

ORIE 4742 - Info Theory and Bayesian ML

Lecture 4: Source Coding

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entropy and information

rv X taking values $\mathcal{X} = \{a_1, a_2, \dots, a_k\}$, with pmf $\mathbb{P}[X = a_i] = p_i$

Shannon's entropy function

- outcome $X = a_i$ has *information content*: $h(a_i) = \log_2 \left(\frac{1}{p_i} \right)$
- random variable X has *entropy*: $H(X) = \mathbb{E}[h(X)] = \sum_{i=1}^k p_i \log_2 \left(\frac{1}{p_i} \right)$
 - only depends on distribution of X (i.e., $H(X) = H(p_1, p_2, \dots, p_k)$)
 - $H(X) \geq 0$ for all X
 - if $X \perp\!\!\!\perp Y$, then $H(X, Y) = H(X) + H(Y)$
where **joint entropy** $H(X, Y) \triangleq \sum_{(x,y)} p(x, y) \log_2 1/p(x, y)$
 - if $X \sim$ uniform on $\mathcal{X}$, then $H(X) = \log_2 |\mathcal{X}|$; else, $H(X) \leq \log_2 |\mathcal{X}|$

the source coding problem

suppose we are given a database $D = (X_1 X_2 \dots X_N)$, where each X_i is a letter in an alphabet $\mathcal{X}$, generated iid according to $X_i \sim \{p_1, p_2, \dots, p_k\}$

lossless compression

compress D into a *codeword* $L = \phi(D)$ such that can recover $D = \phi^{-1}(L)$

Shannon's source coding theorem

if X has entropy $H(X)$, then for any $\epsilon > 0$ and $0 < \delta < 1$, there exists N_0 s.t. for all $N > N_0$, we have a lossless code $L = \phi(X^N)$ s.t.

$$\left| \frac{\mathbb{E}[L]}{N} - H(X) \right| \leq \epsilon$$

Moreover, this is the best possible, i.e., no lossless code has $\frac{\mathbb{E}[L]}{N} < (1-\epsilon)H(X)$

lossless compression via **typical set** encoding

typical set

iid source produces $X^N = (X_1 X_2 \dots X_N)$; each $X_i \in \mathcal{X}$ has entropy $H(X)$

then X^N is **very likely** to be one of $\approx 2^{NH(X)}$ **typical strings**,
all of which have probability $\approx 2^{-NH(X)}$

Typical Set

- size $\sim 2^{NH(X)}$
- $\sim$ Uniform distn
- Total prob $\geq 1-\delta$

④ size $2^{N(1-H(X))}$
prob $< \delta$

practical source coding solutions

symbol codes

$$X_1 X_2 \dots X_n \rightarrow \phi(X_1) \phi(X_2) \dots \phi(X_n)$$

map each symbol $X_i \rightarrow \phi(x_i)$

Eg - Morse code, Huffman code

stream codes

$$X_1 X_2 \dots X_n \rightarrow \phi(X_1) \phi(X_2 | X_1) \phi(X_3 | X_1 X_2) \dots \phi(X_n | X_1 X_2 \dots X_{n-1})$$

maps entire data base to a code_word

Eg - LZ W

Lempel-Zis-Welch code, arithmetic coding

symbol codes

expected length of symbol code

let $X \sim \{p(x)\}_{x \in \mathcal{X}}$, and consider code $C(\cdot)$, and let $\ell(x) = |C(x)|$
the expected length of C is $\mathbb{E}[L(C, X)] = \sum_x p(x)\ell(x)$

what we want from symbol code C :

→ $\forall x \neq y$, want $C(x) \neq C(y)$ (singular code)

- **unique decodability**: $\forall x_1 x_2 \dots x_n \neq y_1 y_2 \dots y_n$, we have

$$C(x_1)C(x_2) \dots C(x_n) \neq C(y_1)C(y_2) \dots C(y_n)$$

- easy to decode

- small $\mathbb{E}[L(C, X)]$

(if sending N symbols $C(x_1)C(x_2) \dots C(x_n)$)

$$\mathbb{E}\left[\sum_{i=1}^n |C(x_i)|\right] = \sum_{i=1}^n \mathbb{E}[|C(x_i)|] = N \mathbb{E}[L(C, X)]$$

