

IDA - Data Mining Solutions

Question 1.

- i) A possible coding scheme that can be used is:

picking a red ball – 00
picking a green ball – 10
picking a blue ball – 01

- ii) The entropy of X is

$$\begin{aligned} H(X) &= \frac{9}{20} \log_2 \left(\frac{20}{9} \right) + \frac{6}{20} \log_2 \left(\frac{20}{6} \right) + \frac{5}{20} \log_2 \left(\frac{20}{5} \right) \\ &= 1.539 \text{ (3 d.p)} \end{aligned}$$

The value we calculated means that Bob should expect *on average* 1.539 bits of information when Alice transmits the realisation. In part i), we have shown that each possibility can be encoded with just two bits so this is not a surprise.

- iii) Let P and Q be two discrete probability distributions on the r.v. X , where P is the correct distribution Alice uses (the new one, after some of the balls are taken) and Q the incorrect one Alice thinks is being used (not knowing that some balls have been removed). So,

$$\begin{aligned} P &= \left\{ \frac{2}{13}, \frac{6}{13}, \frac{5}{13} \right\}, \\ Q &= \left\{ \frac{9}{20}, \frac{6}{20}, \frac{5}{20} \right\}. \end{aligned}$$

We need compute the K-L divergence from P to Q to find the ‘penalty’. So,

$$\begin{aligned} D_{KL}(P||Q) &= \frac{2}{13} \log_2 \left(\frac{\frac{2}{13}}{\frac{9}{20}} \right) + \frac{6}{13} \log_2 \left(\frac{\frac{6}{13}}{\frac{6}{20}} \right) + \frac{5}{13} \log_2 \left(\frac{\frac{5}{13}}{\frac{5}{20}} \right) \\ &= 0.288 \text{ (3 d.p)} \end{aligned}$$

Hence, on average the transmission will use 0.288 additional bits when using the ”wrong” distribution.

Question 2.

i) For convenience, we let

$$D_{KL}(P||Q) = - \sum_{x \in A} P(x) \log_2 \left(\frac{Q(x)}{P(x)} \right).$$

Also, we will work with the natural logarithm (\log), which will not change anything as for $a \in \mathbb{R}$,

$$\log_2 a = \frac{\log a}{\log 2}.$$

Furthermore, it can be verified that for $a > 0$,

$$\log a \leq a - 1, \tag{1}$$

with equality if (and only if) $a = 1$ (plot the graphs of $\log a$ and $(a - 1)!$). Now,

$$D_{KL}(P||Q) \geq - \sum_{x \in A} P(x) \left(\frac{Q(x)}{P(x)} - 1 \right) = - \sum_{x \in A} Q(x) + \sum_{x \in A} P(x) = -1 + 1 = 0.$$

If $D_{KL}(P||Q) = 0$, then by (1) this can only happen when

$$\log \frac{Q(x)}{P(x)} = \frac{Q(x)}{P(x)} - 1, \text{ for every } x \in A \Leftrightarrow Q(x) = P(x), \text{ for every } x \in A.$$

It follows that $D_{KL}(P||Q) = 0 \Leftrightarrow P = Q$ as the converse is trivial.

This inequality we have just proven has a special name called *Gibbs' inequality* and it has many applications in information theory.

ii) Let Q be a uniform distribution over X i.e. $Q(x) = \frac{1}{n}$ for every $x \in A$. Then by part i),

$$\begin{aligned} D_{KL}(P||Q) &= - \sum_{x \in A} P(x) \log_2 \frac{1}{nP(x)} \\ &= - \left(\sum_{x \in A} P(x) \log_2 \left(\frac{1}{P(x)} \right) + \sum_{x \in A} P(x) \log_2 \left(\frac{1}{n} \right) \right) \\ &= -(H(P) - \log_2 n) \\ &\geq 0. \end{aligned}$$

It follows that $H(P) \leq \log_2 n$.

Question 3.

- i) Delta - it appears less frequently in the documents compared to the other terms. Also note that it shows up more frequently in d^3 which better 'represents' the document.
- ii) The computed vector of weights for each document are¹

$$\begin{aligned}\mathbf{x}^1 &= (1.66 \times 10^{-3}, 8.3 \times 10^{-4}, 1.66 \times 10^{-3}, 2 \times 10^{-3})^T, \\ \mathbf{x}^2 &= (8.3 \times 10^{-4}, 1.66 \times 10^{-3}, 0, 0)^T, \\ \mathbf{x}^3 &= (0.0249, 0.0332, 0.0249, 0.2), \\ \mathbf{x}^4 &= (0, 0, 8.3 \times 10^{-3}, 0)^T.\end{aligned}$$

Question 4.

- i) First, we transform each document into a set of weights using TFIDF:

$$\begin{aligned}\mathbf{x}^1 &= (0.0222, 0.0971)^T, \\ \mathbf{x}^2 &= (2.22 \times 10^{-3}, 1.94 \times 10^{-3})^T, \\ \mathbf{x}^3 &= (0.0445, 0.0194)^T, \\ \mathbf{x}^4 &= (4, 45 \times 10^{-4}, 0)^T, \\ \mathbf{x}^5 &= (0, 0)^T, \\ \mathbf{x}^6 &= (0.0111, 0.0311)^T, \\ \mathbf{x}^7 &= (0.0222, 0.0728)^T.\end{aligned}$$

Next, we find the co-variance matrix \mathbf{C} of these data points and the eigenvalues and eigenvectors:

$$\begin{aligned}\mathbf{u}_1 &= (-0.976, 0.216)^T, \lambda_1 = 1.72 \times 10^{-4} \\ \mathbf{u}_2 &= (-0.216, -0.976)^T, \lambda_2 = 1.34 \times 10^{-3}\end{aligned}$$

We will use the eigenvector that preserves the most variability in the data, which is \mathbf{u}_2 . The projected data points are

$$\begin{aligned}\tilde{\mathbf{x}}^1 &= -0.0996, \\ \tilde{\mathbf{x}}^2 &= -0.00238, \\ \tilde{\mathbf{x}}^3 &= -0.0286, \\ \tilde{\mathbf{x}}^4 &= -9.62 \times 10^5, \\ \tilde{\mathbf{x}}^5 &= 0, \\ \tilde{\mathbf{x}}^6 &= -0.0327, \\ \tilde{\mathbf{x}}^7 &= -0.0759.\end{aligned}$$

¹logarithm is base 2

- ii) One possible concept present in the documents can be *'learning how to use the command line in Linux'*.
- iii) Let our query document be $\mathbf{d}_Q = (0, 1)^T$. Projecting \mathbf{d}_Q onto the concept space, we get $\tilde{\mathbf{d}}_Q = -0.976$. In fact, using cosine similarity, we see that, with the exception of d^5 , every document appears to be a good match for what we want!