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SENG 474 Assignment 2

1. a) Success rate = $(1)(\frac{1}{3}) + (0)(\frac{1}{3}) + (0)(\frac{1}{3}) = \frac{1}{3}$
 Error rate = $1 - \text{success rate} = 1 - \frac{1}{3} = \boxed{\frac{2}{3}}$

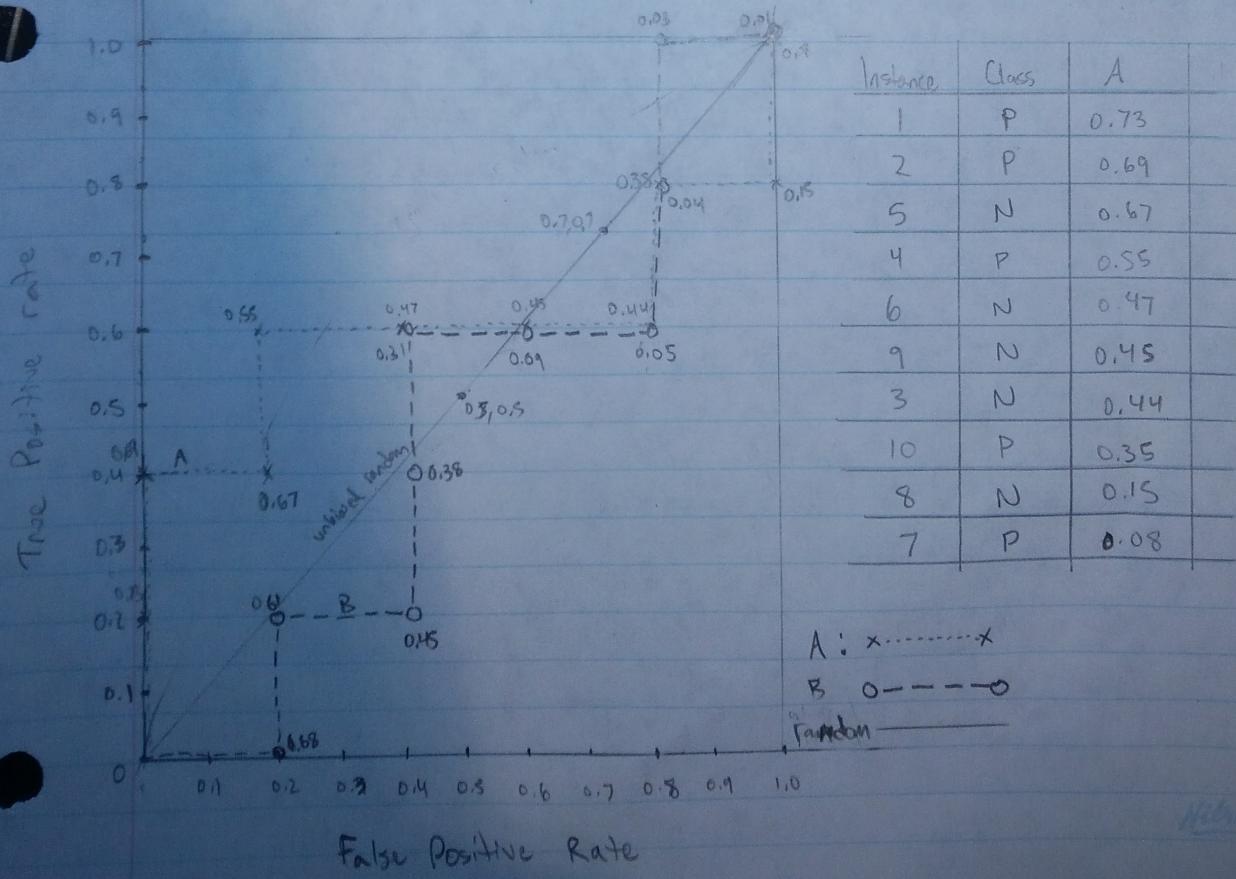
b) Success rate = $(0.7)(\frac{1}{3}) + (0.3)(\frac{1}{3}) + (0)(\frac{1}{3}) = \frac{1}{3}$
 Error rate = $1 - \text{success rate} = 1 - \frac{1}{3} = \boxed{\frac{2}{3}}$

c) Success rate = $(1)(\frac{1}{2}) + (0)(\frac{1}{4}) + (0)(\frac{1}{4}) = \frac{1}{2}$
 Error rate = $1 - \text{success rate} = 1 - \frac{1}{2} = \boxed{\frac{1}{2}}$

d) Success rate = $(0.7)(\frac{1}{2}) + (0.3)(\frac{1}{4}) + (0)(\frac{1}{4}) = 0.425$
 Error rate = $1 - \text{success rate} = 1 - 0.425 = \boxed{0.575}$

