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Data Science FA19-CSE-40647-CX-01
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Homework 2 Solutions

Solution 1:

Part A:

Prior Probability:

$$P(Y = 0) = \frac{3}{6} = 0.5 \text{ and } P(Y = 1) = \frac{3}{6} = 0.5.$$

Likelihood Probability:

$$P(A = 1 | Y = 1) = \frac{2}{3} \text{ and } P(A = 1 | Y = 0) = \frac{1}{3}$$

$$P(B = 0 | Y = 1) = \frac{1}{3} \text{ and } P(B = 0 | Y = 0) = \frac{1}{3}$$

$$P(C = 0 | Y = 1) = \frac{2}{3} \text{ and } P(C = 0 | Y = 0) = \frac{1}{3}$$

$$P(X|Y = 1) = \left(\frac{2}{3}\right) * \left(\frac{1}{3}\right) * \left(\frac{2}{3}\right) = \frac{4}{27} \text{ and } P(X|Y = 0) = \left(\frac{1}{3}\right) * \left(\frac{1}{3}\right) * \left(\frac{1}{3}\right) = \frac{1}{27}$$

Posteriori Probability:

$$P(Y = 1|X) = \left(\frac{4}{27}\right) * \left(\frac{1}{2}\right) = \left(\frac{2}{27}\right) \text{ and } P(Y = 0|X) = \left(\frac{1}{27}\right) * \left(\frac{1}{2}\right) = \left(\frac{1}{54}\right)$$

We predict that $Y=1$ with Naive Bayes.

Part B:

Step 1:

$$Y = \{1 * 3, 0 * 3\}$$

$$H(Y) = -\left(\frac{1}{2}\right)\log\left(\frac{1}{2}\right) - \left(\frac{1}{2}\right)\log\left(\frac{1}{2}\right) = 0.301$$

$$X_A = \{1 * 3, 0 * 3\}$$

$$H(Y | X_A) = H(Y | A_1) + H(Y | A_0) = \left(\frac{1}{2}\right) * \left(-\left(\frac{2}{3}\right)\log\left(\frac{2}{3}\right) - \left(\frac{1}{3}\right)\log\left(\frac{1}{3}\right)\right) + \left(\frac{1}{2}\right) * \left(-\left(\frac{1}{3}\right)\log\left(\frac{1}{3}\right) - \left(\frac{2}{3}\right)\log\left(\frac{2}{3}\right)\right) = 0.276$$

$$IG(Y|X_A) = 0.301 - 0.276 = 0.025$$

$$X_B = \{1 * 4, 0 * 2\}$$

$$H(Y | X_B) = H(Y | B_1) + H(Y | B_0) = \left(\frac{2}{3}\right) * \left(-\left(\frac{1}{2}\right)\log\left(\frac{1}{2}\right) - \left(\frac{1}{2}\right)\log\left(\frac{1}{2}\right)\right) + \left(\frac{1}{3}\right) * \left(-\left(\frac{1}{2}\right)\log\left(\frac{1}{2}\right) - \left(\frac{1}{2}\right)\log\left(\frac{1}{2}\right)\right) = 0.301$$

$$IG(Y|X_C) = 0.301 - 0.301 = 0$$

$$X_C = \{1 * 3, 0 * 3\}$$

$$H(Y | X_C) = H(Y | C_1) + H(Y | C_0) = \left(\frac{1}{2}\right) * \left(-\left(\frac{1}{3}\right)\log\left(\frac{1}{3}\right) - \left(\frac{2}{3}\right)\log\left(\frac{2}{3}\right)\right) + \left(\frac{1}{2}\right) * \left(-\left(\frac{2}{3}\right)\log\left(\frac{2}{3}\right) - \left(\frac{1}{3}\right)\log\left(\frac{1}{3}\right)\right) = 0.276$$

$$IG(Y|X_C) = 0.301 - 0.276 = 0.025$$

Note that we could have chosen C instead of A since the information gain for both is the same.

