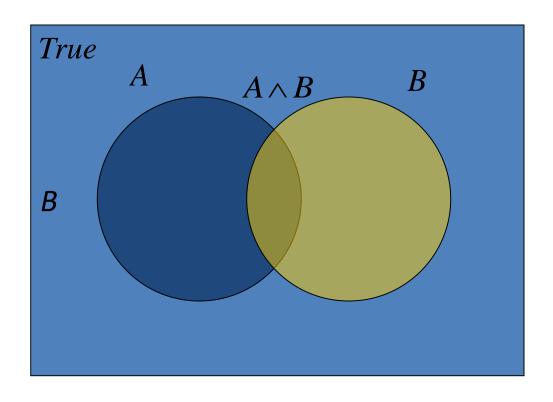


Robotics Group Project - 5CCS2RGP

Lecture 4: Fundamentals for Probabilistic Robotics

Fundamentals in Probability

$$Pr(A \lor B) = Pr(A) + Pr(B) - Pr(A \land B)$$



$$Pr(A) + Pr(\emptyset A) = 1$$

 $Pr(\emptyset A) = 1 - Pr(A)$

Joint and Conditional Probability

- P(X=x and Y=y) = P(x,y)
- If X and Y are independent then P(x,y) = P(x) P(y)
- $P(x \mid y)$ is the probability of x given y $P(x \mid y) = P(x,y) / P(y)$ $P(x,y) = P(x \mid y) P(y)$
- If X and Y are independent then $P(x \mid y) = P(x)$

Law of Total Probability, Marginals

Discrete case

Continuous case

$$\sum_{x} P(x) = 1$$

$$\int p(x) \, dx = 1$$

$$P(x) = \sum_{y} P(x, y)$$

$$p(x) = \int p(x, y) \, dy$$

$$P(x) = \sum_{y} P(x \mid y) P(y)$$

$$p(x) = \int p(x | y) p(y) dy$$

Law of Total Probability, Marginals

Discrete case

$$\sum_{x} P(x) = 1$$

$$P(x) = \sum_{y} P(x, y)$$

$$P(x) = \sum_{y} P(x \mid y) P(y)$$

Or

When Y=yellow light

Or

When Y= red light

Bayes Formula

$$P(x, y) = P(x | y)P(y) = P(y | x)P(x)$$

$$\Rightarrow$$

$$P(x \mid y) = \frac{P(y \mid x) \ P(x)}{P(y)} = \frac{\text{likelihood } \cdot \text{prior}}{\text{evidence}}$$

Normalization

$$P(x|y) = \frac{P(y|x) P(x)}{P(y)} = h P(y|x) P(x)$$

$$\sum_{x} P(x \mid y) = 1$$

Normalization

$$P(x|y) = \frac{P(y|x)P(x)}{P(y)} = \eta P(y|x)P(x)$$

$$\sum_{x} P(x \mid y) = 1$$

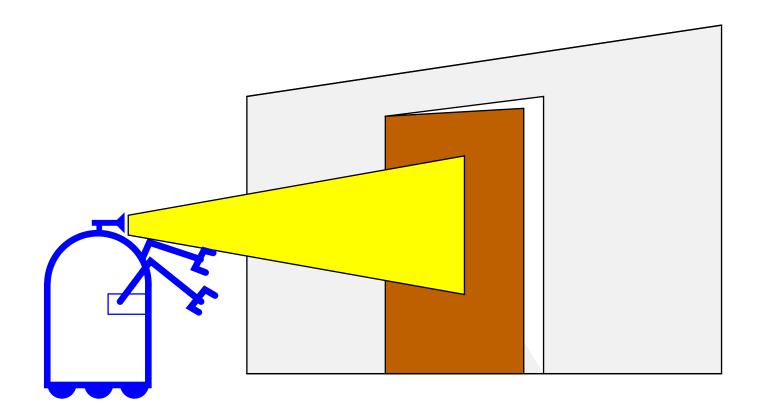
$$\eta \sum_{x} P(y \mid x) P(x) = 1$$



$$h = P(y)^{-1} = \frac{1}{\overset{\circ}{a}P(y|x)P(x)}$$

Simple Example of State Estimation

- Suppose a robot obtains measurement z
- What is P(open|z)?



Causal vs. Diagnostic Reasoning

- P(open|z) is diagnostic.
- P(z|open) is sausal.
- Often causal knowledge is easier to obtain
- Bayes rule allows us to use causalknowledge:

$$P(open | z) = \frac{P(z | open)P(open)}{P(z)}$$

Example

•
$$P(z/open) = 0.6$$
 $P(z/open) = 0.3$

• $P(open) = P(\neg open) = 0.5$

$$P(open \mid z) = \frac{P(z \mid open)P(open)}{P(z \mid open)p(open) + P(z \mid \neg open)p(\neg open)}$$

$$P(open \mid z) = \frac{0.6 \cdot 0.5}{0.6 \cdot 0.5 + 0.3 \cdot 0.5} = \frac{2}{3} = 0.67$$

Z raises the probability that the door is open.

Combining Evidence

- Suppose our robot obtains another observation z_2 .
- How can we integrate this new information?
- More generally, how can we estimate $P(x/z_1...z_n)$?

