

## Uncertainty

CPS 170  
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## Why do we need uncertainty?

- Reason: Sh\*t happens
- Actions don't have deterministic outcomes
- Can logic be the "language" of AI???
- Problem:
  - General logical statements are almost always false
- Truthful and accurate statements about the world would seem to require an endless list of *qualifications*
- How do you start a car?
- Call this "The Qualification Problem"

## The Qualification Problem

- Is this a real concern?
- YES!
- Systems that try to avoid dealing with uncertainty tend to be brittle.
- Plans fail
- Finding shortest path to goal isn't that great if the path doesn't really get you to the goal

## Probabilities

- Natural way to represent uncertainty
- People have intuitive notions about probabilities
- Many of these are wrong or inconsistent
- Most people *don't get* what probabilities mean
- Finer details of this question still debated

## Understanding Probabilities

- Initially, probabilities are "relative frequencies"
- This works well for dice and coin flips
- For more complicated events, this is problematic
- What is the probability that the democrats will control Congress in 2007?
  - This event only happens once
  - We can't count frequencies
  - Still seems like a meaningful question
- In general, all events are unique
- "Reference Class" problem

## Probabilities and Beliefs

- Suppose I have rolled a die and hidden the outcome
- What is  $P(\text{Die} = 3)$ ?
- Note that this is a statement about a *belief*, not a statement about the world
- The world is in exactly one state and it is in that state with probability 1.
- Assigning truth values to probability statements is very tricky business
- Must reference speakers state of knowledge

## Frequentism and Subjectivism

- Frequentists hold that probabilities must come from relative frequencies
- This is a purist viewpoint
- This is corrupted by the fact that relative frequencies are often unobtainable
- Often requires complicated and convoluted assumptions to come up with probabilities
- Subjectivists: probabilities are degrees of belief
  - Taints purity of probabilities
  - Often more practical

## The Middle Ground

- No two events are ever identical, but
- No two events are ever totally unique either
- What is probability that Hillary Clinton will be elected Vice President?
  - Women have run for VP before
  - People like Hillary Clinton have run before
  - Have background knowledge about the electorate

## Why probabilities are good

- Subjectivists: probabilities are degrees of belief
- Are all degrees of belief probability?
  - AI has used many notions of belief:
    - Certainty Factors
    - Fuzzy Logic
- Can prove that a person who holds a system of beliefs inconsistent with probability theory can be tricked into accepted a sequence of bets that is guaranteed to lose (Dutch book)

## What are probabilities?

- Probabilities are defined over random variables
- Random variables are usually represented with capitals: X,Y,Z
- Random variables take on values from a finite domain  $d(X)$ ,  $d(Y)$ ,  $d(Z)$
- We use lower case letters for values from domains
  
- $X=x$  asserts: RV X has taken on value x
- $P(x)$  is shorthand for  $P(X=x)$

## Domains

- In the simplest case, domains are boolean
- In general may include many different values
- Most general case: domains may be continuous
- This introduces some special complications

## Kolmogorov's axioms of probability

- $0 \leq P(a) \leq 1$
- $P(\text{true}) = 1$ ;  $P(\text{false}) = 0$
- $P(a \text{ or } b) = P(a) + P(b) - P(a \text{ and } b)$
- Subtract to correct for double counting
  
- This is sufficient to completely specify probability theory for discrete variables
- Continuous variables need density functions

## Atomic Events

- When several variables are involved, it is useful to think about atomic events
- An atomic event is a complete assignment to variables in the domain (compare with states in search)
- Atomic events are mutually exclusive
- Exhaust space of all possible events
- For  $n$  binary variables, how many unique atomic events are there?

## Joint Distributions

- A joint distribution is an assignment of probabilities to every possible atomic event
- We can define all other probabilities in terms of the joint probabilities by *marginalization*:

$$P(a) = P(a \wedge b) + P(a \wedge \neg b)$$

$$P(a) = \sum_{e_i \in e(a)} P(e_i)$$

## Example

- $P(\text{cold} \wedge \text{headache}) = 0.4$
- $P(\neg \text{cold} \wedge \text{headache}) = 0.2$
- $P(\text{cold} \wedge \neg \text{headache}) = 0.3$
- $P(\neg \text{cold} \wedge \neg \text{headache}) = 0.1$
  
- What are  $P(\text{cold})$  and  $P(\text{headache})$ ?

