

lec 9: Entropy rateRecap

- \* stationary random sequence  $\{x_n\}$   
(Random process)
- \* Markov chain or Markov process
- \* Time invariant Markov chains
  - irreducible, aperiodic, example
  - stationary distribution

\* entropy rate

$H(\mathcal{X}_0) = \lim_{n \rightarrow \infty} \frac{H(x_1, \dots, x_n)}{n}$  when the limit exists

$= H(X)$  if  $\{x_n\}$  iid

- saw an example where  $x_i$ 's are independent but not identical  
- where limit does not exist

TODAY

- specialize to case of stationary process.
- Show that the limit corresponding to  $H(\mathcal{X}_0)$  exists.
- Compute for a stationary Markov chain (Example)

Define:

$H'(\mathcal{X}_0) = \lim_{n \rightarrow \infty} H(x_n | x_1, \dots, x_{n-1})$   
(when the limit exists)

Thm: For a stationary random process

$$H(\mathcal{X}_0) = H'(\mathcal{X}_0)$$

Pf: We will first show that  $\lim_{n \rightarrow \infty} H(x_n | x_1, \dots, x_{n-1})$  exists

Note that  $H(x_{n+1} | x_1, \dots, x_n) \leq H(x_{n+1} | x_2, \dots, x_n)$   
(conditioning reduces entropy)

$0 \leq H(x_{n+1} | x_1, \dots, x_n) \leq H(x_n | x_1, \dots, x_{n-1})$   
(by stationarity)  $\leftarrow$  monotonically

$\therefore H(x_n | x_1, \dots, x_{n-1})$  is a decreasing (non-increasing) sequence and is lower bounded by 0.

Hence the limit exists

(See fundamental concepts of Analysis, Rudin)

Lemma: (Cesaro mean)

If  $a_n \rightarrow a$  and  $b_n \triangleq \frac{\sum_{i=1}^n a_i}{n}$ , then  $b_n \rightarrow a$  as well.

Goal is to show that

$$\lim_{n \rightarrow \infty} \frac{H(x_1, \dots, x_n)}{n} \rightarrow H'(\mathcal{X}_0) \text{ as well.}$$

$$\lim_{n \rightarrow \infty} \frac{H(x_1, \dots, x_n)}{n} = H(\mathcal{X}_0)$$

Natural

Pf (of lemma)

Goal: Given <sup>any</sup>  $\epsilon > 0$ , to show that  $\exists n_\epsilon \in \mathbb{N}$  such that  $\forall n \geq n_\epsilon$   
 $|b_n - a| \leq \epsilon$

Consider

$$|b_n - a| = \left| \frac{\sum_{k=1}^n a_k}{n} - a \right| = \frac{1}{n} \left| \sum_{k=1}^n (a_k - a) \right|$$

$$\leq \frac{1}{n} \sum_{k=1}^n |a_k - a|$$

Now choose  $M_\epsilon$  st  $|a_k - a| \leq \epsilon/2 \quad \forall k > M_\epsilon$

$$\text{then } \frac{1}{n} \sum_{k=1}^n |a_k - a| = \frac{1}{n} \sum_{k=1}^{M_\epsilon} |a_k - a| + \frac{1}{n} \sum_{k=M_\epsilon+1}^n |a_k - a|$$

$$\leq \frac{M_\epsilon}{n} \max_{k=1}^{M_\epsilon} (a_k - a) + \frac{\epsilon}{2}$$

Now choose  $n_\epsilon$  large enough st

$$\text{st } \frac{M_\epsilon}{n_\epsilon} \max_{k=1}^{M_\epsilon} (a_k - a) \leq \epsilon/2$$

$$\text{i.e., } n_\epsilon > \frac{2M_\epsilon}{\epsilon} \max_{k=1}^{M_\epsilon} (a_k - a)$$

for that  $n_\epsilon$ ,  $\forall n \geq n_\epsilon$

$$|b_n - a| \leq \epsilon.$$

Assume  $a_n = H(X_n | X_1 \dots X_{n-1})$ .

then  $b_n = \frac{H(X_1, \dots, X_n)}{n}$ , It follows that

$$H(X_0) = \lim_{n \rightarrow \infty} b_n = \lim_{n \rightarrow \infty} a_n = H'(X_0) \quad //$$

