

# MFML2 - Homework 6

Group 7:  
Thanh Nam Nguyen,  
Lorenz Hermann Huber,  
Alexander Dmitrievic Efremov,  
Noah Frederik Krumbüge

November 30, 2025

## 6.1

(a) We prove by induction on  $d \in \mathbb{N}$  that there exists a Gray code  $G_d$  of length  $2^d$  on  $\{0, 1\}^d$ .

For  $d = 1$  set

$$G_1 := (g_0, g_1) := (0, 1).$$

Then  $\{g_0, g_1\} = \{0, 1\} = \{0, 1\}^1$ , and the Hamming distance satisfies  $d_H(g_1, g_0) = 1$ , so  $G_1$  is a Gray code in dimension 1.

Assume that for some  $d \in \mathbb{N}$  there exists a Gray code

$$G_d = (g_0, g_1, \dots, g_{2^d-1})$$

on  $\{0, 1\}^d$ , i.e.  $\{g_0, \dots, g_{2^d-1}\} = \{0, 1\}^d$  and  $d_H(g_i, g_{i-1}) = 1$  for all  $i = 1, \dots, 2^d - 1$ .

We construct a Gray code  $G_{d+1}$  on  $\{0, 1\}^{d+1}$  as follows:

$$G_{d+1} := ((g_0, 0), \dots, (g_{2^d-1}, 0), (g_{2^d-1}, 1), (g_{2^d-2}, 1), \dots, (g_0, 1)). \quad \checkmark$$

The first block  $(g_0, 0), \dots, (g_{2^d-1}, 0)$  contains all vectors in  $\{0, 1\}^{d+1}$  whose last coordinate is 0, since  $\{g_0, \dots, g_{2^d-1}\} = \{0, 1\}^d$ . The second block  $(g_{2^d-1}, 1), \dots, (g_0, 1)$  analogously contains all vectors whose last coordinate is 1. Thus every vector in  $\{0, 1\}^{d+1}$  appears exactly once in  $G_{d+1}$ .

For  $i = 1, \dots, 2^d - 1$ ,

$$d_H((g_i, 0), (g_{i-1}, 0)) = d_H(g_i, g_{i-1}) = 1, \quad \checkmark$$

since appending the same last coordinate does not change Hamming distance and  $G_d$  is a Gray code.

Between the last element of the first block and the first element of the second block we have

$$d_H((g_{2^d-1}, 0), (g_{2^d-1}, 1)) = 1, \quad \checkmark$$

because these vectors differ only in the last coordinate.

For  $i = 2^d - 1, \dots, 1$ , we consider consecutive vectors  $(g_i, 1)$  and  $(g_{i-1}, 1)$  in the reversed order. Again,

$$d_H((g_i, 1), (g_{i-1}, 1)) = d_H(g_i, g_{i-1}) = 1,$$

since reversing the sequence does not affect the pairwise Hamming distances and the last coordinate is the same.

Thus every pair of consecutive vectors in  $G_{d+1}$  has Hamming distance 1.

Thus  $G_{d+1}$  is a Gray code on  $\{0, 1\}^{d+1}$ . By induction, there exists a Gray code  $G_d$  for all  $d \in \mathbb{N}$ .

(b) Let  $d \in \mathbb{N}$  and let

$$G_d = (g_0, g_1, \dots, g_{2^d-1})$$

be a Gray code on  $\{0, 1\}^d$ , i.e.  $\{g_0, \dots, g_{2^d-1}\} = \{0, 1\}^d$  and  $d_H(g_i, g_{i-1}) = 1$  for all  $i = 1, \dots, 2^d - 1$ .

Let  $\pi \in \text{Sym}(d)$  be a permutation of the coordinate indices and define

$$\pi(g_i) := (g_{i,\pi(1)}, \dots, g_{i,\pi(d)}), \quad \pi(G_d) := (\pi(g_0), \dots, \pi(g_{2^d-1})).$$

We first show that consecutive vectors in  $\pi(G_d)$  still have Hamming distance 1. For any  $i = 1, \dots, 2^d - 1$  we have 

$$d_H(\pi(g_i), \pi(g_{i-1})) = |\{k : g_{i,\pi(k)} \neq g_{i-1,\pi(k)}\}| = |\{j : g_{i,j} \neq g_{i-1,j}\}| = d_H(g_i, g_{i-1}) = 1.$$

Thus the “distance = 1” property is invariant under permutation of coordinates.

Next, we verify that  $\pi(G_d)$  still visits every corner of the  $d$ -dimensional unit cube exactly once. Since  $\{g_0, \dots, g_{2^d-1}\} = \{0, 1\}^d$  and  $\pi$  is a bijection on  $\{0, 1\}^d$ , the set

$$\{\pi(g_0), \dots, \pi(g_{2^d-1})\}$$

is again equal to  $\{0, 1\}^d$ .

