

Recap

Jensen's: For a convex f , $\mathbb{E}[f(x)] \geq f(\mathbb{E}[x])$

Entropy: $H(x) = \sum_{i=1}^n p_i \log \frac{1}{p_i}$

$$0 \leq H(x) \leq \log n$$

Prefix-free codes:

$$H(x) \leq \mathbb{E}[|C(x)|] \leq H(x) + 1$$

for all C

for Shannon code

Joint entropy

$$Z = (X, Y)$$

$$H(Z) = H(X, Y)$$

$$= \sum_{x, y} p(x, y) \cdot \log \frac{1}{p(x, y)}$$

$$= \sum_{x, y} p(x) \cdot p(y|x) \cdot \log \frac{1}{p(x) \cdot p(y|x)}$$

$$= \sum_x p(x) \left(\sum_y p(y|x) \right) \cdot \log \frac{1}{p(x)} + \sum_x p(x) \cdot \sum_y p(y|x) \cdot \log \frac{1}{p(y|x)}$$

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

$$\frac{\sum_x H(Y|X=x)}{H(Y|X)}$$

Chain rule for entropy

$$H(X, Y) = H(X) + \underbrace{H(Y|X)} \\ = \mathbb{E}_x [H(Y|X=x)]$$

$$\triangleright \text{Ex: } H(X_1, X_2|Y) = H(X_1|Y) + H(X_2|Y, X_1)$$

$$H(X_1, X_2, \dots, X_m) = H(X_1) + H(X_2 \dots X_m | X_1) \\ = H(X_1) + H(X_2 | X_1) + H(X_3 \dots X_m | X_1, X_2) \\ \vdots \\ = H(X_1) + H(X_2 | X_1) + \dots + H(X_m | X_1 \dots X_{m-1})$$

An example

$$(X, Y) = \begin{cases} 01 & \text{w. p. } \frac{1}{3} \\ 10 & \text{w. p. } \frac{1}{3} \\ 11 & \text{w. p. } \frac{1}{3} \end{cases}$$

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

$$H(X, Y) = \log_2 3$$

$$H(X) = H(X, Y) - H(Y|X) = H(X)$$

$$H(Y) = \frac{1}{3} \log 3 + \frac{2}{3} (\log 3 - 1) = \log 3 - \frac{2}{3}$$

$$H(Y|X=0) = 0 \quad \left(H(X, Y) - H(X|Y) \right)$$

$$H(Y|X=1) = 1$$

$$H(Y|X) = \frac{1}{3} \cdot 0 + \frac{2}{3} \cdot 1 = \frac{2}{3}$$

Conditioning reduces entropy on average

$$\triangleright \underline{H(Y|X)} \leq H(Y)$$

Conditional entropy

Proof:

$$\mathbb{E}_x H(Y|X=x) \leq H(Y)$$

$$\sum_x P(x) \sum_y \frac{P(y|x)}{P(y|x)} \log \frac{1}{P(y|x)} - \sum_y P(y) \log \frac{1}{P(y)}$$

$$\sum_{y,x} P(x,y) \log \frac{1}{P(y)}$$

$$= \sum_{x,y} P(x,y) \log \frac{P(y) P(x)}{P(x,y)}$$

$$Z = \frac{P(y) \cdot P(x)}{P(x,y)}$$

$$= \mathbb{E} \log Z \leq \log \left(\sum P(x,y) \cdot \frac{P(y)P(x)}{P(x,y)} \right) \leq 0$$

$$\blacktriangleright H(Z|X, Y) \leq H(Z|Y)$$

\blacktriangleright Use that \log is **strictly concave** to show

$H(Y|X) = H(Y)$ if and only if X, Y are independent

$$\begin{aligned} H(X_1, X_2, \dots, X_m) &= H(X_1) + \underbrace{H(X_2|X_1)} + \dots + H(X_m|X_1, \dots, X_{m-1}) \\ &\leq H(X_2) \leq H(X_3) \dots \leq H(X_m) \\ &\leq H(X_1) + \dots + H(X_m) \end{aligned}$$

equality when X_1, \dots, X_m are independent

Improved Source Coding

$$\exists C: X^m \rightarrow \{0,1\}^* \text{ s.t. } \mathbb{E}_{x_1, \dots, x_m} [C(x_1, \dots, x_m)] \leq m \cdot H(X) + 1$$

