

Introduction to Mobile Robotics

Probabilistic Robotics

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Probabilistic Robotics

Key idea:

Explicit representation of uncertainty

(using the calculus of probability theory)

- Perception = state estimation
- Action = utility optimization

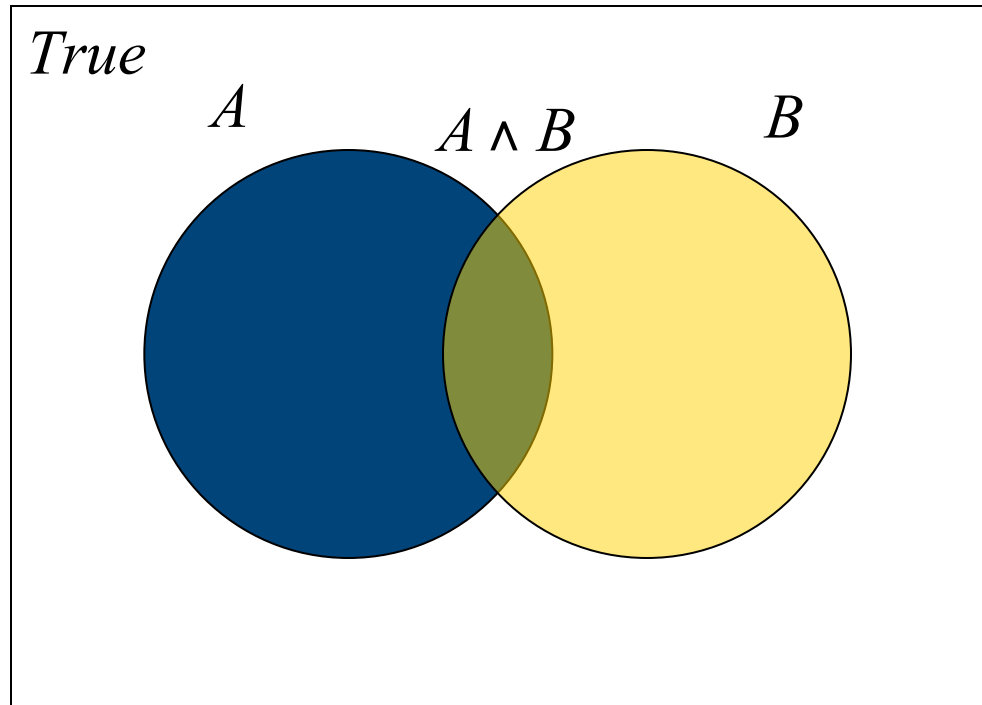
Axioms of Probability Theory

$\Pr(A)$ denotes probability that proposition A is true.

- $0 \leq \Pr(A) \leq 1$
- $\Pr(\textit{True}) = 1$ $\Pr(\textit{False}) = 0$
- $\Pr(A \vee B) = \Pr(A) + \Pr(B) - \Pr(A \wedge B)$

