SNS COLLEGE OF TECHNOLOGY

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DEPARTMENT OF INFORMATION TECHNOLOGY

19CSE303 - ARTIFICIAL INTELLIGENCE
III YEAR IV SEM

UNIT IV – **UNCETRAIN KNOWLEDGE AND REASONING**

TOPIC – Knowledge Representation and Reasoning

Abduction

- **Abduction** is a reasoning process that tries to form plausible explanations for abnormal observations
  - Abduction is distinctly different from deduction and induction
  - Abduction is inherently uncertain
- Uncertainty is an important issue in abductive reasoning
- Some major formalisms for representing and reasoning about uncertainty
  - Mycin's certainty factors (an early representative)
  - **Probability theory (esp. Bayesian belief networks)**
  - Dempster-Shafer theory
  - Fuzzy logic
  - Truth maintenance systems
  - Nonmonotonic reasoning

Abduction

- **Definition** (Encyclopedia Britannica): reasoning that derives an explanatory hypothesis from a given set of facts
  - The inference result is a **hypothesis** that, if true, could **explain** the occurrence of the given facts
- **Examples**
  - Dendral, an expert system to construct 3D structure of chemical compounds
    - Fact: mass spectrometer data of the compound and its chemical formula
    - KB: chemistry, esp. strength of different types of bounds
    - Reasoning: form a hypothetical 3D structure that satisfies the chemical formula, and that would most likely produce the given mass spectrum

Abduction examples (cont.)

– Medical diagnosis
  - Facts: symptoms, lab test results, and other observed findings (called manifestations)
  - KB: causal associations between diseases and manifestations
  - Reasoning: one or more diseases whose presence would causally explain the occurrence of the given manifestations

– Many other reasoning processes (e.g., word sense disambiguation in natural language process, image understanding, criminal investigation) can also been seen as abductive reasoning

Comparing abduction, deduction, and induction

Deduction:	major premise:	All balls in the box are black	**A => B** **A** **---------** **B**
	minor premise:	These balls are from the box	
	conclusion:	These balls are black	
Abduction:	rule:	All balls in the box are black	**A => B** **B** **-------------** **Possibly A**
	observation:	These balls are black	
	explanation:	These balls are from the box	
Induction:	case:	These balls are from the box	**Whenever A then B** **-------------** **Possibly A => B**
	observation:	These balls are black	
	hypothesized rule:	All ball in the box are black	

Deduction reasons from causes to effects

Abduction reasons from effects to causes

Induction reasons from specific cases to general rules

Characteristics of abductive reasoning

- “Conclusions” are **hypotheses**, not theorems (may be false *even if* rules and facts are true)
  - E.g., misdiagnosis in medicine

- There may be multiple plausible hypotheses
  - Given rules A => B and C => B, and fact B, both A and C are plausible hypotheses
  - Abduction is inherently uncertain
  - Hypotheses can be ranked by their plausibility (if it can be determined)

Characteristics of abductive reasoning (cont.)

- Reasoning is often a hypothesize-and-test cycle
  - **Hypothesize**: Postulate possible hypotheses, any of which would explain the given facts (or at least most of the important facts)
  - **Test**: Test the plausibility of all or some of these hypotheses
  - One way to test a hypothesis H is to ask whether something that is currently unknown–but can be predicted from H–is actually true
    - If we also know A => D and C => E, then ask if D and E are true
    - If D is true and E is false, then hypothesis A becomes more plausible (**support** for A is increased; **support** for C is decreased)

Characteristics of abductive reasoning (cont.)

- Reasoning is **non-monotonic**
  - That is, the plausibility of hypotheses can increase/decrease as new facts are collected
  - In contrast, deductive inference is **monotonic:** it never change a sentence’s truth value, once known
  - In abductive (and inductive) reasoning, some hypotheses may be discarded, and new ones formed, when new observations are made

Sources of uncertainty

- Uncertain **inputs**
  - Missing data
  - Noisy data
- Uncertain **knowledge**
  - Multiple causes lead to multiple effects
  - Incomplete enumeration of conditions or effects
  - Incomplete knowledge of causality in the domain
  - Probabilistic/stochastic effects
- Uncertain **outputs**
  - Abduction and induction are inherently uncertain
  - Default reasoning, even in deductive fashion, is uncertain
  - Incomplete deductive inference may be uncertain
- Probabilistic reasoning only gives probabilistic results (summarizes uncertainty from various sources)