Proof: Use Shannon code for $Z = (X_1, \dots, X_m)$

$$\begin{aligned} \mathbb{E} [C(x_1, \dots, x_m)] &\leq H(x_1, \dots, x_m) + 1 \\ &= H(X_1) + \dots + H(X_m) + 1 \\ &= m \cdot H(X) + 1 \end{aligned}$$

Binary entropy

$$X = \begin{cases} 1 & \text{w.p. } p \\ 0 & \text{w.p. } 1-p \end{cases}$$

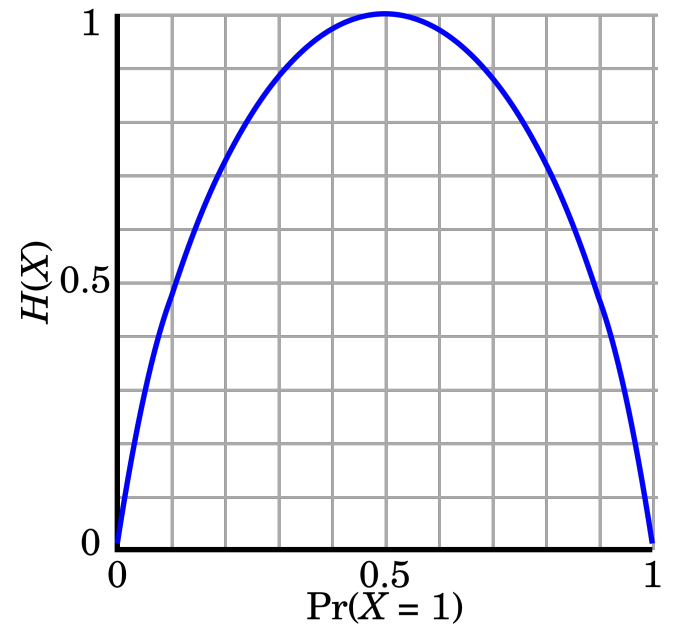
$$H(X) = p \log \frac{1}{p} + (1-p) \log \frac{1}{1-p} = H_2(p)$$

- $H_2(p) \leq 1 = H_2(1/2)$

- $H_2(p)$ is concave

To show: $\alpha \cdot H_2(p_1) + (1-\alpha) \cdot H_2(p_2) \leq H_2(\alpha \cdot p_1 + (1-\alpha) \cdot p_2)$

$$X = \begin{cases} 1 & \text{w.p. } \alpha \\ 0 & \text{w.p. } 1-\alpha \end{cases} \quad \underline{Y} | X=1 = \begin{cases} 1 & \text{w.p. } p_1 \\ 0 & \text{w.p. } 1-p_1 \end{cases}$$
$$\underline{Y} | X=0 = \begin{cases} 1 & \text{w.p. } p_2 \\ 0 & \text{w.p. } 1-p_2 \end{cases}$$



(Source: Wikipedia)

~~$H_2(p)$~~ $H_2(p)$ is increasing for $p \leq 1/2$

Application: Estimating binomial sums

$$\text{Estimate: } \binom{n}{0} + \binom{n}{1} + \dots + \binom{n}{k} \quad (\text{for } k \leq \frac{n}{2})$$

equivalently, for $S = \{ (x_1, \dots, x_n) \in \{0, 1\}^n \mid \sum x_i \leq k \}$