A Closer Look at Axiom 3

$$\Pr(A \vee B) = \Pr(A) + \Pr(B) - \Pr(A \wedge B)$$



Using the Axioms

$$\Pr(A \vee \neg A) = \Pr(A) + \Pr(\neg A) - \Pr(A \wedge \neg A)$$

$$\Pr(\textit{True}) = \Pr(A) + \Pr(\neg A) - \Pr(\textit{False})$$

$$1 = \Pr(A) + \Pr(\neg A) - 0$$

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

Discrete Random Variables

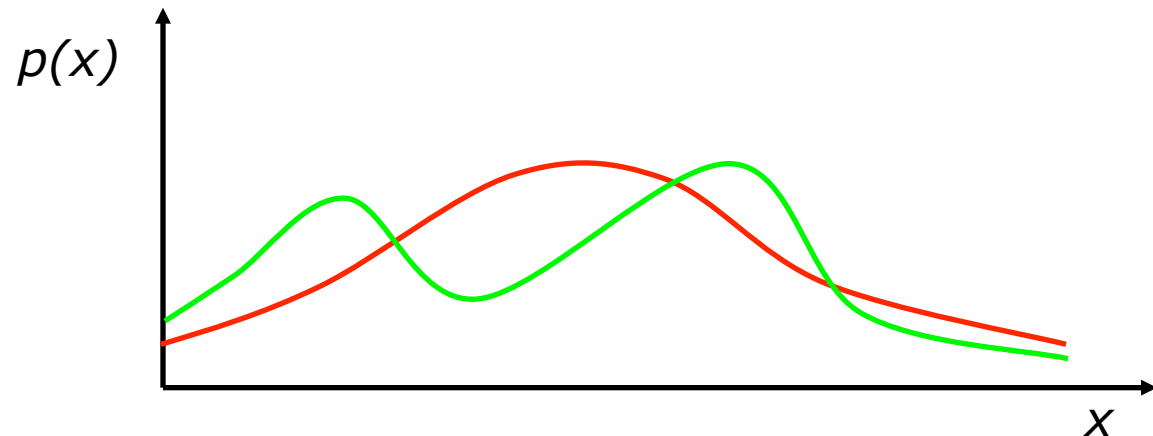
- X denotes a **random variable**
- X can take on a countable number of values in $\{x_1, x_2, \dots, x_n\}$
- $P(X=x_i)$ or $P(x_i)$ is the **probability** that the random variable X takes on value x_i
- $P(\cdot)$ is called **probability mass function**
- E.g. $P(\text{Room}) = \langle 0.7, 0.2, 0.08, 0.02 \rangle$

Continuous Random Variables

- X takes on values in the continuum.
- $p(X=x)$ or $p(x)$ is a **probability density function**

$$\Pr(x \in (a, b)) = \int_a^b p(x) dx$$

- E.g.



“Probability Sums up to One”

Discrete case

$$\sum_x P(x) = 1$$

Continuous case

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

Joint and Conditional Probability

- $P(X=x \text{ and } Y=y) = P(x,y)$
- If X and Y are **independent** then
$$P(x,y) = P(x) P(y)$$
- $P(x | y)$ is the probability of **x given y**
$$P(x | y) = P(x,y) / P(y)$$
$$P(x,y) = P(x | y) P(y)$$
- If X and Y are **independent** then
$$P(x | y) = P(x)$$

Law of Total Probability

Discrete case

$$P(x) = \sum_y P(x | y)P(y)$$

Continuous case

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

Marginalization

Discrete case

$$P(x) = \sum_y P(x, y)$$

Continuous case

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

Bayes Formula

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

\Rightarrow

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

Normalization

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

$$\eta = P(y)^{-1} = \frac{1}{\sum_x P(y|x)P(x)}$$

Algorithm:

