### COMS 4701 - Homework 4 - Written

Sankalp, Apharande

spa2138

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# Question 1

#### Answer:

1. 
$$GINI = 1 - p_+^2 - p_-^2$$

$$GAIN(S, A) = Gini(S) - \sum_{v \in Values(A)} \frac{|S_v|}{|S|} \cdot Gini(S_v)$$

1. 
$$P(TRUE) = \frac{3}{4}$$

$$P(FALSE) = \frac{1}{4}$$

GINI index (Root) = 
$$1 - (\frac{3}{4})^2 - (\frac{1}{4})^2 = \frac{6}{16} = 0.375$$

2. Gain(root, word1) = 
$$Gini(root) - \frac{2}{4} \cdot 0 - \frac{2}{4} \cdot 0.5$$
  
Gain(root, word1) =  $0.375 - \frac{2}{4} \cdot 0 - \frac{2}{4} \cdot 0.5$ 

Gain(root, word1) = 
$$0.375 - \frac{2}{4} \cdot 0 - \frac{2}{4} \cdot 0.5$$

$$Gain(root, word1) = 0.125$$

$$\operatorname{Gain}(\operatorname{root},\,\operatorname{word2}) = \operatorname{Gini}(\operatorname{root}) - \tfrac{1}{4} \cdot 0 - \tfrac{3}{4} \cdot \tfrac{4}{9}$$

Gain(root, word2) = 
$$0.375 - \frac{1}{4} \cdot 0 - \frac{3}{4} \cdot \frac{4}{9}$$

$$Gain(root, word2) = 0.375 - \frac{1}{3} = 0.0416$$

$$Gain(root, word1) > Gain(root, word2)$$

Hence word1 will be picked up as a feature at the root. Because Gain is maximum gain while splitting.

### Question 2

#### 1. Answer:

f(x) is predicted final score if midterm score is x.

$$f(x) = \beta_0 + \beta_1 \cdot x$$
  
$$\beta_0 = -8 \text{ and } \beta_1 = 1.2$$

$$f(x) = -8 + 1.2 \cdot x$$

$$f(80) = 1.2 \cdot 80 - 8 = 88$$

The predicted final score is 88.

2. 
$$(x_1, y_1) = (55, 67)$$

$$(x_1, y_1) = (60, 63)$$

$$(x_1, y_1) = (66, 72)$$

$$(x_1, y_1) = (72, 90)$$

$$(x_1, y_1) = (85, 93)$$

$$(x_1, y_1) = (90, 92)$$

$$\beta_0 = -8 \text{ and } \beta_1 = 1.2$$

$$f(x) = 1.2 \cdot x - 8$$

$$f(x_1) = 1.2 \cdot 55 - 8 = 58$$

$$y_{pred} = 58 \& y_{actual} = 67$$

$$f(x_1) = 1.2 \cdot 60 - 8 = 64$$

$$y_{pred} = 64 \& y_{actual} = 63$$

$$f(x_1) = 1.2 \cdot 66 - 8 = 71.2$$

$$y_{pred} = 71.2 \ \& \ y_{actual} = 72$$

$$f(x_1) = 1.2 \cdot 72 - 8 = 78.4$$

$$y_{pred} = 78.4 \& y_{actual} = 90$$

$$f(x_1) = 1.2 \cdot 85 - 8 = 94$$

$$y_{pred} = 94 \& y_{actual} = 93$$

$$f(x_1) = 1.2 \cdot 90 - 8 = 100$$

$$y_{pred} = 100 \& y_{actual} = 92$$

$$n = 6 \ Cost = \frac{1}{2n} \cdot \sum_{i=1}^{n} (y_i + 8 - 1.2 \cdot x_i)^2$$

$$Cost = \frac{1}{12} \cdot \sum_{i=1}^{n} (y_{actual} - y_{predicted})^2$$

$$n = 6 \ Cost = \frac{1}{2^n} \cdot \sum_{i=1}^n (y_i + 8 - 1.2 \cdot x_i)^2$$

$$Cost = \frac{1}{12} \cdot \sum_{i=1}^n (y_{actual} - y_{predicted})^2$$

$$Cost = \frac{1}{12} \cdot [(58 - 67)^2 + (64 - 63)^2 + (71.2 - 72)^2 + (78.4 - 90)^2 + (94 - 93)^2 + (100 - 92)^2]$$

$$Cost = \frac{1}{12} \cdot [282.2] = 23.51666667$$

$$Cost = \frac{29}{12} \sum_{1 \le 0 \le 0 \le 7} (282.2) = 23.51666667$$

 $Cost = 2\overline{3}.51666667$ 

#### 3. a. Incorrect.

Because if we have  $\beta_0$  and  $\beta_1$  zero, then equation becomes zero. i.e.  $f(x) = \beta_0 + \beta_1 \cdot x = 0$ .

i.e 
$$y_{pred} = 0$$

But 
$$Cost = \frac{1}{2n} \cdot \sum_{i=1}^{n} (y_{actual} - y_{predicted})^2 = \frac{1}{2n} \cdot \sum_{i=1}^{n} (y_{actual})^2$$
 may not be zero.

b. Correct.

The linear regressor perfectly fit the data. Because  $R = Cost = \frac{1}{12} \cdot \sum_{i=1}^{n} (y_{actual} - y_{predicted})^2$ . It will be zero if and only if each term is zero. Hence our reggressor perfectly fit the data.

We can't do a perfect prediction test set because its highly possible that our model has over-fitted the training set. And it is highly possible that it will give completely wrong prediction on new data point.

## Question 3

### Answer

$$P(TRUE) = \frac{6}{10} = 0.6$$
  $P(FALSE) = \frac{4}{10} = 0.4$ 

$$P(A|TRUE) = \frac{2}{6} = \frac{1}{3} = 0.3333$$
  $P(A|FALSE) = \frac{3}{4} = 0.75$ 

$$P(\neg B|TRUE) = \frac{1}{6} = 0.166 \qquad \qquad P(\neg B|FALSE) = \frac{2}{4} = 0.5$$

$$P(C|TRUE) = \frac{3}{6} = \frac{1}{2} = 0.5$$
  $P(C|FALSE) = \frac{4}{4} = 1$ 

$$P(TRUE) \cdot P(A|TRUE) \cdot P(\neg B|TRUE) \cdot P(C|TRUE) = 0.6 \cdot 0.333 \cdot 0.166 \cdot 0.5 = 0.016667$$

$$P(FALSE) \cdot P(A|FALSE) \cdot P(\neg B|FALSE) \cdot P(C|FALSE) = 0.4 \cdot 0.75 \cdot 0.5 \cdot 1 = 0.15$$

We assign the label which maximises the  $p(y) \prod_{j} p(a_{j}|y)$ 

Here  $P(new_label = True) < P(new_label = False)$ 

Hence the label for (A = 1, B = 0, C = 1) is FALSE