

ÉCOLE POLYTECHNIQUE FÉDÉRALE DE LAUSANNE  
School of Computer and Communication Sciences

**Handout 28**

Solutions to Homework 11

Information Theory and Coding  
Dec. 16, 2019

PROBLEM 1.

(a) Suppose  $\mathbf{x}$  and  $\mathbf{x}'$  are two codewords in  $\mathcal{C}$ . Then for  $\forall i = 0, 1, \dots, m-1$ ,

$$\begin{aligned} x_0 + x_1\alpha_i + \dots + x_{n-1}\alpha_i^{n-1} &= 0 \\ x'_0 + x'_1\alpha_i + \dots + x'_{n-1}\alpha_i^{n-1} &= 0 \end{aligned}$$

Therefore,

$$(x_0 + x'_0) + (x_1 + x'_1)\alpha_i + \dots + (x_{n-1} + x'_{n-1})\alpha_i^{n-1} = 0 \quad \text{for } \forall i = 0, 1, \dots, m-1.$$

which shows  $\mathbf{x} + \mathbf{x}'$  is also a codeword.

(b)  $x(D) = x_0 + x_1D + \dots + x_{n-1}D^{n-1}$  is a polynomial of degree (at most)  $n-1$  and  $(x_0, \dots, x_{n-1})$  is a codeword if  $\alpha_0, \alpha_1, \dots, \alpha_{m-1}$  are  $m$  of its roots. This means

$$x(D) = (D - \alpha_0)(D - \alpha_1) \dots (D - \alpha_{m-1})h(D) = g(D)h(D)$$

for some  $h(D)$ . Note that  $h(D)$  can have degree (at most)  $n-m-1$ . On the other side, there is a one-to-one correspondence between the codewords of  $\mathcal{C}$  and degree  $n-1$  polynomials. Since  $g(D)$  is fixed for all codewords, a polynomial  $x(D)$  corresponding to a codeword  $\mathbf{x}$  is determined by choosing the coefficients of  $h(D) = h_0 + h_1D + \dots + h_{n-m-1}D^{n-m-1}$ . Since  $h_j \in \mathcal{X}$  for  $j = 0, 1, \dots, n-m-1$  we have  $q^{n-m}$  different  $h(D)$ s and, thus,  $q^{n-m}$  codewords.

(c) For every column vector  $\mathbf{u} = [u_0, u_1, \dots, u_{m-1}]^T$ ,  $A\mathbf{u} = [u(1), u(\beta), \dots, u(\beta^{n-1})]^T$ . Consequently,  $A\mathbf{u} = \mathbf{0}$  means  $u(D)$  has  $n$  roots which is impossible (since it is a polynomial of degree  $m-1 < n$ ).

(d) Using the same reasoning as in (c) one can verify that  $\mathbf{x} = (x_1, \dots, x_n)$  is a codeword iff  $\mathbf{x}A = \mathbf{0}$ . This means  $A$  is the parity-check matrix of the code  $\mathcal{C}$ . Since the code is linear, using Problem 4 of Homework 11 we know that has minimum distance  $d$  iff every  $d-1$  rows of  $H$  are linearly independent and some  $d$  rows are linearly dependent. That  $A$  has rank  $m$  implies there are no  $m$  linearly dependent rows thus  $d \geq m+1$ . On the other side, we know from the Singleton bound that a code with  $q^{n-m}$  codewords and block-length  $n$  has minimum distance  $d \leq m+1$ . Thus we conclude that  $d = m+1$ .

PROBLEM 2.