$$\forall x : \text{aux}_{x|y} = P(y|x) P(x)$$

$$\eta = \frac{1}{\sum_x \text{aux}_{x|y}}$$

$$\forall x : P(x|y) = \eta \text{aux}_{x|y}$$

Bayes Rule with Background Knowledge

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

Conditional Independence

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

- Equivalent to $P(x | z) = P(x | z, y)$

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

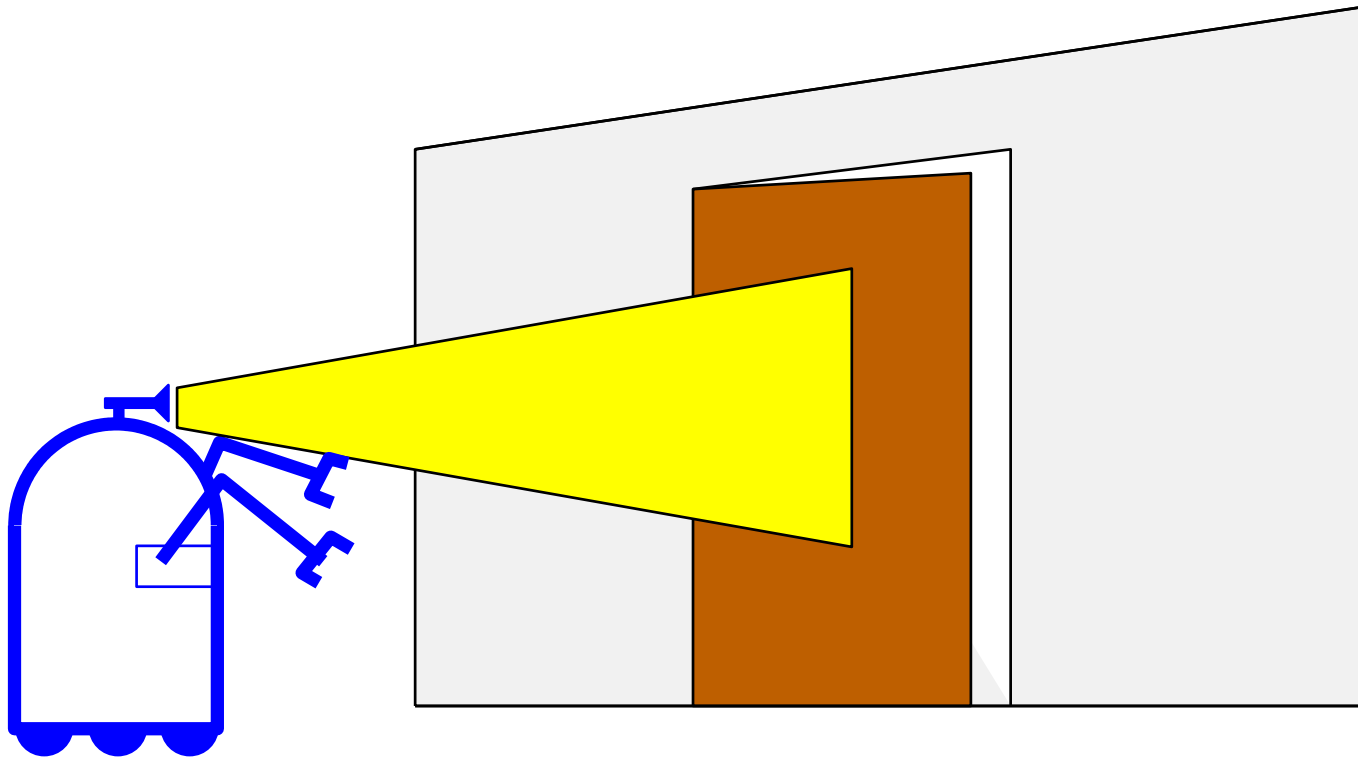
- But this does not necessarily mean

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

(independence/marginal independence)

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 **causal**
- Often **causal** knowledge is easier to obtain **count frequencies!**
- Bayes rule allows us to use causal knowledge:

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

Example

- $P(z|open) = 0.6$ $P(z|\neg open) = 0.3$
- $P(open) = P(\neg open) = 0.5$

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

$$P(open | z) = \frac{0.6 \cdot 0.5}{0.6 \cdot 0.5 + 0.3 \cdot 0.5} = \frac{0.3}{0.3 + 0.15} = 0.67$$

- 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 $P(x | z_1 \dots z_n)$?

Recursive Bayesian Updating

$$P(x | z_1, \dots, z_n) = \frac{P(z_n | x, z_1, \dots, z_{n-1}) P(x | z_1, \dots, z_{n-1})}{P(z_n | z_1, \dots, z_{n-1})}$$

Markov assumption:

z_n is independent of z_1, \dots, z_{n-1} if we know x

$$\begin{aligned} P(x | z_1, \dots, z_n) &= \frac{P(z_n | x) P(x | z_1, \dots, z_{n-1})}{P(z_n | z_1, \dots, z_{n-1})} \\ &= \eta P(z_n | x) P(x | z_1, \dots, z_{n-1}) \\ &= \eta_{1\dots n} \prod_{i=1\dots n} P(z_i | x) P(x) \end{aligned}$$

