BAYESIAN NETWORKS

Today

□ Reading
   ▫ AIMA Chapter 14.1-14.4

□ Goals
   ▫ Bayesian networks

□ Announcements
   ▫ Midterm exam is March 12th

Checking independence

- □ Are X and Y independent?

p(X,Y)		X		
		1	2	3
	1	0	1/6	1/12
Y	2	1/5	1/9	0
	3	2/15	1/4	1/18

Moving away from numerical quantities

"The traditional definition of independence uses equality of numerical quantities, as in

$$p(x, y) = p(x)p(y)$$

suggesting that one must test whether the joint distribution of X and Y is equal to the product of their marginals in order to determine whether X and Y are independent. By contrast people can easily and confidently detect dependencies, even though they may not be able to provide precise numerical estimates of probabilities. A person who is reluctant to estimate the probability of being burglarized the next day or of having a nuclear war within five years can nevertheless state with ease whether the two events are dependent, namely, whether knowing the truth of one proposition will alter the belief of the other."
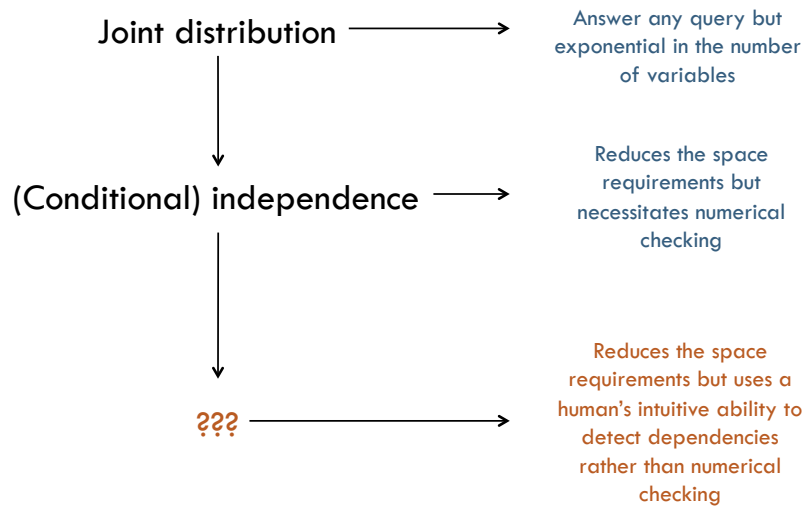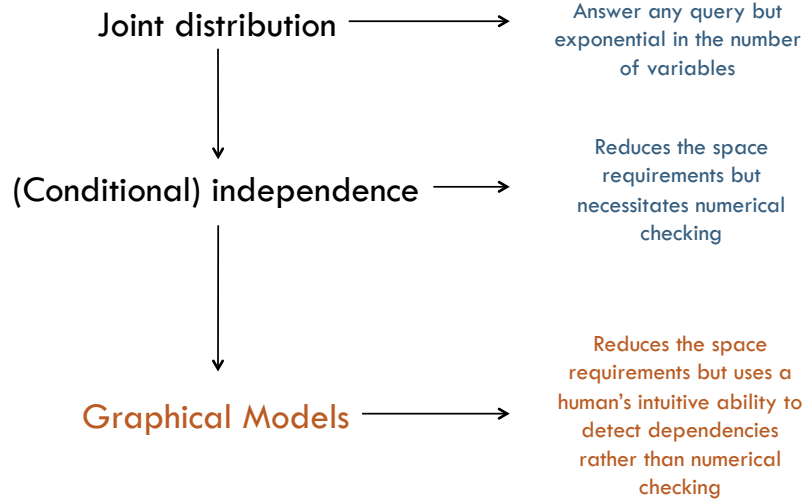
- Judea Pearl

Moving away from numerical quantities

"It is usually easy for a domain expert to decide what direct influences exist in the domain – much easier, in fact, than actually specifying the probabilities themselves"

