

ΣΕΕ6310

3/13/2018

$$\text{PMF} \quad P_X(k) = P(X=k) \quad k = \dots$$

$$\mu_X = E(X) = \sum_{k=0}^{\infty} k P_X(k) \quad E(X^2) = \sum_{k=0}^{\infty} k^2 P_X(k)$$

mean

$$\text{MGF} \quad M(u) = E(e^{uX}) = \sum_{k=0}^{\infty} e^{uk} P_X(k) \Leftrightarrow M(0) = 1$$

$$\left. \frac{dM}{du} \right|_{u=0} = E(X e^{uX}) \Big|_{u=0} = E(X)$$

2 or more variables

$$P_{XY}(k,l) = P(X=k \wedge Y=l)$$

$$E(XY) = \sum_{k=0}^{\infty} \sum_{l=0}^{\infty} kl P_{XY}(k,l) \leftarrow$$

Covariance

$$E((X - \mu_x)(Y - \mu_y)) = \sigma_{xy} = E(XY) - \mu_x \mu_y$$

def

thm

Variance

$$\sigma_x^2 = E((X - \mu_x)^2) = E(X^2) - \mu_x^2$$

def

thm

Correlation

X and Y are independent if

$$P_{xy}(k, l) = P_x(k) P_y(l)$$

for all k, l

X and Y are uncorrelated if $E(XY) = \mu_x \mu_y$

ind \Rightarrow unc

unc \nRightarrow ind

$$X \text{ and } Y \text{ ind} \Rightarrow Z = X + Y$$

$$P_Z = P_X \otimes P_Y$$

$$k=1,2,3$$

$$P_X(k) = \left[\frac{1}{2}, 0, \frac{1}{2} \right] = \frac{1}{2} [1, 0, 1]$$

$$P_Y(l) = \left[\frac{1}{4}, \frac{1}{4}, \frac{1}{4}, \frac{1}{4} \right] = \frac{1}{4} [1, 1, 1, 1]$$

$$l=1,2,3,4$$

3	3	2	4
1	3	2	0
0	0	0	0
1	3	2	4

$$\begin{array}{r} 33 \\ 5724 \end{array}$$

$$P(Z=2) = \frac{3}{24}$$

$$M=2$$

$$24$$

Sums of RVs

$$Z = X + Y$$

X and Y may not be ind.

$$E(Z) = E(X+Y) = E(X) + E(Y) = \mu_x + \mu_y$$

$$\text{Var}(Z) = E((X+Y - \mu_x - \mu_y)^2)$$

$$= E(((X - \mu_x) + (Y - \mu_y))^2)$$

$$= E((X - \mu_x)^2 + 2(X - \mu_x)(Y - \mu_y) + (Y - \mu_y)^2)$$

$$= \underbrace{E((X - \mu_x)^2)}_{\sigma_x^2} + 2 \underbrace{E((X - \mu_x)(Y - \mu_y))}_{\sigma_{xy}} + \underbrace{E((Y - \mu_y)^2)}_{\sigma_y^2}$$

$$Z = V + X + Y$$

$$E(Z) = E(V) + E(X) + E(Y)$$

$$\sigma_Z^2 = \sigma_V^2 + \sigma_X^2 + \sigma_Y^2 + 2\sigma_{XY} + 2\sigma_{VX} + 2\sigma_{VY}$$

