

Filtre particulaire

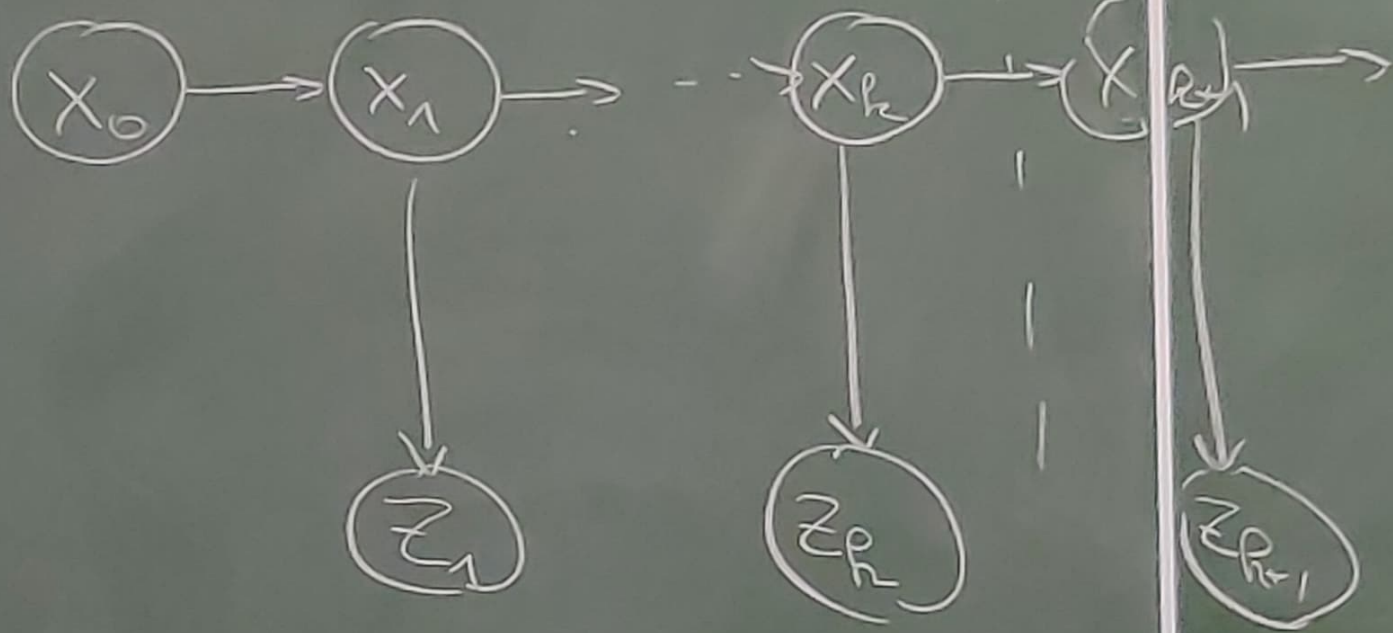
10h

(Sequential Monte Carlo method(s))

(Particle filtering)

