

# Probability

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$$p(x|y) = \frac{p(x) \cdot p(y|x)}{p(y)}$$

$x$  &  $y$  are independent

$$p(x|y) = \frac{p(x) \cdot p(y)}{p(y)} = p(x)$$

✓ Theorem of total probability.

$$p(x) = \sum_y p(x|y) \cdot p(y) \quad \text{discrete case}$$

$$p(x) = \int p(x|y) \cdot p(y) dy \quad \text{continuous case}$$

✓ Bayes rule

$$p(x|y) = \frac{p(y|x) \cdot p(x)}{p(y)} = \frac{p(y|x) \cdot p(x)}{\sum_{x'} p(y|x') \cdot p(x')} \quad (\text{discrete})$$

$$p(x|y) = \frac{p(y|x) \cdot p(x)}{p(y)} = \frac{p(y|x) \cdot p(x)}{\int p(y|x') \cdot p(x') dx'} \quad (\text{continuous})$$

~~Functions: 1) Optimization, 2) Predict Sigma points~~

$p(y)$  does not depend on  $x$ . Thus, the factor  $p(y)^{-1}$  is often written as a 'normalizer' equation variable denoted by  $(\eta)$

$$\Rightarrow p(x|y) = \frac{1}{N} (p(y|x) \cdot p(x))$$

\* We simply use normalizer 'N' to indicate that the final result has to be normalized to 1.

✓ Expectation of random variable  $X$  is given by:

$$E(X) = \sum_x x \cdot p(x)$$

$$E(X) = \int x \cdot p(x) \cdot dx$$

$$E(aX+b) = a \cdot E[X] + b$$

$$\text{Var}[X] = E[X - E[X]]^2 = E[X^2] - E[X]^2$$

✓ for a discrete random variable, entropy is given by:

$$H(P) = E[-\log_2 p(x)] = - \sum_x p(x) \log_2 p(x)$$

✓ Conditioning Bayes rule:

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

$$p(x, y|z) = p(x|z) \cdot p(y|z)$$

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

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



$$p(x, y|z) = p(x|z) \cdot p(y|z) \not\Rightarrow p(x, y) = p(x) \cdot p(y)$$

✓ belief over state variable  $x_t$ .

$$\Rightarrow \text{bel}(x_t) = p(x_t | z_{1:t}, u_{1:t})$$

W.K.T

$$p(a|b) = \underbrace{p(b|a)}_{\text{likelihood}} \cdot \underbrace{p(a)}_{\text{prior}}$$

$\uparrow$  Normalizing Constant

$\uparrow$  posterior

calculate a posterior before incorporating  $z_t$ ,  
just after emitting the control  $u_t$ .  
hence posterior is denoted as:

$$\bar{\text{bel}}(x_t) = p(x_t | z_{t-1}, u_{1:t})$$

↳ predicts the state at time  $t$  based on the previous state posterior, before incorporating the measurement at time  $t$ .

Calculating  $\text{bel}(x_t)$  from  $\bar{\text{bel}}(x_t)$  is called measurement update.

## Algorithm for Bayes filter

Algorithm Bayes-filter ( $\text{bel}(x_{t-1}), U_t, Z_t$ ):

for all  $x_t$  do:

$$\bar{\text{bel}}(x_t) = \int p(x_t | U_t, x_{t-1}) \text{bel}(x_{t-1}) dx$$

$$\text{bel}(x_t) = \eta p(Z_t | x_t) \cdot \bar{\text{bel}}(x_t)$$

end for

return  $\text{bel}(x_t)$ .

## Derivation of Bayes filter

$$p(x_t | Z_{1:t}, U_{1:t}) = p(x_t | Z_t, Z_{1:t-1}, U_{1:t})$$

$$= p(Z_t | x_t, Z_{1:t-1}, U_{1:t}) p(x_t | Z_{1:t-1}, U_{1:t})$$

$$p(Z_t | Z_{1:t-1}, U_{1:t})$$

$$= \eta p(Z_t | x_t, Z_{1:t-1}, U_{1:t}) \cdot p(x_t | Z_{1:t-1}, U_{1:t})$$

$$p(Z_t | x_t, Z_{1:t-1}, U_{1:t}) = p(Z_t, U_t)$$

→ If we (hypothetically) knew the state  $x_t$  and were interested in predicting the measurement  $Z_t$ , we perform control & observe w/o information measurement



$$p(x_t | z_{1:t}, u_{1:t}) = \eta_t \cdot p(z_t | x_t) \cdot p(x_t | z_{1:t-1}, u_{1:t})$$

hence,

$$\text{bel}(x_t) = \eta_t \cdot p(z_t | x_t) \cdot \bar{\text{bel}}(x_t)$$

next, expand term  $\bar{\text{bel}}(x_t)$ .

$$\begin{aligned} \bar{\text{bel}}(x_t) &= p(x_t | z_{1:t-1}, u_{1:t}) \\ &= \int p(x_t | x_{t-1}, z_{1:t-1}, u_{1:t}) \cdot \\ &\quad p(x_{t-1} | z_{1:t-1}, u_{1:t}) \cdot dx_{t-1} \end{aligned}$$

w.k.T  $\int p(A) = \int p(A|B') \cdot p(B') \cdot dB'$

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

→ This implies if we know  $x_{t-1}$ , past measurements & controls convey no information regarding  $x_t$ . This gives above equation.

Here we retain the control p/p  $u_t$ , since it does not kill the state  $x_{t-1}$ .

$$\bar{\text{bel}}(x_t) = \int p(x_t | x_{t-1}, u_t) \cdot p(x_{t-1} | z_{1:t-1}, u_{1:t-1}) \cdot dx_{t-1}$$