Entropy & Information Theory

$$H(X) = - \sum_{k=0}^{\infty} P_X(k) \log_2 P_X(k)$$

= bits

$$\log_2 8 = 3$$

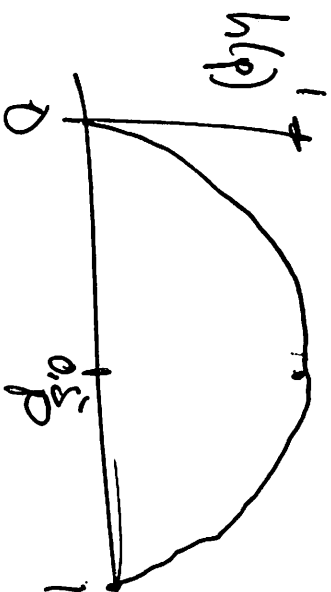
$$\Rightarrow 2^3 = 8$$

= measure of how random X is

Ex. X is Bernoulli RV $P(X=1)=p$ $P(X=0)=1-p=q$

$$H(X) = h(p) = -\sum_{k=0}^1 p(k) \log_2 p(k) \quad H(X) \geq 0$$

$$= -q \log_2 q - p \log_2 p = -(1-p) \log_2 (1-p) - p \log_2 p$$



Ex X uniform $k=1, 2, \dots, m$

$$H(X) = -\sum_{k=1}^m p(k) \log_2 p(k) = -\sum_{k=1}^m \frac{1}{m} \log_2 \left(\frac{1}{m}\right) = \log_2(m)$$

Theorem if $P(X=k) = p(k) \quad k=1, \dots, m,$

$$0 \leq t(x) \leq \log_2 m$$

Calculus of Variations

$$\begin{aligned} \max_{P(k)} \quad & H(X) = - \sum p(k) \log_2 p(k) \\ \text{s.t.} \quad & p(k) \geq 0 \quad \text{and} \quad \sum_{k=1}^m p(k) = 1 \end{aligned}$$

$$\Rightarrow \max_{P(k), \lambda} \quad H(X) + \lambda \left(1 - \sum_{k=1}^m p(k) \right)$$

Lagrange multiplier

$$\frac{\partial \mathcal{L}}{\partial p(k)} = -\log p(k) - 1 - \lambda = 0$$

$k=1, 2, \dots, m$

$$\frac{\partial \mathcal{L}}{\partial \lambda} = 1 - \sum_{k=1}^m p(k) = 0$$

Lagrange multiplier

$$H(X) = - \sum_{k=1}^m p(k) \log p(k)$$

$$\begin{aligned} \frac{d}{dp} p \log p &= \log p + p \cdot \frac{1}{p} \\ &= (\log p + 1) \end{aligned}$$