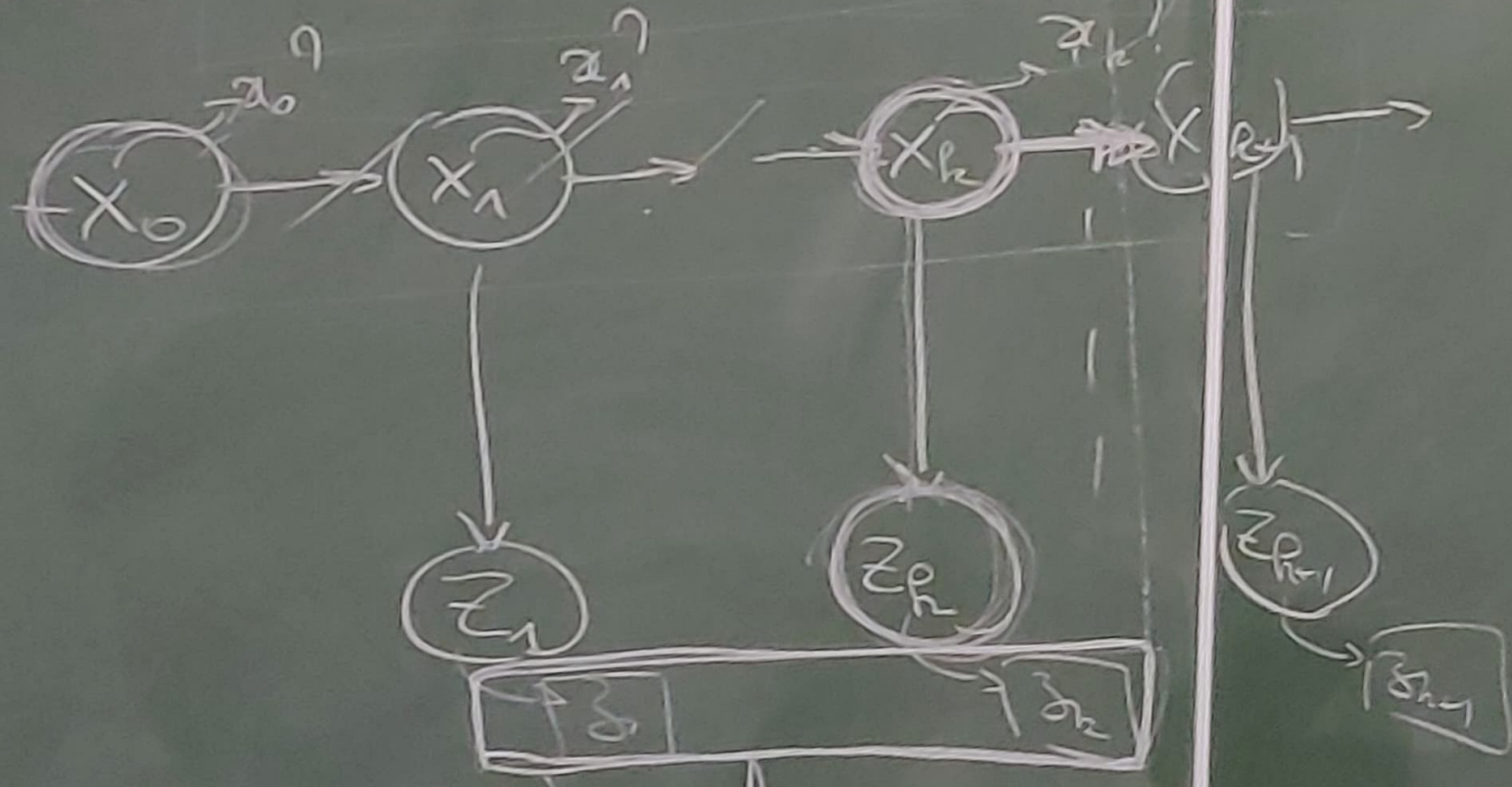
- * Pourquoi ?
- très utilisé pour filtrage Bayésien
NL non Gaussien
 - \exists solution emblématique du SLAM
(algs FASTSLAM / "gmapping")

1. Rappels : filtrage Bayésien

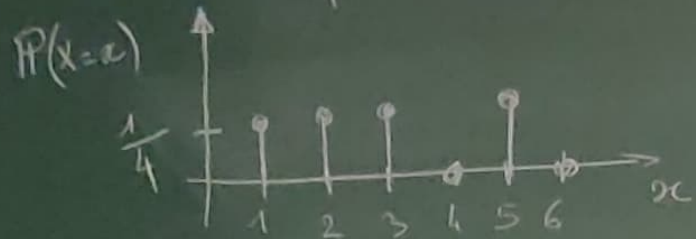


- séquence d'états cachés $x_{0:k} = x_0, x_1, \dots, x_k$
- séquence d'observations $z_{1:k} = z_1, z_2, \dots, z_k$

