

Probability and Random Processes

Irvin Avalos

1 Information Theory

Defintion 1.1 (Entropy).

$$H(X) = \mathbb{E} [-\log_2 p(x)] = \sum_{x \in X} -p(x) \log_2 p(x)$$

If $X \sim B(p)$, then

$$H(X) = p - \log_2 p + (1 - p) \log_2 (1 - p) \triangleq h(p)$$

called the **binary entropy function**.

Defintion 1.2 (Joint Entropy).

$$H(X, Y) = \mathbb{E} [-\log_2 p(x, y)] = \sum_x \sum_y -p_{x,y}(x, y) \log_2 p(x, y)$$

If X, Y are independent, then $H(X, Y) = H(X) + H(Y)$.

Proof.

$$\begin{aligned} H(X, Y) &= \mathbb{E} [-\log_2 p(x, y)] \\ &= \mathbb{E} [-\log_2 p(x) p(y)] \\ &= \mathbb{E} [-\log_2 p(x) - \log_2 p(y)] \\ &= \mathbb{E} [-\log_2 p(x)] + \mathbb{E} [-\log_2 p(y)] \\ &= H(X) + H(Y) \end{aligned}$$

□

Defintion 1.3 (Conditional Entropy).

$$H(Y | X) = \mathbb{E}_{XY} [-\log_2 p(y | x)] \quad H(X, Y) - H(X)$$

Defintion 1.4 (Mutual Information).

$$\begin{aligned} I(X; Y) &\triangleq H(X) - H(X | Y) \\ &= H(Y) - H(Y | X) \\ &= H(X) + H(Y) - H(X, Y) \end{aligned}$$

Theorem 1.5 (Asymptotic Equipartition). *If X_1, X_2, \dots, X_n are iid $\sim p(X)$, then*

$$\frac{-\log_2 p(X_1, X_2, \dots, X_n)}{n} \xrightarrow{p} H(X).$$