Next, we focus on the case of a markov chain. that is stationary  
 for a markov chain (we assume time invariance)

$$H(X_n | X_1 \dots X_{n-1}) = H(X_n | X_{n-1})$$

$$\begin{aligned} &= H(X_2 | X_1) \\ &= \sum_i P_{X_1}(i) \sum_j P_{X_2|X_1}(j|i) \log P_{X_2|X_1}(j|i) \end{aligned}$$

$= \sum_{X_{n-1}} P(X_{n-1}) \sum_{X_n} P(X_n | X_{n-1}) \log P(X_n | X_{n-1})$   
 $\log P(X_n | X_{n-1})$

*by time invariance*

Hence the limit is easily

$$\begin{aligned}
 H(X_m | X_1, \dots, X_{m-1}) &= H(X_m | X_{m-1}) \quad \text{\{ By definition of markov chain \}} \\
 &= \sum_{x_{m-1}} P_{X_{m-1}}(x_{m-1}) \sum_{x_m} P_{X_m | X_{m-1}}(x_m | x_{m-1}) \log \frac{1}{P_{X_m | X_{m-1}}(x_m | x_{m-1})} \\
 &\stackrel{\text{By stationarity}}{\longleftarrow} \sum_{x_{n-1}} P_1(x_{n-1}) \sum_{x_n} P_{X_2 | X_1}(x_n | x_{n-1}) \log \frac{1}{P_{X_2 | X_1}(x_n | x_{n-1})} \quad \text{\{ by time invariance \}} \\
 &= \sum_{x_1} P_1(x_1) \sum_{x_2} P_{X_2 | X_1}(x_2 | x_1) \log \frac{1}{P_{X_2 | X_1}(x_2 | x_1)}
 \end{aligned}$$

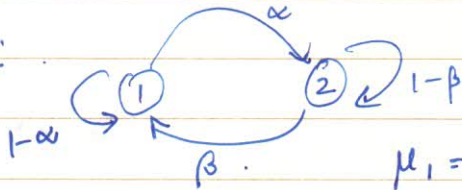
$= H(X_2 | X_1)$  Hence the limit is easily computed  
 let  $[\mu_1, \mu_2, \dots, \mu_m]$  represent the stationary distribution of the markov chain. Then

$$\mu_j = \sum_{i \in \mathcal{X}_0} \mu_i P_{ij} \quad m = |\mathcal{X}|$$

↓  
P(j|i)

$$H(X_2 | X_1) = \sum_i \mu_i \sum_j P_{ij} \log \frac{1}{P_{ij}} = \sum_i \mu_i H(P_{i1}, P_{i2}, \dots, P_{im})$$

Eq:



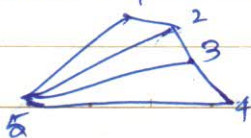
$$\mu_1 = \frac{\beta}{\alpha + \beta}, \quad \mu_2 = \frac{\alpha}{\alpha + \beta}$$

$$\therefore H(X_2 | X_1) = \frac{\beta}{\alpha + \beta} H(\alpha) + \frac{\alpha}{\alpha + \beta} H(\beta)$$

$$\mu_1 \left( P_{11} \log \frac{1}{P_{11}} + P_{12} \log \frac{1}{P_{12}} \right) + \mu_2 \left( P_{21} \log \frac{1}{P_{21}} + P_{22} \log \frac{1}{P_{22}} \right)$$

$\underbrace{\hspace{10em}}_{H(\alpha, 1-\alpha)} \quad \quad \quad \underbrace{\hspace{10em}}_{H(\beta, 1-\beta)}$

Eq: Consider a random walk on graph.



Assume that the weights are given by

$$w_{ij} \quad \text{\textcircled{1}} \xrightarrow{w_{ij}} \text{\textcircled{j}}$$

$$\text{\textcircled{1}} \xleftarrow{w_{ji}} \text{\textcircled{j}}$$

Assume an undirected graph i.e.,  $W_{ij} = W_{ji}$

Define  $W_i = \sum_j W_{ij}$  (the sum of weights of outgoing edges)

$$\text{Prob } i \rightarrow j = P_{ij} = P(j|i) = \frac{W_{ij}}{\sum_j W_{ij}}$$

What is the stationary distribution?

