

Prof. Dr. Rudolf Mathar, Dr. Michael Reyer

Tutorial 4 - Proposed Solution -

Friday, May 10, 2019

Solution of Problem 1

Theorem 4.3 shall be proven.

a) X is a discrete random variable with $p_i = P(X = x_i)$, $i = 1, \dots, m$. It holds

$$H(X) = - \sum_i p_i \log(p_i) \geq 0,$$

as $p_i \geq 0$ and $-\log(p_i) \geq 0$ for $0 < p_i \leq 1$ and $0 \cdot \log 0 = 0$ per definition.

Equality holds, if all addends are zero, i.e.,

$$p_i \log(p_i) = 0 \Leftrightarrow p_i \in \{0, 1\} \quad i = 1, \dots, m,$$

as $p_i > 0$ and $-\log(p_i) > 0$, thus, $-p_i \log(p_i) > 0$ for $0 < p_i < 1$.

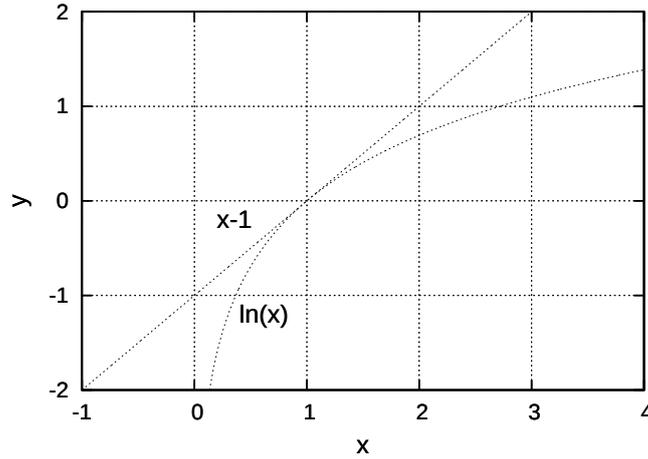
b) It holds

$$\begin{aligned} H(X) - \log(m) &= - \sum_i p_i \log(p_i) - \underbrace{\sum_i p_i}_{=1} \log(m) \\ &= \sum_{i:p_i>0} p_i \log\left(\frac{1}{p_i m}\right) \\ &= (\log e) \sum_{i:p_i>0} p_i \ln\left(\frac{1}{p_i m}\right) \\ &\stackrel{\ln(x) \leq x-1}{\leq} (\log e) \sum_{i:p_i>0} p_i \left(\frac{1}{p_i m} - 1\right) \\ &= (\log e) \sum_{i:p_i>0} \left(\frac{1}{m} - p_i\right) = 0 \end{aligned}$$

As $\ln(x) = x - 1$ only holds for $x = 1$ it follows that equality holds iff $p_i = 1/m$, $i = 1, \dots, m$. In particular, as $p_i = \frac{1}{m}$, it follows $p_i > 0$, $i = 1, \dots, m$.

c) Define for $i = 1, \dots, m$ and $j = 1, \dots, d$

$$p_{i|j} = P(X = x_i \mid Y = y_j).$$



Show $H(X | Y) - H(X) \leq 0$ which is equivalent to the claim.

$$\begin{aligned}
 H(X | Y) - H(X) &= - \sum_{i,j} p_{i,j} \log(p_{i|j}) + \sum_i p_i \log(p_i) \\
 &= - \sum_{i,j} p_{i,j} \log\left(\frac{p_{i,j}}{p_j}\right) + \sum_i \underbrace{\sum_j p_{i,j}}_{=p_i} \log(p_i) \\
 &= (\log e) \sum_{i,j:p_{i,j}>0} p_{i,j} \ln\left(\frac{p_i p_j}{p_{i,j}}\right) \\
 &\stackrel{\ln(x) \leq x-1}{\leq} (\log e) \sum_{i,j:p_{i,j}>0} p_{i,j} \left(\frac{p_i p_j}{p_{i,j}} - 1\right) \\
 &= (\log e) \sum_{i,j:p_{i,j}>0} (p_i p_j - p_{i,j}) = 0
 \end{aligned}$$

Note that from $p_{i,j} > 0$ it follows $p_i, p_j > 0$. Equality holds for $p_i p_j = p_{i,j}$ which is equivalent to X and Y being stochastically independent.

This means that the mutual information $I(X, Y) = H(X) - H(X | Y)$ is nonnegative.

d) It holds

$$\begin{aligned}
 H(X, Y) &= - \sum_{i,j} p_{i,j} \log(p_{i,j}) \\
 &= - \sum_{i,j} p_{i,j} [\log(p_{i,j}) - \log(p_i) + \log(p_i)] \\
 &= - \sum_{i,j} p_{i,j} \log\left(\frac{p_{i,j}}{p_i}\right) - \sum_i \underbrace{\sum_j p_{i,j}}_{=p_i} \log(p_i) \\
 &= H(Y | X) + H(X).
 \end{aligned}$$

e) It holds

$$H(X, Y) \stackrel{(d)}{=} H(X) + H(Y | X) \stackrel{(c)}{\leq} H(X) + H(Y)$$

with equality as in (c) iff X and Y are stochastically independent.