(a) For every  $0 \leq p \leq 1$ , define  $\bar{p} := 1 - p$ . We have:

$$h_2(\bar{p}) = -\bar{p} \log \bar{p} - p \log p = -p \log p - \bar{p} \log \bar{p} = h_2(p). \quad (1)$$

On the other hand, it is easy to check that for every  $0 \leq p', p'' \leq 1$ , we have:

$$\bar{p}' * p'' = p' * \bar{p}'' = \bar{p}' * p'' \quad \text{and} \quad \bar{p}' * \bar{p}'' = p' * p''.$$

Now (1) implies that

$$h_2(\bar{p}' * p'') = h_2(p' * \bar{p}'') = h_2(\bar{p}' * p'') = h_2(p' * p''). \quad (2)$$

Let  $p' = \mathbb{P}[X_1 = 1]$  and  $p'' = \mathbb{P}[X_2 = 1]$ . We have the following:

- $\mathbb{P}[X_1 \oplus X_2 = 1] = \mathbb{P}[X_1 = 1]\mathbb{P}[X_2 = 0] + \mathbb{P}[X_1 = 0]\mathbb{P}[X_2 = 1] = p'p'' + \bar{p}'p'' = p' * p''$ . Therefore,  $H(X_1 \oplus X_2) = h_2(p' * p'')$ .
- Since  $H(X_1) = h_2(p_1)$ , then we have either  $p' = p_1$  or  $p' = 1 - p_1$ . I.e., we have  $p_1 = p'$  or  $p_1 = 1 - p' = \bar{p}'$ .
- Since  $H(X_2) = h_2(p_2)$ , then we have either  $p'' = p_2$  or  $p'' = 1 - p_2$ . I.e., we have  $p_2 = p''$  or  $p_2 = 1 - p'' = \bar{p}''$ .

Now (2) implies that  $H(X_1 \oplus X_2) = h_2(p' * p'') = h_2(p_1 * p_2)$ .

(b) We have  $H(X_1|Y) = \sum_{y \in \mathcal{Y}} H(X_1|Y = y)\mathbb{P}_Y(y) = \sum_{y \in \mathcal{Y}} h_2(p_1(y))q(y)$ .

Now for every  $y \in \mathcal{Y}$ ,  $X_1$  and  $X_2$  are independent conditioned on  $Y = y$ . Moreover,  $H(X_1|Y = y) = h_2(p_1(y))$  and  $H(X_2|Y = y) = H(X_2) = h_2(p_2)$  since  $X_2$  and  $Y$  are independent. Therefore, part (a) implies that  $H(X_1 \oplus X_2|Y = y) = h_2(p_1(y) * p_2)$ .

We conclude that

$$\begin{aligned} H(X_1 \oplus X_2|Y) &= \sum_{y \in \mathcal{Y}} H(X_1 \oplus X_2|Y = y)\mathbb{P}_Y(y) \\ &= \sum_{y \in \mathcal{Y}} h_2(p_1(y) * p_2)q(y) = \sum_{y \in \mathcal{Y}} h_2(p_2 * p_1(y))q(y). \end{aligned}$$

(c) Note that  $p_2 * p = p(1 - p_2) + p_2(1 - p) = \beta p + p_2$ , where  $\beta = 1 - 2p_2 \geq 0$ . Let  $g(p) = \frac{\frac{\partial}{\partial p}h_2(p_2 * p)}{\frac{\partial}{\partial p}h_2(p)} = \frac{\frac{\partial}{\partial p}h_2(\beta p + p_2)}{\frac{\partial}{\partial p}h_2(p)} = \frac{\beta h_2'(\beta p + p_2)}{h_2'(p)}$ . We have

$$\begin{aligned} g'(p) &= \frac{\beta^2 h_2''(\beta p + p_2)h_2'(p) - \beta h_2''(p)h_2'(\beta p + p_2)}{h_2'(p)^2} \\ &= \frac{\beta h_2''(\beta p + p_2)h_2''(p)}{h_2'(p)^2} \left[ \beta \frac{h_2'(p)}{h_2''(p)} - \frac{h_2'(\beta p + p_2)}{h_2''(\beta p + p_2)} \right]. \end{aligned}$$

