ASSESSMENT COVER SHEET

Assignment Details

Course: Machine Learning

Semester/Academic Year: Sem 2, 2015

Assignment title: Assignment 3

Assessment Criteria

Assessment Criteria are included in the Assignment Descriptions that are published on each course's web site.

Plagiarism and Collusion

Plagiarism: using another person's ideas, designs, words or works without appropriate acknowledgement.

Collusion: another person assisting in the production of an assessment submission without the express requirement, or consent or knowledge of the assessor.

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DECLARATION

I declare that all material in this assessment is my own work except where there is clear acknowledgement and reference to the work of others. I have read the University Policy Statement on Plagiarism, Collusion and Related Forms of Cheating:

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SIGNATURE AND DATE 29/10, 2015.

Question1.

1. $P(A=a, B=b) = \sum_{C} P(a,b,C) = P(a,b,c) + P(a,b,\neg c)$

$= 0.02$

2. $P(B=b) = \sum_{A,C} P(A,b,C) = 0.01 + 0.01 + 0.04 + 0.04 = 0.1$

3. $P(A=a \mid B=b) = \dfrac{P(a,b)}{P(B=b)} = \dfrac{0.02}{0.1} = 0.2$

4. $P(A=\neg a \mid B=b) = 1 - P(A=a \mid B=b) = 0.8$

Question2.

1.

B	P(B)
1	1/3
2	1/3
3	1/3

B	P(apple|B)	P(orange|B)
1	1	0
2	0	1
3	$\frac{1}{2}$	$\frac{1}{2}$

2. $P(B=1, F=\text{apple}) = P(F=\text{apple} \mid B=1) \times P(B=1) = 1 \times \frac{1}{3} = \frac{1}{3}.$

3. $P(B=1 \mid F=\text{apple}) = \dfrac{P(F=\text{apple} \mid B=1) \cdot P(B=1)}{P(F=\text{apple})} = \dfrac{\frac{1}{3}}{P(\text{apple})}.$

$\because P(\text{apple}) = \sum_{B} P(B, \text{apple}) = \sum_{B} P(\text{apple} \mid B) \cdot P(B)$

$= 1 \times \frac{1}{3} + 0 \times \frac{1}{3} + \frac{1}{2} \times \frac{1}{3} = \frac{1}{2}.$

$\therefore P(B=1 \mid F=\text{apple}) = \dfrac{\frac{1}{3}}{\frac{1}{2}} = \frac{2}{3}.$

Question 3.

1. $P(G) = \sum_{D,I,S,L} P(D,I,G,S,L)$

$= \sum_{D,I,S,L} P(D)\,P(I)\,P(G|D,I)\,P(S|I)\,P(L|G)$

$= \sum_{D,I,S} P(D)P(I)P(G|D,I)P(S|I) \sum_{L} P(L|G)$

$= \sum_{D,I,S} P(D)P(I)P(G|D,I)\,P(S|I)$

$= \sum_{D,I} P(D)\,P(I)\,P(G|D,I) \sum_{S} P(S|I).$

$= \sum_{D,I} P(D)\,P(I)\,P(G|D,I)$

$= \sum_{D} P(D) \sum_{I} P(I)\,P(G|D,I)$

$= \sum_{D} P(D)\,m_1(G,D)$

$= m_2(G).$

2. Parameters are: $P(D)$, $P(I)$, $P(G|D,I)$, $P(S|I)$, $P(L|G)$.

Question 4.

$$\sum_{A} \hat{P}(A|B=0,C=0) = \sum_{A} \frac{N(A,B=0,C=0)+N_r}{N(B=0,C=0)+(\#A)\times N_r}$$

$$= \frac{\sum_{A} N(A,B=0,C=0) + \sum_{A} N_r}{N(B=0,C=0)+(\#A)\times N_r}$$

$\because \sum_{A} N_r = (\#A)\times N_r.$

$\because \sum_{A} N(A,B=0,C=0) = N(B=0,C=0$

$$\therefore = \frac{N(B=0,C=0)+(\#A)\times N_r}{N(B=0,C=0)+(\#A)\times N_r} = 1. \quad \#$$

Question 5.

$\cancel{P(S) = \sum_{A,G} P}$ $P(S=1) = \dfrac{N(S=1)}{\sum_{S} N(S)} = \dfrac{4}{6} = \dfrac{2}{3}$,

$P(S=0) = 1 - P(S=1) = \dfrac{1}{3}$.

$\because \hat{p}(A|S) = \dfrac{N(A,S)+1}{N(S)+2\times 1}$, $\hat{p}(G|S) = \dfrac{N(G,S)+1}{N(S)+2\times 1}$.

$\therefore \hat{p}(A=0|S=0) = \dfrac{2+1}{2+2} = \dfrac{3}{4}$, $\hat{p}(A=1|S=0) = \dfrac{0+1}{2+2} = \dfrac{1}{4}$.

$\hat{p}(A=0|S=1) = \dfrac{2+1}{4+2} = \dfrac{1}{2}$, $\hat{p}(A=1|S=1) = \dfrac{2+1}{4+2} = \dfrac{1}{2}$.

$\therefore \hat{p}(G=0|S=0) = \dfrac{1+1}{2+2} = \dfrac{1}{2}$, $\hat{p}(G=1|S=0) = \dfrac{1+1}{2+2} = \dfrac{1}{2}$.

