CS 383 HW2

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1. Table summary:

count(+) =
$$3 + 4 + 4 + 1 = 12$$
, count(-) = $0 + 1 + 3 + 5 = 9$, total = $12 + 9 = 21$
 $P(+) = \frac{12}{21}$, $P(-) = \frac{9}{21}$

(a) What is the sample entropy, H(Y), from this training data (using log base 2)?

$$H(Y) = -\sum_{i}^{n} P(v_i) \log_2(P(v_i))$$

$$\implies H(+, -) = -\left(\frac{12}{21} \log_2\left(\frac{12}{21}\right) + \frac{9}{21} \log_2\left(\frac{9}{21}\right)\right) = 0.9852$$

(b) What are the information gains for branching on variables x_1 and x_2 ?

$$T1 = \begin{bmatrix} 1 & 1 & 3 \\ 1 & 0 & 4 \\ 1 & 1 & 0 \\ 1 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ 1 \\ 0 \\ 0 \end{bmatrix}, F1 = \begin{bmatrix} 0 & 1 & 4 \\ 0 & 0 & 1 \\ 0 & 1 & 3 \\ 0 & 0 & 5 \end{bmatrix} \begin{bmatrix} 1 \\ 1 \\ 0 \\ 0 \end{bmatrix}$$

$$count(+_{T1}) = 3 + 4 = 7, count(-_{T1}) = 0 + 1 = 1, total = 7 + 1 = 8 \implies W_{T1} = \frac{8}{21}$$

$$count(+_{F1}) = 4 + 1 = 5, count(-_{F1}) = 3 + 5 = 8, total = 5 + 8 = 13 \implies W_{F1} = \frac{13}{21}$$

$$count(+_{T2}) = 3 + 4 = 7, count(-_{T2}) = 0 + 3 = 3, total = 7 + 3 = 10 \implies W_{T2} = \frac{10}{21}$$

$$count(+_{F2}) = 4 + 1 = 5, count(-_{F2}) = 1 + 5 = 6, total = 5 + 6 = 11 \implies W_{F2} = \frac{11}{21}$$

$$P(+_{T1}) = \frac{7}{8}, P(-_{T1}) = \frac{1}{8}, P(+_{F1}) = \frac{5}{13}, P(-_{T1}) = \frac{8}{13}$$

$$P(+_{T2}) = \frac{7}{10}, P(-_{T2}) = \frac{3}{10}, P(+_{F2}) = \frac{5}{11}, P(-_{T2}) = \frac{6}{11}$$

$$E_1 = -(W_{T1}E_{T1} + W_{F1}E_{F1}), E_2 = -(W_{T2}E_{T2} + W_{F2}E_{F2})$$

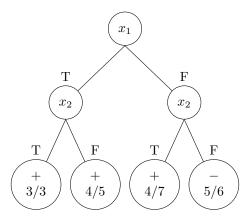
$$E_1 = -\left[\frac{8}{21}\left(\frac{1}{8}\log_2\left(\frac{1}{8}\right)\right) + \frac{7}{8}\log_2\left(\frac{7}{8}\right) + \frac{13}{21}\left(\frac{5}{13}\log_2\left(\frac{5}{13}\right)\right) + \frac{8}{13}\log_2\left(\frac{8}{13}\right)\right] = .8021$$

$$E_2 = -\left[\frac{10}{21}\left(\frac{7}{10}\log_2\left(\frac{7}{10}\right)\right) + \frac{3}{10}\log_2\left(\frac{3}{10}\right) + \frac{11}{21}\left(\frac{5}{11}\log_2\left(\frac{5}{11}\right)\right) + \frac{6}{11}\log_2\left(\frac{6}{11}\right)\right] = .9403$$

$$\implies I(x_1) = H(+, -) - E_1 = .1831$$

$$\implies I(x_2) = H(+, -) - E_1 = .0449$$

(c) Draw the decision tree that would be learned by the ID3 algorithm without pruning from this training data.