Note that  $h_2'(p) = \log \frac{1-p}{p}$  and  $h_2''(p) = \frac{-1}{p(1-p)\ln 2}$ , which implies that  $h_2''(\beta p + p_2) \leq 0$  and  $h_2''(p) \leq 0$ . Therefore,  $\frac{\beta h_2''(\beta p + p_2)h_2''(p)}{h_2'(p)^2} \geq 0$  and so it is sufficient to show that we have  $\beta \frac{h_2'(p)}{h_2''(p)} - \frac{h_2'(\beta p + p_2)}{h_2''(\beta p + p_2)} \geq 0$ . Now define  $\alpha = 1 - 2p$ . It is easy to check the following:

- $p = \frac{1}{2}(1 - \alpha)$ .
- $1 - p = \frac{1}{2}(1 + \alpha)$ .
- $\beta p + p_2 = \frac{1}{2}(1 - \alpha\beta)$ .
- $1 - (\beta p + p_2) = \frac{1}{2}(1 + \alpha\beta)$ .

Therefore, we have

$$\beta \frac{h_2'(p)}{h_2''(p)} = -\beta(\ln 2)p(1 - p) \log \frac{1 - p}{p} = -\frac{\beta \ln 2}{4}(1 - \alpha^2) \log \frac{1 + \alpha}{1 - \alpha},$$

and

$$\frac{h_2'(\beta p + p_2)}{h_2''(\beta p + p_2)} = -(\ln 2)(\beta p + p_2)(1 - \beta p - p_2) \log \frac{1 - \beta p - p_2}{\beta p + p_2} = -\frac{\ln 2}{4}(1 - (\alpha\beta)^2) \log \frac{1 + \alpha\beta}{1 - \alpha\beta}.$$

Using the formula  $\log(1+x) = \sum_{k \geq 1} (-1)^{k-1} \frac{x^k}{k}$ , we get

$$\begin{aligned} \log \frac{1+x}{1-x} &= \log(1+x) - \log(1-x) = \left( \sum_{k \geq 1} (-1)^{k-1} \frac{x^k}{k} \right) - \left( \sum_{k \geq 1} (-1)^{k-1} \frac{(-x)^k}{k} \right) \\ &= \sum_{k \geq 1} ((-1)^{k-1} + 1) \frac{x^k}{k} = 2 \sum_{\substack{k \geq 1 \\ k \text{ is odd}}} \frac{x^k}{k}. \end{aligned}$$

Therefore,

$$\begin{aligned} -(1-x^2) \log \frac{1+x}{1-x} &= -2 \sum_{\substack{k \geq 1 \\ k \text{ is odd}}} \frac{x^k}{k} + 2 \sum_{\substack{k \geq 1 \\ k \text{ is odd}}} \frac{x^{k+2}}{k} = -2x - 2 \sum_{\substack{k \geq 3 \\ k \text{ is odd}}} \frac{x^k}{k} + 2 \sum_{\substack{k \geq 3 \\ k \text{ is odd}}} \frac{x^k}{k-2} \\ &= -2x + 2 \sum_{\substack{k \geq 3 \\ k \text{ is odd}}} \left( \frac{1}{k-2} - \frac{1}{k} \right) x^k. \end{aligned}$$

Hence,

$$\begin{aligned} \beta \frac{h'_2(p)}{h''_2(p)} &= -\frac{\beta \ln 2}{4} (1 - \alpha^2) \log \frac{1+\alpha}{1-\alpha} = \frac{\beta \ln 2}{4} \left[ -2\alpha + 2 \sum_{\substack{k \geq 3 \\ k \text{ is odd}}} \left( \frac{1}{k-2} - \frac{1}{k} \right) \alpha^k \right] \\ &= -\frac{\alpha \beta \ln 2}{2} + \frac{\ln 2}{2} \sum_{\substack{k \geq 3 \\ k \text{ is odd}}} \left( \frac{1}{k-2} - \frac{1}{k} \right) \beta \alpha^k, \end{aligned}$$