Step 2a:

$$Y = \{1 * 2, 0 * 1\}$$

$$H(Y) = -\left(\frac{1}{3}\right)\log\left(\frac{1}{3}\right) - \left(\frac{2}{3}\right)\log\left(\frac{2}{3}\right) = 0.276$$

$$X_B = \{1 * 2, 0 * 1\}$$

$$H(Y | X_B) = H(Y | B_1) + H(Y | B_0) = \left(\frac{2}{3}\right) * \left(-\left(\frac{1}{2}\right)\log\left(\frac{1}{2}\right) - \left(\frac{1}{2}\right)\log\left(\frac{1}{2}\right)\right) + \left(\frac{1}{3}\right) * \left(-\left(\frac{1}{1}\right)\log\left(\frac{1}{1}\right)\right) = 0.200$$

$$IG(Y|X_B) = 0.276 - 0.200 = 0.076$$

$$X_C = \{1 * 2, 0 * 1\}$$

$$H(Y | X_C) = H(Y | C_1) + H(Y | C_0) = \left(\frac{2}{3}\right) * \left(-\left(\frac{1}{2}\right)\log\left(\frac{1}{2}\right) - \left(\frac{1}{2}\right)\log\left(\frac{1}{2}\right)\right) + \left(\frac{1}{3}\right) * \left(-\left(\frac{1}{1}\right)\log\left(\frac{1}{1}\right)\right) = 0.200$$

$$IG(Y|X_C) = 0.276 - 0.200 = 0.076$$

Note that we could have chosen C instead of B since the information gain for both is the same.

Step 2b:

$$Y = \{1 * 1, 0 * 2\}$$

$$H(Y) = -\left(\frac{1}{3}\right)\log\left(\frac{1}{3}\right) - \left(\frac{2}{3}\right)\log\left(\frac{2}{3}\right) = 0.276$$

$$X_B = \{1 * 2, 0 * 1\}$$

$$H(Y | X_B) = H(Y | B_1) + H(Y | B_0) = \left(\frac{2}{3}\right) * \left(-\left(\frac{1}{2}\right)\log\left(\frac{1}{2}\right) - \left(\frac{1}{2}\right)\log\left(\frac{1}{2}\right)\right) + \left(\frac{1}{3}\right) * \left(-\left(\frac{1}{1}\right)\log\left(\frac{1}{1}\right)\right) = 0.200$$

$$IG(Y|X_B) = 0.276 - 0.200 = 0.076$$

$$X_C = \{1 * 1, 0 * 2\}$$

$$H(Y | X_C) = H(Y | C_1) + H(Y | C_0) = \left(\frac{1}{3}\right) * \left(-\left(\frac{1}{1}\right)\log\left(\frac{1}{1}\right)\right) + \left(\frac{2}{3}\right) * \left(-\left(\frac{1}{2}\right)\log\left(\frac{1}{2}\right) - \left(\frac{1}{2}\right)\log\left(\frac{1}{2}\right)\right) = 0.200$$

$$IG(Y|X_C) = 0.276 - 0.200 = 0.076$$

Note that we could have chosen C instead of B since the information gain for both is the same.

Step 3a:

$$Y = \{1 * 1, 0 * 1\}$$

$$H(Y) = -\left(\frac{1}{2}\right)\log\left(\frac{1}{2}\right) - \left(\frac{1}{2}\right)\log\left(\frac{1}{2}\right) = 0.301$$

$$X_C = \{1 * 1, 0 * 1\}$$

$$H(Y | X_B) = H(Y | B_1) + H(Y | B_0) = \left(\frac{1}{2}\right) * \left(-\left(\frac{1}{1}\right)\log\left(\frac{1}{1}\right) - \left(\frac{1}{1}\right)\log\left(\frac{1}{1}\right)\right) + \left(\frac{1}{2}\right) * \left(-\left(\frac{1}{1}\right)\log\left(\frac{1}{1}\right)\right) = 0.00$$

Pure branches (nothing learned via split) so if C = 0 then Y = 1 and if C = 1 then Y = 0

Step 3b:

$$Y = \{1 * 1, 0 * 1\}$$

$$H(Y) = -\left(\frac{1}{1}\right)\log\left(\frac{1}{1}\right) - \left(\frac{0}{1}\right)\log\left(\frac{0}{1}\right) = 0$$

