Overall,

$$\frac{H(X) = \frac{1}{4} \text{ bits}}{\int I(X;Y) = \frac{1}{8} \text{ bits}} = \frac{H(Y) - H(Y|X)}{H(X|Y) = \frac{1}{8} \text{ bits}} = \frac{H(Y) = 2 \text{ bits}}{H(Y|X) = \frac{1}{8} \text{ bits}}$$

Conditioning can help achieve better compression! Gain = I(X;Y)

- Joint Entropy and Mutual Information

Joint Entropy: Uncertainty about the joint sources X and Y.

$$H(X,Y) = -\sum_{x \in X} \sum_{y \in Y} P(x,y) \log_{2} P(x,y)$$

$$P(x,y) = P(y) \cdot P(x|y), by Bayes' Rule$$

$$= -\sum_{x \in X} \sum_{y \in Y} P(x,y) \log_{2} P(y) - \sum_{x \in X} \sum_{y \in Y} P(x,y) \log_{2} P(x|y)$$

$$= H(Y) + H(x|Y)$$
Similarly,
$$H(X,Y) = -\sum_{x \in X} \sum_{y \in Y} P(x,y) \log_{2} P(x,y)$$

$$P(x,y) = P(x) \cdot P(y|x), by Bayes' Rule$$

$$= -\sum_{x \in X} \sum_{y \in Y} P(x,y) \log_{2} P(x) - \sum_{x \in X} \sum_{y \in Y} P(x,y) \log_{2} P(y|x)$$

$$= H(X) + H(Y|X)$$

In summary,

$$H(X,Y) = H(X) + H(Y|X) = H(Y) + H(X|Y) = 7/4 + 13/8 = 27/8 \text{ bits} = 2 + 11/8$$

$$I(X;Y) = I(Y;X) = H(X) - H(X|Y) = H(Y) - H(Y|X)$$

$$\frac{H(Y) = 2 \text{ bits}}{\int I(Y;X) = \frac{3}{5} \text{ bits}} = \frac{H(Y) - H(Y|X)}{\int I(Y;X) = \frac{3}{5} \text{ bits}}$$

$$H(Y|X) = \frac{13}{5} \text{ bits}$$

Compare: H(X,Y) = 27/8 bits < H(X) + H(Y) = 7/4 + 2 = 15/4 bits, H(X) + H(Y) - H(X,Y) = 15/4 - 27/8 = 3/8 bit = I(X;Y)

Blocking can help achieve better compression! Gain = I(X;Y)

Go back to the relation between joint entropy and mutual information:

 $\frac{H(X,Y) = H(X) + H(Y|X) = H(X) + H(Y) - I(X;Y)}{Where I(X;Y) = I(Y;X) = H(X) - H(X|Y) = H(Y) - H(Y|X) => H(Y|X) = H(Y) - I(X;Y)}$



$$\begin{array}{ll} H(x) & H(\gamma) \\ = \frac{7}{4} & = 2 \end{array}$$

If X and Y are independent, then $P(x,y) = P(x) \cdot P(y)$, and P(x|y) = P(x) $p(x, y) = p(x|y) \cdot p(y)$ in general - Mutual Information I(X;Y) $I(\chi; \gamma) = \sum_{x \in V} \sum_{y \in Y} P(x, y) \log_{2} \left(\frac{P(x|y)}{P(x)} \right) = \sum_{x \in \chi} \sum_{y \in \gamma} P(x, y) \log_{2} | = 0$ xex yer $\frac{p(x)}{p(x)} = 1$ H(X,Y) = H(X) + H(Y|X) = H(X) + H(Y)And H(Y) = H(Y|X)Similarly, H(X) = H(X|Y) $H(\chi, \gamma) = H(\chi) + H(\gamma)$ H(X) = H(X|Y)H(Y) = H(Y|X)- KL Divergence (KL Distance) between two distributions P(i) and Q(i)kullback - Leibler $D_{KL}(P||Q) = \sum_{i} \left\{ P(i) \log_{2} \left(\frac{P(i)}{Q(i)} \right) \right\}, \text{ where } i = 1, 2, \cdots,$ Joint Distribution P(X,Y): $\mathbb{D}_{\mathsf{KL}}(X \parallel Y)$

$$= \sum_{i=1}^{4} P(\chi=i) \log_{2} \frac{P(\chi=i)}{P(\chi=i)}$$

XY	1	2	3	4	Σ
1	18	16	⊥ 32	32	p(Y=1) = 4
2	16	4	1 32	32	P(Y=2) = t

$$= \sum_{i=1}^{4} P(X=i) \log_{2} \frac{P(X=i)}{P(Y=i)}$$

$$= \frac{1}{2} \log_{2} \frac{1}{4} + \frac{1}{4} \log_{2} \frac{1}{4} + \frac{1}{8} \log_{2} \frac{1}{4}$$

$$= \frac{1}{2} + 0 - \frac{1}{8} - \frac{1}{8} = \frac{1}{4}$$

$$\stackrel{1}{8} \overline{16} \overline{32} \overline{32} P(Y=i) = 4$$

$$\stackrel{1}{8} \overline{16} \overline{32} \overline{32} P(Y=i) = 4$$

$$\stackrel{1}{8} \overline{16} \overline{16} \overline{16} \overline{16} \overline{16} \overline{16} P(Y=i) = 4$$

$$\stackrel{1}{8} \overline{16} \overline{1$$

$$D_{KL}(\boldsymbol{Q} \parallel \boldsymbol{P}) = \sum_{i} \left\{ \boldsymbol{Q}(i) \mid \boldsymbol{D}\boldsymbol{g}_{2}\left(\frac{\boldsymbol{Q}(i)}{\boldsymbol{P}(i)}\right) \right\}, \text{ where } i = 1, 2, \cdots,$$

How about

$$\mathbb{D}^{\mathsf{kr}}(\lambda \| x) = \mathsf{s}$$

In general,

$$P_{kL}(P || Q) \neq D_{kL}(Q || P)$$

- Look back at the Mutual Information I(X;Y)

$$I(\chi;Y) = \sum_{x \in \chi} \sum_{y \in Y} P(x,y) \log_{2} \left(\frac{P(x|y)}{P(x)} \right) = \sum_{x \in \chi} \sum_{y \in Y} \frac{P(x,y)}{P(x,y)} \log_{2} \left(\frac{P(x,y)}{P(x)} \right)$$

Joint Distribution P(X,Y):

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 $P(x=1) \quad P(x=2) \quad P(x=3) \quad P(x=4)$

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P(Y=1) = 4

P(Y=2) = ╁

P(Y=3) = 4

 $P(Y=4) = \frac{1}{4}$

Thus, the mutual info. Is the KL distance between the Joint PMF and Product of marginal PMFs.

$$I(X;Y) = D_{KL}\{P(x,y) \mid | P(x)P(y)\}$$

$$= \sum_{x \in X} \sum_{y \in Y} P(x,y) \left[\log_{2} \frac{P(x,y)}{P(x)P(y)} \right]$$

$$= P(x=1,Y=1) \left[\log_{2} \frac{P(x=1,Y=1)}{P(x=1) \cdot P(Y=1)} \right]$$

$$+ \dots$$

$$I6 \text{ terms in total}$$

$$= \frac{3}{8} \text{ bit (Verify this!)}$$

In X and Y are independent, P(x,y) = P(x)P(y), thus P(x,y)/P(x)P(y) = 1, $I(X;Y) = D_{kL}{P(x,y) || P(x)P(y)} = 0$.

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