Decision making with uncertainty

- **Rational** behavior:
  - For each possible action, identify the possible outcomes
  - Compute the **probability** of each outcome
  - Compute the **utility** of each outcome
  - Compute the probability-weighted **(expected) utility** over possible outcomes for each action
  - Select the action with the highest expected utility (principle of **Maximum Expected Utility**)

Bayesian reasoning

- Probability theory
- Bayesian inference
  - Use probability theory and information about independence
  - Reason diagnostically (from evidence (effects) to conclusions (causes)) or causally (from causes to effects)
- Bayesian networks
  - Compact representation of probability distribution over a set of propositional random variables
  - Take advantage of independence relationships

Other uncertainty representations

- Default reasoning
  - Nonmonotonic logic: Allow the retraction of default beliefs if they prove to be false
- Rule-based methods
  - Certainty factors (Mycin): propagate simple models of belief through causal or diagnostic rules
- Evidential reasoning
  - Dempster-Shafer theory: Bel(P) is a measure of the evidence for P; Bel(¬P) is a measure of the evidence against P; together they define a belief interval (lower and upper bounds on confidence)
- Fuzzy reasoning
  - Fuzzy sets: How well does an object satisfy a vague property?
  - Fuzzy logic: “How true” is a logical statement?

Uncertainty tradeoffs

- **Bayesian networks:** Nice theoretical properties combined with efficient reasoning make BNs very popular; limited expressiveness, knowledge engineering challenges may limit uses
- **Nonmonotonic logic:** Represent commonsense reasoning, but can be computationally very expensive
- **Certainty factors:** Not semantically well founded
- **Dempster-Shafer theory:** Has nice formal properties, but can be computationally expensive, and intervals tend to grow towards [0,1] (not a very useful conclusion)
- **Fuzzy reasoning:** Semantics are unclear (fuzzy!), but has proved very useful for commercial applications

Bayesian Reasoning

Outline

- Probability theory
- Bayesian inference
  - From the joint distribution
  - Using independence/factoring
  - From sources of evidence

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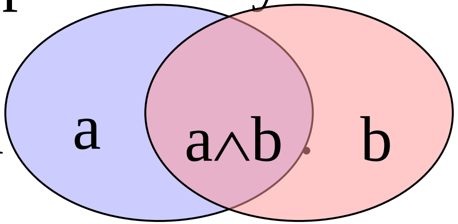
Why probabilities anyway?

- Kolmogorov showed that three simple axioms lead to the rules of probability theory
  - De Finetti, Cox, and Carnap have also provided compelling arguments for these axioms

1. All probabilities are between 0 and 1:
   - $0 \leq P(a) \leq 1$
2. Valid propositions (tautologies) have probability 1, and unsatisfiable propositions have probability 0:
   - $P(true) = 1$; $P(false) = 0$
3. The probability of a disjunction is given by:
   - $P(a \vee b) = P(a) + P(b) - P(a \wedge b)$



Probability theory

- **Random variables**
  - Domain
- **Atomic event**: complete specification of state
- **Prior probability**: degree of belief without any other evidence
- **Joint probability**: matrix of combined probabilities of a set of variables

- Alarm, Burglary, Earthquake
  - Boolean (like these), discrete, continuous
- (Alarm=True ∧ Burglary=True ∧ Earthquake=False) or equivalently (alarm ∧ burglary ∧ ¬earthquake)
- P(Burglary) = 0.1
- P(Alarm, Burglary) =

	alarm	¬alarm
burglary	0.09	0.01
¬burglary	0.1	0.8

Probability theory (cont.)

- **Conditional probability**: probability of effect given causes
- **Computing conditional probs**:
  - $P(a \mid b) = P(a \wedge b) / P(b)$
  - P(b): **normalizing** constant
- **Product rule**:
  - $P(a \wedge b) = P(a \mid b) P(b)$
- **Marginalizing**:
  - $P(B) = \Sigma_a P(B, a)$
  - $P(B) = \Sigma_a P(B \mid a) P(a)$ (**conditioning**)

- P(burglary | alarm) = 0.47
  P(alarm | burglary) = 0.9
- P(burglary | alarm) =
  P(burglary ∧ alarm) / P(alarm)
  = 0.09 / 0.19 = 0.47
- P(burglary ∧ alarm) =
  P(burglary | alarm) P(alarm) =
  0.47 * 0.19 = 0.09
- P(alarm) =
  P(alarm ∧ burglary) +
  P(alarm ∧ ¬burglary) =
  0.09 + 0.1 = 0.19