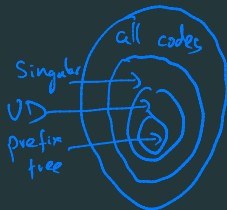
types of symbol codes

consider source producing $X \sim \{a, b, c, d\}$ with prob $\{\frac{1}{2}, \frac{1}{4}, \frac{1}{8}, \frac{1}{8}\}$

Symbols	info content(bits)	Code 1	$l(x)$	Code 2	$l(x)$
a	1	1000	4	00	2
b	2	0100	4	01	2
c	3	0010	4	10	2
d	3	0001	4	11	2
$\frac{7}{4} = 1.75 \text{ bits}$		4 bits		2 bits	
		on avg per symbol			

prefix codes (variable length codes, VLC)

Symbols	Info content	(Prefix code) Code 3	(Uniquely decodable) Code 4
a	1	0	0
b	2	10	01
c	3	110	011
d	3	111	111
	<u>1.75</u>	<u>$E[L(C,x)] = 1.75$</u>	<u>$E[L(C,x)] = 1.75$</u>



prefix code $\equiv C(x)$ is not the 'prefix' of any
(instantaneous code) $C(y) \forall x, y$

the limits of unique decodability

Kraft-McMillan inequality

for any $C \equiv$ **uniquely decodable** binary code over $\mathcal{X}$, with $\ell(x) = |C(x)|$

$$\sum_{x \in \mathcal{X}} 2^{-\ell(x)} \leq 1 \quad (*)$$

moreover, for any $\{\ell(x)\}$ satisfying this, we can find a **prefix code**

Kraft's Ineq- Prefix code iff $(*)$

McMillan - $(*)$ true for any uniquely decodable code

the limits of unique decodability

Kraft's inequality: for prefix codes

Kraft's symbol-code supermarket

Kraft's inequality: for prefix codes $\sum_{x \in \mathcal{X}} 2^{-\ell(x)} \leq 1$

Cost

2^{-1}

2^{-2}

2^{-3}

2^{-4}

0	00	000	0000	The total symbol code budget
			0001	
		001	0010	
			0011	
	01	010	0100	
			0101	
		011	0110	
			0111	
1	10	100	1000	
			1001	
		101	1010	
			1011	
	11	110	1100	
			1101	
		111	1110	
			1111	

Budget = 1

Kraft's symbol-code supermarket

• Note - If C satisfies $\sum_i 2^{-l_i} = 1$, then 'complete code'

C_0

0	00	000	0000
		0001	
		0010	
	001	0011	
	01	0100	
		0101	
		0110	
	011	0111	
1	10	100	1000
		1001	
		1010	
		1011	
	11	110	
		1101	
		1110	
		1111	

C_3

0	00	000	0000
		0001	
		0010	
	001	0011	
	01	010	0100
		0101	
		0110	
	011	0111	
1	10	100	1000
		1001	
		1010	
		1011	
	11	110	1100
		1101	
		1110	
		1111	

C_4

0	00	000	0000
		0001	
		0010	
	001	0011	
	01	0100	
		0101	
		0110	
	011	0111	
1	10	100	1000
		1001	
		1010	
		1011	
	11	110	1100
		1101	
		1110	
		1111	

C_6

0	00	000	0000
		0001	
		0010	
	001	0011	
	01	010	0100
		0101	
		0110	
	011	0111	
1	10	100	1000
		1001	
		1010	
		1011	
	11	110	1100
		1101	
		1110	
		1111	

a	0	00	0
b	10	01	01
c	110	10	011
d	111	11	111

complete codes

optimizing expected code length

let $X \sim \{p(x)\}_{x \in \mathcal{X}}$, and consider code $C(\cdot)$, and let $\ell(x) = |C(x)|$
the expected length of C is $\mathbb{E}[L(C, X)] = \sum_x p(x) \ell(x)$

$$\max \sum_{x \in \mathcal{X}} p(x) \ell(x) \quad \text{s.t.} \quad \sum_{x \in \mathcal{X}} 2^{-\ell(x)} \leq 1$$
$$\ell(x) \in \{1, 2, \dots\}$$

