicates()
    print('Number of rows after discarding duplicates = %d' % (data2.shape[0]))

Number of rows before discarding duplicates = 699
Number of rows after discarding duplicates = 463
```