- 2. We decided that maybe we can use the number of characters and the average word length an essay to determine if the student should get an A in a class or not.
 - (a) What are the class priors, P(A=Yes), P(A=No)? $P(Yes) = \frac{3}{5}, P(No) = \frac{2}{5}$
 - (b) Find the parameters of the Gaussians necessary to do Gaussian Naive Bayes classification on this decision to give an A or not. Standardize the features first over all the data together so that there is no unfair bias towards the features of different scales.

$$D = \begin{bmatrix} 216 & 5.68 \\ 69 & 4.78 \\ 302 & 2.31 \\ 60 & 3.16 \\ 393 & 4.2 \end{bmatrix} \implies \mu = \begin{bmatrix} 208 & 4.026 \end{bmatrix}, \ \sigma = \begin{bmatrix} 145.2154 & 1.3256 \end{bmatrix}$$

$$\implies D_s = \begin{bmatrix} (216 - 208)/145.2154 & (5.68 - 4.026)/1.19 \\ (69 - 208)/145.2154 & (4.78 - 4.026)/1.19 \\ (60 - 208)/145.2154 & (2.31 - 4.026)/1.19 \\ (60 - 208)/145.2154 & (3.16 - 4.026)/1.19 \\ (393 - 208)/145.2154 & (4.2 - 4.026)/1.19 \\ (393 - 208)/145.2154 & (4.2 - 4.026)/1.19 \end{bmatrix} = \begin{bmatrix} 0.055091 & 1.247714 \\ -0.957199 & 0.568789 \\ 0.647314 & -1.294484 \\ -1.019176 & -0.653277 \\ 1.273970 & 0.131259 \end{bmatrix}$$

$$\mu(A, C) = (0.055091 - 0.957199 - 1.019176)/3 = -0.6404$$

$$\mu(A, W) = (1.247714 + 0.568789 - 0.653277)/3 = 0.3877$$

$$\sigma^2(A, C) = ((0.0555 + 0.6404)^2 + (-0.957 + 0.6404)^2 + (-1.019 + 0.6404)^2)/3 = 0.2425$$

$$\sigma^2(A, W) = ((1.247 - 0.3877)^2 + (0.568 - 0.3877)^2 + (-0.653 - 0.3877)^2)/3 = 0.6187$$

$$\mu(\neg A, C) = (0.64731446 + 1.27396994)/2 = 0.9606$$

$$\mu(\neg A, W) = (-1.29448434 + 0.1312589)/2 = -0.5816$$

$$\sigma^2(\neg A, C) = ((0.64731446 - 0.9606)^2 + (1.27396994 - 0.9606)^2)/2 = 0.098174$$

$$\sigma^2(\neg A, C) = ((-1.29448434 + 0.5816)^2 + (0.1312589 + 0.5816)^2)/2 = 0.5082$$

(c) Using your response from the prior question, determine if an essay with 242 characters and an average word length of 4.56 should get an A or not.

$$S = \begin{bmatrix} 242 & 4.56 \end{bmatrix} \implies S_s = \begin{bmatrix} (242 - 208)/145.2154 & (4.56 - 4.026)/1.3256 \end{bmatrix} = \begin{bmatrix} 0.2341 & 0.4028 \end{bmatrix}$$

$$\begin{split} P(A \mid C, W) &= P(A)P(C \mid A)P(C \mid A); \ P(x \mid y) = \frac{1}{\sqrt{2\pi\sigma_y^2}} \exp\left(-\frac{(x-\mu_y)^2}{2\sigma_y^2}\right) \\ & \Longrightarrow P(A \mid S_s) = \frac{3}{10\pi\sigma(A, C)\sigma(A, W)} \exp\left(-\frac{(x_1-\mu(A, C))^2}{2\sigma^2(A, C)}\right) \exp\left(-\frac{(x_2-\mu(A, W))^2}{2\sigma^2(A, W)}\right) \\ & \Longrightarrow P(A \mid S_s) = 0.050931 \\ P(\neg A \mid C, W) &= P(\neg A)P(C \mid \neg A)P(C \mid \neg A) \\ & \Longrightarrow P(\neg A \mid S_s) = \frac{1}{5\pi\sigma(\neg A, C)\sigma(\neg A, W)} \exp\left(-\frac{(x_1-\mu(\neg A, C))^2}{2\sigma^2(\neg A, C)}\right) \exp\left(-\frac{(x_2-\mu(\neg A, W))^2}{2\sigma^2(\neg A, W)}\right) \\ & \Longrightarrow P(\neg A \mid S_s) = 7.4685 * 10^{-3} \\ & \text{Since } P(A \mid S_s) > P(\neg A \mid S_s), \text{ an essay with 242 characters and an average word length} \\ & \text{of 4.56 should get an A.} \end{split}$$

- 3. Consider the following questions pertaining to a k-Nearest Neighbors algorithm:
 - (a) How could you use a *validation* set to determine the user-defined parameter k?

 The simplest way would be to try various values of k and record the error for each iteration, then pick the k with the least error. A more complex way that may yield better results would be to use cross-folds validation by splitting the data into n partitions (folds) and then iterating through each fold, changing the validation each time, and averaging out the error yielded by each k.