☐ Humans can "easily and confidently" detect dependencies

☐ Move away from numerical representation of the joint distribution (or the conditional distributions) to a representation that encodes dependencies
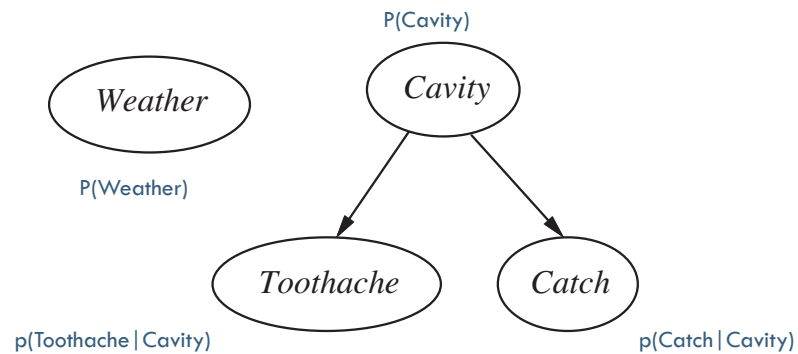
Probabilistic Inference

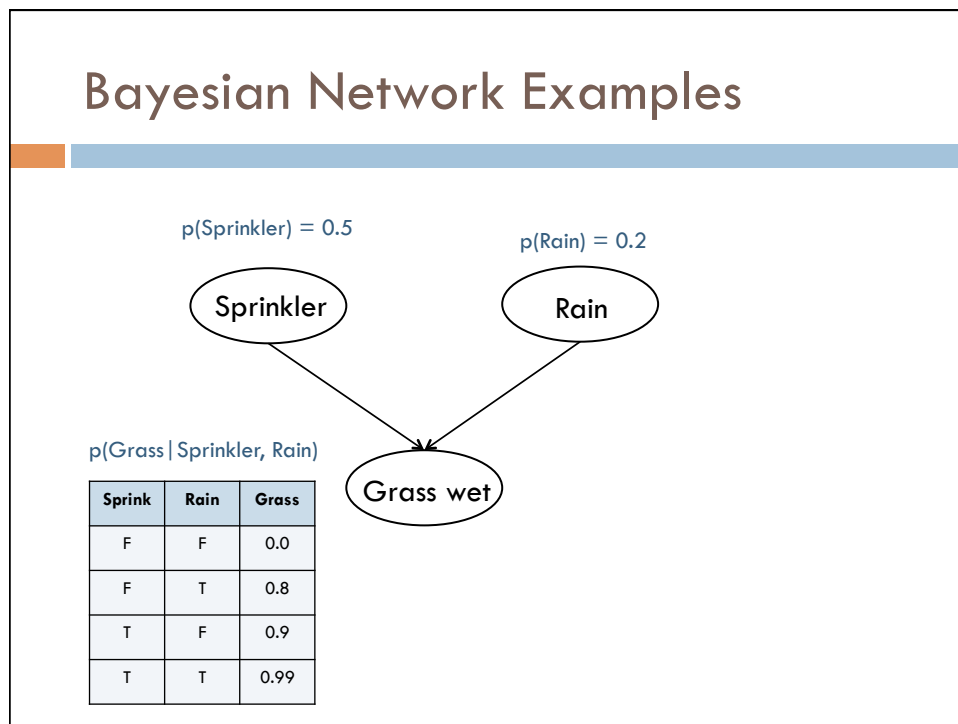Joint distribution ⟶ Answer any query but exponential in the number of variables

⬇

(Conditional) independence ⟶ Reduces the space requirements but necessitates numerical checking

⬇

??? ⟶ Reduces the space requirements but uses a human's intuitive ability to detect dependencies rather than numerical checking

Probabilistic Inference

Joint distribution $\longrightarrow$ Answer any query but exponential in the number of variables

$\downarrow$

(Conditional) independence $\longrightarrow$ Reduces the space requirements but necessitates numerical checking

$\downarrow$

Graphical Models $\longrightarrow$ Reduces the space requirements but uses a human's intuitive ability to detect dependencies rather than numerical checking