Example: Inference from the joint

	alarm		¬alarm	
	earthquake	¬earthquake	earthquake	¬earthquake
burglary	0.01	0.08	0.001	0.009
¬burglary	0.01	0.09	0.01	0.79

P(Burglary | alarm) = α P(Burglary, alarm)
= α [P(Burglary, alarm, earthquake) + P(Burglary, alarm, ¬earthquake)
= α [(0.01, 0.01) + (0.08, 0.09)]
= α [(0.09, 0.1)]

Since P(burglary | alarm) + P(¬burglary | alarm) = 1, α = 1/(0.09+0.1) = 5.26
(i.e., P(alarm) = 1/α = 0.109 **Quizlet**: how can you verify this?)

P(burglary | alarm) = 0.09 * 5.26 = 0.474

P(¬burglary | alarm) = 0.1 * 5.26 = 0.526

Exercise: Inference from the joint

p(smart ∧ study ∧ prep)	smart		¬smart	
	study	¬study	study	¬study
prepared	0.432	0.16	0.084	0.008
¬prepared	0.048	0.16	0.036	0.072

- **Queries:**
  - **What is the prior probability of *smart*?**
  - **What is the prior probability of *study*?**
  - **What is the conditional probability of *prepared*, given *study* and *smart*?**
- **Save these answers for next time! ☺**

Independence

- When two sets of propositions do not affect each others' probabilities, we call them **independent**, and can easily compute their joint and conditional probability:
  - Independent (A, B) $\leftrightarrow$ $P(A \land B) = P(A) P(B)$, $P(A \mid B) = P(A)$
- For example, {moon-phase, light-level} might be independent of {burglary, alarm, earthquake}
  - Then again, it might not: Burglars might be more likely to burglarize houses when there's a new moon (and hence little light)
  - But if we know the light level, the moon phase doesn't affect whether we are burglarized
  - Once we're burglarized, light level doesn't affect whether the alarm goes off
- We need a more complex notion of independence, and methods for reasoning about these kinds of relationships

Exercise: Independence

p(smart ∧ study ∧ prep)	smart		¬smart	
	study	**¬study**	**study**	**¬study**
prepared	0.432	0.16	0.084	0.008
¬prepared	0.048	0.16	0.036	0.072

- **Queries:**
  - **Is *smart* independent of *study*?**
  - **Is *prepared* independent of *study*?**

Conditional independence

- Absolute independence:
  - A and B are **independent** if and only if $P(A \wedge B) = P(A)\,P(B)$; equivalently, $P(A) = P(A \mid B)$ and $P(B) = P(B \mid A)$
- A and B are **conditionally independent** given C if and only if
  - $P(A \wedge B \mid C) = P(A \mid C)\,P(B \mid C)$
- This lets us decompose the joint distribution:
  - $P(A \wedge B \wedge C) = P(A \mid C)\,P(B \mid C)\,P(C)$
- Moon-Phase and Burglary are ***conditionally independent given*** Light-Level
- Conditional independence is weaker than absolute independence, but still useful in decomposing the full joint probability distribution

Exercise: Conditional independence

p(smart ∧ study ∧ prep)	smart		¬smart	
	study	¬study	study	¬study
prepared	0.432	0.16	0.084	0.008
¬prepared	0.048	0.16	0.036	0.072

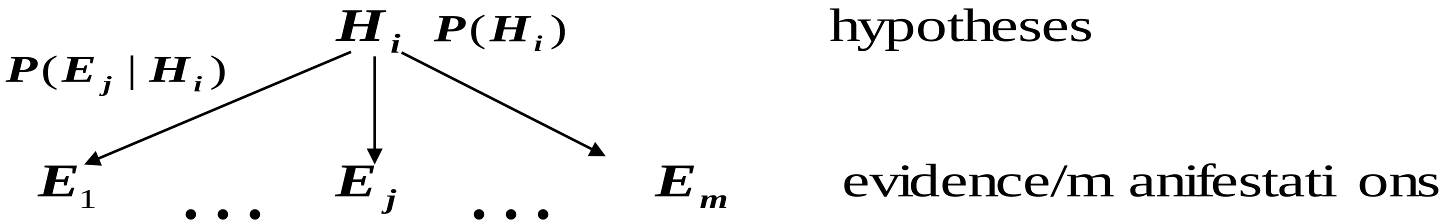
- **Queries:**
  - **Is *smart* conditionally independent of *prepared*, given *study*?**
  - **Is *study* conditionally independent of *prepared*, given *smart*?**

