# CS 440 Introduction to Artificial Intelligence

Lecture 15:

**Markov Processes** 

5 March 2020

- We computed probability of a call given that there is a burglary
  - P(call|burglary)
- How could we compute probability that there is a burglary given that you received a call?
  - P(burglary|call)
- One option use Bayes theorem
  - P(burglary|call) = P(burglary) \* P(call|burglary) / P(call)
  - Compute P(call) given enumeration tree

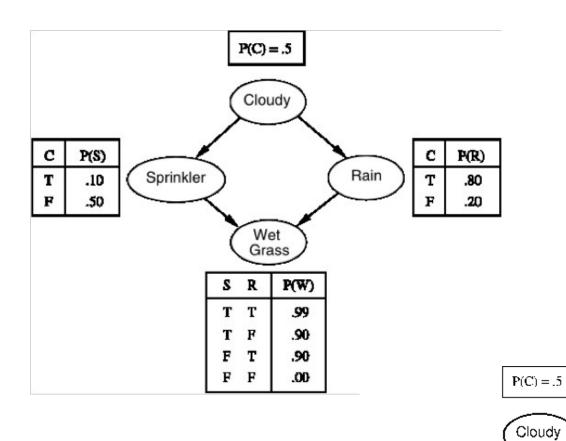
#### RUTGERS

## Bayesian Network: Formal Definition

- Network used for burglary problem and example of a neural network.
- Nodes correspond to variables
- Connections indicate cause and effect
  - Example burglary effects probability alarm will go off
- Each node stores probability of variable given all possible settings of parents
  - Non-discrete variables need function mapping all possible settings of parents to probability distribution of child

- Given a Bayesian network
- Observe a variable in the network
- What other variables are effected by observation?
  - Variables whose probability is effected by observation

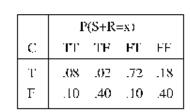
## Multiply Connected Network



S+R	P(W)
тт	.99
T 1	.90
Fτ	.90
FF	.00

Spr+Rain

Wet Grass



#### RUTGERS

## Bayes' Theorem Example

- Assume you are given the following
  - P(c) probability someone in construction business
  - P(a) probability someone is exposed to asbestos
  - P(a|c) probability someone exposed to asbestos given they work in construction
  - P(s) probability someone is a smoker
  - P(I) probability someone develops lung cancer
  - P(I|a) probability someone develops ling cancer given they were exposed to asbestos
  - p(l|s) probability of developing lung cancer given that someone is a smoker
- What is the probability someone who has lung cancer works in construction?
- What is the probability a smoker who works in construction will develop lung cancer?
- What is the probability someone who has lung cancer is both a smoker and works in construction?

#### Markov Processes

- Consider an environment
  - Environment may transition to different states
    - Due to actions selected by agent
    - Due to things outside of agent's control
- Example: Autonomous car
  - State of road changes based on what agent does as well as what other agents do
    - Agent may turn, change lanes, accelerate/decelerate, ect.
    - Other cars may move, change lanes, cut you off, ect.
- Very complicated
  - Impossible to predict exactly
- Given state of environment possible to estimate future state
  - Give you position of cars with current speed
    - Predict likely position of cars after certain amount of time has passed

- Markovian assumption
  - Future state only depend on current state
  - Only matters where cars currently are on road
    - Doesn't matter what maneuvers they took to get there
  - Assumption makes solving problems a lot easier
    - Only need to keep track of current state
      - As opposed to history of previous states
    - Only need to reason over current state

## Types of Markov Processes

- Discrete vs continuous
- Passive vs active
  - Active process: The agent's actions influence process
- Observable state vs partially observable state
  - Observable state: agent can observe state directly
  - Partially observable state:
    - Example: Wumpus world

	Observable State	Hidden State
Passive	Markov Chain	Hidden Markov Model
Active	Markov Decision Process (MPD)	Partially Observable Markov Decision Process (POMPD)

- May be discrete or continuous
- Passive state of environment does not depend of actions of agent
- Fully observable
- May be discrete or continuous
  - Discrete Markov chains can be represented as finite state machines

- Example: Bit flip
  - String of bits
    - State: string of 1s and 0s
  - At each time step each bit has a p probability of flipping

- Given an environment in a known state
  - What could the environment look like after n steps?
  - Probability of being in each state
- Solve inductively
  - Assume we know the probability you are in each state s at step i
    - p<sub>si</sub> for all s∈S
  - Compute probability for each state at step i+1
    - p<sub>s',i+1</sub> for all s'∈S
  - Probability we will transition from state s to s' at step i+1 equal to probability we are in state s at step i times the transition probability from s to s'
    - $p_{s',i+1} = p(s'|s)*p_{s,i}$
  - Probability we will be in state s' at step i+1
    - $p_{s',i+1} = \sum_{s' \in S} p(s'|s)*p_{s,i}$

- Example: Bit flip
  - String of bits 2
    - States 00, 01, 10, 11
    - Transitions: Each bit has a p probability of flipping

		00	01	10	11
	00	$(1-p)^2$	p(1-p)	p(1-p)	p <sup>2</sup>
<b>T</b> =	01	p(1-p)	(1-p) <sup>2</sup>	p <sup>2</sup>	p(1-p)
	10	p(1-p)	p <sup>2</sup>	(1-p) <sup>2</sup>	p(1-p)
	11	p <sup>2</sup>	(1-p) <sup>2</sup>	(1-p) <sup>2</sup>	(1-p) <sup>2</sup>

Probability at step n

n	00	01	10	11
0	1.0	0	0	0
1	(1-p) <sup>2</sup> = .81	p(1-p) = .09	p(1-p) = .09	p <sup>2</sup> = .01
2	.6724	.1476	.1476	.0324

Can we formulate as a matrix multiplication problem?

- Let  $P_i = \{P_{s1,i}, P_{s2,i}, P_{s3,i}, ...\}$
- Let  $P_{i+1} = \{P_{s1,i+1}, P_{s2,i+1}, P_{s3,i+1}, ...\}$
- Let T be a transition function
- $P_{i+1} = T * P_i^T$
- Compute P<sub>i+1</sub> by repetitively multiplying by T

$$- P_{i+1} = T^{i+1} * P_0^T$$

Can use parallel computing to expedite these computations

#### Rutgers

#### Markov Decision Problem

- May be discrete or continuous
- Active agents actions effect state
- Fully observable
- May be discrete or continuous
- Formalization
  - State space S
  - Set of actions A
  - Transition function T(s,a)
    - Result of taking action a while in state s
    - Returns a probability distribution over S
      - probability that taking action a in state s will yield each s'∈S
  - Reward function R
    - Could define reward of being in a state, R(s)
    - Could define reward of performing action while in state R(s,a)
    - Could be reward of performing action that ends up in a particular state R(a,s')
- Immediate objective: Determine the best action to take given your current state
  - Action that maximizes expected future reward

## Markov Chains Example

- Robot in a grid with noisy actions
  - Robot can choose Left/Right/Up/Down
  - Actions may bring robot to wrong cell

		+1000
	-100	