Bayesian Network Examples

- Weather = {rainy, sunny, cloudy, snowy}
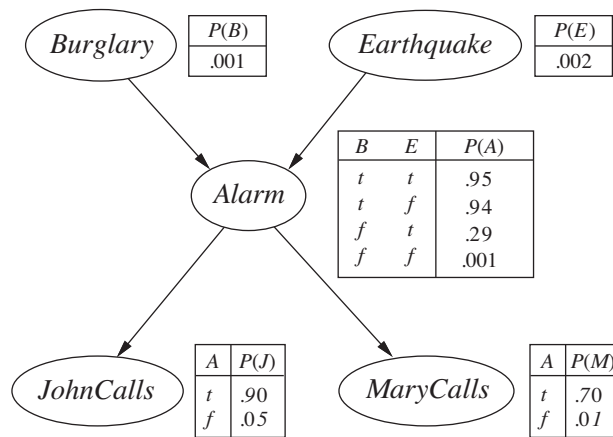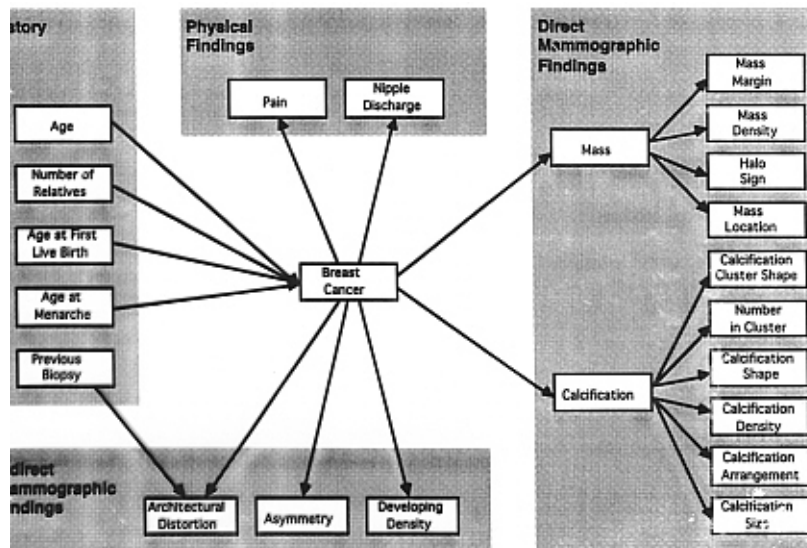- Cavity = { yes, no}
- Toothache = {yes, no}
- Catch = {yes, no}

P(Cavity)

Weather

P(Weather)

Cavity

Toothache   *Catch*

p(Toothache|Cavity)   p(Catch|Cavity)

Bayesian Network Examples

p(Sprinkler) = 0.5   p(Rain) = 0.2

```
   Sprinkler              Rain
        \                 /
         \               /
          \             /
           Grass wet
```

p(Grass | Sprinkler, Rain)

Sprink	Rain	Grass
F	F	0.0
F	T	0.8
T	F	0.9
T	T	0.99

Bayesian Network Examples

p(Sprinkler | Rain)

Rain	Sprink
F	0.5
T	0.01

p(Rain) = 0.2

```
   Sprinkler  ←  Rain
        \        /
         \      /
       Grass wet
```

p(Grass | Sprinkler, Rain)