Actions

- Often the world is dynamic since
 - actions carried out by the robot,
 - actions carried out by other agents,
 - or just the time passing by change the world.

How can we incorporate such actions?

Typical Actions

- The robot turns its wheels to move
- The robot uses its manipulator to grasp an object
- Plants grow over time...

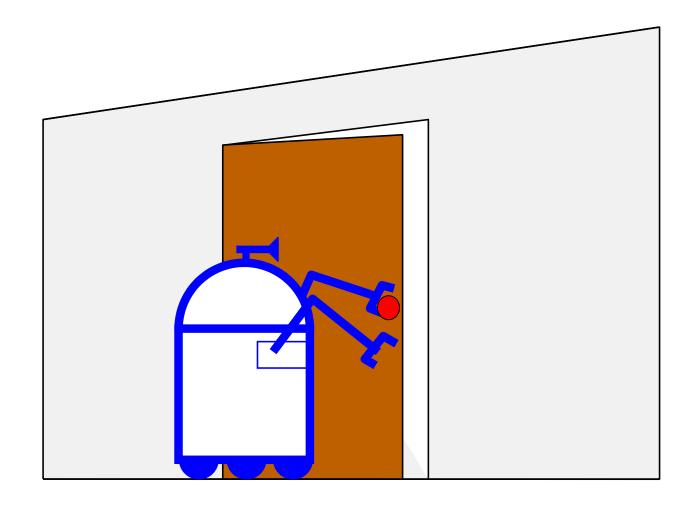
- Actions are never carried out with absolute certainty.
- In contrast to measurements, actions generally increase the uncertainty.

Modeling Actions

To incorporate the outcome of an action u into the current "belief", we use the conditional pdf(probability density function)
 P(x|u, x')

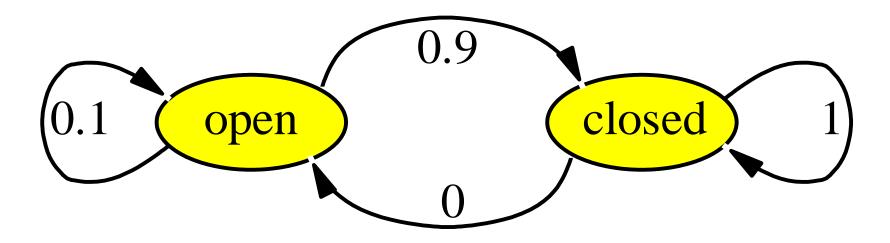
This term specifies the pdf that executing u changes the state from x 'to x.

Example: Closing the door



State Transitions

P(x|u,x') for u = "close door":



If the door is open, the action "close door" succeeds in 90% of all cases.

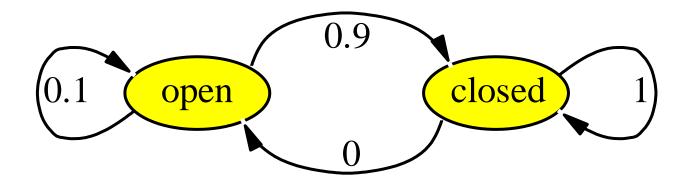
Integrating the Outcome of Actions

Continuous case:

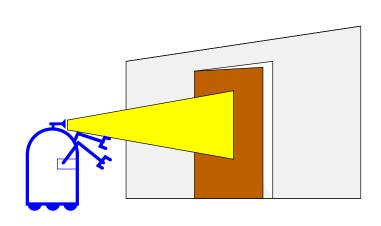
$$P(x \mid u) = \int P(x \mid u, x') P(x') dx'$$

Discrete case:

$$P(x | u) = \sum_{x'} P(x | u, x') P(x')$$



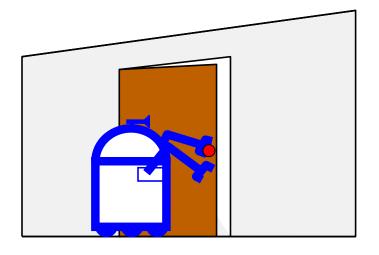
Initial condition: Open =0.5, close = 0.5



Initial condition: Open =0.5, close = 0.5



After observation: Open =0.67, close = 0.33



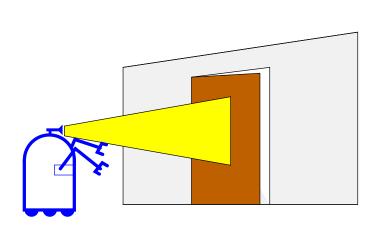
Initial condition: Open =0.5, close = 0.5

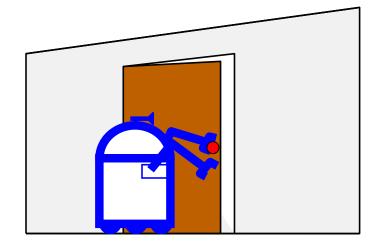


After one action: Open =0.05, close = 0.95

Question

 How to iterate the process to cope with continued motions of a robot





► Initial P : Open =0.5, close = 0.5



After observation P: Open =0.67, close = 0.33

→ updated P: Open =0.67, close = 0.33



After one action P: Open =?, close =?

updated probability

Question

 How to extend the binary state to multiple states (in our case, discretized grids)?