and

$$\begin{aligned} \frac{h'_2(\beta p + p_2)}{h''_2(\beta p + p_2)} &= -\frac{\ln 2}{4} (1 - (\alpha \beta)^2) \log \frac{1+\alpha\beta}{1-\alpha\beta} = \frac{\ln 2}{4} \left[ -2\alpha\beta + 2 \sum_{\substack{k \geq 3 \\ k \text{ is odd}}} \left( \frac{1}{k-2} - \frac{1}{k} \right) (\alpha\beta)^k \right] \\ &= -\frac{\alpha \beta \ln 2}{2} + \frac{\ln 2}{2} \sum_{\substack{k \geq 3 \\ k \text{ is odd}}} \left( \frac{1}{k-2} - \frac{1}{k} \right) \beta^k \alpha^k. \end{aligned}$$

We conclude that

$$\beta \frac{h'_2(p)}{h''_2(p)} - \frac{h'_2(\beta p + p_2)}{h''_2(\beta p + p_2)} = \frac{\ln 2}{2} \sum_{\substack{k \geq 3 \\ k \text{ is odd}}} \left( \frac{1}{k-2} - \frac{1}{k} \right) (\beta - \beta^k) \alpha^k \stackrel{(*)}{\geq} 0,$$

where  $(*)$  follows from the fact that  $\beta = 1 - 2p_2 \leq 1$  which implies that  $\beta^k \leq \beta$ . Therefore,  $g'(p) \geq 0$  and so  $g(p)$  is increasing. We conclude that the function  $f$  is convex.

(d) We have

$$\begin{aligned} H(X_1 \oplus X_2 | Y) &= \sum_{y \in \mathcal{Y}} h_2(p_2 * p_1(y)) q(y) = \sum_{y \in \mathcal{Y}} h_2(p_2 * h_2^{-1}(H(X_1 | Y = y))) q(y) \\ &= \sum_{y \in \mathcal{Y}} f(H(X_1 | Y = y)) q(y) \stackrel{(*)}{\geq} f\left(\sum_{y \in \mathcal{Y}} H(X_1 | Y = y) q(y)\right) \\ &= f(H(X_1 | Y)) = h_2(p_2 * h_2^{-1}(H(X_1 | Y))) = h_2(p_2 * p_1) = h_2(p_1 * p_2), \end{aligned}$$

where  $(*)$  follows from the convexity of the function  $f$ .

(e) For every  $y_1 \in \mathcal{Y}_1$ , let  $0 \leq p_1(y_1) \leq \frac{1}{2}$  be such that  $H(X_1|Y_1 = y_1) = h_2(p_1(y_1))$  and let  $q_1(y_1) = \mathbb{P}_{Y_1}(y_1)$ . Similarly, for every  $y_2 \in \mathcal{Y}_2$ , let  $0 \leq p_2(y_2) \leq \frac{1}{2}$  be such that  $H(X_2|Y_2 = y_2) = h_2(p_2(y_2))$  and let  $q_2(y_2) = \mathbb{P}_{Y_2}(y_2)$ . For every  $y_1 \in \mathcal{Y}_1$ , define the mapping  $f_{y_1} : [0, 1] \rightarrow \mathbb{R}$  as  $f_{y_1}(h) = h_2(p_1(y) * h_2^{-1}(h))$ . Part (c) implies that  $f_{y_1}$  is convex for every  $y_1 \in \mathcal{Y}_1$ . We have