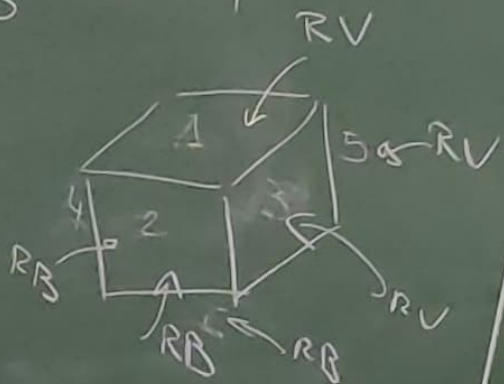
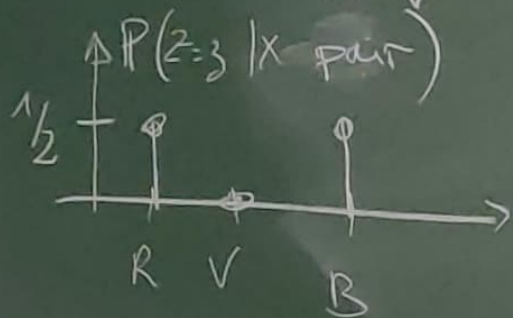
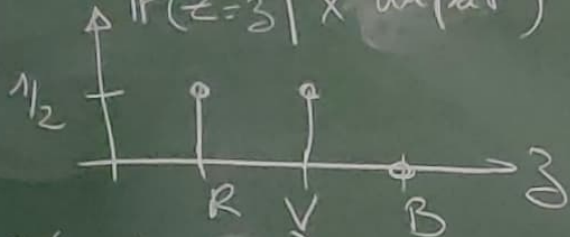
λ ω



• loi a priori

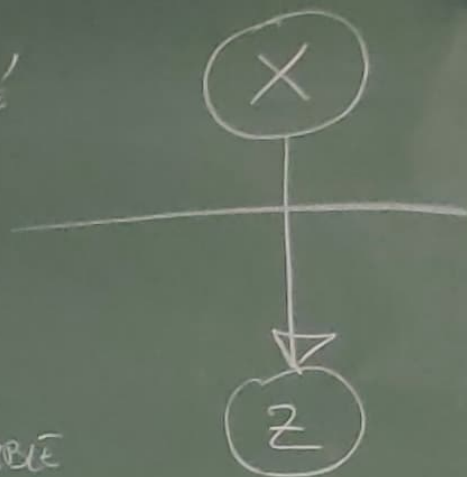


• modèle d'observation
 $P(Z=3 | X \text{ impair})$



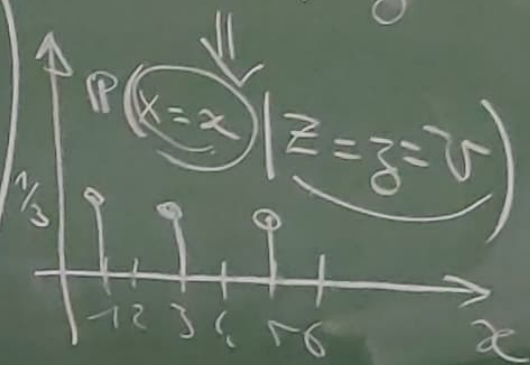
CACHE'

ACCESSIBLE



• Estimation

$\rightarrow w: Z(w) = 3 = V$



observation

$$\int x_k p(x_k | z_{1:k}) dx_k$$

ESTIMATE

$$E \left[x_k | z_{1:k} = z_k \right]$$

MNSE estimate

→ quelle est l'espérance de X ? (Valeur moyenne des issues possibles de X)?

