

Uncertainty

CS 486/686
University of Waterloo
October 1, 2009

CS486/686 Lecture Slides (c) 2009 K. Larson and P. Poupart

1

A Decision Making Scenario

- You are considering to buy a used car...
 - Is it in good condition?
 - How much are you willing to pay?
 - Should you get it inspected by a mechanics?
 - Should you buy the car?

CS486/686 Lecture Slides (c) 2009 K. Larson and P. Poupart

2

In the next few lectures

- Probability theory
 - Model uncertainty
- Utility theory
 - Model preferences
- Decision theory
 - Combine probability theory and utility theory

CS486/686 Lecture Slides (c) 2009 K. Larson and P. Poupart

3

Introduction

- Logical reasoning breaks down when dealing with uncertainty
- Example: Diagnosis
 - $\forall p \text{ Symptom}(p, \text{Toothache}) \Rightarrow \text{Disease}(p, \text{Cavity})$
 - But not all people with toothaches have cavities...
 - $\forall p \text{ Symptom}(p, \text{Toothache}) \Rightarrow \text{Disease}(p, \text{Cavity}) \vee \text{Disease}(p, \text{GumDisease}) \vee \text{Disease}(p, \text{Hit in the Jaw}) \vee \dots$
 - Can't enumerate all possible causes and not very informative
 - $\forall p \text{ Disease}(p, \text{Cavity}) \Rightarrow \text{Symptom}(p, \text{Toothache})$
 - Does not work since not all cavities cause toothaches...

CS486/686 Lecture Slides (c) 2009 K. Larson and P. Poupart

4

Introduction

- Logic fails because
 - **We are lazy**
 - Too much work to write down all antecedents and consequences
 - **Theoretical ignorance**
 - Sometimes there is just no complete theory
 - **Practical ignorance**
 - Even if we knew all the rules, we might be uncertain about a particular instance (not collected enough information yet)

CS486/686 Lecture Slides (c) 2009 K. Larson and P. Poupart

5

Probabilities to the rescue

- For many years AI danced around the fact that the world is an uncertain place
- Then a few AI researchers decided to go back to the 18th century
 - Revolutionary
 - Probabilities allow us to deal with uncertainty that comes from our laziness and ignorance
 - Clear semantics
 - Provide principled answers for
 - Combining evidence, predictive and diagnostic reasoning, incorporation of new evidence
 - Can be learned from data
 - Intuitive for humans (?)

CS486/686 Lecture Slides (c) 2009 K. Larson and P. Poupart

6

Discrete Random Variables

- Random variable A describes an outcome that cannot be determined in advance (i.e. roll of a dice)
 - Discrete random variable means that its possible values come from a countable domain (sample space)
 - E.G If X is the outcome of a dice throw, then $X \in \{1,2,3,4,5,6\}$
 - **Boolean random variable** $A \in \{\text{True}, \text{False}\}$
 - A = The Canadian PM in 2040 will be female
 - A = You have Ebola
 - A = You wake up tomorrow with a headache

CS486/686 Lecture Slides (c) 2009 K. Larson and P. Poupart

7

Events

- An **event** is a complete specification of the state of the world in which the agent is uncertain
 - Subset of the sample space
- Example:
 - $\text{Cavity}=\text{True} \wedge \text{Toothache}=\text{True}$
 - $\text{Dice}=2$
- Events must be
 - Mutually exclusive
 - Exhaustive (at least one event must be true)

CS486/686 Lecture Slides (c) 2009 K. Larson and P. Poupart

8

Probabilities

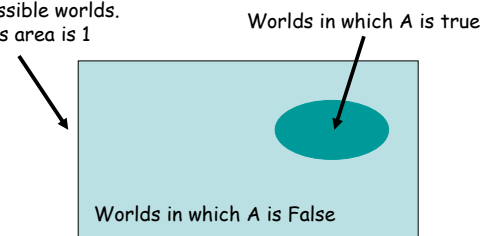
- We let $P(A)$ denote the "degree of belief" we have that statement A is true
 - Also "fraction of worlds in which A is true"
 - Philosophers like to discuss this (but we won't)
- Note:
 - $P(A)$ DOES NOT correspond to a degree of truth
 - Example: Draw a card from a shuffled deck
 - The card is of some type (e.g ace of spades)
 - Before looking at it $P(\text{ace of spades}) = 1/52$
 - After looking at it $P(\text{ace of spades}) = 1$ or 0

