

# HW3

November 1, 2018

## 0.1 Problem 1

$$Cost(A) = -1 * (25) + 100 * (25) + 1 * (0) = 2475$$

$$Cost(B) = -1 * (30) + 100 * (20) + 1 * (20) = 1990$$

$$Cost(C) = -1 * (25) + 100 * (25) + 1 * (25) = 2500$$

B would be chosen

## 0.2 Problem 2

$$\text{Accuracy} = (98 + 143) / (98 + 143 + 37 + 20) = .81$$

$$\text{Precision} = 98 / (98 + 37) = .73$$

$$\text{Recall} = 98 / (98 + 20) = .83$$

Cost =

Sensitivity = Recall

$$\text{Specificity} = (147) / (37 + 143) = .82$$

$$\text{False Positive Rate} = (37) / (37 + 143) = .21$$

## 0.3 Problem 3

Recall = Retrieved and Relevant Documents / Relevant Documents = TP / 10  
Precision = Retrieved and Relevant Documents / Retrieved Documents = TP / (TP + FP)

### 0.3.1 a)

If recall is 40%, then TP = 4.

$$\text{Precision}(A) = 4 / 10$$

$$\text{Precision}(B) = 4 / 12$$

### 0.3.2 b)

If only 15 documents are retrieved, then

$$\text{Recall}(A) = 6 / 10$$

$$\text{Precision}(A) = 6 / 15$$

$$F(A) = .48$$

$$\text{Recal}(B) = 5 / 10$$

$$\text{Precision}(B) = 5 / 15$$

$$F(B) = .4$$

## 0.4 Problem 4

```
In [57]: from sklearn import datasets
        from sklearn import tree
        from sklearn.model_selection import cross_val_score
        import numpy as np

        # import some data to play with
        iris = datasets.load_iris()

In [58]: print(iris.feature_names)
        print(iris.data[0:10]) # Show 10 examples

['sepal length (cm)', 'sepal width (cm)', 'petal length (cm)', 'petal width (cm)']
[[5.1 3.5 1.4 0.2]
 [4.9 3.  1.4 0.2]
 [4.7 3.2 1.3 0.2]
 [4.6 3.1 1.5 0.2]
 [5.  3.6 1.4 0.2]
 [5.4 3.9 1.7 0.4]
 [4.6 3.4 1.4 0.3]
 [5.  3.4 1.5 0.2]
 [4.4 2.9 1.4 0.2]
 [4.9 3.1 1.5 0.1]]

In [59]: clf = tree.DecisionTreeClassifier()

In [60]: cross_val_score(clf, iris.data, iris.target, cv=3)

Out[60]: array([0.98039216, 0.92156863, 0.97916667])

In [61]: cross_val_score(clf, iris.data, iris.target, cv=5)

Out[61]: array([0.96666667, 0.96666667, 0.9        , 0.96666667, 1.        ])

In [62]: cross_val_score(clf, iris.data, iris.target, cv=10)

Out[62]: array([1.        , 0.93333333, 1.        , 0.93333333, 0.93333333,
               0.86666667, 0.93333333, 1.        , 1.        , 1.        ])

In [67]: clf2 = tree.DecisionTreeClassifier(max_leaf_nodes=5)

In [68]: cross_val_score(clf2, iris.data, iris.target, cv=3)

Out[68]: array([0.98039216, 0.92156863, 1.        ])

In [69]: cross_val_score(clf2, iris.data, iris.target, cv=5)

Out[69]: array([0.96666667, 0.96666667, 0.9        , 1.        , 1.        ])

In [70]: cross_val_score(clf2, iris.data, iris.target, cv=10)

Out[70]: array([1.        , 0.93333333, 1.        , 0.93333333, 0.93333333,
               0.86666667, 0.93333333, 1.        , 1.        , 1.        ])
```

## 0.5 Problem 5

### 0.5.1 a)

```
In [4]: import math
```

```
Gain_r1 = 12 * (math.log(12. / 15, 2) - math.log(29. / 50, 2))
Gain_r1
```

```
Out[4]: 5.567365197117486
```

```
In [5]: Gain_r2 = 7 * (math.log(7. / 10, 2) - math.log(29. / 50, 2))
Gain_r2
```

```
Out[5]: 1.8991141527217605
```

```
In [ ]: Gain_r3 = 8 * (math.log(8. / 12, 2) - math.log(29. / 50, 2))
Gain_r3
```

```
In [6]: # R1 is the best rule
```

```
Out[6]: 1.6073015514079714
```

### 0.5.2 b)

```
In [10]: laplace_r1 = (12 + 1) / (15 + 2)
laplace_r1
```

```
Out[10]: 0.7647058823529411
```

```
In [11]: laplace_r2 = (7 + 1) / (10 + 2)
laplace_r2
```

```
Out[11]: 0.6666666666666666
```

```
In [ ]: laplace_r3 = (8 + 1) / (12 + 2)
laplace_r3
```

```
In [12]: # R1 is the best rule
```

```
Out[12]: 0.6428571428571429
```

### 0.5.3 c)

```
In [16]: m_r1 = (12 + 2 * 29 / 50) / (15 + 2)
m_r1
```

```
Out[16]: 0.7741176470588236
```

```
In [17]: m_r2 = (7 + 2 * 29 / 50) / (10 + 2)
m_r2
```

Out[17]: 0.68

```
In [18]: m_r3 = (8 + 2 * 29 / 50) / (12 + 2)
          m_r3
```

Out[18]: 0.6542857142857142

```
In [19]: # R1 is the best rule
```

#### 0.5.4 d)

```
In [20]: accuracy_r1 = (12 / 15)
          accuracy_r1
```

Out[20]: 0.8

```
In [21]: accuracy_r2 = (7 / 10)
          accuracy_r2
```

Out[21]: 0.7

```
In [22]: accuracy_r3 = (8 / 12)
          accuracy_r3
```

Out[22]: 0.6666666666666666

```
In [23]: # R1 is the best rule
```

#### 0.5.5 e)

```
In [27]: accuracy_r1 = (3/3)
          accuracy_r1
```

Out[27]: 1.0

```
In [28]: accuracy_r2 = (7/10)
          accuracy_r2
```

Out[28]: 0.7

```
In [31]: accuracy_r3 = (6/10)
          accuracy_r3
```

Out[31]: 0.6

```
In [32]: # R1 is the best rule
```

### 0.5.6 f)

```
In [35]: accuracy_r2 = (7/10)
         accuracy_r2
```

```
Out[35]: 0.7
```

```
In [36]: accuracy_r3 = (6/8)
         accuracy_r3
```

```
Out[36]: 0.75
```

```
In [37]: # R3 is the best rule
```

## 0.6 Problem 6

a) 3- : Square 5 : Circle

b)

Euclidean

$$\begin{aligned} \text{Circles} &= 1 \\ \text{Squares} &= \frac{1}{1^2 + 1^2} + \frac{1}{2^2 + 1^2} = \frac{7}{10} \end{aligned}$$

Circles win

Manhattan

$$\begin{aligned} \text{Circles} &= 1 \\ \text{Squares} &= \frac{1}{(1+1)^2} + \frac{1}{(2+1)^2} = .36 \end{aligned}$$

Circles win again