$$\bar{x} = E[X] = E_{P_X(x)}[X] = \int_{\mathbb{R}} x \left[\sum_{i=1}^N w_i \delta(x-x_i) \right] dx = \sum_{i=1}^N w_i \underbrace{\int_{\mathbb{R}} x \delta(x-x_i) dx}_{= x_i} = \sum_i w_i x_i$$

→ comment se comporte X autour de $E[X]$?

$$\text{Var}[X] = E_{P_X(x)} \left[(X - E[X])^2 \right] = \dots = \text{avec } E[X^2] - (E[X])^2$$

noté σ_x^2

$$\text{avec } \sigma_x^2 = \int_{\mathbb{R}} (x - \bar{x})^2 P_X(x) dx = \sum_{i=1}^N w_i (x_i - \bar{x})^2$$

$$\begin{aligned} &= f(x_i) \delta(x-x_i) \\ &\int_{\mathbb{R}} f(x) \delta(x-x_i) dx = f(x_i) \end{aligned}$$

→ (dans le cas discret ^(N valeurs possibles) multivarié (dans \mathbb{R}^M)
 quelle est l'espérance de x ? (valeur moyenne des issues possibles de x)?

si les valeurs possibles sont $x^{(1)} \dots x^{(N)} \in \mathbb{R}^M$ avec les poids (probas) respectifs $w^{(1)} \dots w^{(N)}$

$$\bar{x} = \mathbb{E}[x] = \int_{\mathbb{R}^M} \begin{pmatrix} x_1 \\ \vdots \\ x_M \end{pmatrix} \sum_{i=1}^N w^{(i)} \delta \left(\begin{pmatrix} x_1 \\ \vdots \\ x_M \end{pmatrix} - \begin{pmatrix} x_1^{(i)} \\ \vdots \\ x_M^{(i)} \end{pmatrix} \right) \underbrace{dx_1 \dots dx_M}_{dx} = \sum_{i=1}^N w^{(i)} x^{(i)}$$

x

$$p_X(x) = \sum_{i=1}^N w^{(i)} \delta(x - x^{(i)}) = \sum_{i=1}^N w^{(i)} \delta(x_1 - x_1^{(i)}) \dots \delta(x_M - x_M^{(i)})$$

j^{th} component

$$\int_{\mathbb{R}^M} x_j \left(\sum_{i=1}^N w^{(i)} \frac{\delta(x_1 - x_1^{(i)}) \cdots \delta(x_j - x_j^{(i)})}{\delta(x_M - x_M^{(i)})} \right) dx_1 \cdots dx_j \cdots dx_M$$

$$\sum_{i=1}^N w^{(i)} \int_{\mathbb{R}} x_j \delta(x_j - x_j^{(i)}) = \sum_{i=1}^N w^{(i)} x_j^{(i)}$$

$$\Delta \quad X \in \mathbb{R}^M \sim \mathcal{CP}\left(\overset{\substack{\uparrow \\ \mathbb{R}^M}}{m}, \overset{\substack{\uparrow \\ \mathbb{R}^{M \times M}}}{P}\right)$$

$$p_X(x) = \frac{1}{\sqrt{\det(2\pi P)}} \exp\left[-\frac{1}{2} (x-m)^T P^{-1} (x-m)\right]$$

$$\det \sqrt{\det(2\pi P)} = \sqrt{(2\pi)^M \det(P)} = \sqrt{(2\pi)^M} \sqrt{\det(P)}$$

$$\rightarrow \bar{x} := \mathbb{E}[X] = \int_{\mathbb{R}^M} x \, \mathcal{CP}(x; m, P) \, dx = \dots = m !$$

$$\rightarrow \text{Cov}[X] = \mathbb{E}\left[(X-\bar{x})(X-\bar{x})^T\right] = \int_{\mathbb{R}^M} (x-\bar{x})(x-\bar{x})^T \mathcal{CP}(x; m, P) \, dx = \dots = P !$$

$$\rightarrow \mathcal{E}_\alpha = \left\{ x, (x-m)^T P^{-1} (x-m) \leq \alpha^2 \right\}$$