CS486/686 Lecture Slides (c) 2009 K. Larson and P. Poupart

9

Visualizing A

Event space of all possible worlds.
It's area is 1



$P(A) = \text{Area of oval}$

CS486/686 Lecture Slides (c) 2009 K. Larson and P. Poupart

10

The Axioms of Probability

- $0 \leq P(A) \leq 1$
- $P(\text{True}) = 1$
- $P(\text{False}) = 0$
- $P(A \vee B) = P(A) + P(B) - P(A \wedge B)$
- These axioms limit the class of functions that can be considered as probability functions

CS486/686 Lecture Slides (c) 2009 K. Larson and P. Poupart

11

Interpreting the axioms

- $0 \leq P(A) \leq 1$
- $P(\text{True}) = 1$
- $P(\text{False}) = 0$
- $P(A \vee B) = P(A) + P(B) - P(A \wedge B)$

The area of A can't be smaller than 0



A zero area would mean no world could ever have A as true

CS486/686 Lecture Slides (c) 2009 K. Larson and P. Poupart

12

Interpreting the axioms

- $0 \leq P(A) \leq 1$
- $P(\text{True}) = 1$
- $P(\text{False}) = 0$
- $P(A \vee B) = P(A) + P(B) - P(A \wedge B)$

The area of A can't be larger than 1



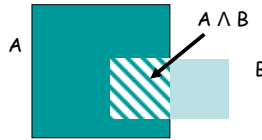
An area of 1 would mean no world could ever have A as true

CS486/686 Lecture Slides (j) 2009 K. Larson and P. Poupart

13

Interpreting the axioms

- $0 \leq P(A) \leq 1$
- $P(\text{True}) = 1$
- $P(\text{False}) = 0$
- $P(A \vee B) = P(A) + P(B) - P(A \wedge B)$



CS486/686 Lecture Slides (j) 2009 K. Larson and P. Poupart

14

Take the axioms seriously!

- There have been attempts to use different methodologies for uncertainty
 - Fuzzy logic, three valued logic, Dempster-Shafer, non-monotonic reasoning,...
- But if you follow the axioms of probability then no one can take advantage of you 😊

CS486/686 Lecture Slides (j) 2009 K. Larson and P. Poupart

15

A Betting Game [di Finetti 1931]

- Propositions A and B
- Agent 1 announces its "degree of belief" in A and B ($P(A)$ and $P(B)$)
- Agent 2 chooses to bet for or against A and B at stakes that are consistent with $P(A)$ and $P(B)$
- If Agent 1 does not follow the axioms, it is guaranteed to lose money

	Agent 1 Proposition Belief	Agent 2 Bet Odds	Outcome for Agent 1			
			$A \wedge B$	$A \wedge \sim B$	$\sim A \wedge B$	$\sim A \wedge \sim B$
A	0.4	A 4 to 6	-6	-6	4	4
B	0.3	B 3 to 7	-7	3	-7	3
$A \vee B$	0.8	$\sim(A \vee B)$ 2 to 8	2	2	2	-8
			-11	-1	-1	-1

CS486/686 Lecture Slides (j) 2009 K. Larson and P. Poupart

16

Theorems from the axioms

- Thm: $P(\sim A) = 1 - P(A)$
- Proof: $P(A \vee \sim A) = P(A) + P(\sim A) - P(A \wedge \sim A)$
 $P(\text{True}) = P(A) + P(\sim A) - P(\text{False})$
 $1 = P(A) + P(\sim A) - 0$
 $P(\sim A) = 1 - P(A)$