Pure branch (nothing learned via split) so if C = 0 or C = 1 then Y = 1

Step 3c:

$$Y = \{1 * 1, 0 * 1\}$$

$$H(Y) = -\left(\frac{1}{2}\right)\log\left(\frac{1}{2}\right) - \left(\frac{1}{2}\right)\log\left(\frac{1}{2}\right) = 0.301$$

$$X_C = \{1 * 1, 0 * 1\}$$

$$H(Y | X_B) = H(Y | B_1) + H(Y | B_0) = \left(\frac{1}{2}\right) * \left(-\left(\frac{1}{1}\right)\log\left(\frac{1}{1}\right) - \left(\frac{1}{1}\right)\log\left(\frac{1}{1}\right)\right) + \left(\frac{1}{2}\right) * \left(-\left(\frac{1}{1}\right)\log\left(\frac{1}{1}\right)\right) = 0.00$$

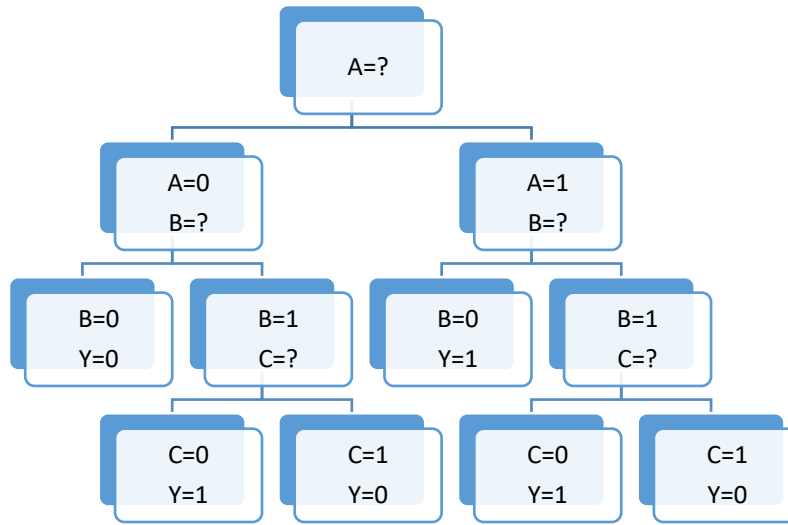
Pure branches (nothing learned via split) so if $C = 0$ then $Y = 1$ and if $C = 1$ then $Y = 0$

Step 3d:

$$Y = \{1 * 1, 0 * 1\}$$

$$H(Y) = -\left(\frac{1}{1}\right)\log\left(\frac{1}{1}\right) - \left(\frac{0}{1}\right)\log\left(\frac{0}{1}\right) = 0$$

Pure branch (nothing learned via split) so if $C = 0$ or $C = 1$ then $Y = 0$



Solution 2:

We have $K(x_i, x_j) = (x_i x_j + 1)^3$. Note that for $x = (x_1, x_2)$ this is $(x_{i1} x_{j1} + x_{i2} x_{j2} + 1)^3$, so:

$$K(x_i, x_j) = (x_i x_j + 1)^3$$

$$= (x_{i1} x_{j1} x_{i1} x_{j1} + x_{i1} x_{j1} x_{i2} x_{j2} + x_{i1} x_{j1} + x_{i2} x_{j2} x_{i1} x_{j1} + x_{i2} x_{j2} x_{i2} x_{j2} + x_{i2} x_{j2} + x_{i1} x_{j1} + x_{i2} x_{j2} + 1)(x_{j1} x_{i1} + x_{j2} x_{i2} + 1)$$

$$= (x_{j1}^2 x_{i1}^2 + 2x_{j1} x_{i1} + 2x_{j1} x_{j2} x_{i1} x_{i2} + x_{j2}^2 x_{i2}^2 + 2x_{j2} x_{i2} + 1)(x_{j1} x_{i1} + x_{j2} x_{i2} + 1)$$

