COGS 300 **Detection 03** Oct 14/25

warm up: Draw as many networks as you can with different topologies. eg.

tree

cyclic

How may topologies can you find?

Upcoming CSS Events

1. Pomodoro study social tonight @ the lounge, 5pm

2. Alumni student mixer @ Koerners, Oct 17th 6pm.

Probabilistic thinking

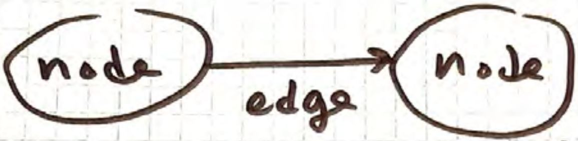
$$P(A) = \frac{\# \text{case}}{\text{total}}$$

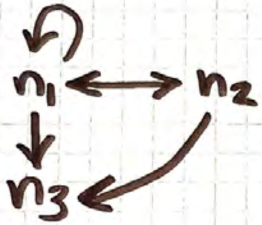
$$P(A|B) = \frac{P(A)P(B|A)}{P(B)}$$

bel[i] = model(obs, expect[i]) · bel[i]

wet grass ?

cloudy	rain	sprinkler	wet grass	time
c	y	n	y	6 pm
c	y	y	y	6 am
c	n	n	n	10 am
c	n	n	n	9 am
S	y	n	y	12 pm
S	n	n	n	7 pm
S	n	n	y	6 am
S	n	y	y	6 am

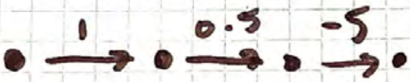




adjacency matrix

	n_1	n_2	n_3
n_1	✓	✓	✓
n_2	✓	X	✓
n_3	X	X	X

isomorphism



Bayes Net.

4

P(Cloudy)

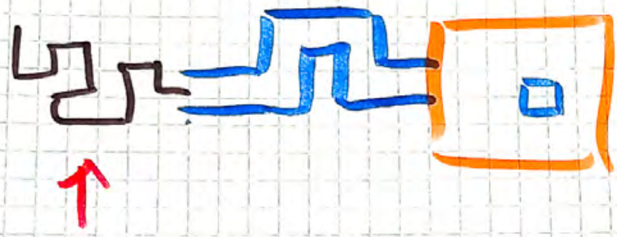
Cloudy = F	Cloudy = T
0.5	0.5

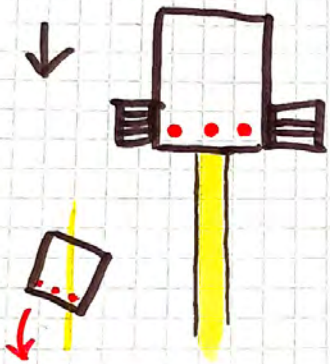
P(Rain | Cloudy)

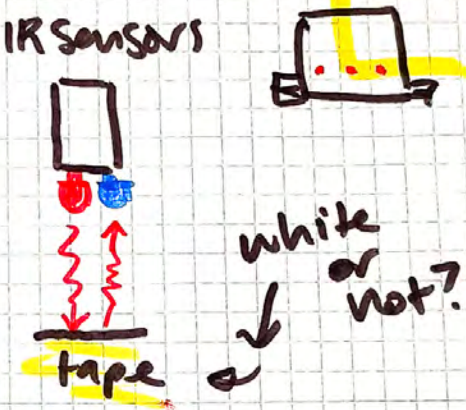
Cloudy	Rain = F	Rain = T
F	0.8	0.2
T	0.2	0.8

P(Wetgrass | sprinkler, rain)

Sp.	Rain	Wet = F	Wet = T
F	F	1.0	0.0
F	T	0.1	0.9
T	F	0.1	0.9
T	T	0.01	0.99







Naive algorithm?

Draw
every
difficulty.

Cases?

model causality w/
Bayes Net?

- which vars to include?
- which do you know a priori?
- which vars influence each other?

encoders - motors

↓

on line

↙ ↓ ↘

s_1 s_2 s_3

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We've been talking about Bayes for a few classes. There's the formula:

$$P(A|B) = \frac{P(A)\,P(B|A)}{P(B)}$$

which is like a single observation.

There's the iterated version, called the Bayes Filter:

$$bel[i] = model(obs, expect[i]) \cdot bel[i]$$

But both of these are just statements about conditional probability:

cloudy/sunny	Rain?	sprinkler?	wet grass?	time of day
c	y	n	y	6 pm
c	y	y	y	6 am
c	n	n	n	10 am
c	n	n	n	9 am
s	y	n	y	12 pm
s	n	n	n	7 pm
s	n	n	y	6 am
s	n	~~n~~ y	y	6 am

cond on cloudy

cond on 6am

cond on sprinkler = yes.

cond on wet = yes

Some observations are not very interesting. eg.