$$\begin{aligned}
H(X_1 \oplus X_2|Y_1, Y_2) &= \sum_{y_1 \in \mathcal{Y}_1} \sum_{y_2 \in \mathcal{Y}_2} h_2(p_1(y_1) * p_2(y_2)) \mathbb{P}_{Y_1, Y_2}(y_1, y_2) \\
&= \sum_{y_1 \in \mathcal{Y}_1} \sum_{y_2 \in \mathcal{Y}_2} h_2(p_1(y_1) * p_2(y_2)) q_1(y_1) q_2(y_2) \\
&= \sum_{y_1 \in \mathcal{Y}_1} q_1(y_1) \sum_{y_2 \in \mathcal{Y}_2} h_2(p_1(y_1) * h_2^{-1}(H(X_2|Y_2 = y_2))) q_2(y_2) \\
&= \sum_{y_1 \in \mathcal{Y}_1} q_1(y_1) \sum_{y_2 \in \mathcal{Y}_2} f_{y_1}(H(X_2|Y_2 = y_2)) q_2(y_2) \\
&\stackrel{(*)}{\geq} \sum_{y_1 \in \mathcal{Y}_1} q_1(y_1) f_{y_1} \left( \sum_{y_2 \in \mathcal{Y}_2} H(X_2|Y_2 = y_2) q_2(y_2) \right) \\
&= \sum_{y_1 \in \mathcal{Y}_1} q_1(y_1) f_{y_1}(H(X_2|Y_2)) = \sum_{y_1 \in \mathcal{Y}_1} q_1(y_1) h_2(p_1(y_1) * h_2^{-1}(H(X_2|Y_2))) \\
&= \sum_{y_1 \in \mathcal{Y}_1} q_1(y_1) h_2(p_1(y_1) * p_2) = \sum_{y_1 \in \mathcal{Y}_1} h_2(p_2 * h_2^{-1}(H(X_1|Y_1 = y_1))) q_1(y_1) \\
&= \sum_{y_1 \in \mathcal{Y}_1} f(H(X_1|Y_1 = y_1)) q_1(y_1) \stackrel{(**)}{\geq} f \left( \sum_{y_1 \in \mathcal{Y}_1} H(X_1|Y_1 = y_1) q(y_1) \right) \\
&= f(H(X_1|Y_1)) = h_2(p_2 * h_2^{-1}(H(X_1|Y_1))) = h_2(p_2 * p_1) = h_2(p_1 * p_2),
\end{aligned}$$

where (\*) follows from the convexity of the functions  $\{f_{y_1} : y_1 \in \mathcal{Y}_1\}$  and (\*\*) follows from the convexity of  $f$ .

PROBLEM 3.

- (a) Any codeword of  $\mathcal{C}$  is of the form  $\langle \mathbf{a}, \mathbf{a} \oplus \mathbf{b} \rangle$  with  $\mathbf{a} \in \mathcal{C}_1$  and  $\mathbf{b} \in \mathcal{C}_2$ . Given two codewords  $\langle \mathbf{u}', \mathbf{u}' \oplus \mathbf{v}' \rangle$  and  $\langle \mathbf{u}'', \mathbf{u}'' \oplus \mathbf{v}'' \rangle$  of  $\mathcal{C}$ , their sum is  $\langle \mathbf{u}, \mathbf{u} \oplus \mathbf{v} \rangle$  with  $\mathbf{u} = \mathbf{u}' \oplus \mathbf{u}''$  and  $\mathbf{v} = \mathbf{v}' \oplus \mathbf{v}''$ . Since  $\mathcal{C}_1$  and  $\mathcal{C}_2$  are linear codes  $\mathbf{u} \in \mathcal{C}_1$  and  $\mathbf{v} \in \mathcal{C}_2$ . Thus the sum of any two codewords of  $\mathcal{C}$  is a codeword of  $\mathcal{C}$  and we conclude that  $\mathcal{C}$  is linear.
- (b) If  $(\mathbf{u}, \mathbf{v}) \neq (\mathbf{u}', \mathbf{v}')$ , then either  $\mathbf{u} \neq \mathbf{u}'$ , or,  $\mathbf{u} = \mathbf{u}'$  and  $\mathbf{v} \neq \mathbf{v}'$ . In either case  $\langle \mathbf{u} | \mathbf{u} \oplus \mathbf{v} \rangle \neq \langle \mathbf{u}' | \mathbf{u}' \oplus \mathbf{v}' \rangle$ : in the first case the first halves differ, in the second case the second halves differ. Thus no two of the  $(\mathbf{u}, \mathbf{v})$  pairs are mapped to the same element of  $\mathcal{C}$ , and the code has exactly  $M_1 M_2$  elements. Its rate is  $\frac{1}{2n} \log(M_1 M_2) = \frac{1}{2} R_1 + \frac{1}{2} R_2$ .
- (c) As  $\mathbf{v} = \mathbf{u} \oplus \mathbf{u} \oplus \mathbf{v}$ ,