## Independence

- If A and B are independent:  
 $P(A \wedge B) = P(A)P(B)$
  
- $P(\text{cold} \wedge \text{headache}) = 0.4$
- $P(\neg \text{cold} \wedge \text{headache}) = 0.2$
- $P(\text{cold} \wedge \neg \text{headache}) = 0.3$
- $P(\neg \text{cold} \wedge \neg \text{headache}) = 0.1$
  
- Are cold and headache independent?

## Independence

- If A and B are independent:  
 $P(A \vee B) = P(A) + P(B)$  (Why?)
  
- Examples of independent events:
  - Duke winning NCAA, Dem. winning white house
  - Two successive fair coin flips
  - My car starting and my stereo working
  - etc.

## Why Probabilities Are Messy

- Probabilities are not truth-functional
- To compute  $P(a \text{ and } b)$  we need to consult the joint distribution
  - sum out all of the other variables from the distribution
  - It is not a function of  $P(a)$  and  $P(b)$
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- This fact led to many approximations methods such as certainty factors and fuzzy logic (Why?)
- Neat vs. Scruffy...

## The Scruffy Trap

- Reasoning about probabilities correctly requires knowledge of the joint distribution
- This is exponentially large
- Very convenient to assume independence
- Assuming independence when there is not independence leads to incorrect answers
- Examples:
  - ANDing symptoms
  - ORing symptoms

## Conditional Probabilities

- Ordinary probabilities for random variables:  
*unconditional or prior probabilities*
- $P(a|b) = P(a \text{ AND } b)/P(b)$
- This tells us the probability of a **given that we know *only* b**
- If we know c and d, we can't use  $P(a|b)$  directly
- Annoying, but solves the qualification problem...

## Probability Solves the Qualification Problem

- $P(\text{disease}|\text{symptom1})$
- This defines the probability of a disease given that we have observed only symptom1
- The conditioning bar indicates that the probability is defined with respect to a particular state of knowledge, *not as an absolute thing*

## Conditioning and Belief Update

- Suppose we know  $P(ABCDE)$  ← Joint
- Observe  $B=b$ , update our beliefs:

$$P(acde|b) = \frac{P(abcde)}{P(b)} = \frac{P(abcde)}{\sum_{ACDE} P(AbCDE)}$$

## Condition with Bayes's Rule

$$P(A \wedge B) = P(B \wedge A)$$

$$P(A|B)P(B) = P(B|A)P(A)$$

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

## Example Revisited

- $P(\text{cold} \wedge \text{headache}) = 0.4$
- $P(\neg \text{cold} \wedge \text{headache}) = 0.2$
- $P(\text{cold} \wedge \neg \text{headache}) = 0.3$
- $P(\neg \text{cold} \wedge \neg \text{headache}) = 0.1$
- What is  $P(\text{cold}|\text{headache})$ ?

## Let's Play Doctor

- Suppose  $P(\text{cold}) = 0.7$ ,  $P(\text{headache}) = 0.6$
- $P(\text{headache}|\text{cold}) = 0.57$
- What is  $P(\text{cold}|\text{headache})$ ?

$$P(c|h) = \frac{P(h|c)P(c)}{P(h)}$$

$$= \frac{0.57 * 0.7}{0.6} = 0.665$$

- **IMPORTANT:** Not always symmetric

## Expectation

- Most of us use expectation in some form when we compute averages
- What is the average value of a die roll?
- $(1+2+3+4+5+6)/6 = 3.5$

## Bias

- What if not all events are equally likely?
- Suppose weighted die makes 6 2X more likely than anything else. What is average value of outcome?
- $(1 + 2 + 3 + 4 + 5 + 6 + 6)/7 = 3.86$
- Probs:  $1/7$  for  $1 \dots 5$ , and  $2/7$  for 6
- $(1 + 2 + 3 + 4 + 5) * 1/7 + 6 * 2/7 = 3.86$

## Expectation in General

- Suppose we have some RV  $X$
- Suppose we have some function  $f(X)$
- What is the expected value of  $f(X)$ ?

$$E_x f(x) = \sum_x P(X) f(X)$$

## Sums of Expectations

- Suppose we have  $f(X)$  and  $g(Y)$ .
- What is the expected value of  $f(X)+g(Y)$ ?

$$E_{X,Y} f(X) + g(Y) = \sum_{X,Y} P(X \wedge Y) (f(X) + g(Y))$$

$$= \sum_{X,Y} P(X \wedge Y) f(X) + \sum_{X,Y} P(X \wedge Y) g(Y)$$

$$= \sum_X P(X) f(X) + \sum_Y P(Y) g(Y)$$

*Linearity of Expectation*

$$= \sum_X f(x) P(X) + \sum_Y g(y) P(Y)$$

$$= E_X f(X) + E_Y g(Y)$$