CS486/686 Lecture Slides (j) 2009 K. Larson and P. Poupart

17

Theorems from axioms

- Thm: $P(A) = P(A \wedge B) + P(A \wedge \sim B)$
- Proof: For you to do

Why? Because it is good for you

CS486/686 Lecture Slides (j) 2009 K. Larson and P. Poupart

18

Multivalued Random Variables

- Assume domain of A (sample space) is $\{v_1, v_2, \dots, v_k\}$
- A can take on exactly one value out of this set
 - $P(A=v_i \wedge A=v_j) = 0$ if $i \neq j$
 - $P(A=v_1 \vee A=v_2 \vee \dots \vee A=v_k) = 1$

CS486/686 Lecture Slides (c) 2009 K. Larson and P. Poupart

19

Terminology

- **Probability distribution:**
 - A specification of a probability for each event in our sample space
 - Probabilities must sum to 1
- Assume the world is described by two (or more) random variables
 - **Joint probability distribution**
 - Specification of probabilities for all combinations of events

CS486/686 Lecture Slides (c) 2009 K. Larson and P. Poupart

20

Joint distribution

- Given two random variables A and B :
- Joint distribution:
 - $\Pr(A=a \wedge B=b)$ for all a, b
- **Marginalisation (sumout rule):**
 - $\Pr(A=a) = \sum_b \Pr(A=a \wedge B=b)$
 - $\Pr(B=b) = \sum_a \Pr(A=a \wedge B=b)$

CS486/686 Lecture Slides (c) 2009 K. Larson and P. Poupart

21

Example: Joint Distribution

	sunny		~sunny	
	cold	~cold	cold	~cold
headache	0.108	0.012	0.072	0.008
~headache	0.016	0.064	0.144	0.576

$$P(\text{headache} \wedge \text{sunny} \wedge \text{cold}) = 0.108 \quad P(\sim \text{headache} \wedge \text{sunny} \wedge \sim \text{cold}) = 0.064$$

$$P(\text{headache} \vee \text{sunny}) = 0.108 + 0.012 + 0.072 + 0.008 + 0.016 + 0.064 = 0.28$$

$$P(\text{headache}) = 0.108 + 0.012 + 0.072 + 0.008 = 0.2$$

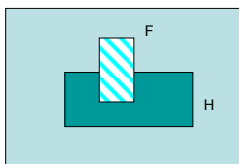
marginalization

CS486/686 Lecture Slides (c) 2009 K. Larson and P. Poupart

22

Conditional Probability

- $P(A|B)$ fraction of worlds in which B is true that also have A true



H="Have headache"
F="Have Flu"

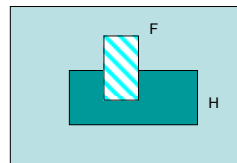
$$P(H)=1/10 \\ P(F)=1/40 \\ P(H|F)=1/2$$

Headaches are rare and flu is rarer, but if you have the flu, then there is a 50-50 chance you will have a headache

CS486/686 Lecture Slides (c) 2009 K. Larson and P. Poupart

23

Conditional Probability



$P(H|F)$ = Fraction of flu inflicted worlds in which you have a headache

$$= \frac{(\# \text{ worlds with flu and headache})}{(\# \text{ worlds with flu})}$$

$$= \frac{(\text{Area of "H and F" region})}{(\text{Area of "F" region})}$$

$$= P(H \wedge F) / P(F)$$

H="Have headache"
F="Have Flu"

$$P(H)=1/10 \\ P(F)=1/40 \\ P(H|F)=1/2$$

CS486/686 Lecture Slides (c) 2009 K. Larson and P. Poupart

24

Conditional Probability

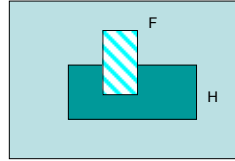
- Definition:
 - $P(A|B) = P(A \cap B) / P(B)$
- Chain rule:
 - $P(A \cap B) = P(A|B) P(B)$

Memorize these!