$$w_H(\mathbf{v}) = w_H(\mathbf{u} \oplus \mathbf{u} \oplus \mathbf{v}) \leq w_H(\mathbf{u}) + w_H(\mathbf{u} \oplus \mathbf{v})$$

by the triangle inequality. Noting that the right hand side is  $w_H(\langle \mathbf{u} | \mathbf{u} \oplus \mathbf{v} \rangle)$  completes the proof.

- (d) If  $\mathbf{v} = \mathbf{0}$  we have  $\langle \mathbf{u} | \mathbf{u} \oplus \mathbf{v} \rangle = \langle \mathbf{u} | \mathbf{u} \rangle$  which has twice the Hamming weight of  $\mathbf{u}$ . Otherwise (c) gives  $w_H(\langle \mathbf{u} | \mathbf{u} \oplus \mathbf{v} \rangle) \geq w_H(\mathbf{v})$ .

(e) Since  $\mathcal{C}$  is linear its minimum distance equals the minimum weight of its non-zero codewords. If  $\langle \mathbf{u} | \mathbf{u} \oplus \mathbf{v} \rangle$  is non-zero either  $\mathbf{v} \neq \mathbf{0}$ , or,  $\mathbf{v} = \mathbf{0}$  and  $\mathbf{u} \neq \mathbf{0}$ . By (d), in the first case  $w_H(\langle \mathbf{u} | \mathbf{u} \oplus \mathbf{v} \rangle) \geq w_H(\mathbf{v}) \geq d_1$ , in the second case  $w_H(\langle \mathbf{u} | \mathbf{u} \oplus \mathbf{v} \rangle) \geq 2w_H(\mathbf{u}) \geq 2d_2$ . Thus  $d \geq \min\{2d_1, d_2\}$ .

(f) Let  $\mathbf{u}_0$  be the minimum weight non-zero codeword of  $\mathcal{C}_1$  and let  $\mathbf{v}_0$  be the minimum weight non-zero codeword of  $\mathcal{C}_2$ . Note that  $\langle \mathbf{u}_0 | \mathbf{u}_0 \rangle$  is a non-zero codeword of  $\mathcal{C}$  (corresponding to the choice  $\mathbf{u} = \mathbf{u}_0, \mathbf{v} = \mathbf{0}$ ). It has weight  $2d_1$ . Similarly,  $\langle \mathbf{0} | \mathbf{v}_0 \rangle$  is also a non-zero codeword of  $\mathcal{C}$  (corresponding to the choice  $\mathbf{u} = \mathbf{0}, \mathbf{v} = \mathbf{v}_0$ ). It has weight  $d_2$ . Consequently  $d \leq \min\{2d_1, d_2\}$ . In light of (e) we find  $d = \min\{2d_1, d_2\}$ .

This method of constructing a longer code from two shorter ones is known under several names: ‘Plotkin construction’, ‘bar product’, ‘( $u|u+v$ ) construction’ appear regularly in the literature. Compare this method to the ‘obvious’ method of letting the codewords to be  $\langle \mathbf{u} | \mathbf{v} \rangle$ . The simple method has the same block-length and rate as we have here, but its minimum distance is only  $\min\{d_1, d_2\}$ . The factor two gained in  $d_1$  by the bar product is significant, and many practical code families can be built from very simple base codes by a recursive application of the bar product. Notable among them are the family of Reed–Muller codes.

PROBLEM 4.