2. a)

ROC Graph



Instance	Class	B
3	N	0.68
1	P	0.61
5	N	0.45
7	P	0.38
4	P	0.31
6	N	0.09
8	N	0.05
10	P	0.04
2	P	0.03
9	N	0.01

b) $t = 0.5$

$$\text{Precision: } \frac{3}{3+1} = 75\% \text{ Precise}$$

$$\text{Recall: } \frac{3}{3+2} = 60\% \text{ Recall}$$

$$\text{F-measure: } 2 \times \frac{(P \times R)}{(P + R)} = 2 \times \frac{(0.75)(0.6)}{0.75 + 0.6} = \frac{2}{3} = 66.6\%$$

c) $t = 0.5$

$$\text{Precision: } \frac{1}{1+1} = 50\% \text{ Precise}$$

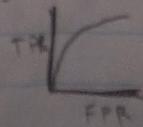
$$\text{Recall: } \frac{1}{1+4} = 20\% \text{ Recall}$$

$$\text{F-measure: } 2 \times \frac{(P \times R)}{(P + R)} = 2 \times \frac{(0.5)(0.2)}{0.5 + 0.2} = \frac{2}{7} = 28.6\%$$

Since A has a greater F-measure (F1) than B, A is a better classifier. This is expected based on the ROC from part a) since classifier A clearly has a better precision and recall for $t = 0.5$.

d) A performs better than the unbiased random classifier between $t = 0.45$ and $t = 1$. B performs better than the unbiased random classifier between $t = 0.01$ and $t = 0.09$, as well as between $t = 0.09$ and $t = 0.38$. Unbiased random is a straight line from bottom left to top right.

e) This is plotted approximately as follows.



See graph for details.

Midway

$$3.a) P(D|\theta) = \prod_{i=1}^N P(x_i|\theta)$$

α_T is # True = 7 (from D)
 α_F is # false = 3

$$= \prod_{i=1}^N \theta^{x_i} (1-\theta)^{1-x_i}$$

$$= \theta^{\alpha_T} (1-\theta)^{\alpha_F}$$

solve for
max θ

$$\frac{d}{d\theta} P(D|\theta) = \frac{d}{d\theta} \theta^{\alpha_T} (1-\theta)^{\alpha_F}$$

\Rightarrow set derivative

to 0

$$0 = \alpha_T \theta^{\alpha_T-1} (1-\theta)^{\alpha_F} - \alpha_F \theta^{\alpha_T} (1-\theta)^{\alpha_F-1}$$

$$\alpha_T \theta^{\alpha_T-1} (1-\theta)^{\alpha_F} = \alpha_F \theta^{\alpha_T} (1-\theta)^{\alpha_F-1}$$

$$7\theta^6 (1-\theta)^3 = 3\theta^7 (1-\theta)^2$$

$$7(1-\theta) = 3\theta$$

$$7 - 7\theta = 3\theta$$

$$7 = 10\theta$$

$$P(X=T) = \theta = \frac{7}{10}$$

$$3. b) \text{ Beta} \sim \theta^{\beta_1-1} (1-\theta)^{\beta_2-1}$$

$$\beta_1 = 4, P(X=T) = \frac{1}{2}, \alpha_T = 7, \alpha_F = 3$$

$$P(X=T) = \frac{\beta_1 - 1}{(\beta_1 - 1) + (\beta_2 - 1)} = \frac{1}{2}$$

$$\frac{4-1}{(4-1) + (\beta_2 - 1)} = \frac{1}{2}$$

$$\frac{3}{\beta_2 + 2} = \frac{1}{2}$$

$$b = \beta_2 + 2$$

$$\beta_2 = 4$$

$$\begin{aligned} p(\theta|D) &\propto p(D|\theta)p(\theta) \\ &= \theta^{\alpha_T} (1-\theta)^{\alpha_F} \theta^{\beta_1-1} (1-\theta)^{\beta_2-1} \\ &= \theta^{10} (1-\theta)^6 \end{aligned}$$

