

# Homework 3 in Advanced Methods of Cryptography - Proposal for Solution -

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## Solution to Exercise 8.

(a) Claim:  $\text{Var}(I_C) = \kappa(1 - \kappa) + \frac{4}{3}(n - 2)(\beta - \kappa^2)$  with  $\kappa = \sum_{l=1}^m p_l^2$  and  $\beta = \sum_{l=1}^m p_l^3$ .

Recall:  $I_C = \frac{1}{\binom{n}{2}} \sum_{i < j} Y_{ij}$ , where  $Y_{ij} = \begin{cases} 1 & C_i = C_j \\ 0 & \text{otherwise} \end{cases}$  and  $E(Y_{ij}) = \sum_{l=1}^m p_l^2 = \kappa$ .

Then it holds

$$\begin{aligned} \text{Var}(I_C) &= \text{Var}\left(\frac{1}{\binom{n}{2}} \sum_{i < j} Y_{ij}\right) = \frac{1}{\binom{n}{2}} \left( \sum_{i < j} \text{Var}(Y_{ij}) + \sum_{i < j} \sum_{\substack{k < l \\ (i,j) \neq (k,l)}} \text{Cov}(Y_{ij}, Y_{kl}) \right) \\ &\stackrel{(1)}{=} \frac{1}{\binom{n}{2}} \left( \sum_{i < j} \text{Var}(Y_{ij}) + 2 \sum_{i < j} \sum_{\substack{k < l \\ (i,j) < (k,l)}} \text{Cov}(Y_{ij}, Y_{kl}) \right) \\ &\stackrel{(2),(3)}{=} \frac{1}{\binom{n}{2}} \left( \sum_{i < j} \kappa(1 - \kappa) + \frac{2}{3}n(n-1)(n-2)(\beta - \kappa^2) \right) \\ &= \kappa(1 - \kappa) + \frac{4}{3}(n-2)(\beta - \kappa^2) \end{aligned}$$

(1) This equality holds for the definition:

$$(i, j) < (k, l) \Leftrightarrow i < k \vee ((i = k) \wedge (j < l)).$$

(2) It holds

$$\text{Var}(Y_{ij}) = E(Y_{ij}^2) - E(Y_{ij})^2 = 1^2 \cdot P(Y_{ij} = 1) - \kappa^2 = E(Y_{ij}) - \kappa^2 = \kappa(1 - \kappa).$$

(3) For the covariance it holds

$$\text{Cov}(Y_{ij}, Y_{kl}) = E(Y_{ij} \cdot Y_{kl}) - E(Y_{ij}) \cdot E(Y_{kl}) = E(Y_{ij} \cdot Y_{kl}) - \kappa^2$$

Investigate:  $Y_{ij} \cdot Y_{kl} = 1 \Leftrightarrow Y_{ij} = Y_{kl} = 1 \Leftrightarrow C_i = C_j \wedge C_k = C_l = C_l$ .

There are three disjoint cases (i)-(iii):

(i)  $\mathbf{i = k}$ : In that case  $j < l$  must hold with respect to (1). Hence,

$$\begin{aligned} Y_{ij} \cdot Y_{il} &= 1 \Leftrightarrow Y_{ij} = Y_{il} = 1 \Leftrightarrow C_i = C_j \wedge C_i = C_l \Leftrightarrow C_i = C_j = C_l \\ \Rightarrow E(Y_{ij} \cdot Y_{il}) &= 1 \cdot P(Y_{ij} \cdot Y_{il} = 1) = P(C_i = C_j = C_l) = \sum_{n=1}^m p_n^3 = \beta \\ \Rightarrow \text{Cov}(Y_{ij}, Y_{il}) &= E(Y_{ij} \cdot Y_{il}) - \kappa^2 = \beta - \kappa^2 = \alpha \end{aligned}$$

(ii)  $\mathbf{i} < \mathbf{k} \wedge \mathbf{j} = \mathbf{l}$ : In that case it holds

$$\begin{aligned} Y_{ij} \cdot Y_{kj} = 1 &\Leftrightarrow Y_{ij} = Y_{kj} = 1 \Leftrightarrow C_i = C_j \wedge C_k = C_j \Leftrightarrow C_i = C_j = C_k \\ \Rightarrow E(Y_{ij} \cdot Y_{kj}) &= 1 \cdot P(Y_{ij} \cdot Y_{kj} = 1) = P(C_i = C_j = C_k) = \sum_{n=1}^m p_n^3 = \beta \\ \Rightarrow \text{Cov}(Y_{ij}, Y_{kj}) &= E(Y_{ij} \cdot Y_{kj}) - \kappa^2 = \beta - \kappa^2 = \alpha \end{aligned}$$

