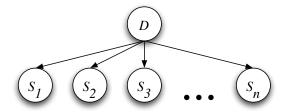
### CSE 150. Assignment 2

Out: Tue Jan 22 Due: Tue Jan 29

**Reading**: Russell & Norvig, Chapter 14; Korb & Nicholson, Chapter 2.

#### 2.1 Probabilistic reasoning

A patient is known to have contracted a rare disease which comes in two forms, represented by the values of a binary random variable  $D \in \{0,1\}$ . Symptoms of the disease are represented by the binary random variables  $S_k \in \{0,1\}$ , and knowledge of the disease is summarized by the belief network:



The conditional probability tables (CPTs) for this belief network are as follows. In the absence of evidence, both forms of the disease are equally likely, with prior probabilities:  $P(D=0) = P(D=1) = \frac{1}{2}$ . In the first form of the disease (D=0), the first symptom occurs with probability one,

$$P(S_1=1|D=0)=1,$$

while the  $k^{\rm th}$  symptom (with  $k \ge 2$ ) occurs with probability

$$P(S_k=1|D=0) = \frac{f(k-1)}{f(k)},$$

where the function f(k) is defined by

$$f(k) = 2^k + (-1)^k.$$

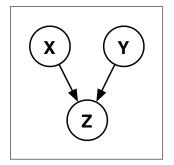
By contrast, in the second form of the disease (D=1), all the symptoms are uniformly likely to be observed, with  $P(S_k=1|D=1)=\frac{1}{2}$  for all k.

Suppose that on the  $k^{\rm th}$  day of the month, a test is done to determine whether the patient is exhibiting the  $k^{\rm th}$  symptom, and that each such test returns a positive result. Thus, on the  $k^{\rm th}$  day, the doctor observes the patient with symptoms  $\{S_1=1,S_2=1,\ldots,S_k=1\}$ . Based on the cumulative evidence, the doctor makes a new diagnosis each day by computing the ratio:

$$r_k = \frac{P(D=1|S_1=1, S_2=1, \dots, S_k=1)}{P(D=0|S_1=1, S_2=1, \dots, S_k=1)}.$$

If this ratio is greater than 1, the doctor diagnoses the patient with the D=1 form of the disease; otherwise, with the D=0 form. Compute the ratio  $r_k$  as a function of k. How does the doctor's diagnosis depend on the day of the month? Does the diagnosis become more or less certain as more symptoms are observed? Explain.

## 2.2 Noisy-OR



**Nodes:** 
$$X \in \{0,1\}, Y \in \{0,1\}, Z \in \{0,1\}$$

**Noisy-OR CPT:** 
$$P(Z = 1|X, Y) = 1 - (1 - p_x)^X (1 - p_y)^Y$$

**Parameters:** 
$$p_x \in [0, 1], p_y \in [0, 1], p_y < p_x$$

Suppose that the nodes in this network represent binary random variables and that the CPT for P(Z|X,Y) is parameterized by a noisy-OR model, as shown above. Suppose also that

$$0 < P(X = 1) < 1,$$

$$0 < P(Y=1) < 1,$$

while the parameters of the noisy-OR model satisfy:

$$0 < p_u < p_x < 1$$
.

Consider the following pairs of probabilities. In each case, indicate whether the probability on the left is equal (=), greater than (>), or less than (<) the probability on the right.

(a) 
$$P(Z=1|X=0,Y=1)$$
  $P(Z=1|X=0,Y=0)$ 

(b) 
$$P(Z=1|X=1,Y=0)$$
  $P(Z=1|X=0,Y=1)$ 

(c) 
$$P(Z=1|X=1,Y=0)$$
  $P(Z=1|X=1,Y=1)$ 

(d) 
$$P(X=1|Z=1)$$
  $P(X=1)$ 

(e) 
$$P(X=1|Y=1)$$
  $P(X=1)$ 

(f) 
$$P(X=1|Z=1)$$
  $P(X=1|Y=1,Z=1)$ 

(g) 
$$P(X=1) P(Y=1) P(Z=1)$$
  $P(X=1, Y=1, Z=1)$ 

### 2.3 Conditional independence

For the belief network shown below, indicate whether the following statements of conditional independence are **true** (**T**) or **false** (**F**).

(a) 
$$P(A,B) = P(A)P(B)$$

(b) 
$$P(A|E) = P(A)$$

(c) 
$$P(A, B|C, D, E) = P(A|C, D) P(B|D, E)$$

(d) 
$$P(A, B, | C, D, E) = P(A, B | C, D, E, F, G)$$

(e) 
$$P(C, D) = P(C) P(D)$$

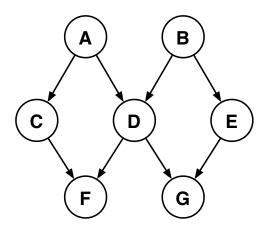
(f) 
$$P(C|E) = P(C)$$

(g) 
$$P(C,D,E) = P(C)P(D|C)P(E|D)$$

(h) 
$$P(D|A, B, F, G) = P(D|A, B, F, G, C)$$

(i) 
$$P(C, D|A, F) = P(C|A, F) P(D|A, F)$$

(j) 
$$P(G|D) = P(G|A,D)$$



# 2.4 Subsets

For the DAG shown below, consider the following statements of conditional independence. Indicate the largest subset of nodes  $S \subseteq \{A, B, C, D, E, F\}$  for which each statement is true. Note that one possible answer is the empty set  $S = \emptyset$  or  $S = \{\}$  (whichever notation you prefer).

(a) 
$$P(A) = P(A|S)$$

(b) 
$$P(A|C) = P(A|S)$$

(c) 
$$P(A|B,C) = P(A|S)$$

(d) 
$$P(B) = P(B|S)$$

(e) 
$$P(B|A,E) = P(B|S)$$

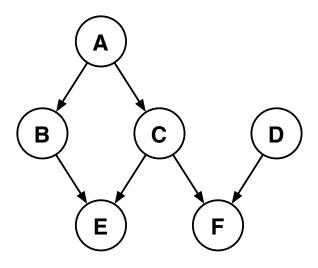
(f) 
$$P(B|A,C,E) = P(B|S)$$

$$(g) P(D) = P(D|S) \underline{\hspace{1cm}}$$

(h) 
$$P(D|F) = P(D|S)$$

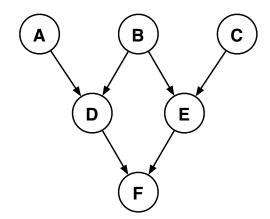
(i) 
$$P(D|C,F) = P(D|S)$$

$$(j) P(F) = P(F|S) \underline{\hspace{1cm}}$$



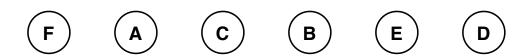
# 2.5 Node ordering

Consider the following belief network with node ordering  $\{A,B,C,D,E,F\}$  and directed acyclic graph (DAG) shown below:



By adding appropriate edges between the nodes shown below, draw the minimal DAG that would be required to represent the same joint distribution for the following alternative node orderings.

(a) 
$$\{F, A, C, B, E, D\}$$



(b) 
$$\{D, E, F, A, B, C\}$$