Example: Second Measurement

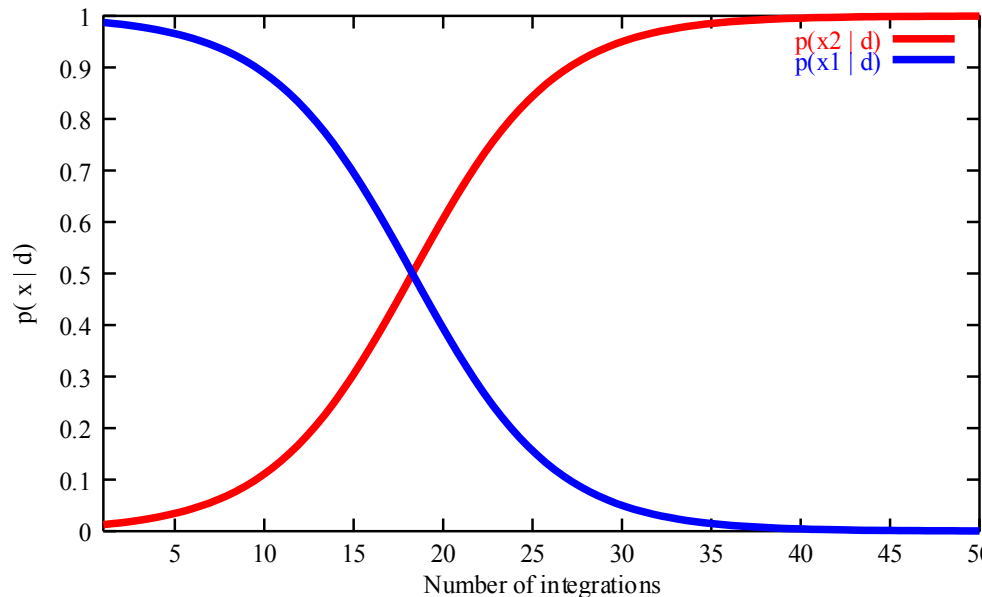
- $P(z_2|open) = 0.5$ $P(z_2|\neg open) = 0.6$
- $P(open|z_1) = 2/3$

$$\begin{aligned} P(open | z_2, z_1) &= \frac{P(z_2 | open) P(open | z_1)}{P(z_2 | open) P(open | z_1) + P(z_2 | \neg open) P(\neg open | z_1)} \\ &= \frac{\frac{1}{2} \cdot \frac{2}{3}}{\frac{1}{2} \cdot \frac{2}{3} + \frac{3}{5} \cdot \frac{1}{3}} = \frac{\frac{1}{3}}{\frac{1}{3} + \frac{1}{5}} = \frac{\frac{1}{3}}{\frac{8}{15}} = \frac{5}{8} = 0.625 \end{aligned}$$

- z_2 lowers the probability that the door is open

A Typical Pitfall

- Two possible locations x_1 and x_2
- $P(x_1) = 0.99$
- $P(z|x_2) = 0.09$ $P(z|x_1) = 0.07$