Hence  $\pi(G_d)$  satisfies both defining properties of a Gray code: it consists of all  $2^d$  binary vectors in  $\{0, 1\}^d$ , and consecutive vectors have Hamming distance 1. Therefore  $\pi(G_d)$  is a Gray code for every permutation  $\pi \in \text{Sym}(d)$ . 

## 6.2

We have

$$p(y | x) = \frac{p(x, y)}{p(x)}.$$

where

$$\begin{aligned} p(x) &= \sum_{y \in \{0,1\}^U} p(x, y) = \sum_{y \in \{0,1\}^U} \frac{1}{Z(\theta)} \exp(x^\top \Theta y + \theta_x^\top x + \theta_y^\top y) \\ &= \frac{\exp(\theta_x^\top x)}{Z(\theta)} \sum_{y \in \{0,1\}^U} \exp(x^\top \Theta y + \theta_y^\top y) \end{aligned}$$

Therefore

$$p(y | x) = \frac{\frac{1}{Z(\theta)} \exp(x^\top \Theta y + \theta_x^\top x + \theta_y^\top y)}{\frac{\exp(\theta_x^\top x)}{Z(\theta)} \sum_{y \in \{0,1\}^U} \exp(x^\top \Theta y + \theta_y^\top y)} = \frac{\exp(x^\top \Theta y) \exp(\theta_y^\top y)}{\sum_{y \in \{0,1\}^U} \exp(x^\top \Theta y) \exp(\theta_y^\top y)}$$


We use

$$\exp(\theta_y^\top y) = \exp\left(\sum_{j=1}^U \theta_{y_j}^\top y_j\right) = \prod_{j=1}^U \exp(\theta_{y_j}^\top y_j)$$

$$\exp(x^\top \Theta y) = \exp\left(\sum_{j=1}^U \sum_{i=1}^W x_i \Theta_{i,j} y_j\right) = \prod_{j=1}^U \exp(x^\top \Theta_j y_j)$$

Where  $\Theta_j$  is the  $j_{th}$  column of  $\Theta$ . Additionally

$$\sum_{y \in \{0,1\}^U} \exp(x^\top \Theta y) \exp(\theta_y^\top y) = \sum_{y_1 \in \{0,1\}} \dots \sum_{y_U \in \{0,1\}} \prod_{j=1}^U \exp(x^\top \Theta_j y_j) \exp(\theta_{y_j}^\top y_j)$$

and with

$$\sum_{i=1}^n \sum_{j=1}^m a_i b_j = \sum_{i=1}^n a_i \sum_{j=1}^m b_j$$

$$\sum_{y \in \{0,1\}^U} \exp(x^\top \Theta y) \exp(\theta_y^\top y) = \prod_{j=1}^U \sum_{y_j \in \{0,1\}} \exp(x^\top \Theta_j y_j) \exp(\theta_{y_j}^\top y_j) \quad \checkmark$$

and

$$p(y \mid x) = \prod_{j=1}^U \frac{\exp(x^\top \Theta_j y_j) \exp(\theta_{y_j}^\top y_j)}{\sum_{y_j \in \{0,1\}} \exp(x^\top \Theta_j y_j) \exp(\theta_{y_j}^\top y_j)} = \prod_{j=1}^U p(y_j \mid x)$$

## 6.3

Choose  $k \in \mathbb{N}$  so that the grid spacing  $2^{-k}$  satisfies

$$2^{-k} \leq \frac{\varepsilon}{2}.$$

Therefore  $k = \lceil \log_2(2/\varepsilon) \rceil$ . Then the push-forward  $b_k(\mu)$  satisfies

$$W_1(\mu, b_k(\mu)) \leq 2^{-k} \leq \frac{\varepsilon}{2}.$$

So it suffices to approximate the discrete measure  $\nu := b_k(\mu)$  on the finite grid up to  $W_1$ -error  $\varepsilon/2$ . Since  $[0,1]$  has diameter 1, we have

$$W_1(\mu, \nu) \leq d_{TV}(\mu, \nu)$$

3.1

and with theorem 26.4 we can with  $2^{W-1} - 1$  where  $W = k = \lceil \log_2(2/\varepsilon) \rceil$  meaning in  $\mathcal{O}(\frac{1}{\varepsilon})$  hidden neurons approximate  $b_k(\mu)$  with RBM  $p$  with

$$W_1(b_k(\mu), p) \leq \frac{\varepsilon}{2}$$

and with triangular inequality

$$W_1(\mu, p) \leq \varepsilon \quad \checkmark$$

Using  $k = \lceil \log_2(2/\varepsilon) \rceil$  visible and in  $\mathcal{O}(\frac{1}{\varepsilon})$  hidden neurons, gives us a parameter bound in  $\mathcal{O}(\log_2(\frac{1}{\varepsilon}) \frac{1}{\varepsilon})$

# Index der Kommentare

---

3.1      What about the assumptions of thm. 26.4?