CS4386/686 Lecture Slides (c) 2009 K. Larson and P. Poupart

25

Inference



One day you wake up with a headache. You think "Drat! 50% of flues are associated with headaches so I must have a 50-50 chance of coming down with the flu"

H="Have headache"
F="Have Flu"

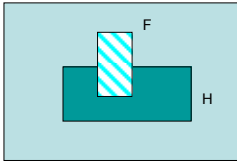
$P(H)=1/10$
 $P(F)=1/40$
 $P(H|F)=1/2$

Is your reasoning correct?

CS4386/686 Lecture Slides (c) 2009 K. Larson and P. Poupart

26

Inference



One day you wake up with a headache. You think "Drat! 50% of flues are associated with headaches so I must have a 50-50 chance of coming down with the flu"

H="Have headache"
F="Have Flu"

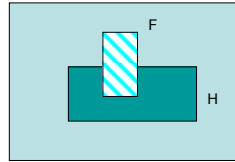
$P(F \cap H) = P(F)P(H|F) = 1/80$

$P(H)=1/10$
 $P(F)=1/40$
 $P(H|F)=1/2$

CS4386/686 Lecture Slides (c) 2009 K. Larson and P. Poupart

27

Inference



One day you wake up with a headache. You think "Drat! 50% of flues are associated with headaches so I must have a 50-50 chance of coming down with the flu"

H="Have headache"
F="Have Flu"

$P(F \cap H) = P(F)P(H|F) = 1/80$

$P(H)=1/10$
 $P(F)=1/40$
 $P(H|F)=1/2$

$P(F|H) = P(F \cap H) / P(H) = 1/8$

CS4386/686 Lecture Slides (c) 2009 K. Larson and P. Poupart

28

Example: Joint Distribution

	sunny		~sunny	
	cold	~cold	cold	~cold
headache	0.108	0.012	0.072	0.008
~headache	0.016	0.064	0.144	0.576

$$P(\text{headache} \wedge \text{cold} \mid \text{sunny}) = P(\text{headache} \wedge \text{cold} \wedge \text{sunny}) / P(\text{sunny})$$

$$= 0.108 / (0.108 + 0.012 + 0.016 + 0.064)$$

$$= 0.54$$

$$P(\text{headache} \wedge \text{cold} \mid \sim \text{sunny}) = P(\text{headache} \wedge \text{cold} \wedge \sim \text{sunny}) / P(\sim \text{sunny})$$

$$= 0.072 / (0.072 + 0.008 + 0.144 + 0.576)$$

$$= 0.09$$

CS4386/686 Lecture Slides (c) 2009 K. Larson and P. Poupart

29

Bayes Rule

- Note
 - $P(A|B)P(B) = P(A \cap B) = P(B \cap A) = P(B|A)P(A)$
- Bayes Rule
 - $P(B|A) = [P(A|B)P(B)] / P(A)$

Memorize this!

CS4386/686 Lecture Slides (c) 2009 K. Larson and P. Poupart

30

Using Bayes Rule for inference

- Often we want to form a hypothesis about the world based on what we have observed
- Bayes rule is vitally important when viewed in terms of stating the belief given to hypothesis H, given evidence e

$$P(H|e) = \frac{P(e|H)P(H)}{P(e)}$$

Likelihood → $P(e|H)$ $P(H)$ ← Prior probability
Posterior probability ← $P(H|e)$ $P(e)$ ← Normalizing constant

CS4386/686 Lecture Slides (c) 2009 K. Larson and P. Poupart

31

More General Forms of Bayes Rule

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

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

$$P(A = v_i|B) = \frac{P(B|A = v_i)P(A = v_i)}{\sum_{k=1}^n P(B|A = v_k)P(A = v_k)}$$

CS4386/686 Lecture Slides (c) 2009 K. Larson and P. Poupart

32

Example

- A doctor knows that Asian flu causes a fever 95% of the time. She knows that if a person is selected at random from the population, they have a 10^{-7} chance of having Asian flu. 1 in 100 people suffer from a fever.
- You go to the doctor complaining about the symptom of having a fever. What is the probability that Asian flu is the cause of the fever?

