Informatics 2D – Reasoning and Agents Semester 2, 2019–2020

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informatics



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Where are we?

Last time ...

- Previous part of course discussed planning as an efficient way of determining actions that will achieve goals
- Used more elaborate representations than in search, but avoided full complexity of logical reasoning
- Allowed uncertainty to some extent (e.g. conditional planning, replanning)
- However the approaches seen so far don't allow for a quantification of uncertainty

Today ...

Acting under uncertainty

Handling uncertain knowledge Uncertainty and rational decisions Design for a decision-theoretic agent

Handling uncertain knowledge

- So far we have always assumed that propositions are assumed to be true, false, or unknown
- But in reality, we have hunches rather than complete ignorance or absolute knowledge
- Approaches like conditional planning and replanning handle things that might go wrong
- But they don't tell us how likely it is that something might go wrong...
- And rational decisions (i.e. 'the right thing to do') depend on the relative importance of various goals and the likelihood that (and degree to which) they will be achieved

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Handling uncertain knowledge

- To develop theories of uncertain reasoning we must look at the nature of uncertain knowledge
- Example: rules for dental diagnosis
 - A rule like ∀p Symptom(p, Toothache) ⇒ Disease(p, Cavity) is clearly wrong
 - Disjunctive conclusions require long lists of potential diagnoses:

 $\forall p \; Symptom(p, Toothache) \Rightarrow$

 $Disease(p, Cavity) \lor Disease(p, GumDisease) \lor Disease(p, Abscess)...$

- Causal rules like ∀p Disease(p, Cavity) ⇒ Symptom(p, Toothache) can also cause problems
- Even if we know all possible causes, what if the cavity and the toothache are not connected?

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Uncertain knowledge, logic, and probabilities

- Clearly, using (classical) logic is not very useful to capture uncertainty, because of . . .
 - complexity (can be impractical to include all antecedents and consequents in rules, and/or too hard to use them)
 - theoretical ignorance (don't know a rule completely)
 - practical ignorance (don't know the current state)
 - How likely an unknown factor is influences how we reason and act
- One possible approach: express degrees of belief in propositions using probability theory

Probability can **summarise** the uncertainty that comes from our 'laziness' and ignorance

Probabilities between 0 and 1 express the degree to which we believe a proposition to be true

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Degrees of belief and probabilities

- In probability theory, propositions themselves are actually true or false!
- Degrees of truth are the subject of other methods (like fuzzy logic) not dealt with here
- Degrees of belief depend on evidence and should change with new evidence
- Don't confuse this with change in the world that might make the proposition itself true or false!
- Before evidence is obtained we speak of prior/unconditional probability, after evidence of posterior probability

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Uncertainty and rational decisions

- Logical agent has a goal and executes any plan guaranteed to achieve it
- Different with degrees of belief: If plan P has a 90% chance of success, how about another P' with a higher probability? Or how about P" with higher cost but same probability?
- Agent must have **preferences** over **outcomes** of plans
- Utility theory can be used to reason about those preferences
- Based on idea that every state has a degree of usefulness and agents prefer states with higher utility
- Utilities vary from one agent to another.

Decision theory

- A general theory of rational decision making
- Decision theory = probability theory + utility theory
- Foundation of decision theory:

An agent is rational if and only if it chooses the action that yields the highest expected utility, averaged over all possible outcomes of the action

- Principle of Maximum Expected Utility
- Although we follow it here, some points of criticism:
 - Knowledge of preferences?
 - Consistency of preferences?
 - Risk-taking attitude?

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Are We Rational?

A: 100% chance of £3000 B: 80% chance of £4000 C: 25% chance of £3000 D: 20% chance of £4000

- ▶ 88% of you chose lottery A over lottery B.
- ▶ 84% of you chose lottery *D* over lottery *C*.
- So lots of you chose A and D, which is irrational!
 - If U(3000) > 0.8 * U(4000), then 0.25 * U(3000) > 0.2 * U(4000)!!
- Our ability to MEU also affected by emotion, social relationships, relationships among our choices...
- In fact, we're predictably irrational.
- If we were always rational, we wouldn't have self-help, life coaches etc.