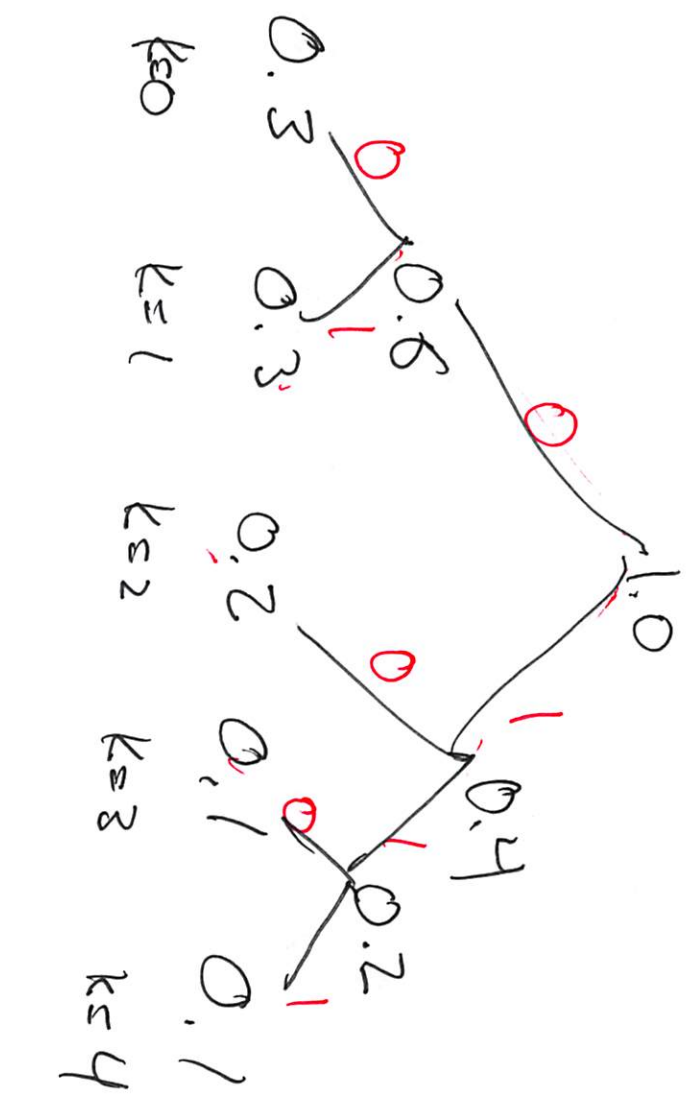
$$O = -\log p(x) = 1 - \lambda$$

$$\Rightarrow \log_2 p(x) = -1 - \lambda \quad p = 1, 2, \dots, m$$

$$\Rightarrow \log_2 p(x) = \text{const}$$

$$\Rightarrow p(x) = \text{const} \Rightarrow p(x) = \frac{1}{m}$$

Theorem: transmitting X requires at least $h(X)$ bits on average.



Code book

k	0	1	2	3	4
0	00	01	10	11	11
1	00	01	10	11	11
2	00	01	10	11	11
3	00	01	10	11	11
4	00	01	10	11	11

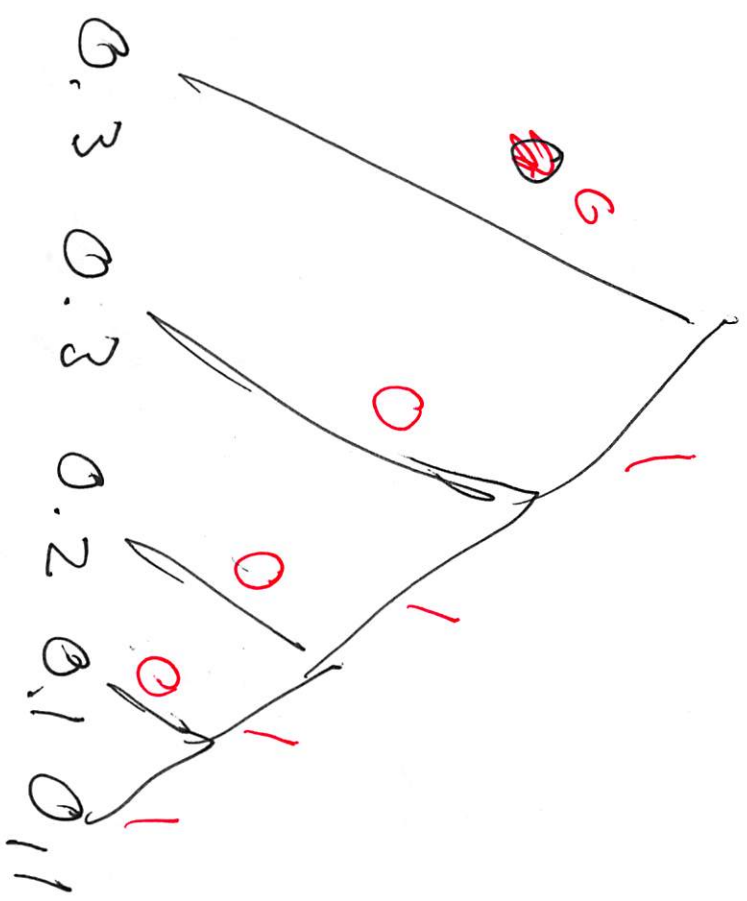
Huffman algorithm

$L(X) = \# \text{ bits required to transmit } X$

$$E(L(X)) = \sum_{k=0}^4 L(k) P(k) = 2 \times 0.3 + 2 \times 0.3 + 2 \times 0.2 + 3 \times 0.1 + 3 \times 0.1 = 2.2 \text{ bits}$$

$$E(L(x)) = 1 \times 0.3 + 2 \times 0.3 + 3 \times 0.2 + 4 \times 0.1$$

~~2.4~~ bits
2.3



	111			
0	0	0	0	0
1	0	1	0	1
2	0	0	1	0
3	0	0	0	1
4	0	0	0	0