estimate $|S|$

$$S = \{(x_1, \dots, x_n) \in \{0, 1\}^n \mid \sum x_i \leq R\}$$

Let $Z = (X_1, \dots, X_n)$ be uniform on S

$$\log |S| = H(X_1, \dots, X_n)$$

$$\leq H(X_1) + \dots + H(X_n)$$

$$= n \cdot H(X_1)$$

$$\leq n \cdot H_2\left(\frac{R}{n}\right)$$

$$\therefore |S| \leq 2^{n \cdot H_2(R/n)}$$

$$n \cdot \mathbb{E}[X_1]$$

$$= \mathbb{E}[X_1 + \dots + X_n] \leq R$$

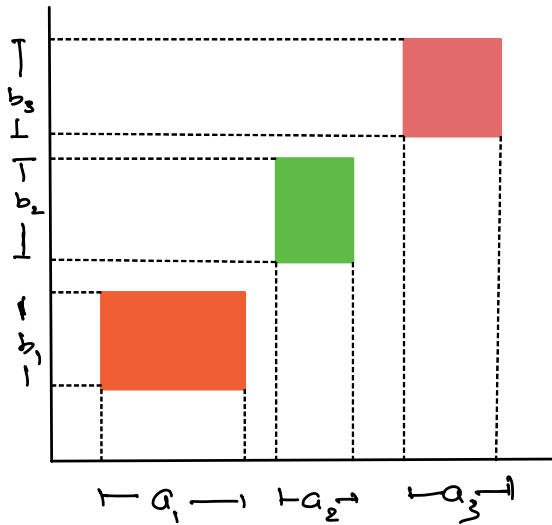
$$\Rightarrow \mathbb{E}[X_1] \leq \frac{R}{n}$$

$$\therefore H(X_1) \leq H_2\left(\frac{R}{n}\right)$$

Counting Points

$$a_1, \dots, a_n \in \mathbb{N}$$

$$b_1, \dots, b_n \in \mathbb{N}$$



- Consider n disjoint rectangles of dimensions $a_1 \times b_1, \dots, a_n \times b_n$

- Pick R w. p. proportional to area

$$P[R = r_i] = \frac{a_i \cdot b_i}{\sum_j a_j \cdot b_j}$$

- Pick two independent points $(x_1, y_1), (x_2, y_2) \in R$

$$(\sum a_i b_i)^2 \leq (\sum a_i^2) (\sum b_i^2)$$

$$2 \log(\sum a_i b_i) = H(x_1, y_1, R) + H(x_2, y_2, R)$$

$$= 2H(R) + H(x_1, y_1 | R) + H(x_2, y_2 | R)$$

$$= 2H(R) + H(x_1 | R) + H(y_1 | R) + H(x_2 | R) + H(y_2 | R)$$

$$= \underbrace{H(x_1, x_2, R)}_{\leq \log(\sum a_i^2)} + \underbrace{H(y_1, y_2, R)}_{\leq \log(\sum b_i^2)}$$

Hypergraphs, entropy and inequalities [Friedgut 04]

eg. $\sum a_i b_i \leq \left(\sum a_i^{1/\theta}\right)^\theta \left(\sum b_i^{1/(1-\theta)}\right)^{1-\theta}$ [Hölder's ineq]

$$\left(\text{Tr}(ABC)\right)^2 \leq \text{Tr}(AA^T) \cdot \text{Tr}(BB^T) \cdot \text{Tr}(CC^T)$$