Sprink	Rain	Grass
F	F	0.0
F	T	0.8
T	F	0.9
T	T	0.99

Bayesian Network Examples

		P(B)
		.001

Burglary

		P(E)
		.002

Earthquake

Alarm

B	E	P(A)
t	t	.95
t	f	.94
f	t	.29
f	f	.001

JohnCalls

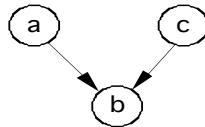| A	P(J)
t	.90
f	.05

MaryCalls

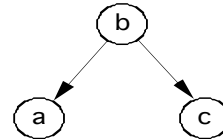| A	P(M)
t	.70
f	.01
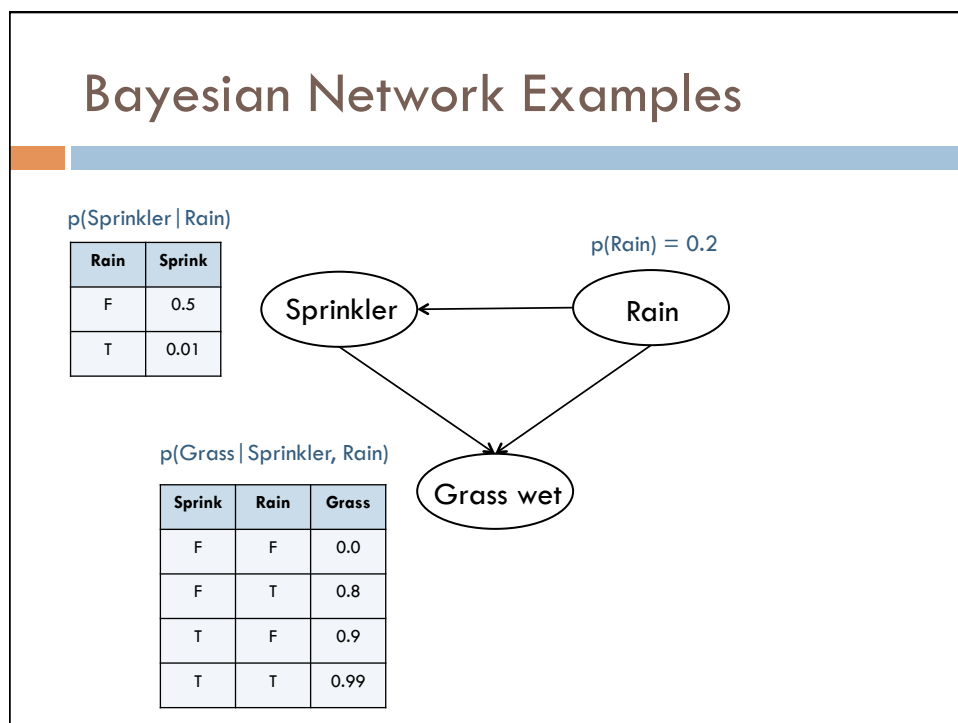
Example: MammoNet

# Three Types of Connections

Linear
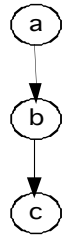
Converging
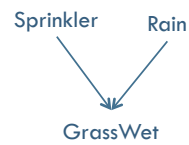
**Diverging**
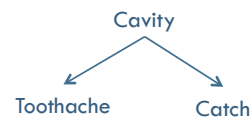
Connection patterns and independence

- **Linear connection:** The two end variables are dependent on each other. The middle variable renders them independent.

- **Converging connection:** The two end variables are independent of each other. The middle variable renders them dependent.

- **Divergent connection:** The two end variables are dependent on each other. The middle variable renders them independent.
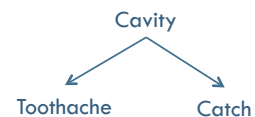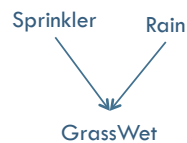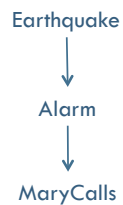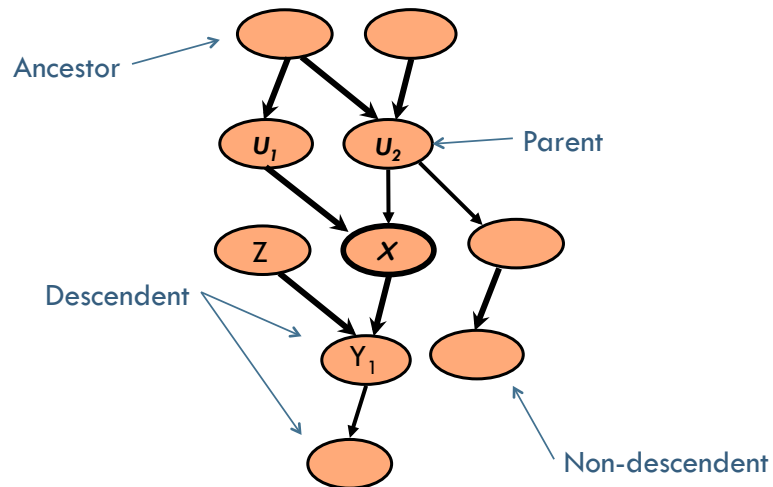
D-Separation