$\hat{p}(G=0|S=1) = \dfrac{3+1}{4+2} = \dfrac{2}{3}$, $\hat{p}(G=1|S=1) = \dfrac{1+1}{4+2} = \dfrac{1}{3}$.

Question 6.

1. $X \perp\!\!\!\perp Y | Z \Rightarrow P(X,Y|Z) = P(X|Z)P(Y|Z)$

$\because P(X,Y|Z) = P(Y,X|Z)$,

$\therefore P(Y,X|Z) = P(X|Z)P(Y|Z) = P(Y|Z)\cdot P(X|Z)$.

$\therefore Y \perp\!\!\!\perp X | Z$.

2. $\because X \perp\!\!\!\perp Y,W|Z$

$\therefore P(X,Y,W|Z) = P(X|Z)\cdot P(Y,W|Z)$.

$$\therefore \frac{P(X,Y,W,Z)}{P(Z)} = \frac{P(X,Z)}{P(Z)} \frac{P(Y,W,Z)}{P(Z)}$$

$$\therefore P(X,Y,W,Z) = \frac{P(X,Z)}{P(Z)} \cdot P(Y,W,Z). \quad ①$$

Sum on W, we get

$$\sum_W P(X,Y,W,Z) = \frac{P(X,Z)}{P(Z)} \sum_W P(Y,W,Z)$$

$$\therefore P(X,Y,Z) = \frac{P(X,Z)}{P(Z)} \cdot P(Y,Z).$$

$$\Rightarrow \frac{P(X,Y,Z)}{P(Z)} = \frac{P(X,Z)}{P(Z)} \cdot \frac{P(Y,Z)}{P(Z)}.$$

$$P(X,Y|Z) = P(X|Z) \cdot P(Y|Z)$$

$$\therefore X \perp\!\!\!\perp Y | Z.$$

The same operation, sum on Y for formula ①.

$$\sum_Y P(X,Y,W,Z) = \frac{P(X,Z)}{P(Z)} \sum_Y P(Y,W,Z).$$

$$\Rightarrow \frac{P(X,W,Z)}{P(Z)} = \frac{P(X,Z)}{P(Z)} \cdot \frac{P(W,Z)}{P(Z)}$$

$$\Rightarrow P(X,W|Z) = P(X|Z) \cdot P(W|Z).$$

$$\Rightarrow X \perp\!\!\!\perp W | Z.$$

Question 7.

1. if X_i, X_j are independent.

for each (x_i, x_j), $P(x_i, x_j) = P(x_i)P(x_j)$

$\therefore I(X_i, X_j) = \sum_{x_i, x_j} P(x_i, x_j) \cdot \log 1 = \sum_{x_i, x_j} P(x_i, x_j) \cdot 0 = 0$;

if $I(X_i, X_j) = 0$, and $P(x_i, x_j)$ is the joint probability.

$\Rightarrow P(x_i, x_j) > 0$.

$\because I(X_i, X_j) = \sum_{x_i, x_j} P(x_i, x_j) \cdot \log \frac{P(x_i, x_j)}{P(x_i)P(x_j)}$

$\therefore$ for any (x_i, x_j), we must have $\log \frac{P(x_i, x_j)}{P(x_i)P(x_j)} = 0$

$\Rightarrow \frac{P(x_i, x_j)}{P(x_i)P(x_j)} = 1 \quad \Rightarrow \quad X_i \perp\!\!\!\perp X_j$

2. if $P(X) = P'(X)$

$KL(P(X) \| P'(X)) = \sum_x P(x) \cdot \log \frac{P(x)}{P'(x)} = \sum_x P(x) \log 1 = 0$;

if $KL(P(X) \| P'(X)) = 0$, we get

$\sum_x P(x) \log \frac{P(x)}{P'(x)} = 0$,

$\because P(x) > 0$. $\therefore$ for any x, $\log \frac{P(x)}{P'(x)} = 0$

$\therefore \frac{P(x)}{P'(x)} = 1$

$\therefore$ for any x, $P(x) = P'(x)$.

$\Rightarrow P(X) = P'(X)$.

Question 8.

1. Since $k(\vec{u},\vec{v})$ is a valid kernel.

$k(\vec{u},\vec{v}) = \phi(\vec{u})\cdot\phi(\vec{v})$. Thus the kernel matrix K_s should be $(K_s)_{ij} = \phi(\vec{x_i})\cdot\phi(\vec{x_j})$. Let $V = [\phi(x_1), \cdots \phi(x_n)]$, in the expression $\phi(x_i)$ is a column vector.

Then, $K_s = V^T V$.

Then, for any vector $\vec{z}$ in original space. we must ensure $(z^T V^T)(Vz) \geq 0$. $\therefore$ $K_s = V^T V$ must be ≥ 0, must be PSD.

2. Dual form of binary SVM in soft margin case using kernel:

Maximize $L_D = \sum_i a_i - \frac{1}{2}\sum_{i,j} a_i a_j y_i y_j \cdot K(\vec{x_i},\vec{x_j})$.

subject to $0 \leq a_i \leq C$, $\sum_i a_i y_i = 0$.

3. ① Could map a non-linear problem to a high-dimension space, and in that space, the non-linear problem become a linear problem.

② Simple computation of the dot product in a potentially infinite dimensional feature space by means on the kernel function.

③ Simple construction of PSD kernels from other PSD kernels.

④ Given an algorithm formulated in terms of a PSD kernel k, we can formulate another algorithm by replacing k with another PSD kernel.