• Define : $q(x) = \frac{2^{-\ell(x)}}{\sum_{y \in \mathcal{X}} 2^{-\ell(y)}} = \frac{2^{-\ell(x)}}{Z}$

$$\Rightarrow \mathbb{E}[L(C, X)] = \sum_{x \in \mathcal{X}} p(x) \log_2 \left(\frac{1}{Z q(x)} \cdot \frac{p(x)}{p(x)} \right)$$
$$= H(X) + \sum_{x \in \mathcal{X}} p(x) \log_2 \left(\frac{p(x)}{q(x)} \right) - \log_2 Z$$

relative entropy and Gibb's inequality

relative entropy (or Kullback-Leibler (KL) divergence)

the relative entropy $D_{KL}(p||q)$ between two distributions $p(x)$ and $q(x)$ defined over alphabet $\mathcal{X}$ is

$$D_{KL}(P||Q) = \sum_{x \in \mathcal{X}} p(x) \ln \left(\frac{p(x)}{q(x)} \right)$$

$$= -\sum p(x) \ln q(x) - H(x)$$

relative entropy and Gibb's inequality

the relative entropy $D_{KL}(p||q) = \sum_{x \in \mathcal{X}} p(x) \ln \left(\frac{p(x)}{q(x)} \right) \geq 0$ for all p, q

- Jensen's Inequality

- $g(x) = x \ln x$, $g'(x) = 1 + \ln(x) \uparrow$
 $\Rightarrow g(x)$ is convex

- $$\sum_x q(x) \left[\underbrace{\left(\frac{p(x)}{q(x)} \right) \ln \left(\frac{p(x)}{q(x)} \right)}_{g(p(x)/q(x))} \right] \geq \underbrace{\left(\sum_x \frac{p(x) \cdot q(x)}{q(x)} \right)}_{=0} \ln \left(\sum_x \frac{p(x) \cdot q(x)}{q(x)} \right)$$

optimizing expected code length

- entropy of X : $H(X) = \sum_{i \in \mathcal{X}} p_i \log_2 \left(\frac{1}{p_i} \right)$
- Kraft-McMillan inequality: UD code $\{\ell_i\}_{i \in \mathcal{X}}$ satisfies $\sum_{i \in \mathcal{X}} 2^{-\ell_i} \leq 1$

Given codeword lengths ℓ_i , define 'implicit probability'

$$\forall i \in \mathcal{X}, \quad q_i \triangleq \frac{2^{-\ell_i}}{\sum_{j \in \mathcal{X}} 2^{-\ell_j}} \Rightarrow \ell_i = -\log_2 q_i - \log_2 Z$$

$Z = \text{normalizing constant (partition function)}$

• From Kraft, $Z \leq 1 \Rightarrow \log_2 Z \leq 0$, 0 only for complete codes

$$\bullet \mathbb{E}[L(C, X)] = \sum_i p_i \ell_i = \left(\sum_i -p_i \log q_i \right) - \log_2 Z$$

optimizing expected code length

let $X \sim \{p(x)\}_{x \in \mathcal{X}}$, and consider code $C(\cdot)$, and let $\ell(x) = |C(x)|$
the expected length of C is $\mathbb{E}[L(C, X)] = \sum_x p(x) \ell(x)$

$$\bullet \text{ Aim - } \min \sum_i p_i l_i \quad \text{s.t.} \quad \sum_i 2^{-l_i} \leq 1$$

$$\Rightarrow \min \underbrace{\sum_i p_i \log_2(1/q_i)}_{\log_2 Z}, \quad \log_2 Z \leq 0$$

$$= H(p) + \sum_i p_i \left(\underbrace{\log_2 p_i + \log_2(1/q_i)}_{\log_2(p_i/q_i)} \right) + \log_2(1/Z)$$