Bayes's rule

- Bayes's rule is derived from the product rule:
  - P(Y | X) = P(X | Y) P(Y) / P(X)
- Often useful for diagnosis:
  - If X are (observed) effects and Y are (hidden) causes,
  - We may have a model for how causes lead to effects (P(X | Y))
  - We may also have prior beliefs (based on experience) about the frequency of occurrence of effects (P(Y))
  - Which allows us to reason abductively from effects to causes (P(Y | X)).

Bayesian inference

- In the setting of diagnostic/evidential reasoning



$P(H_i)$

$P(E_j \mid H_i)$

$P(H_i \mid E_j)$

  – Know prior probability of hypothesis

    conditional probability

  – Want to compute the *posterior probability*

$$P(H_i \mid E_j) = P(H_i)P(E_j \mid H_i) / P(E_j)$$

- Bayes' theorem (formula 1):

Simple Bayesian diagnostic reasoning

- Knowledge base:
  - Evidence / manifestations: $E_1, \ldots, E_m$
  - Hypotheses / disorders: $H_1, \ldots, H_n$
    - E_j and H_i are **binary**; hypotheses are **mutually exclusive** (non-overlapping) and **exhaustive** (cover all possible cases)
  - Conditional probabilities: $P(E_j \mid H_i), i = 1, \ldots, n; j = 1, \ldots, m$
- Cases (evidence for a particular instance): $E_1, \ldots, E_m$
- Goal: Find the hypothesis H_i with the highest posterior
  - $\text{Max}_i \, P(H_i \mid E_1, \ldots, E_m)$

Bayesian diagnostic reasoning II

- Bayes' rule says that
  - $P(H_i \mid E_1, \ldots, E_m) = P(E_1, \ldots, E_m \mid H_i)\, P(H_i) / P(E_1, \ldots, E_m)$
- Assume each piece of evidence E_i is conditionally independent of the others, *given* a hypothesis H_i, then:
  - $P(E_1, \ldots, E_m \mid H_i) = \prod^{m}_{j=1} P(E_j \mid H_i)$
- If we only care about relative probabilities for the H_i, then we have:
  - $P(H_i \mid E_1, \ldots, E_m) = \alpha\, P(H_i) \prod^{m}_{j=1} P(E_j \mid H_i)$

Limitations of simple Bayesian inference

- Cannot easily handle multi-fault situation, nor cases where intermediate (hidden) causes exist:
  - Disease D causes syndrome S, which causes correlated manifestations M_1 and M_2
- Consider a composite hypothesis $H_1 \wedge H_2$, where H_1 and H_2 are independent. What is the relative posterior?
  - $P(H_1 \wedge H_2 \mid E_1, \ldots, E_m) = \alpha\, P(E_1, \ldots, E_m \mid H_1 \wedge H_2)\, P(H_1 \wedge H_2)$
    $= \alpha\, P(E_1, \ldots, E_m \mid H_1 \wedge H_2)\, P(H_1)\, P(H_2)$
    $= \alpha \prod^{m}_{j=1} P(E_j \mid H_1 \wedge H_2)\, P(H_1)\, P(H_2)$
- How do we compute $P(E_j \mid H_1 \wedge H_2)$??

Limitations of simple Bayesian inference II

- Assume H_1 and H_2 are independent, given $E_1, \ldots, E_m$?
  - $P(H_1 \wedge H_2 \mid E_1, \ldots, E_m) = P(H_1 \mid E_1, \ldots, E_m)\, P(H_2 \mid E_1, \ldots, E_m)$
- This is a very unreasonable assumption
  - Earthquake and Burglar are independent, but *not* given Alarm:
    - P(burglar | alarm, earthquake) << P(burglar | alarm)
- Another limitation is that simple application of Bayes's rule doesn't allow us to handle causal chaining:
  - A: this year's weather; B: cotton production; C: next year's cotton price
  - A influences C indirectly: A→ B → C
  - P(C | B, A) = P(C | B)
- Need a richer representation to model interacting hypotheses, conditional independence, and causal chaining
- Next time: conditional independence and Bayesian networks!

THANK YOU