$$= x_{j1}^2 x_{i1}^2 x_{j1} x_{i1} + x_{j1}^2 x_{i1}^2 x_{i2} x_{j2} + x_{j1}^2 x_{i1}^2 + 2x_{j1} x_{i1} x_{j1} x_{i1} + 2x_{j1} x_{i1} x_{i2} x_{j2} + 2x_{j1} x_{i1} + 2x_{j1} x_{j2} x_{i2} x_{i1} x_{i1} x_{j1} + 2x_{j1} x_{j2} x_{i2} x_{i1} x_{i2} x_{j2} + 2x_{j1} x_{j2} x_{i1} x_{i2} + x_{j2}^2 x_{i2}^2 x_{i1} x_{j1} + x_{j2}^2 x_{i2}^2 x_{j2} x_{i2} + x_{j2}^2 x_{i2}^2 + 2x_{j2} x_{i2} x_{i1} x_{j1} + 2x_{j2} x_{i2} x_{i2} x_{j2} + 2x_{j2} x_{i2} + x_{i1} x_{j1} + x_{j2} x_{i2} + 1$$

$$= x_{j1}^3 x_{i1}^3 + 3x_{j1}^2 x_{i1}^2 + 3x_{j1}^2 x_{j2} x_{i1}^2 x_{i2} + 3x_{j1} x_{i1} + 3x_{j1} x_{j2}^2 x_{i1} x_{i2}^2 + 6x_{j1} x_{j2} x_{i1} x_{i2} + x_{j2}^3 x_{i2}^3 + 3x_{j2}^2 x_{j2}^2 + 3x_{j2} x_{i2} + 1$$

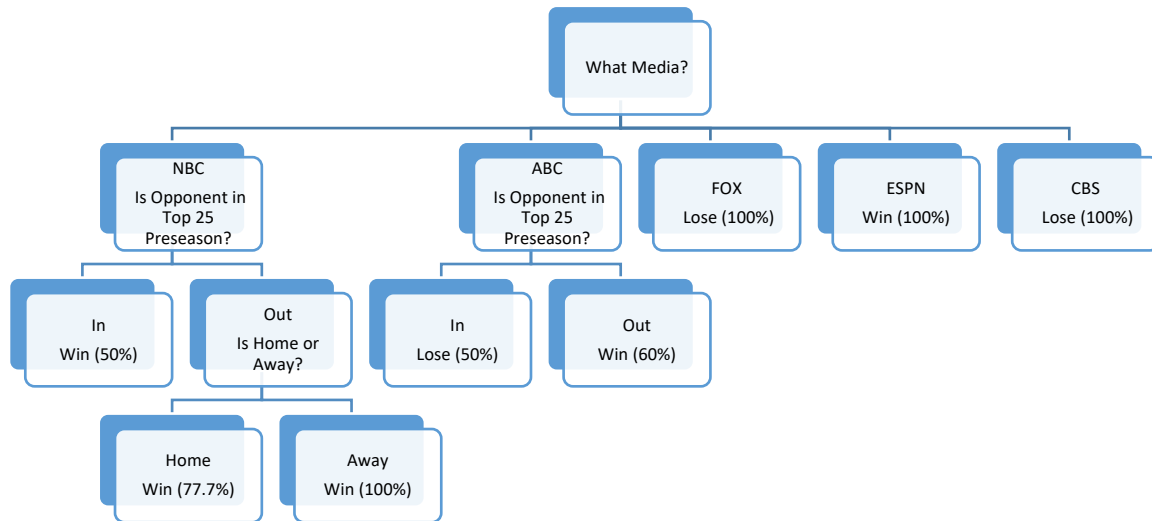
So then:

$$\Phi(x) = x_1^3 + \sqrt{3}x_1^2 + \sqrt{3}x_1^2 x_2 + \sqrt{3}x_1 + \sqrt{3}x_1 x_2^2 + \sqrt{6}x_1 x_2 + x_2^3 + \sqrt{3}x_2^2 + \sqrt{3}x_2 + 1$$

Solution 3:

