## 12. SCORE-BASED STRUCTURE LEARNING

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ABSTRACT. This document contains the solutions to the proposed exercises from Lecture 12.

## 1. Solutions

**Exercise 1.** Prove that the following statements are true.

- (i)  $0 \leq \mathbb{H}_p(\mathcal{X}) \leq \ln|dom(\mathcal{X})|$
- (ii)  $\mathbb{H}_p(\mathcal{X}) = 0$  if and only if p is degenerate (i.e., it assigns all mass to a single configuration).
- (iii)  $\mathbb{H}_p(\mathcal{X} \cup \mathcal{Y}) = \mathbb{H}_p(\mathcal{X}) + \mathbb{H}_p(\mathcal{Y})$  if and only if  $\mathcal{X} \perp \mathcal{Y}$  (under p).

Solution.

(i) Assume that  $\mathbb{H}_p(\mathcal{X}) < 0$ . Then  $\sum_{\mathcal{X}} p(\mathcal{X}) \ln p(\mathcal{X}) \geq 0$ . But since  $0 \leq p(\mathcal{X}) \leq 1$ ,  $\ln p(\mathcal{X}) \leq 0$ . Therefore  $p(\mathcal{X}) \ln p(\mathcal{X}) \leq 0$  and  $\sum_{\mathcal{X}} p(\mathcal{X}) \ln p(\mathcal{X}) \leq 0$ , which contradicts our earlier hypothesis. Consequently we know that  $\mathbb{H}_p(\mathcal{X}) > 0$ . We also know that for  $p(\mathcal{X}) = 1$ ,  $\sum_{\mathcal{X}} p(\mathcal{X}) \ln p(\mathcal{X}) = 0$ . Thus  $\mathbb{H}_p(\mathcal{X}) \geq 0$ . To find the upper bound of  $\mathbb{H}_p$ , we must maximize the function wrt  $p(\mathcal{X})$ . This is true when all events are equiprobable. Let  $p(\mathcal{X}) = 1$ .

$$\max \mathbb{H}_p(\mathcal{X}) = \sum_{i=1}^n \frac{1}{n} \ln \frac{1}{n} = -\sum_{i=1}^n \frac{1}{n} (\ln 1 - \ln n) =$$

$$= -\sum_{i=1}^n \frac{1}{n} (-\ln n) = (-\ln n) \underbrace{\left(-\sum_{i=1}^n \frac{1}{n}\right)}_{1} = \ln n =$$

$$= \ln |dom(\mathcal{X})|$$

(ii) Assume a degenerate distribution where a variable  $X_1$  from the distribution has all mass  $\Pr(X_1)=1$  and thus all  $\Pr(X_2)=\ldots=\Pr(X_n)=0$  since  $\sum_X \Pr(X)=1$ . Then we have that

$$\mathbb{H}_p(\mathcal{X}) = -\sum_{i=1}^n \Pr(X_i) \ln \Pr(X_i)$$

 $\mathbb{H}_p(\mathcal{X}) = 1 \cdot \ln 1 + 0 \cdot \ln 0 + \cdots + 0 \cdot \ln 0$  since p is degenerate.

$$\mathbb{H}_n(\mathcal{X}) = 1 \times 0 + 0 + \dots + 0 = 0$$

Therefore if p is degenerate, then  $\mathbb{H}_p(\mathcal{X}) = 0$ .

Now consider an entropy function over a distribution p and  $\mathbb{H}_p(\mathcal{X}) = 0$ .

$$\mathbb{H}_p(\mathcal{X}) = 0 = -\sum_{i=1}^n \Pr(X_i) \ln \Pr(X_i)$$

The sum of all  $Pr(X_i) \ln Pr(X_i)$  must be zero. Since each  $Pr(X_i) \ln Pr(X_i)$ is a non-positive number, then each term must be equal to zero. This is only true if either  $\Pr(X_i) = 0$  or  $\Pr(X_i) = 1$ . Since  $\sum_{i=1}^n \Pr(X_i) = 1$ , there can only be one  $Pr(X_i) = 1$  and the rest will be equal to zero. But this is the definition of a degenerate probability distribution. Thus, the converse is also true.

## (iii) (Incomplete solution)

A set of variables  $\mathcal{X}$  is independent of another set of variables  $\mathcal{Y}$  if and only if  $p(\mathcal{X} \cap \mathcal{Y}) = p(\mathcal{X})p(\mathcal{Y})$ . Consider an entropy function  $\mathbb{H}_p$ . Let  $n = |\mathcal{X} \cup \mathcal{Y}|$ .

$$\mathbb{H}_p(\mathcal{X} \cup \mathcal{Y}) = -\sum_{\mathcal{X} \cup \mathcal{Y}} p(\mathcal{X} \cup \mathcal{Y}) \ln p(\mathcal{X} \cup \mathcal{Y})$$

But since  $\mathcal{X}$  and  $\mathcal{Y}$  are independent:  $p(\mathcal{X} \cup \mathcal{Y}) = p(\mathcal{X}) + p(\mathcal{Y}) + p(\mathcal{X})p(\mathcal{Y})$ 

$$\mathbb{H}_p(\mathcal{X} \cup \mathcal{Y}) = -\sum_{\mathcal{X} \cup \mathcal{Y}} (p(\mathcal{X}) + p(\mathcal{Y}) + p(\mathcal{X})p(\mathcal{Y})) \ln(p(\mathcal{X}) + p(\mathcal{Y}) + p(\mathcal{X})p(\mathcal{Y}))$$

Exercise 2. Prove that the following statements are true

$$\begin{array}{l} (1) \ \mathbb{I}_p(\mathcal{X},\mathcal{Y}) = \mathbb{I}_p(\mathcal{Y},\mathcal{X}) \\ (2) \ \mathbb{I}_p(\mathcal{X},\mathcal{Y}) = \mathbb{H}_p(\mathcal{X}) + \mathbb{H}_p(\mathcal{Y}) - \mathbb{H}_p(\mathcal{X} \cup \mathcal{Y}) \end{array}$$

(3)  $\mathbb{I}_p(\mathcal{X},\mathcal{Y}) \geq 0$ 

(4) 
$$\mathbb{I}_p(\mathcal{X}, \mathcal{Y}) = 0$$
 iff  $\mathcal{X} \perp \mathcal{Y}$  (under p)

Solution.

(i)

$$\mathbb{I}_{p}(\mathcal{X}, \mathcal{Y}) = \sum_{\mathcal{X}, \mathcal{Y}} p(\mathcal{X} \cup \mathcal{Y}) \ln \frac{p(\mathcal{X} \cup \mathcal{Y})}{p(\mathcal{X})p(\mathcal{Y})}$$

$$\mathbb{I}_p(\mathcal{Y}, \mathcal{X}) = \sum_{\mathcal{Y}, \mathcal{X}} p(\mathcal{Y} \cup \mathcal{X}) \ln \frac{p(\mathcal{Y} \cup \mathcal{X})}{p(\mathcal{Y})p(\mathcal{X})}$$

Since probability functions are commutative under product,  $\mathbb{I}_p(\mathcal{X}, \mathcal{Y}) =$  $\mathbb{I}_p(\mathcal{Y},\mathcal{X}).$