$$\Rightarrow \mathbb{E}[L(C, X)] = H(p) + \underbrace{D_{KL}(p \parallel q)}_{\text{Kullback-Leibler Divergence}} + \log_2(1/Z)$$

relative entropy and Gibb's inequality

relative entropy (or Kullback-Leibler (KL) divergence)

the relative entropy $D_{KL}(p||q)$ between two distributions $p(x)$ and $q(x)$ defined over alphabet $\mathcal{X}$ is

$$D_{KL}(P||Q) = \sum_{x \in \mathcal{X}} p(x) \ln \left(\frac{p(x)}{q(x)} \right)$$

Think of it
as a 'distance'
between P, Q

- Fact - $D_{KL}(P||P) = 0$
- Fact - $D_{KL}(P||Q) \neq D_{KL}(Q||P)$
- (Not yet) Fact - $D_{KL}(P||Q) \geq 0$

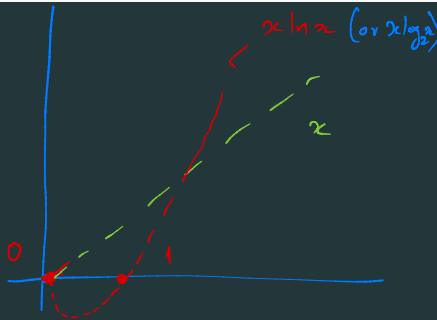
the function $\phi(x) = x \ln x$ ~~$\log_2 x$~~

$$\lim_{x \rightarrow 0} \left(\frac{\ln x}{1/x} \right) = \lim_{x \rightarrow 0} \left(\frac{1/x}{-1/x^2} \right) = 0$$

$$\frac{d\phi(x)}{dx} = 1 + \ln x$$

$$\frac{d^2\phi(x)}{dx^2} = \frac{1}{x} > 0 \quad \forall x > 0 \Rightarrow \phi(x) \text{ is convex}$$

$$\text{Jensen's Ineq} \quad \mathbb{E}[\phi(x)] \geq \phi(\mathbb{E}[x])$$



relative entropy and Gibb's inequality

the relative entropy $D_{KL}(p||q) = \sum_{x \in \mathcal{X}} p(x) \ln \left(\frac{p(x)}{q(x)} \right) \geq 0$ for all p, q

p absolutely cont w.r.t q

- $D_{KL}(p||q) = \sum_x q(x) \left(\frac{p(x)}{q(x)} \right) \ln \left(\frac{p(x)}{q(x)} \right)$ (i.e., $q(x) > 0 \forall x$ s.t. $p(x) > 0$)

Define $Y = p(x)/q(x)$ with prob $q(x) \forall x \in \mathcal{X}$

$$\Rightarrow D_{KL}(p||q) = \mathbb{E}_q[Y \ln Y]$$

$$\geq (\mathbb{E}_q Y) \ln (\mathbb{E}_q Y) \geq 0$$

$$\mathbb{E}_q(Y) = \sum_x q(x) \cdot \left(\frac{p(x)}{q(x)} \right) = 1$$



optimizing expected code length

$$E[L(c, x)] = H(p) + D_{KL}(P \parallel Q) + \log_2 \frac{1}{Z}$$

$$\left(\text{where } Z = \sum_i 2^{-l_i}, \quad D_{KL}(P \parallel Q) = \sum_i p_i \log\left(\frac{p_i}{q_i}\right) \right)$$

$$\geq H(p) \quad (\text{Via Kraft + Gibbs})$$

Moreover, $E[L(c, x)] = 0$ if $Z = 1$ (ie complete code)

and $p_i = q_i$

$$\Rightarrow l_i = \log_2\left(\frac{1}{p_i}\right) = h(a_i)$$

optimizing expected code length

In practice - choose $l_i = \lceil \log_2 \frac{1}{p_i} \rceil$

- (Check) - $\sum_{i \in X} 2^{-l_i} \leq 1$

- $E[L(C, X)] = \sum_i p_i \underbrace{\lceil \log_2 \frac{1}{p_i} \rceil}_{\leq \left(\log_2 \frac{1}{p_i} \right) + 1}$