Actions

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

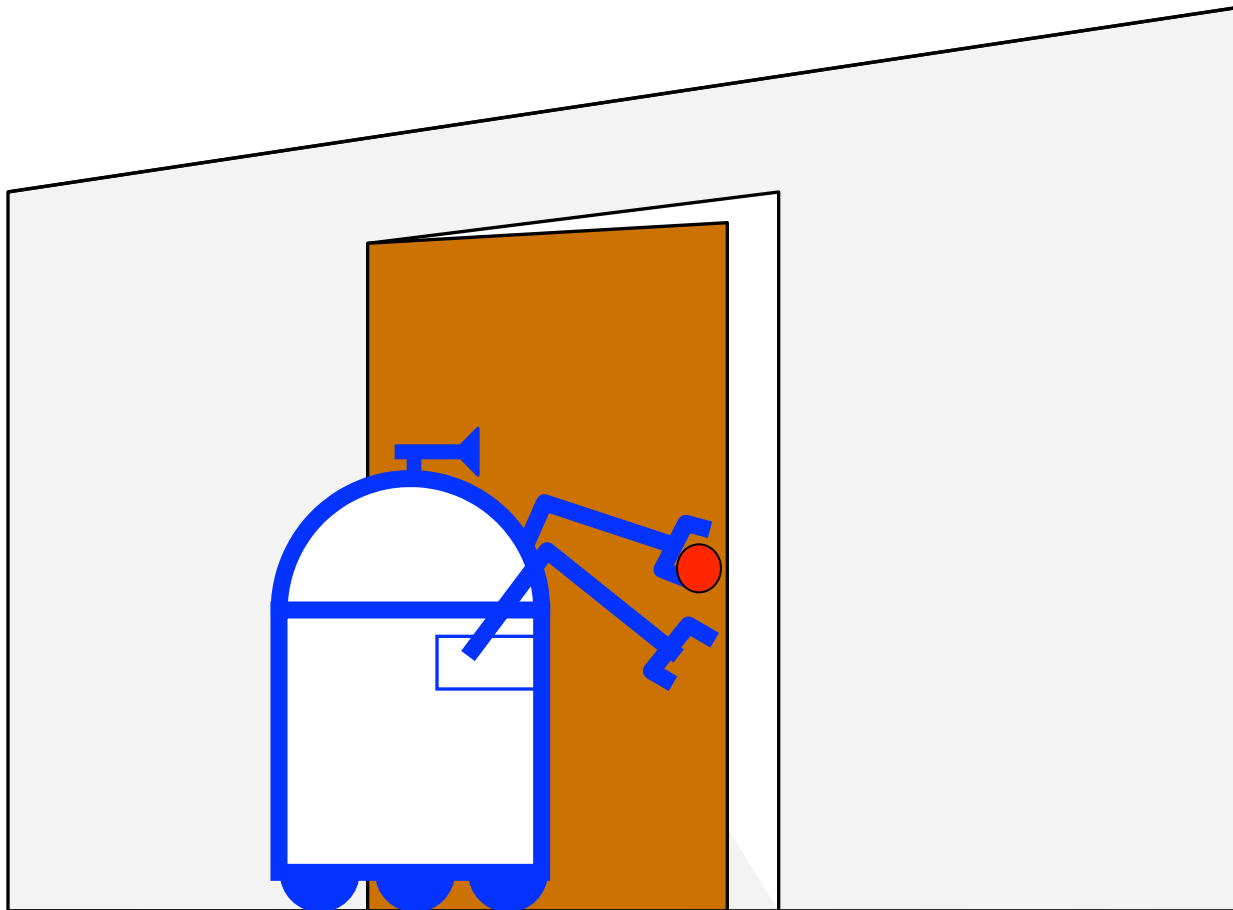
Modeling Actions

- To incorporate the outcome of an action u into the current “belief”, we use the conditional pdf