$$\pi_j = \sum_i \pi_i P_{ij} = \sum_i \pi_i \frac{W_{ij}}{W_i} \quad \text{uniform}$$

$$1 = \sum_j \pi_j = \sum_j \sum_i \pi_i \frac{W_{ij}}{W_i} = \sum_i \pi_i$$

Define:  $\sum_{i>j} W_{ij} = W \Rightarrow \sum_i W_i = 2W$

Guesses

$$\pi_i = \frac{W_i}{2W}$$

Need that

$$\pi_j = \sum_i \pi_i P_{ij} = \sum_i \frac{W_i}{2W} \frac{W_{ij}}{W_i} = \frac{\sum_i W_{ij}}{2W} = \frac{W_j}{2W}$$

$$\left. \begin{aligned} \pi_j P_{ji} &= \pi_i P_{ij} \\ \pi_j \frac{W_{ji}}{W_j} &= \pi_i \frac{W_{ij}}{W_i} \\ \Rightarrow \frac{\pi_j}{\pi_i} &= \frac{W_j}{W_i} \end{aligned} \right\}$$

Thus the stationary distribution is  $\left\{ \frac{W_i}{2W} \right\}_{i=1}^m$

What is  $H(X_2|X_1)$

$$H(X_2|X_1) = \sum_{i=1}^m \pi_i \sum_{j=1}^m P_{ij} \log \frac{1}{P_{ij}} \quad \text{twice } \# \text{ of edges.}$$

$$= \sum_{i=1}^m \frac{W_i}{2W} \sum_{j=1}^m \frac{W_{ij}}{W_i} \log \frac{W_i}{W_{ij}} \quad H\left(\dots, \frac{W_{ij}}{2W}, \dots\right)$$

$$= \sum_{i=1}^m \sum_{j=1}^m \frac{W_{ij}}{2W} \log \frac{W_i}{W_{ij}} = \sum_{i=1}^m \sum_{j=1}^m \frac{W_{ij}}{2W} \log \frac{2W}{W_{ij}}$$

$$= H\left(\dots, \frac{W_{ij}}{2W}, \dots\right) - H\left(\dots, \frac{W_i}{2W}, \dots\right) - \sum_{i=1}^m \sum_{j=1}^m \frac{W_{ij}}{2W} \log \frac{2W}{W_i}$$

$$H\left(\dots, \frac{W_i}{2W}, \dots\right)$$

$m$  terms  
# of nodes.

Natural

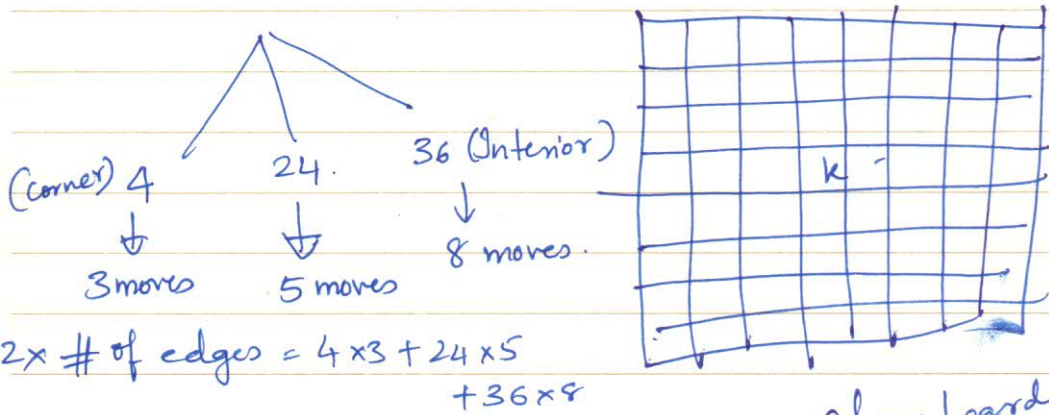
Suppose all wts are 1.

$$W = \# \text{ edges} = E \quad 2W = 2E$$

$$W_{ij} = 1$$

$$\sum_j W_{ij} = d_i \quad (\text{degree of node } i)$$

$$H(X_2|X_1) = \log 2W - \sum_i H\left(\frac{d_i}{2E}, \dots, \frac{d_m}{2E}\right)$$



$$2 \times \# \text{ of edges} = 4 \times 3 + 24 \times 5 + 36 \times 8$$

$$= 12 + 120 + 288 = 420$$

$$E = 210$$

$$\log(420) - H(\dots)$$

$$= 0.52 \log 8$$