$$\leq H(p) + 1$$

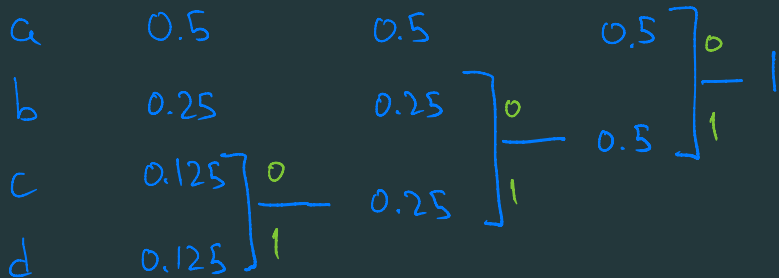
aside: cross entropy

the **cross entropy** of p given q : $H_p(q) = \sum_{x \in \mathcal{X}} p(x) \ln \left(\frac{1}{q(x)} \right)$
– avg length of message from if ' p mis-estimated as q '

- $D_{KL}(P \parallel Q) = \sum p_i \log \frac{p_i}{q_i} \geq H(P) = \sum p_i \log \frac{1}{p_i}$
- $H_p(Q) = D_{KL}(P \parallel Q) + H(P)$ (?)

Huffman code

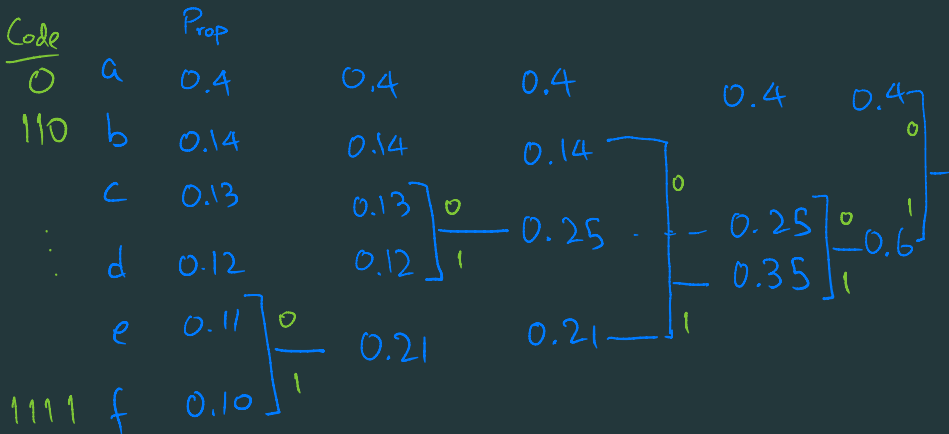
consider $X \sim \{a, b, c, d, \text{~~fff~~}\}$ with prob $\{0.5, 0.25, 0.125, 0.125\}$



$$\Rightarrow \{0, 10, 110, 111\}$$

Huffman code

consider $X \sim \{a, b, c, d, e, f\}$ with prob $\{0.4, 0.14, 0.13, 0.12, 0.11, 0.10\}$



aside: information content in a perfect code

let C be a perfect code for X , and given database $X_1 X_2 \dots X_n$, suppose we pick one bit at random from the encoded sequence $C(X_1)C(X_2) \dots C(X_n)$. what is the probability this bit is a 1?

P	alphabet	code	'# of 1's'
$1/2$	a	0	0
$1/4$	b	10	$1/2$
$1/8$	c	110	$2/3$
$1/8$	d	111	1

$$\begin{aligned} \times \left[\mathbb{P}[\text{bit} = 1] \right] &= 0 + 1/8 + 2/24 + 1/8 \\ &= 1/3 \\ &= \sum p_i f_i \quad \times \end{aligned}$$

$$\mathbb{P}[\text{bit} = 1] = \frac{\sum p_i \cdot f_i \cdot l_i}{\sum p_i \cdot l_i} = 0.5$$