(iii)  $\mathbf{i} < \mathbf{k} \wedge \mathbf{j} \neq \mathbf{l}$ : In that case it holds that the indices are pairwise unequal. Therefore,

$$\begin{aligned} Y_{ij} \cdot Y_{kl} = 1 &\Leftrightarrow Y_{ij} = Y_{kl} = 1 \Leftrightarrow C_i = C_j \wedge C_k = C_l \\ \Rightarrow E(Y_{ij} \cdot Y_{kl}) &= 1 \cdot P(Y_{ij} \cdot Y_{kl} = 1) = P(Y_{ij} = 1) \cdot P(Y_{kl} = 1) = \kappa^2 \\ \Rightarrow \text{Cov}(Y_{ij}, Y_{kl}) &= E(Y_{ij} \cdot Y_{kl}) - \kappa^2 = \kappa^2 - \kappa^2 = 0 \end{aligned}$$

It follows:

$$\begin{aligned} &2 \sum_{i < j} \sum_{k < l, (i,j) < (k,l)} \text{Cov}(Y_{ij}, Y_{kl}) \\ &= 2 \sum_{i < j} \left( \sum_{l=j+1}^n \text{Cov}(Y_{ij}, Y_{il}) + \sum_{k=i+1}^n \left( \text{Cov}(Y_{ij}, Y_{kj}) + \sum_{l=k+1, l \neq j}^n \text{Cov}(Y_{ij}, Y_{kl}) \right) \right) \\ &= 2 \sum_{i < j} \left( \sum_{l=j+1}^n \alpha + \sum_{k=i+1}^n \left( \alpha + \sum_{l=k+1, l \neq j}^n 0 \right) \right) \\ &\stackrel{(4)(5)}{=} 2\alpha \left( \frac{1}{6}n(n-1)(n-2) + \frac{1}{6}n(n-1)(n-2) \right) \\ &= \frac{2}{3}(\beta - \kappa^2)n(n-1)(n-2) \end{aligned}$$

(4) It holds

$$\begin{aligned} \sum_{i < j} \sum_{l=j+1}^n \alpha &= \sum_{i=1}^n \sum_{j=i+1}^n \sum_{l=j+1}^n \alpha = \alpha \sum_{i=1}^{n-1} \sum_{j=i+1}^n (n-j) = \alpha \sum_{i=1}^{n-1} \sum_{j=1}^{n-i-1} j \\ &= \frac{\alpha}{2} \sum_{i=1}^{n-1} (n-i)(n-i-1) = \frac{\alpha}{2} \sum_{i=1}^{n-2} (n^2 - ni - n - ni + i^2 + i) \\ &= \frac{\alpha}{2} \left[ (n-2)(n^2 - n) + (1-2n) \sum_{i=1}^{n-2} i + \sum_{i=1}^{n-2} i^2 \right] \\ &= \frac{\alpha}{2} \left[ (n-2)(n-1)n + (1-2n) \frac{1}{2}(n-1)(n-2) + \frac{1}{3}(n-1)^3 - \frac{1}{2}(n-1)^2 + \frac{1}{6}(n-1) \right] \\ &= \frac{\alpha}{12} (n-1) [6n^2 - 12n - 6n^2 + 15n - 6 + 2n^2 - 4n + 2 - 3n + 3 + 1] \\ &= \frac{\alpha}{12} (n-1) [2n^2 - 4n] = \frac{\alpha}{6} n(n-1)(n-2) \end{aligned}$$

(5) It holds

$$\begin{aligned} \sum_{i < j} \sum_{k=i+1}^n \alpha &= \sum_{i=1}^n \sum_{j=i+1}^n \sum_{k=i+1}^{j-1} \alpha = \alpha \sum_{i=1}^{n-1} \sum_{j=i+1}^n (j-1-i) \\ &= \alpha \sum_{i=1}^n \sum_{j=1}^{n-i-1} j \stackrel{(4)}{=} \frac{\alpha}{6} n(n-1)(n-2) \end{aligned}$$

## Solution to Exercise 9.

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)

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

As  $\ln z = z - 1$  only holds for  $z = 1$  it follows that equality holds iff  $p_i = 1/m$ ,  $i = 1, \dots, m$ . In particular, it follows  $p_i > 0$ ,  $i = 1, \dots, m$ .

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

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

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

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

Note that from  $p_{i,j} > 0$  it follows  $p_i, p_j > 0$ . Equality hold for  $\frac{p_i p_j}{p_{i,j}} = 1$  which is equivalent to X and Y being stochastically independent.

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

(d) It holds

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

(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.