⋮

Generalizing sub-additivity

$$H(x_1, x_2, x_3) \leq H(x_1) + H(x_2) + H(x_3)$$

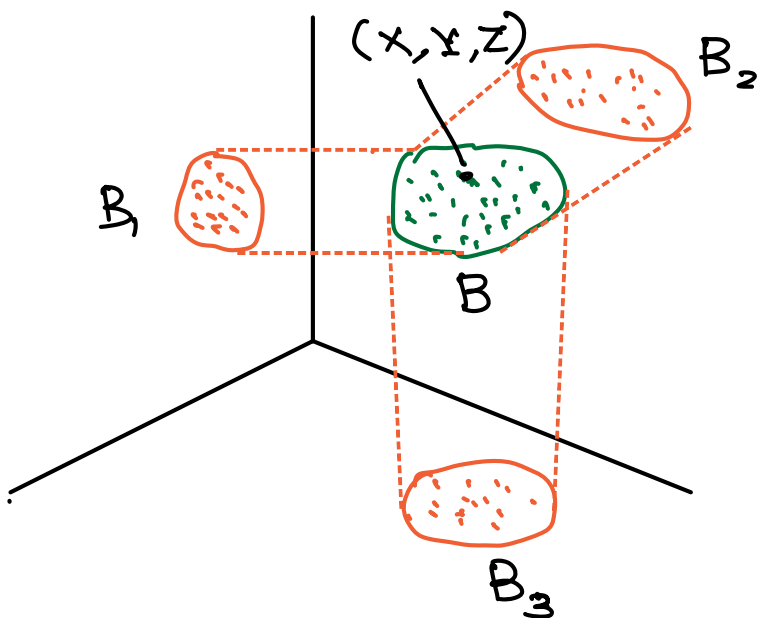
Better bounds using pairs?

$$H(x_1, x_2, x_3) = H(x_1, x_2) + \underbrace{H(x_3 | x_1, x_2)}_{\leq H(x_3)}$$

$$H(x_1, x_2, x_3) = H(x_2, x_3) + \underbrace{H(x_1 | x_2, x_3)}_{\leq H(x_1 | x_3)}$$

$$H(x_1, x_2, x_3) \leq \frac{1}{2} (H(x_1, x_2) + H(x_2, x_3) + H(x_3, x_1))$$

Counting 3D points



$$2H(x, y, z) \leq H(x, y) + H(y, z) + H(z, x)$$

$$2 \log |B| \leq \log |B_1| + \log |B_2| + \log |B_3|$$

$$\text{Vol}(B) \leq \left(\text{area}(B_1) \cdot \text{area}(B_2) \cdot \text{area}(B_3) \right)^{\frac{1}{2}}$$

Loomis - Whitney

Generalizing subadditivity: Shearer's lemma

► Random vars X_1, \dots, X_n . $X_S = \{X_i\}_{i \in S}$

Let \mathcal{F} be a collection of subsets of $[n]$ s.t. each $i \in [n]$ appears in at least t subsets in \mathcal{F}

Then,
$$t \cdot H(X_1, \dots, X_n) \leq \sum_{S \in \mathcal{F}} H(X_S)$$

► (Distributional version): Distribution D on $2^{[n]}$ s.t.
$$\forall i \in [n] \quad \mathbb{P}_{S \sim D} [i \in S] \geq \mu$$

Then,
$$\mu \cdot H(X_1, \dots, X_n) \leq \mathbb{E}_{S \sim D} [H(X_S)]$$

► Ex: Check that second version implies first

$$\text{Let } S = \{i_1, i_2, \dots, i_R\}$$

$$H(X_S) = H(X_{i_1}) + H(X_{i_2} | X_{i_1}) + \dots + H(X_{i_R} | X_{i_1} \dots X_{i_{R-1}})$$

$$= \sum_{i \in S} H(X_i | X_{S \cap [i-1]})$$

$$\geq \sum_{i \in S} H(X_i | X_{[i-1]})$$

$$= \sum_{i \in [n]} \mathbb{1}_{\{i \in S\}} \cdot H(X_i | X_{[i-1]})$$

To prove: $\mathbb{E}_{S \sim D} [H(x_S)] \geq \mu \cdot H(x_1 \dots x_n)$

$$\mathbb{E}_{S \sim D} [H(x_S)] \geq \mathbb{E}_{S \sim D} \left[\sum_{i \in S} \mathbb{1}_{\{i \in S\}} \cdot H(x_i | x_{[i-1]}) \right]$$

$$\mathbb{E}_{S \sim D} [\mathbb{1}_{\{i \in S\}}] \geq \mu$$

$$\geq \mu \cdot \sum_i H(x_i | x_{[i-1]})$$

$$= \mu \cdot H(x_1 \dots x_n)$$