CS4386/686 Lecture Slides (c) 2009 K. Larson and P. Poupart

33

Example

- A doctor knows that Asian flu causes a fever 95% of the time. She knows that if a person is selected at random from the population, they have a 10^{-7} chance of having Asian flu. 1 in 100 people suffer from a fever.
- You go to the doctor complaining about the symptom of having a fever. What is the probability that Asian flu is the cause of the fever?

A=Asian flu Evidence = Symptom (F)
F= fever Hypothesis = Cause (A)

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

$$= \frac{0.95 \times 10^{-7}}{0.01}$$

$$= 0.95 \times 10^{-5}$$

CS4386/686 Lecture Slides (c) 2009 K. Larson and P. Poupart

34

Computing conditional probabilities

- Often we are interested in the posterior joint distribution of some query variables Y given specific evidence e for evidence variables E
- Set of all variables: X
- Hidden variables: $H=X-Y-E$
- If we had the joint probability distribution then could marginalize
- $P(Y|E=e) = \alpha \sum_h P(Y \wedge E=e \wedge H=h)$
 - α is the normalization factor

CS4386/686 Lecture Slides (c) 2009 K. Larson and P. Poupart

35

Computing conditional probabilities

- Often we are interested in the posterior joint distribution of some query variables Y given specific evidence e for evidence variables E
- Set of all variables: X
- Hidden variables: $H=X-Y-E$
- If we had the joint probability distribution then could marginalize
- $P(Y|E=e) = \alpha \sum_h P(Y \wedge E=e \wedge H=h)$
 - α is the normalization factor

Problem: Joint distribution is usually too big to handle

CS4386/686 Lecture Slides (c) 2009 K. Larson and P. Poupart

36

Independence

- Two variables A and B are independent if knowledge of A does not change uncertainty of B (and vice versa)
 - $P(A|B)=P(A)$
 - $P(B|A)=P(B)$
 - $P(A \wedge B)=P(A)P(B)$
 - In general $P(X_1, X_2, \dots, X_n) = \prod_{i=1}^n P(X_i)$

Need only n numbers to specify a joint distribution!

37

CS486/686 Lecture Slides (c) 2009 K. Larson and P. Poupart

Conditional Independence

- Absolute independence is often too strong a requirement
- Two variables A and B are conditionally independent given C if
 - $P(a|b,c)=P(a|c)$ for all a,b,c
 - i.e. knowing the value of B does not change the prediction of A if the value of C is known

38

CS486/686 Lecture Slides (c) 2009 K. Larson and P. Poupart

Conditional Independence

- Diagnosis problem
 - Fl = Flu, Fv = Fever, C = Cough
- Full joint distribution has $2^3 - 1 = 7$ independent entries
- If someone has the flu, we can assume that the probability of a cough does not depend on having a fever
 - $P(C|Fl, Fv) = P(C|Fl)$
- If the patient does not have the Flu, then C and Fv are again conditionally independent
 - $P(C|\sim Fl, Fv) = P(C|\sim Fl)$

39

CS486/686 Lecture Slides (c) 2009 K. Larson and P. Poupart

Conditional Independence

- Full distribution can be written as
 - $P(C, Fl, Fv) = P(C, Fv|Fl)P(Fl)$
 $= P(C|Fl)P(Fv|Fl)P(Fl)$
 - That is we only need 5 numbers now!
 - Huge savings if there are lots of variables

40

CS486/686 Lecture Slides (c) 2009 K. Larson and P. Poupart

Conditional Independence

- Full distribution can be written as
 - $P(C, Fl, Fv) = P(C, Fv|Fl)P(Fl)$
 $= P(C|Fl)P(Fv|Fl)P(Fl)$
 - That is we only need 5 numbers now!
 - Huge savings if there are lots of variables

Such a probability distribution is sometimes called a naive Bayes model.

In practice, they work well - even when the independence assumption is not true

41

CS486/686 Lecture Slides (c) 2009 K. Larson and P. Poupart

Next class

- Bayesian networks
 - Section 14.1 - 14.2

42

CS486/686 Lecture Slides (c) 2009 K. Larson and P. Poupart