(a) We have

$$\begin{aligned}
Q_{i+1} &= \sqrt{Z_{i+1}(1 - Z_{i+1})} = \begin{cases} \sqrt{Z_i^2(1 - Z_i^2)} & \text{w.p. } 1/2 \\ \sqrt{(2Z_i - Z_i^2)(1 - 2Z_i + Z_i^2)} & \text{w.p. } 1/2 \end{cases} \\
&= \begin{cases} \sqrt{Z_i^2(1 - Z_i)(1 + Z_i)} & \text{w.p. } 1/2 \\ \sqrt{(2 - Z_i)Z_i(1 - Z_i)^2} & \text{w.p. } 1/2 \end{cases} \\
&= \begin{cases} \sqrt{Z_i(1 - Z_i)}\sqrt{Z_i(1 + Z_i)} & \text{w.p. } 1/2 \\ \sqrt{Z_i(1 - Z_i)}\sqrt{(2 - Z_i)(1 - Z_i)} & \text{w.p. } 1/2 \end{cases} \\
&= \sqrt{Z_i(1 - Z_i)} \begin{cases} \sqrt{Z_i(1 + Z_i)} & \text{w.p. } 1/2 \\ \sqrt{(2 - Z_i)(1 - Z_i)} & \text{w.p. } 1/2 \end{cases} \\
&= Q_i \begin{cases} f_1(Z_i) & \text{w.p. } 1/2 \\ f_2(Z_i) & \text{w.p. } 1/2 \end{cases},
\end{aligned}$$

where  $f_1(z) = \sqrt{z(z+1)}$  and  $f_2(z) = \sqrt{(2-z)(1-z)}$ .

(b) We have

$$f'_1(z) = \frac{2z+1}{2\sqrt{z(z+1)}}$$

so

$$\begin{aligned}
f''_1(z) &= \frac{4\sqrt{z(z+1)} - (2z+1)\frac{2(2z+1)}{2\sqrt{z(z+1)}}}{\left(2\sqrt{z(z+1)}\right)^2} \\
&= \frac{4z(z+1) - (2z+1)^2}{4(z(z+1))^{\frac{3}{2}}} = \frac{-1}{4(z(z+1))^{\frac{3}{2}}} \leq 0.
\end{aligned}$$

Therefore,  $f_1$  is concave. By noticing that  $f_2(z) = f_1(1 - z)$ , we obtain:

$$\begin{aligned} f_1(z) + f_2(z) &= f_1(z) + f_1(1 - z) = 2 \left( \frac{1}{2} f_1(z) + \frac{1}{2} f_1(1 - z) \right) \\ &\stackrel{(*)}{\leq} 2f_1 \left( \frac{1}{2}z + \frac{1}{2}(1 - z) \right) = 2f_1 \left( \frac{1}{2} \right) = 2\sqrt{\frac{1}{2} \left( \frac{1}{2} + 1 \right)} \\ &= 2\sqrt{\frac{1}{2} \cdot \frac{3}{2}} = 2\frac{\sqrt{3}}{2} = \sqrt{3}, \end{aligned}$$

where  $(*)$  follows from the concavity of  $f_1$ . We have

$$\mathbb{E}[Q_{i+1} \mid Z_0, \dots, Z_i] = \frac{1}{2}f_1(Z_i)Q_i + \frac{1}{2}f_2(Z_i)Q_i = \frac{1}{2}(f_1(Z_i) + f_2(Z_i))Q_i \leq \rho Q_i,$$

where  $\rho = \frac{\sqrt{3}}{2} < 1$ .

(c) We will show the claim by induction on  $i \geq 0$ . For  $i = 0$ , we have  $Z_0 = z_0$  with probability 1. Therefore,  $\mathbb{E}Q_0 = \sqrt{z_0(1 - z_0)}$ .

It is easy to see that the function  $[0, 1] \rightarrow \mathbb{R}$  defined by  $z \rightarrow \sqrt{z(1 - z)}$  achieves its maximum at  $z = \frac{1}{2}$ , and so  $\mathbb{E}Q_0 = \sqrt{z_0(1 - z_0)} \leq \sqrt{\frac{1}{2} \left( 1 - \frac{1}{2} \right)} = \frac{1}{2}$ . Therefore, the claim is true for  $i = 0$ .