$$P(x|u,x')$$

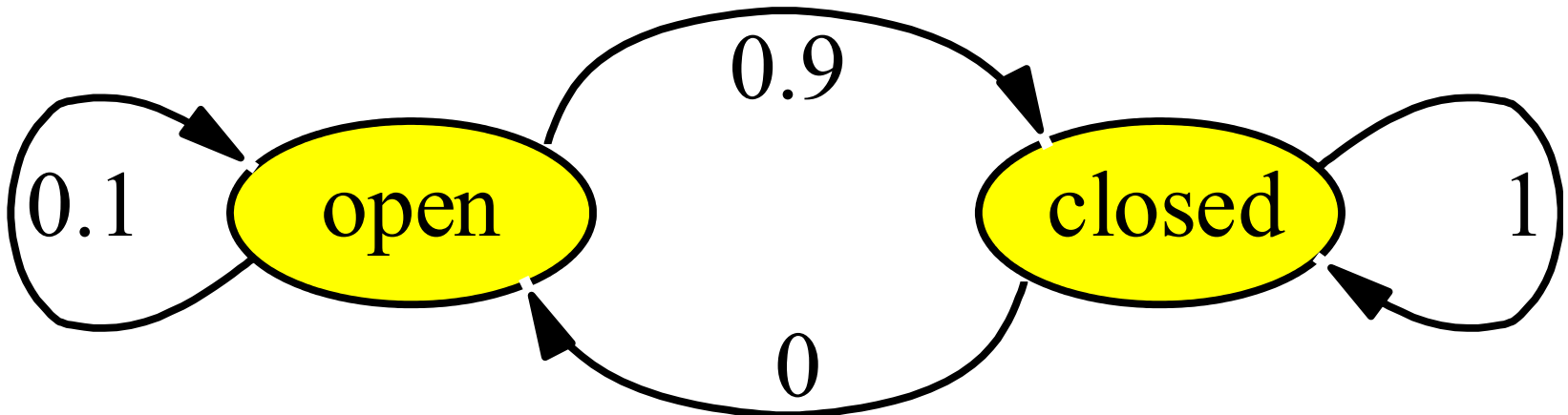
- This term specifies the pdf that **executing u changes the state from x' to x .**

Example: Closing the door



State Transitions

$P(x|u, x')$ for $u = \text{“close door”}$:



If the door is open, the action “close door” succeeds in 90% of all cases

Integrating the Outcome of Actions

Continuous case:

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

Discrete case:

$$P(x | u) = \sum P(x | u, x')P(x')$$

Example: The Resulting Belief

$$\begin{aligned}P(\textit{closed} | u) &= \sum P(\textit{closed} | u, x')P(x') \\ &= P(\textit{closed} | u, \textit{open})P(\textit{open}) \\ &\quad + P(\textit{closed} | u, \textit{closed})P(\textit{closed}) \\ &= \frac{9}{10} * \frac{5}{8} + \frac{1}{1} * \frac{3}{8} = \frac{15}{16}\end{aligned}$$

$$\begin{aligned}P(\textit{open} | u) &= \sum P(\textit{open} | u, x')P(x') \\ &= P(\textit{open} | u, \textit{open})P(\textit{open}) \\ &\quad + P(\textit{open} | u, \textit{closed})P(\textit{closed}) \\ &= \frac{1}{10} * \frac{5}{8} + \frac{0}{1} * \frac{3}{8} = \frac{1}{16} \\ &= 1 - P(\textit{closed} | u)\end{aligned}$$

Bayes Filters: Framework

- **Given:**

- Stream of observations z and action data u :

$$d_t = \{u_1, z_1 \dots, u_t, z_t\}$$

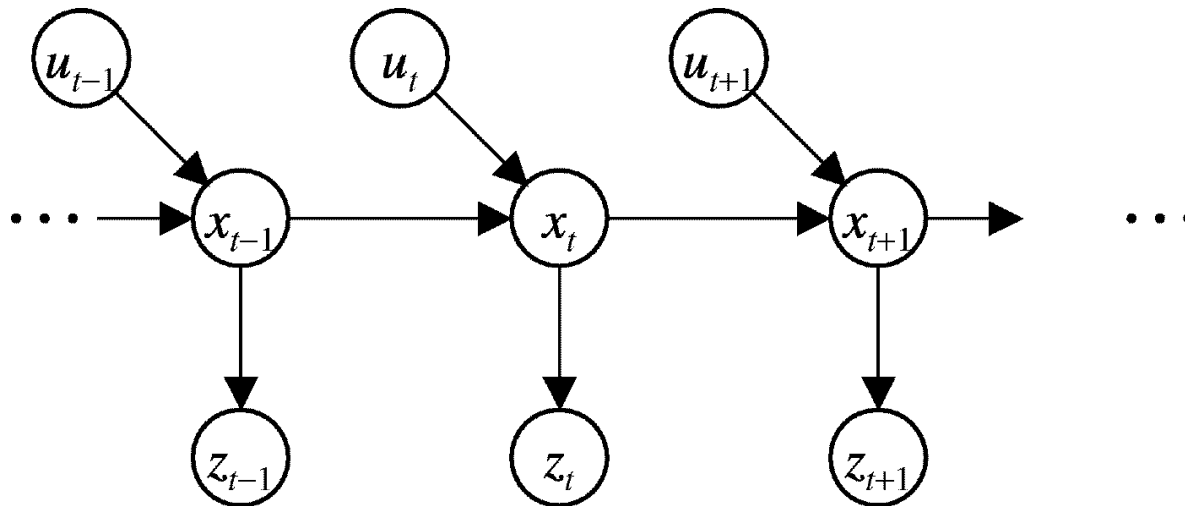
- **Sensor model** $P(z|x)$
- **Action model** $P(x|u, x')$
- **Prior** probability of the system state $P(x)$

