

"States" = cells on 2d grid

actions = attempts to move N, S, E, W.

\* noisy dynamics

\* rewards = feedback from environment

- delayed vs. immediate

- evaluative vs. instructive

More generally: how can autonomous agents learn from experience?

⇒ Markov decision processes, reinforcement learning.

Other "embodied" agents: elevators, helicopters

Other "embedded" agents: game-playing system, spoken dialog system.

### Themes of class

1) Probabilistic models of uncertainty

2) Learning as optimizations

3) Power vs. tractable: how to develop compact representation of complex world?

4) Principles vs. heuristics: optimizations } vs. rules-of-thumb  
calculations }

5) Synergies of AI: inference and learning, perception and action, theory and practice.

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### Motivation

\* Modeling of uncertainty

- Inherent randomness (e.g., radioactive decay)

- Gross statistical description of complex deterministic world. (e.g., coin toss)

\* Probability acts as guardian of commonsense reasoning.

\* Many empirical successes: robotics, language, speech, bioinformatics.

### Review

\* Discrete random variable  $X$

Domain of possible values  $\{x_1, x_2, \dots, x_m\}$

Ex: month  $M$   $\{m_1 = \text{Jan}, m_2 = \text{Feb}, \dots, m_{12} = \text{Dec}\}$

\* Unconditional (prior) probability  $P(X=x_i)$

\* Basic axioms: (i)  $P(X=x_i) \geq 0$

$$(ii) \sum_i P(X=x_i) = 1$$

$$(iii) P(X=x_i \text{ or } X=x_j) = P(X=x_i) + P(X=x_j) \text{ if } x_i \neq x_j$$

Probs add for union of mutually exclusive events.

\* Conditional (or posterior) probabilities

$P(X = x_i | Y = y_j)$  prob that  $X = x_i$  given  $Y = y_j$ .

In general,  $P(X = x_i | Y = y_j) \neq P(X = x_i)$

Ex:  $W = \text{weather}$   $\{w_1 = \text{sunny}, w_2 = \text{rainy}\}$

$$P(W = \text{sunny}) = 0.9$$

$$P(W = \text{sunny} | M = \text{aug}) = 0.97$$

$$P(W = \text{sunny} | M = \text{Jan}) = 0.83$$

} conditional dependence

Ex: conditional independence

Day of week  $D$   $\{d_1 = \text{sun}, d_2 = \text{mon}, \dots, d_n = \text{sat}\}$

$$P(W = \text{sunny} | D = \text{tues}) = P(W = \text{sunny}) = 0.9$$

Also true: (i)  $P(X = x_i | Y = y_j) \geq 0$

$$(ii) \sum_i P(X = x_i | Y = y_j) = 1$$

Note sum over  $i$ , not  $j$ .  $\sum_j P(X = x_i | Y = y_j)$  nothing you can say about this.

\* Joint probability

$P(X = x_i, Y = y_j) = \text{Prob that } X = x_i \text{ and } Y = y_j$ .

(\*) Product rule

$$\text{For all } i, j: P(X = x_i, Y = y_j) = P(X = x_i | Y = y_j) P(Y = y_j)$$

$$P(X = x_i, Y = y_j) = P(Y = y_j | X = x_i) P(X = x_i)$$

\* Marginalization

$$P(X = x_i) = \sum_j P(X = x_i, Y = y_j)$$

$$P(X = x_i, Y = y_j) = \sum_k P(X = x_i, Y = y_j, Z = z_k)$$

\* Intuitively, easier for experts to assess conditional probabilities than joint probabilities.

\* Shorthand notation.

(i) Implied universality

$$P(X, Y) = P(X|Y)P(Y) = P(Y|X)P(X) \text{ implies that equality holds for all assignments } x_i, y_j. \quad (*)$$

(ii) Implied assignment

$$P(x, y, z) = P(X=x, Y=y, Z=z)$$

\* Generalized product rule.

$$P(A, B, C, D, \dots) = P(A)P(B|A)P(C|A, B)P(D|A, B, C) \dots$$

\* Bayes rule:

$$\text{From (*)} \rightarrow P(X|Y) = \frac{P(Y|X)P(X)}{P(Y)}$$

\* Generalized Bayes rule:

$$P(X|Y, Z) = \frac{P(Y|X, Z)P(X|Z)}{P(Y|Z)}$$

### Example

\* Binary random variables

B = burglary

E = earthquake

A = alarm.