$p(10am)$? 1/24 analytically
1/8 experimentally.

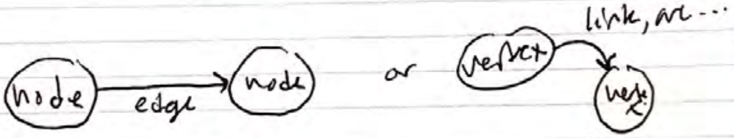
But $p(\text{wet}=\text{yes} \mid 6am) = 100\%$.

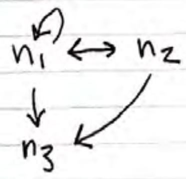
That tells you something!
(experimental)

At the end of the day, a lot of our formulae, models, machine learning etc. are just operations on big tables.

We can use different pictures to help understand, but getting used to tabular view is helpful.

However, one isomorphism is also helpful: the graph





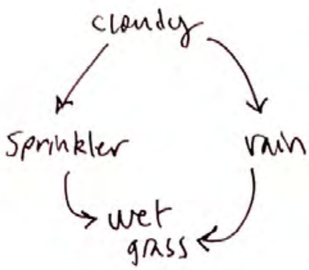
graph

	n_1	n_2	n_3
n_1	X	X	X
n_2	X		X
n_3			

adjacency mtx.

one way of using a graph is a Bayes Net:

Lets say we're trying to infer whether it rained. We could set up the following graph:



In this case, we're using direction to mean dependency

	c	s	r	w
c				
s	x			
r	x			
w		x	x	

Each node needs observation data:

$P(\text{Cloudy})$

cloudy = F	cloudy = T
0.5	0.5

observation.

$P(\text{cloudy}) = 50\%$

$P(\text{Rain} \mid \text{Cloudy})$

cloudy	Rain = F	Rain = T
F	0.8	0.2
T	0.2	0.8

observation

$P(\text{Sprinkler} \mid \text{Cloudy})$

Cloudy	sprinkler = F	Sprinkler = T
F	0.5	0.5
T	0.9	0.1

$P(\text{wetgrass} \mid \text{Sprinkler}, \text{Rain})$

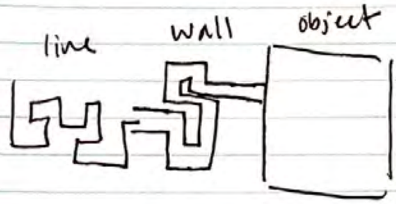
Sp.	Rain	Wet = F	Wet = T
F	F	1.0	0.0
F	T	0.1	0.9
T	F	0.1	0.9
T	T	0.01	0.99

Due to these dependencies, now you can "know" something about cloudy by making an observation "down the chain".

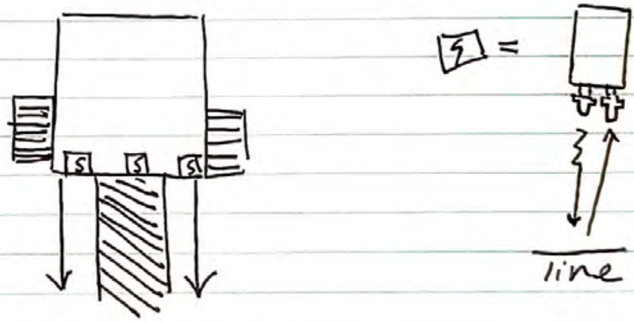
Let's see it in action:

☆ bayesserver.com → open → sprinkler

Your robots. Last time I set up the model tournament:



Let's look at just the line:



☆ Naive algorithm?

☆ problems?

★ Draw a Bayes net to represent line + sensors

→ causality → est. probability.

$$
\begin{tikzcd}
 & \text{On line?} \arrow[dl] \arrow[d] \arrow[dr] & \\
S_1 & S_2 & S_3
\end{tikzcd}
$$

★ add info. for last command.

$$
\begin{tikzcd}
 & \text{command} \arrow[d] & \\
 & \text{on line?} \arrow[dl] \arrow[d] \arrow[dr] & \\
S_1 & S_2 & S_3
\end{tikzcd}
$$

causal thinking is hard!

★ design experiment:

→ what can you observe but robot can't?
→ what can robot observe online?

→ warning about causal assumptions + models.

PLC.