- **Wanted:**

- Estimate of the state X of a **dynamical system**
- The posterior of the state is also called **Belief**:

$$Bel(x_t) = P(x_t | u_1, z_1 \dots, u_t, z_t)$$

Markov Assumption



$$p(z_t \mid x_{0:t}, z_{1:t-1}, u_{1:t}) = p(z_t \mid x_t)$$

$$p(x_t \mid x_{1:t-1}, z_{1:t}, u_{1:t}) = p(x_t \mid x_{t-1}, u_t)$$

Underlying Assumptions

- Static world
- Independent noise
- Perfect model, no approximation errors

z = observation
 u = action
 x = state

Bayes Filters

$$\boxed{Bel(x_t)} = P(x_t | u_1, z_1, \dots, u_t, z_t)$$

Bayes $= \eta P(z_t | x_t, u_1, z_1, \dots, u_t) P(x_t | u_1, z_1, \dots, u_t)$

Markov $= \eta P(z_t | x_t) P(x_t | u_1, z_1, \dots, u_t)$

Total prob. $= \eta P(z_t | x_t) \int P(x_t | u_1, z_1, \dots, u_t, x_{t-1}) P(x_{t-1} | u_1, z_1, \dots, u_t) dx_{t-1}$

Markov $= \eta P(z_t | x_t) \int P(x_t | u_t, x_{t-1}) P(x_{t-1} | u_1, z_1, \dots, u_t) dx_{t-1}$

Markov $= \eta P(z_t | x_t) \int P(x_t | u_t, x_{t-1}) P(x_{t-1} | u_1, z_1, \dots, z_{t-1}) dx_{t-1}$

$$\boxed{= \eta P(z_t | x_t) \int P(x_t | u_t, x_{t-1}) Bel(x_{t-1}) dx_{t-1}}$$

$$Bel(x_t) = \eta P(z_t | x_t) \int P(x_t | u_t, x_{t-1}) Bel(x_{t-1}) dx_{t-1}$$

1. Algorithm **Bayes_filter**($Bel(x), d$):
2. $\eta=0$
3. If d is a perceptual data item z then
4. For all x do
5. $Bel'(x) = P(z | x)Bel(x)$
6. $\eta = \eta + Bel'(x)$
7. For all x do
8. $Bel'(x) = \eta^{-1}Bel'(x)$
9. Else if d is an action data item u then
10. For all x do
11. $Bel'(x) = \int P(x | u, x') Bel(x') dx'$
12. Return $Bel'(x)$

Bayes Filters are Familiar!

$$Bel(x_t) = \eta P(z_t | x_t) \int P(x_t | u_t, x_{t-1}) Bel(x_{t-1}) dx_{t-1}$$

- Kalman filters
- Particle filters
- Hidden Markov models
- Dynamic Bayesian networks
- Partially Observable Markov Decision Processes (POMDPs)

Summary

- Bayes rule allows us to compute probabilities that are hard to assess otherwise.
- Under the Markov assumption, recursive Bayesian updating can be used to efficiently combine evidence.
- Bayes filters are a probabilistic tool for estimating the state of dynamic systems.