\* Joint distribution

$$P(B, E, A) = P(B)P(E|B)P(A|B, E).$$

\* Prior knowledge

$$P(B=1) = 0.001 \iff P(B=0) = 1 - P(B=1) = 0.999$$

$$\left. \begin{aligned} P(E=1|B=0) &= 0.002 \\ P(E=1|B=1) &= 0.002 \end{aligned} \right\} P(E=1|B) = P(E=1) = 0.002$$

(conditional independence)

B	E	$P(A=1 B, E)$	$P(A=0 B, E)$
0	0	0.001	⋮
1	0	0.94	$1 - P(A=1 B, E)$
0	1	0.29	⋮
1	1	0.95	⋮

\* Inferences

Do these probabilities capture commonsense reasoning?

Compare  $P(B=1)$ ,  $P(B=1|A=1)$ , and  $P(B=1|A=1, E=1)$ ?

$$P(B=1) = 0.001.$$

$$P(B=1|A=1) = \frac{P(A=1|B=1)P(B=1)}{P(A=1)} \quad \text{Bayes rule.}$$

$$\begin{aligned} P(A=1|B=1) &= \sum_{e \in \{0,1\}} P(A=1, E=e|B=1) \quad \text{conditional marginalization} \\ &= \sum_e P(A=1|E=e, B=1)P(E=e|B=1) \quad \text{generalized product rule} \\ &= \sum_e P(A=1|E=e, B=1)P(E=e) \quad \text{conditional independence} \\ &= P(A=1|E=1, B=1)P(E=1) + P(A=1|E=0, B=1)P(E=0) \\ &= (0.95)(0.002) + (0.94)(0.998) \\ &= 0.94002 \end{aligned}$$

$$\begin{aligned}
P(A=1) &= \sum_{e,b} P(A=1, E=e, B=b) \quad : \text{marginalization} \\
&= \sum_{e,b} P(A=1 | E=e, B=b) P(E=e | B=b) P(B=b) \quad : \text{product rule} \\
&= \sum_{e,b} P(A=1 | E=e, B=b) P(E=e) P(B=b) \quad : \text{conditional independence} \\
&= (0.95)(0.002)(0.001) + \dots \\
&\quad \quad \quad \{e=b=1\} \quad \quad \quad \text{(other cases)} \\
&= 0.00252.
\end{aligned}$$

From Bayes rule:  $P(B=1 | A=1) = P(A=1 | B=1) P(B=1) / P(A=1)$   
 $= (0.94002)(0.001) / (0.00252)$

$P(B=1   A=1) = 0.37$
$P(B=1) = 0.001$

Compare to

$P(B=1)$  : conditional independence

Now, compute:  $P(B=1 | A=1, E=1) = \frac{P(A=1 | B=1, E=1) P(B=1 | E=1)}{P(A=1 | E=1)}$   
↑ Conditional Bayes rule

$$= (0.95)(0.001) / P(A=1 | E=1)$$

$$P(A=1 | E=1) = P(A=1, E=1) / P(E=1) \quad : \text{product rule}$$

↑ (0.002)

$$\begin{aligned}
P(A=1, E=1) &= \sum_b P(A=1, E=1, B=b) \quad : \text{marginalization} \\
&= \sum_b P(A=1 | E=1, B=b) P(E=1 | B=b) P(B=b) \quad : \text{product rule} \\
&= \sum_b P(A=1 | E=1, B=b) P(E=1) P(B=b) \quad : \text{conditional independence} \\
&\quad \quad \quad \text{(summing over } b = \{0,1\} \text{ and substituting ...)} \\
&= 0.00058.
\end{aligned}$$

Plugging in:  $P(B=1 | A=1, E=1) = \frac{(0.95)(0.001)}{\left(\frac{0.00058}{0.002}\right)} = 0.0033$ .

In sum:  $P(B=1) = 0.001$

$P(B=1 | A=1) = 0.37 \uparrow$

$P(B=1 | A=1, E=1) = 0.0033 \downarrow$

Example of non-monotonic reasoning

$$P(B=1 | A=1, E=1) < P(B=1 | A=1)$$

The earthquake "explains away" the alarm, thus decreasing our belief in burglary.