Solution of Problem 2

Show for any function $f : X(\Omega) \times Y(\Omega) \rightarrow \mathbb{R}$, that $H(X, Y, f(X, Y)) = H(X, Y)$.

By definition, we have:

$$H(X, Y, Z = f(X, Y)) \stackrel{\text{Def.}}{=} - \sum_{x,y,z} P(X = x, Y = y, Z = z) \log(P(X = x, Y = y, Z = z))$$

With

$$P(X = x, Y = y, Z = z) = \begin{cases} P(X = x, Y = y) & , \text{ if } z = f(x, y) \\ 0 & , \text{ if } z \neq f(x, y) \end{cases},$$

it follows that

$$H(X, Y, Z = f(X, Y)) = - \sum_{x,y} P(X = x, Y = y) \log(P(X = x, Y = y)) = H(X, Y).$$

Note: It holds $0 \cdot \log 0 = 0$.

Solution of Problem 3

Prove Theorem 4.13 ' \Rightarrow ' (sufficient solution):

Recall that each element of these sets has a positive probability:

$$\begin{aligned} \mathcal{M}_+ &:= \{M \in \mathcal{M} \mid P(\hat{M} = M) > 0\}, \\ \mathcal{C}_+ &:= \{C \in \mathcal{C} \mid P(\hat{C} = C) > 0\}. \end{aligned}$$

Lemma 4.12 provides conditions of perfect secrecy on \mathcal{M}_+ , \mathcal{K}_+ , \mathcal{C}_+ .

With Lemma 4.12 a), we obtain:

$$|\mathcal{M}_+| \leq |\mathcal{C}_+| \stackrel{(I)}{\leq} |\mathcal{C}| \stackrel{(II)}{=} |\mathcal{M}| \stackrel{(III)}{=} |\mathcal{M}_+|.$$

(I): With $P(\hat{C} = C) > 0 \Rightarrow \mathcal{C}_+ \subseteq \mathcal{C}$.

(II): Given by assumption $|\mathcal{M}| = |\mathcal{K}| = |\mathcal{C}|$.

(III): Given by assumption $P(\hat{M} = M) > 0, \forall M \in \mathcal{M}$.

By the 'sandwich theorem', i.e., the upper and lower bounds are both equal to $|\mathcal{M}_+|$:

$$\begin{aligned} &\Rightarrow |\mathcal{C}_+| = |\mathcal{C}| \Rightarrow \mathcal{C}_+ = \mathcal{C}, \\ &\Rightarrow P(\hat{C} = C) > 0, \forall C \in \mathcal{C}. \end{aligned}$$

Let $M \in \mathcal{M}, C \in \mathcal{C}$:

$$\begin{aligned} 0 &< P(\hat{C} = C) \stackrel{(IV)}{=} P(\hat{C} = C \mid \hat{M} = M) = P(e(\hat{M}, \hat{K}) = C \mid \hat{M} = M) \\ &\stackrel{(V)}{=} P(e(M, \hat{K}) = C) = \sum_{K \in \mathcal{K}: e(M, K) = C} P(\hat{K} = K) \neq 0 \\ &\Rightarrow \forall M \in \mathcal{M}, C \in \mathcal{C} \exists K \in \mathcal{K} : e(M, K) = C. \end{aligned} \tag{1}$$

(IV): With perfect secrecy as given by Corollary 4.11.

(V): Given by the assumption that \hat{M}, \hat{K} are stochastically independent.

However, (1) is not shown to be unique yet!

(i) Fix $M \in \mathcal{M}$:

$$\begin{aligned} |\mathcal{C}_+| &= |\mathcal{C}| = |\{e(M, K) \mid K \in \mathcal{K}_+ = \mathcal{K}\}| \leq |\mathcal{K}| \stackrel{(II)}{=} |\mathcal{C}| \\ \Rightarrow K &\text{ is unique with } K = K(M, C) \text{ by the 'sandwich theorem'}. \end{aligned}$$

(II) Given by assumption $|\mathcal{M}| = |\mathcal{K}| = |\mathcal{C}|$.

Let $M \in \mathcal{M}, C \in \mathcal{C}$:

$$\Rightarrow P(\hat{C} = C) \stackrel{(1)}{=} P(\hat{K} = K(M, C)),$$

because of perfect secrecy this expression is independent of M .

(ii) Fix $C_0 \in \mathcal{C}$:

$$\Rightarrow \{K(M, C_0) \mid M \in \mathcal{M}\} = \mathcal{K},$$

because of injectivity of $e(\cdot, K)$, i.e., $e(M, K) = C_0$, and by the assumption $|\mathcal{M}| = |\mathcal{C}|$.

$$\begin{aligned} \Rightarrow P(\hat{C} = C) &= P(\hat{K} = K) \quad \forall C \in \mathcal{C}, K \in \mathcal{K} \\ \Rightarrow P(\hat{K} = K) &= \frac{1}{|\mathcal{K}|} \quad \forall K \in \mathcal{K}. \quad \square \end{aligned}$$