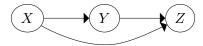
## Topic 15: Graphical Representations of Random Variables

02-680: Essentials of Mathematics and Statistics

November 13, 2024

## 1 Bayesian Networks

Sometimes we need a more complicated conditional description. One way to do this is using a network (graph).



In general for a network such as this we define the probabilities as:

$$p(\langle Q_1, Q_2, ..., Q_d \rangle) = \prod_{i=0}^{d} p\left(Q_i \middle| \bigwedge_{j \in N^{in}(Q_i)} Q_j\right)$$

remember that  $N^{in}(v)$  is the set of in-neighbors of v in a graph.

So for the Bayesian Network above, we may have something like:

							$p(Z \mid Y, X)$	
x	p(X=x)		$p(Y \mid X)$		x	y	z = 1	z = 0
0	$\frac{p(n-\omega)}{0.7}$	$\boldsymbol{x}$	y = 1	y = 0	0	0	0.3	0.7
1 1		0	0.5	0.5	0	1	0.1	0.9
1	0.3	1	0.9	0.1	1	0	0.7	0.3
					1	1	0.4	0.6

But if we alter the network to the following (i.e. remove the dependence of Z on X),

$$X \longrightarrow Y \longrightarrow Z$$

we end up with

x	p(X=x)		$\begin{array}{c c} p(Y \mid X) \\ y = 1 \mid y = 0 \end{array}$			$p(Z \mid Y, X)$	
0	0.7	x			y	z = 1	
1	0.3	0	0.5	0.5	0	0.2	0.8
	0.0	1	0.9	0.1	1	0.7	0.3

## 2 Markov Chains

Markov chains are usually used to model sequences of items. We saw when talking about conditional probabilities that:

$$p(X_n, X_{n-1}, ...X_1) = p(X_n \mid X_{n-1}, ...X_1)p(X_{n-1}, ...X_1)$$
(1)

$$= p(X_n \mid X_{n-1}, ... X_1) p(X_{n-1} \mid X_{n-2}, ... X_1) p(X_{n-2}, ... X_1)$$
 (2)

$$\dots$$
 (3)

$$= p(X_n \mid X_{n-1}, ... X_1) ... p(X_2 \mid X_1) p(X_1)$$
(4)

(5)

The *Markov assumption* is that the probability of  $X_k$  depends on  $X_{k-1}$  alone. This simplifies the computation, but at the cost of long term connections. Anecdotally the Markov assumption says:

the future is independent of the past given the present.

So that means we can rewrite the statement above as:

$$p(X_n, X_{n-1}, ... X_1) = p(X_n \mid X_{n-1}) p(X_{n-1} \mid X_{n-2}) ... p(X_2 \mid X_1) p(X_1).$$

This is the basis for *Hidden Markov Models* which are used a lot in genetics.

**Example.** Consider a sequence of DNA nucleotides modeled as a set of random variables  $N_1 N_2 ... N_n$ , each of which can take on the value  $\{A, T, C, G\}$ . We want to know if the sequence is a CpG island or not.

Looking at the equation above, if we know the initial distribution (that is the probability distribution for  $p(N_1)$ ) for both cases, and the transition distributions ( $p(N_k \mid N_{k-1})$ ) we can determine which is more probable.

$$P_b = \begin{bmatrix} & \mathsf{A} & \mathsf{C} & \mathsf{G} & \mathsf{T} \\ \mathsf{A} & 0.30 & 0.20 & 0.29 & 0.21 \\ \mathsf{C} & 0.32 & 0.30 & 0.08 & 0.30 \\ \mathsf{G} & 0.25 & 0.25 & 0.29 & 0.21 \\ \mathsf{T} & 0.18 & 0.24 & 0.29 & 0.29 \end{bmatrix} \quad P_c = \begin{bmatrix} & \mathsf{A} & \mathsf{C} & \mathsf{G} & \mathsf{T} \\ \mathsf{A} & 0.18 & 0.27 & 0.43 & 0.12 \\ \mathsf{C} & 0.17 & 0.37 & 0.27 & 0.19 \\ \mathsf{G} & 0.16 & 0.34 & 0.37 & 0.13 \\ \mathsf{T} & 0.08 & 0.36 & 0.38 & 0.18 \end{bmatrix}$$

Assuming for both  $p(N_1 = A) = p(N_1 = C) = p(N_1 = T) = p(N_1 = G) = 0.25$ , what is the sequence ACTTC more likely to be a CpG island or not?

## **Useful References**

Degroot and Schervish. "Probability and Statistics"  $\S 3.10$