$$O = \frac{\partial}{\partial \theta} p(\theta|D) = \frac{\partial}{\partial \theta} \theta^{10} (1-\theta)^6$$

$$\frac{d}{d\theta} \log p(\theta|D) = \frac{d}{d\theta} 10 \log \theta + 6 \log(1-\theta)$$

$$O = \frac{10}{\theta} - \frac{6}{1-\theta}$$

$$\frac{10}{\theta} = \frac{6}{1-\theta}$$

$$\frac{1-\theta}{\theta} = \frac{6}{10}$$

$$\frac{1-\theta}{\theta} = \frac{6}{10}$$

$$\frac{1}{\theta} = \frac{16}{10}$$

$$\theta = \frac{10}{16} = \frac{5}{8}$$

Hilary

$$4.a) E(X) = \frac{1}{2N} \sum_{i=1}^N (y_i - w_0 - w_1 x_{i,1} - w_2 x_{i,2})^2$$

$$b) \frac{\partial}{\partial w_0} E(X)$$

$$= \frac{\partial}{\partial w_0} \frac{1}{2N} \sum_{i=1}^N (y_i - w_0 - w_1 x_{i,1} - w_2 x_{i,2})^2$$

$$= \frac{1}{2N} \sum_{i=1}^N \frac{\partial}{\partial w_0} (y_i - w_0 - w_1 x_{i,1} - w_2 x_{i,2})^2$$

$$= \frac{1}{2N} \sum_{i=1}^N 2(y_i - w_0 - w_1 x_{i,1} - w_2 x_{i,2})(-1)$$

$$= -\frac{1}{N} \sum_{i=1}^N (y_i - w_0 - w_1 x_{i,1} - w_2 x_{i,2})$$

so the update for w_0 is

$$w = w - K \left(-\frac{1}{N} \sum_{i=1}^N (y_i - w_0 - w_1 x_{i,1} - w_2 x_{i,2}) \right)$$

$$4. c) \frac{\partial}{\partial w_1} E(X)$$

$$= \frac{\partial}{\partial w_1} \frac{1}{2N} \sum_{i=1}^N (y_i - w_0 - w_1 x_{i,1} - w_2 x_{i,2})^2$$

$$= \frac{1}{2N} \sum_{i=1}^N \frac{\partial}{\partial w_1} (y_i - w_0 - w_1 x_{i,1} - w_2 x_{i,2})^2$$

$$= \frac{1}{2N} \sum_{i=1}^N 2(y_i - w_0 - w_1 x_{i,1} - w_2 x_{i,2}) (-x_{i,1})$$

$$= -\frac{1}{N} \sum_{i=1}^N (y_i - w_0 - w_1 x_{i,1} - w_2 x_{i,2})(x_{i,1})$$

so the update for w_1 is

$$w = w - K \left[-\frac{1}{N} \sum_{i=1}^N (x_{i,1})(y_i - w_0 - w_1 x_{i,1} - w_2 x_{i,2}) \right]$$

$$d) \frac{\partial}{\partial w_2} E(X)$$

$$= \frac{\partial}{\partial w_2} \frac{1}{2N} \sum_{i=1}^N (y_i - w_0 - w_1 x_{i,1} - w_2 x_{i,2})^2$$

$$= \frac{1}{2N} \sum_{i=1}^N \frac{\partial}{\partial w_2} (y_i - w_0 - w_1 x_{i,1} - w_2 x_{i,2})^2$$

$$= \frac{1}{2N} \sum_{i=1}^N 2(y_i - w_0 - w_1 x_{i,1} - w_2 x_{i,2}) (-x_{i,2})$$

$$= -\frac{1}{N} \sum_{i=1}^N (x_{i,2})^2 (y_i - w_0 - w_1 x_{i,1} - w_2 x_{i,2})$$

so the update for w_2 is

$$w = w - K \left[-\frac{1}{N} \sum_{i=1}^N (x_{i,2})^2 (y_i - w_0 - w_1 x_{i,1} - w_2 x_{i,2}) \right]$$