

EE 231A: Information Theory



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EE 231E: Information Theory Lecture 1

- A. Introduction
- B. Entropy
- C. Relative Entropy
- D. Mutual Information

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Relative entropy

- A way to compare how close two distributions are.
- The “penalty” for compressing using the wrong distribution.
- Specifically, if $X \sim p(x)$ but we represent it in a way that would be efficient if $X \sim q(x)$, our representation will require

$$\underbrace{H(p)}_{\text{entropy}} + \underbrace{D(p \parallel q)}_{\text{relative entropy between p and q}} \quad \text{bits}$$

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Relative entropy definition

$$D(p \parallel q) = \sum_x p(x) \log \frac{p(x)}{q(x)}$$

$$D(p \parallel q) = \underbrace{-\sum_x p(x) \log q(x)}_{\text{bits required by assuming } q(x) \text{ when } X \sim p(x)} - \left(\underbrace{-\sum_x p(x) \log p(x)}_{\text{bits required by correct assumption } X \sim p(x)} \right)$$

bits required by
assuming $q(x)$
when $X \sim p(x)$

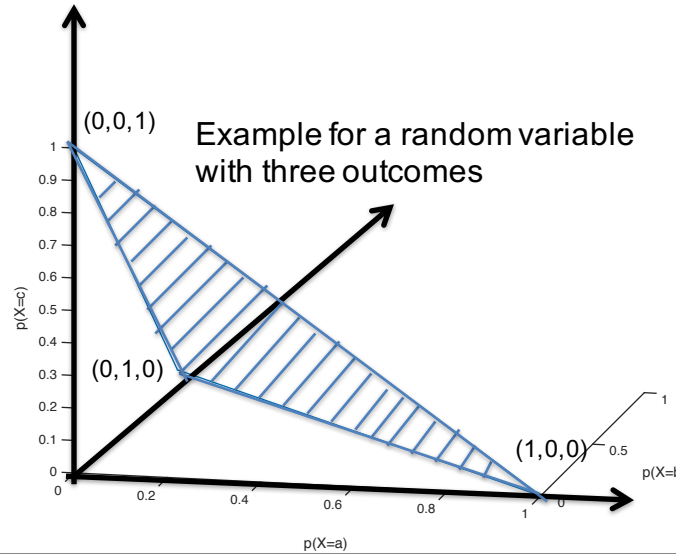
bits required by
correct assumption
 $X \sim p(x)$

- For two distributions $p(x)$ and $q(x)$

$$D(p \parallel q) = E_x[\log p(X)] - E_x[\log q(X)] = E_x \left[\log \frac{p(X)}{q(X)} \right]$$

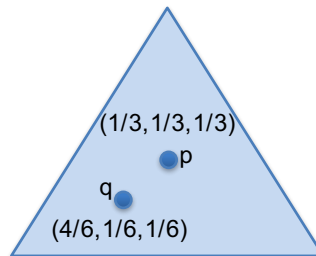
A probability simplex

- A probability simplex is the set of all possible pmf's with a particular number of outcomes.



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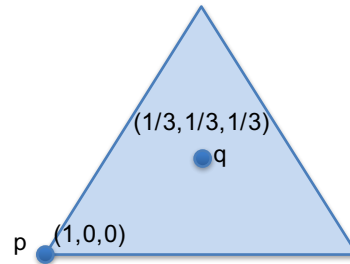
Example $D(p \parallel q)$ Computation



$$\begin{aligned}
 D(p \parallel q) &= \sum_x p(x) \log \frac{p(x)}{q(x)} \\
 &= \frac{1}{3} \log \frac{1/3}{4/6} + \frac{1}{3} \log \frac{1/3}{1/6} + \frac{1}{3} \log \frac{1/3}{1/6} = \frac{1}{3}
 \end{aligned}$$

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$D(p \parallel q)$ at a corner point



$$D(p \parallel q) = 1 \log \frac{1}{1/3} + \underbrace{0 \log \frac{0}{1/3}}_0 + \underbrace{0 \log \frac{0}{1/3}}_0 = \log 3$$

$$D(q \parallel p) = \frac{1}{3} \log \frac{1/3}{1} + \underbrace{\frac{1}{3} \log \frac{1/3}{0}}_{\infty} + \underbrace{\frac{1}{3} \log \frac{1/3}{0}}_{\infty} = \infty$$

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Conditional relative entropy

$$\begin{aligned} D(p(y|x) \parallel q(y|x)) &= E_x E_{Y|X=x} \left[\log \frac{p(y|x)}{q(y|x)} \right] \\ &= \sum_x p(x) \sum_y p(y|x) \log \frac{p(y|x)}{q(y|x)} \\ &= \sum_{x,y} p(x,y) \log \frac{p(y|x)}{q(y|x)} \\ &= E_{p(x,y)} [-\log q(Y|X) - (-\log p(Y|X))] \end{aligned}$$

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Chain rule for relative entropy

$$D(p(x, y) \| q(x, y)) = D(p(x) \| q(x)) + D(p(y | x) \| q(y | x))$$

$$\begin{aligned} D(p(x, y) \| q(x, y)) &= E_{p(x, y)}[-\log q(X, Y)] - E_{p(x, y)}[-\log p(X, Y)] \\ &= E_{p(x, y)}[-\log q(X)q(Y | X)] - E_{p(x, y)}[-\log p(X)p(Y | X)] \\ &= E[-\log q(X)] + E[-\log q(Y | X)] - E[-\log p(X)] - E[-\log p(Y | X)] \\ &= D(p(x) \| q(x)) + D(p(y | x) \| q(y | x)) \end{aligned}$$

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- E. Axiomatic Development of Entropy

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