- ☐ Algorithm to determine independencies in BN
- ☐ Query: Are two variables X_i and X_i independent?
- ☐ Check all paths between X_i and X_i
  - ☐ If all paths are blocked, then independent
  - ☐ If any path is not blocked then not independent

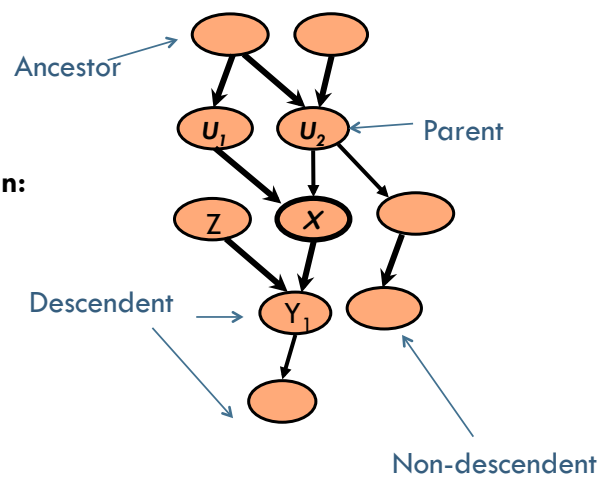# List the independencies in the following Bayesian Network
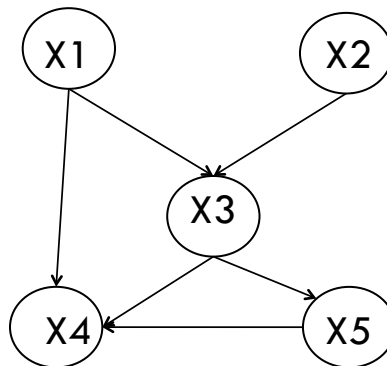
Bayesian Networks terminology

Ancestor

Parent

U_1 U_2

Z X

Descendent

Y_1

Non-descendent

Independence assumptions encoded in the Bayesian Network

Ancestor

Parent

U_1 U_2

Local Markov Assumption:
A node X is independent
of its non-descendants
given its parents

Z X

Descendent Y_1

Non-descendent

Independence assumptions encoded in the Bayesian Network

Markov Blanket:
A node X is conditionally independent of all other nodes given its parents, children, and children's parents

Ancestor

Parent

U_1 U_2

Z X

Descendent

Y_1

Non-descendent
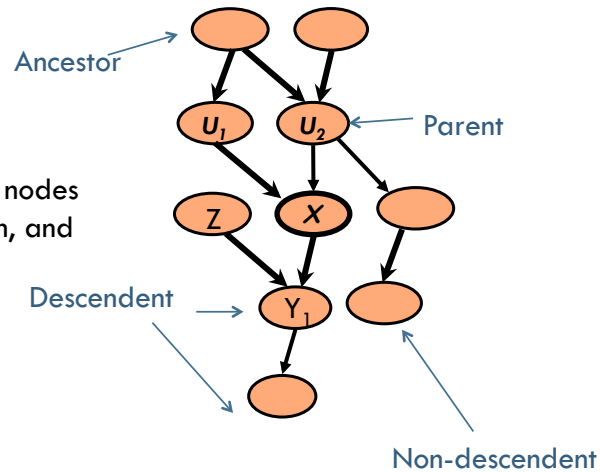
Commonly used Bayesian Networks

□ Naïve (Idiot) Bayes Classifier

■ Commonly used for text classification

■ C is the class (topic or label) of the document

■ The X variables represent the words in the document

C

X_1 X_2 X_3 X_4 … X_n
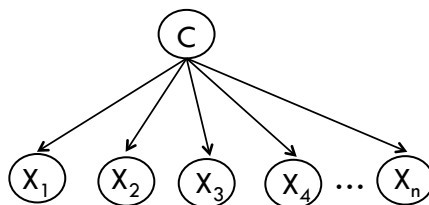
Today an earthquake occurred in Southern California…