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Design for a decision-theoretic agent

- For the time being, we will focus on probability and not utility.
- But still useful to have an idea of general abstract design for a decision-theoretic (utility-based) agent
- Characterised by basic perception-action loop as follows:
 - 1. Update belief state based on previous action and percept
 - 2. Calculate outcome probabilities for actions given action descriptions and belief states
 - 3. Select action with highest expected utility given probabilities of outcomes and utility information
- Very simple but broadly accepted as a general principle for building agents able to cope with real-world environments

Propositions & atomic events

- Degrees of belief concern propositions
- Basic notion: random variable, a part of the world whose status is unknown, with a domain (e.g. Cavity with domain (true, false))
- Can be boolean, discrete or continuous
- Can compose complex propositions from statements about random variables (e.g. Cavity = true \triangle Toothache = false)
- Atomic event = complete specification of the state of the world
 - Atomic events are mutually exclusive
 - Their set is exhaustive
 - Every event entails truth or falsehood of any proposition (like models in logic)
 - Every proposition logically equivalent to the disjunction of all atomic events that entail it

Propositions & atomic events

- Unconditional/prior probability = degree of belief in a proposition *a* in the absence of any other information
- Can be between 0 and 1, write as P(Cavity = true) = 0.1 or P(cavity) = 0.1
- Probability distribution = the probabilities of all values of a random variable
- Write $\mathbf{P}(Weather) = \langle 0.7, 0.2, 0.1 \rangle$ for

P(Weather = sunny) = 0.7P(Weather = rain) = 0.2P(Weather = cloudy) = 0.1

Probability distributions/conditional probabilities

- For a mixture of several variables, we obtain a joint probability distribution (JPD) – cross-product of individual distributions
- A JPD ("joint") describes one's uncertainty about the world as it specifies the probability of every atomic event
- For continuous variables we use probability density function (we cannot enumerate values)
- Will talk about these in detail later
- Conditional probability P(a|b) = the probability of a given that all we know is b
- Example: P(cavity|toothache) = 0.8 means that if patient is observed to have toothache, then there is an 80% chance that he has a cavity

Conditional probabilities

- ► Can be defined using unconditional probabilities: $P(a|b) = \frac{P(a \land b)}{P(b)}$
- Often written as **product rule** $P(a \land b) = P(a|b)P(b)$
- ► Good for describing JPDs (which then become "CPDs") as $\mathbf{P}(X, Y) = \mathbf{P}(X|Y)\mathbf{P}(Y)$

Set of equations, not matrix multiplication (!):

$$P(X = x_1 \land Y = y_1) = P(X = x_1 | Y = y_1)P(Y = y_1)$$

$$P(X = x_1 \land Y = y_2) = P(X = x_1 | Y = y_2)P(Y = y_2)$$

$$P(X = x_n \land Y = y_m) = P(X = x_n | Y = y_m)P(Y = y_m)$$

Conditional probability does not mean logical implication!

The axioms of probability

Kolmogorov's axioms define basic semantics for probabilities:

1.
$$0 \le P(a) \le 1$$
 for any proposition a

2.
$$P(true) = 1$$
 and $P(false) = 0$

3. $P(a \lor b) = P(a) + P(b) - P(a \land b)$

From this, a number of useful facts can be derived, e.g:

$$P(\neg a) = 1 - P(a)$$

- For variable D with domain $\langle d_1, \ldots, d_n \rangle$, $\sum_{i=1}^n P(D = d_i) = 1$
- And so any JPD over finite variables sums to 1
- If e(a) is the set of atomic events that entail a, then (because they are mutually exclusive) it holds that

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

With this, we can calculate the probability of any proposition from a JPD information

Summary

- Explained why logic in itself is insufficient to model uncertainty
- Discussed principles of decision making under uncertainty
 - Decision theory, MEU principle
- Probability theory provides useful tools for quantifying degree of belief/uncertainty in propositions
- Atomic events, propositions, random variables
- Probability distributions, conditional probabilities
- Axioms of probability
- Next time: Introduction to Coursework 2