Now suppose that the claim is true for  $i \geq 0$ , i.e.,  $\mathbb{E}Q_i \leq \frac{1}{2}\rho^i$ . We have

$$\mathbb{E}Q_{i+1} = \mathbb{E}[\mathbb{E}[Q_{i+1} \mid Z_0, \dots, Z_i]] \stackrel{(*)}{\leq} \mathbb{E}[\rho Q_i] = \rho \mathbb{E}[Q_i] \stackrel{(**)}{\leq} \rho \cdot \frac{1}{2}\rho^i = \frac{1}{2}\rho^{i+1},$$

where  $(*)$  follows from Part (b) and  $(**)$  follows from the induction hypothesis. We conclude that  $\mathbb{E}Q_i \leq \frac{1}{2}\rho^i$  for every  $i \geq 0$ .

(d) By noticing that  $\delta < z < 1 - \delta$  if and only if  $z(1 - z) > \delta(1 - \delta)$ , we get:

$$\begin{aligned} \mathbb{P}[Z_i \in (\delta, 1 - \delta)] &= \mathbb{P}[Z_i(1 - Z_i) > \delta(1 - \delta)] = \mathbb{P}[\sqrt{Z_i(1 - Z_i)} > \sqrt{\delta(1 - \delta)}] \\ &= \mathbb{P}[Q_i > \sqrt{\delta(1 - \delta)}] \stackrel{(*)}{\leq} \frac{\mathbb{E}Q_i}{\sqrt{\delta(1 - \delta)}} \stackrel{(**)}{\leq} \frac{\rho^i}{2\sqrt{\delta(1 - \delta)}}, \end{aligned}$$

where  $(*)$  follows from the Markov inequality and  $(**)$  follows from Part (c). Now since  $\rho < 1$ , we have  $\frac{\rho^i}{2\sqrt{\delta(1 - \delta)}} \rightarrow 0$  as  $i \rightarrow \infty$ . We conclude that

$$\mathbb{P}[Z_i \in (\delta, 1 - \delta)] \rightarrow 0 \text{ as } i \text{ gets large.}$$

PROBLEM 5. As we should never represent a 0 with a 1, we are restricted to conditional distributions with  $p_{V|U}(1|0) = 0$ . Consequently, the possible  $p_{V|U}$  are of the type

$$p_{V|U}(0|0) = 1 \quad p_{V|U}(1|0) = 0, \quad p_{V|U}(0|1) = \alpha \quad p_{V|U}(1|1) = 1 - \alpha,$$

and parametrized by  $\alpha \in [0, 1]$ . For  $p_{V|U}$  as above, we have  $\Pr(V = 1) = \frac{1}{2}(1 - \alpha)$ , and

$$E[d(U, V)] = \sum_{u,v} p_U(u)p_{V|U}(v|u)d(u, v) = \alpha/2,$$

$$I(U; V) = H(V) - H(V|U) = h_2\left(\frac{1}{2}(1 - \alpha)\right) - \frac{1}{2}h_2(\alpha) =: f(\alpha).$$

Thus  $R(D) = \min\{f(\alpha) : 0 \leq \alpha \leq \min\{1, 2D\}\}$ , with  $f(\alpha) = h_2\left(\frac{1}{2}(1 - \alpha)\right) - \frac{1}{2}h_2(\alpha)$ . It is not difficult to check that  $f$  is a decreasing function on the interval  $[0, 1]$ , and thus consequently

$$R(D) = \begin{cases} h_2\left(\frac{1}{2} - D\right) - \frac{1}{2}h_2(2D), & 0 \leq D < \frac{1}{2} \\ 0, & D \geq \frac{1}{2}. \end{cases}$$

Note that for  $D \geq \frac{1}{2}$  we can represent any  $u$  with a constant, namely  $v = 0$ , with average distortion  $1/2$ .