Note that if $TP = TN$ we have that $Accuracy = \frac{TP+TN}{Total\ Population} = \frac{TP+TN}{TP+TN+FP+FN} = \frac{2TP}{2TP+FP+FN}$. Now $Precision = \frac{TP}{TP+FP}$ and $Recall = \frac{TP}{TP+FN}$, so if $TP = TN$ we have that $F_1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} = 2 \times \frac{\left(\frac{TP}{TP+FP}\right) \times \left(\frac{TP}{TP+FN}\right)}{\left(\frac{TP}{TP+FP}\right) + \left(\frac{TP}{TP+FN}\right)} = 2 \times \frac{\frac{(TP)^2}{(TP+FP) \times (TP+FN)}}{\frac{(TP)^2}{(TP+FP) \times (TP+FN)}} = 2 \times \left(\frac{(TP)^2}{(TP+FP) \times (TP+FN)}\right) \times \left(\frac{(TP+FP) \times (TP+FN)}{(2(TP)^2) + (TP \times FP) + (TP \times FN)}\right) = 2 \times \left(\frac{(TP)^2}{(2(TP)^2) + (TP \times FP) + (TP \times FN)}\right) = 2 \times \left(\frac{(TP)^2}{(TP) \times ((2TP) + (FP) + (FN))}\right) = 2 \times \left(\frac{TP}{((2TP) + (FP) + (FN))}\right) = \frac{2TP}{2TP+FP+FN}$. Since both **Accuracy** and F_1 can be derived to equivalent expressions we know they are equivalent when $TP = TN$.

Solution 1:

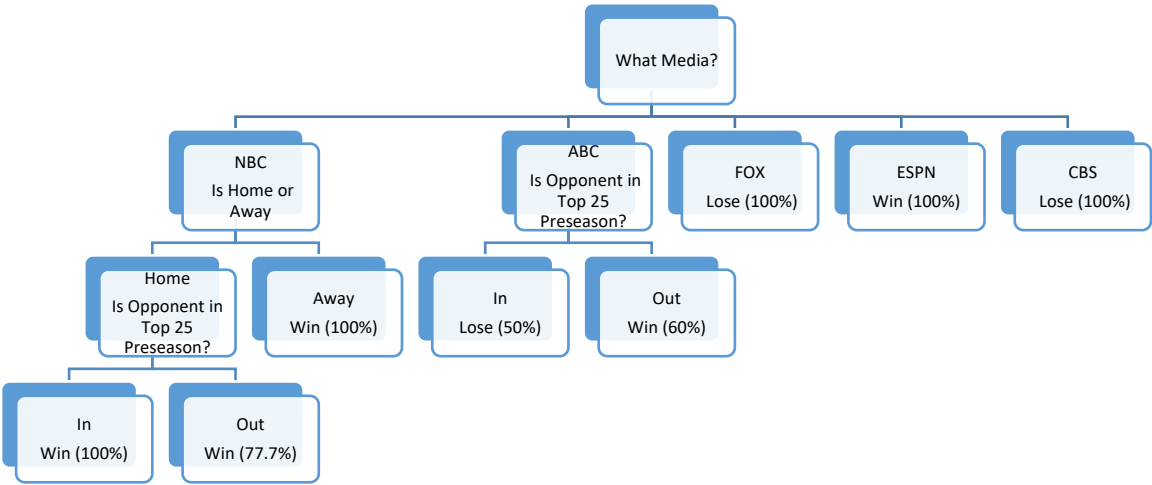


Game #	Predicted Label
1	Win
2	Win
3	Win
4	Lose
5	Win
6	Win
7	Win
8	Win
9	Win
10	Lose
11	Win

12	Lose
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Metric	Value
Accuracy	0.833333333333
Precision	0.888888888889
Recall	0.888888888889
F1 Score	0.444444444444

Solution 2:



Game #	Predicted Label
1	Win
2	Win
3	Win
4	Lose
5	Win
6	Win
7	Win
8	Win
9	Win
10	Lose
11	Win
12	Lose

Metric	Value
Accuracy	0.833333333333
Precision	0.888888888889
Recall	0.888888888889
F1 Score	0.444444444444

Solution 3:

Game #	Predicted Label
1	Win
2	Win
3	Win
4	Lose
5	Win
6	Lose
7	Win
8	Win
9	Win
10	Lose
11	Win
12	Lose

Metric	Value
Accuracy	0.75
Precision	0.875
Recall	0.777777777778
F1 Score	0.411764705882

Solution 4:

