

Plan du Cours

I Filtrage stochastique

- filtrage non linéaire \equiv Formule de Bayes
- Filtre Kalman
- filtre particulaire

II Prédiction déterministe

- évolution distribution de proba

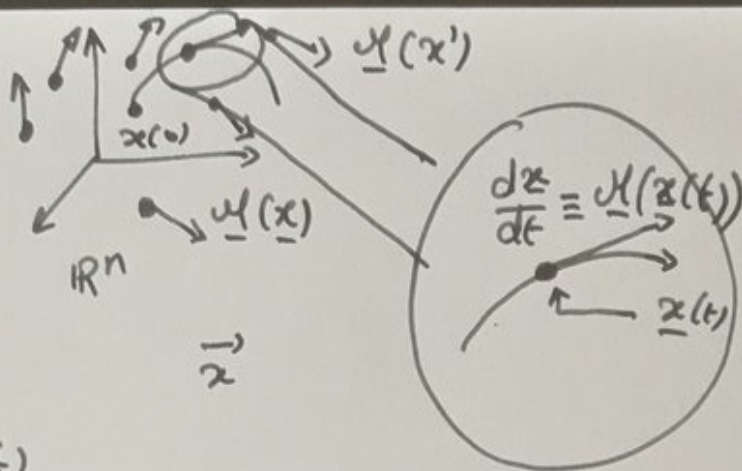
dualité "observable" \longleftrightarrow proba

III Prédiction Stochastique

- intégrale d'Itô
- ——— de Stratonovitch
- 4DVar dans une formulation C^0 .

⁶¹¹⁻¹
Exercice: obtention des équations
du filtre de Kalman ?

I Filtrage Sto
 $\underline{x}(t)$



$$(1) \quad \frac{d\underline{x}}{dt} = \underline{U}(\underline{x})$$

$$\underline{x}(0) \rightarrow \underline{x}(t)$$

$$\underline{A} = [a_{ij}]$$

cas 1

$$(2) \quad \frac{d\underline{x}}{dt} = \underline{M} \underline{x} \rightarrow \underline{x}(t) = e^{\underline{M}t} \underline{x}(0) \quad (3)$$

$$\text{cas où } \underline{U}(\underline{x}) = \underline{M} \underline{x}$$

cas 2 général

$\underline{U}(\underline{x})$ non nécessairement linéaire

$$(4) \quad \ddot{x} + \omega^2 \sin(x) = 0$$

$x(t)$



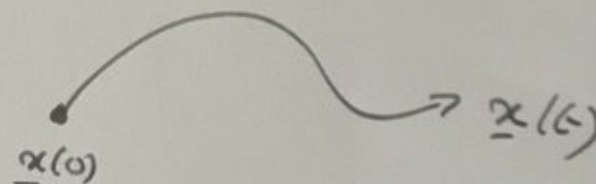
$$\underline{x} \quad \begin{cases} x_1 \equiv x \\ x_2 \equiv \dot{x} \end{cases}$$

611-2

$$\begin{cases} \frac{dx_1}{dt} = x_2 \\ \frac{dx_2}{dt} = \frac{d\dot{x}}{dt} = \ddot{x} = -\omega^2 \sin(x) \end{cases}$$

$$\begin{cases} \frac{dx_1}{dt} = x_2 \\ \frac{dx_2}{dt} = -\omega^2 \sin(x_1) \end{cases} \quad (5)$$

$$\underline{U}(\underline{x}) \quad \begin{vmatrix} x_2 \\ -\omega^2 \sin(x_1) \end{vmatrix} \quad (6)$$



$$\underline{x}(t) \rightarrow \underline{x}(t+dt) \rightarrow \underline{x}(t+2dt)$$

$$\underline{x}(t+dt) = \underline{x}(t) + dt \frac{d\underline{x}}{dt} + o(dt^2)$$

$$\textcircled{7} \quad \underline{x}(t+\delta t) = \underline{x}(t) + \delta t \underbrace{\frac{d\underline{x}}{dt}(t)}_{\mathcal{M}(\underline{x}(t))} + o(\delta t)$$

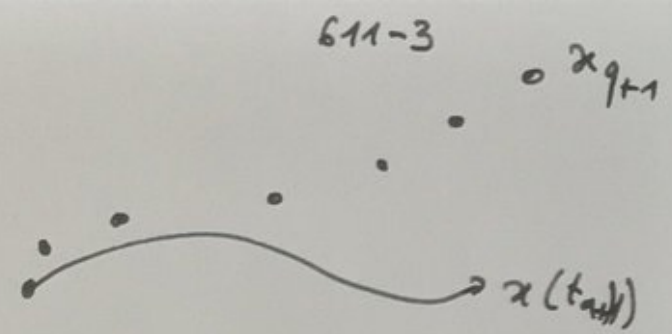
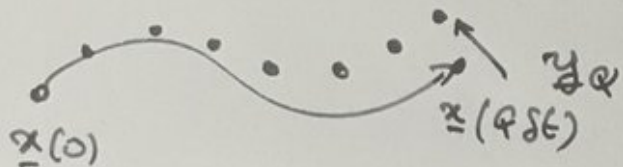
$$y_q \approx \underline{x}(t_q) \quad t_q = q \delta t$$

$$\textcircled{8} \quad \underline{y}_{q+1} = \underline{y}_q + \delta t \mathcal{M}(\underline{y}_q) \quad \text{Euler}$$

$$\textcircled{9} \quad \underline{x}(t+\delta t) = \underline{x}(t) + \delta t \underbrace{\frac{d\underline{x}}{dt}}_{\mathcal{M}(\underline{x}(t))} + \frac{\delta t^2}{2} \underbrace{\frac{d^2 \underline{x}}{dt^2}}_{\text{Passage scalaire}} + \dots$$

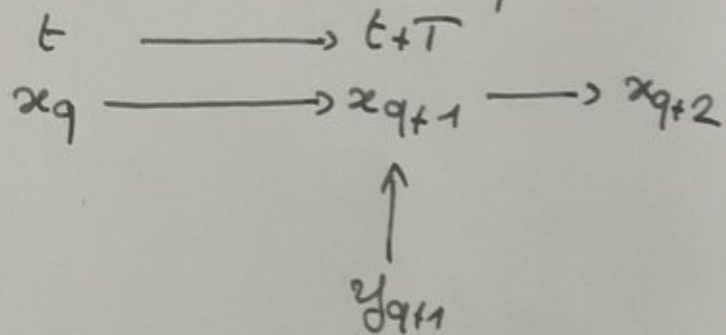
$$\frac{d^2 \underline{x}}{dt^2} = \frac{d}{dt} \left[\frac{d\underline{x}}{dt} \right] = \frac{d}{dt} [\mathcal{M}(\underline{x})] \approx \frac{d\underline{x}}{dt} \cdot \mathcal{M}'(\underline{x})$$

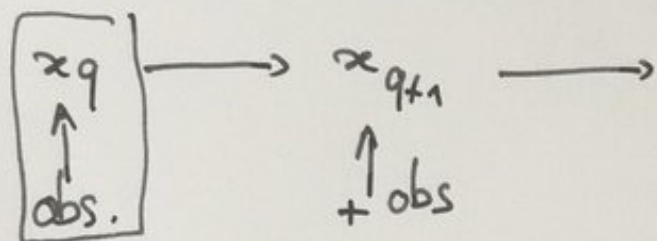
$$\textcircled{10} \quad \begin{cases} \underline{y}_* = \underline{y}_q + \frac{\delta t}{2} \mathcal{M}(\underline{y}_q) \\ \underline{y}_{q+1} = \underline{y}_q + \delta t \mathcal{M}(\underline{y}_*) \end{cases} \quad \text{RK2}$$



\underline{x}_q : état du système à l'instant t_q

\underline{y}_q : observation du système à l'instant t_q .





cycle d'assimilation et de prévision.

$$P(x_q)$$

$$P(x_q / y_{0:q-1})$$

$$P(x_q / y_{0:q}) \propto P(y_q / x_q) \cdot P(x_q / y_{0:q-1})$$

Formule de Bayes

Cas Gaussien

$$P(x_q / y_{0:q-1}) \equiv \mathcal{W}(x_q^f, P_q^f) \quad \swarrow \text{forecast}$$

$$y_q = H x_q + \varepsilon_q^o \quad \text{où} \quad \varepsilon_q^o \sim \mathcal{W}(0, R_q) \quad \uparrow \text{erreur d'observation}$$

$$P(y_q / x_q) \equiv \mathcal{W}(H x_q, R_q)$$

$$\mathcal{W}(\underline{m}, \underline{P}) \equiv \frac{1}{Z} e^{-\frac{1}{2}(\underline{m} - \underline{m})^T \underline{P}^{-1}(\underline{m} - \underline{m})} \quad \underline{m}^T \underline{P}^{-1} \underline{m} \equiv \|\underline{m}\|$$

~~$$\mathcal{W}(\underline{m}, \underline{P}) \equiv \frac{1}{Z} e^{-\frac{1}{2}(\underline{m} - \underline{m})^T \underline{P}^{-1}(\underline{m} - \underline{m})}$$~~

$$\underline{v} \sim \mathcal{W}(\underline{m}, \underline{P})$$

$$P(\underline{v}) = \frac{1}{Z} \exp\left(-\frac{1}{2} \|\underline{v} - \underline{m}\|_{\underline{P}^{-1}}^2\right)$$

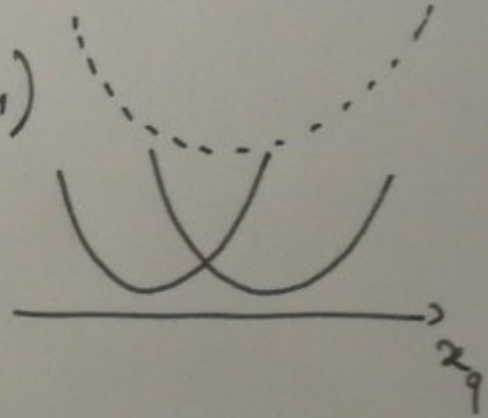
$$\text{où} \quad \|\underline{v} - \underline{m}\|_{\underline{P}^{-1}}^2 \equiv (\underline{v} - \underline{m})^T \underline{P}^{-1} (\underline{v} - \underline{m})$$

$$p(x_q / y_{0:q}) \propto \underset{\substack{\uparrow \\ \text{proportionnel}}}{p(y_q / x_q)} \cdot p(x_q / y_{0:q-1})$$

$$p(x_q / y_{0:q}) \propto \exp\left(-\frac{1}{2} \|y_q - Hx_q\|_{R_q^{-1}}^2\right) \cdot \exp\left(-\frac{1}{2} \|x_q - x_q^f\|_{P_q^{f-1}}^2\right)$$

$$\propto \exp\left(-\frac{1}{2} \|y_q - Hx_q\|_{R_q^{-1}}^2 - \frac{1}{2} \|x_q - x_q^f\|_{P_q^{f-1}}^2\right)$$

$$\propto \exp\left(-\frac{1}{2} \|x_q - x_q^a\|_{(P_q^a)^{-1}}^2\right)$$



$$\begin{aligned} J(x_q) &= \frac{1}{2} \|x_q - x_q^f\|_{(P_q^f)^{-1}}^2 + \frac{1}{2} \|y_q - Hx_q\|_{R_q^{-1}}^2 \\ &= \frac{1}{2} \|x_q - x_q^a\|_{(P_q^a)^{-1}}^2 + C \end{aligned}$$

~~KL~~

$$\nabla J_{x_q^a} = 0 \rightarrow x_q^a$$

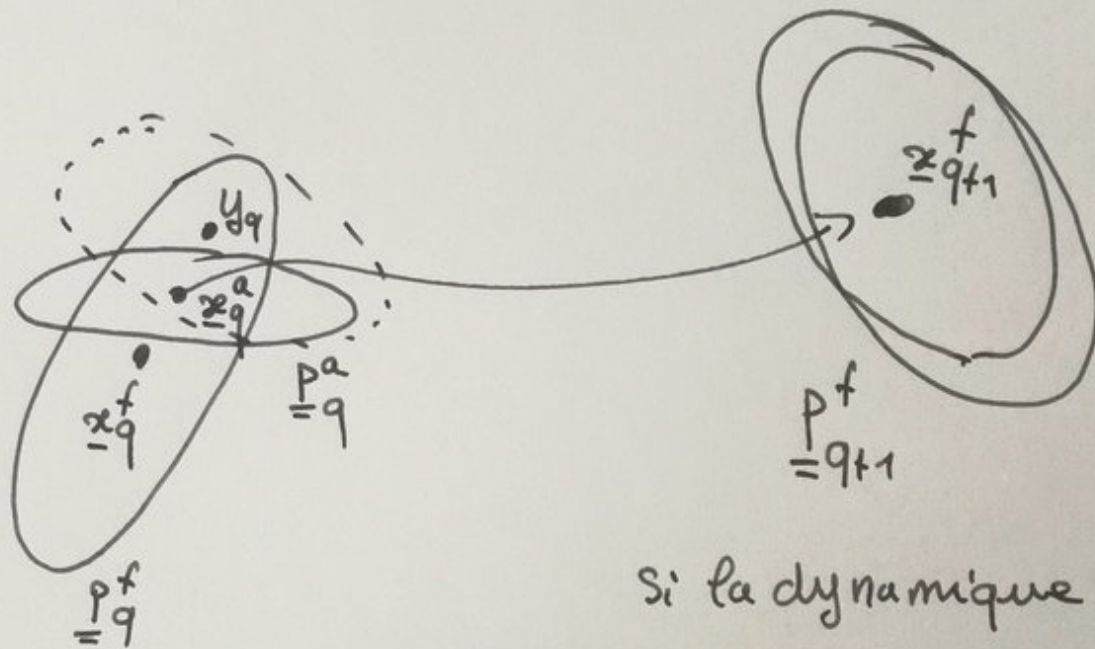
$$J'' = (P_q^a)^{-1}$$

$$(1) \quad x_q^a = x_q^f + K_q (y_q - Hx_q^f)$$

$$\text{où } K_q = P_q^f H_q^T (H_q P_q^f H_q^T + R_q)^{-1}$$

$$(2) \quad P_q^a = (I - K_q H) P_q^f$$

Filtre Kalman pour l'analyse



Si la dynamique s'exprime

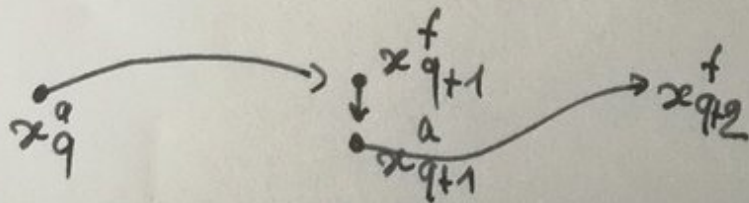
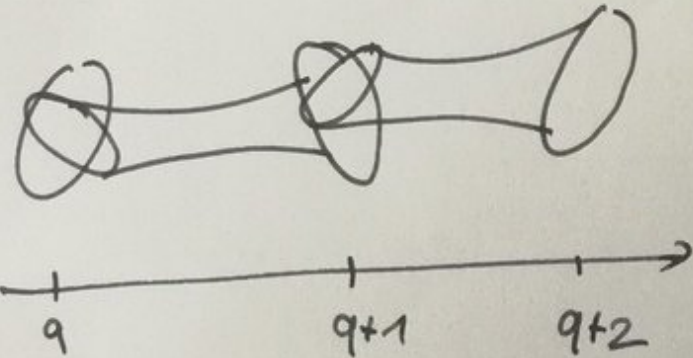
$$\underline{x}_{q+1} = \underline{M} \underline{x}_q$$

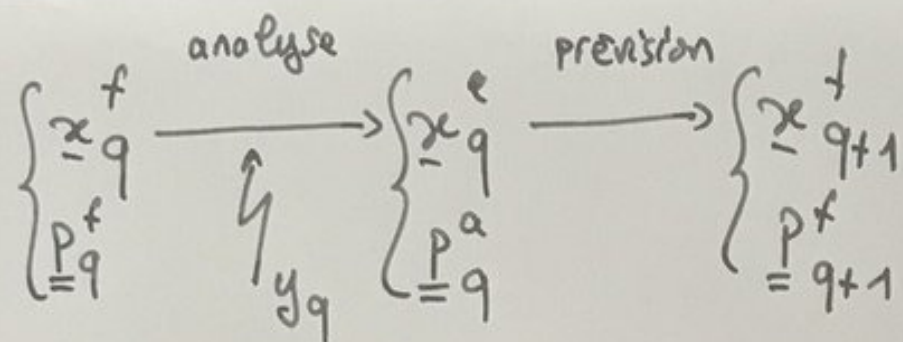
$$\textcircled{3} \underline{x}_{q+1}^f = \underline{M} \underline{x}_q^a$$

$$\textcircled{4} \underline{P}_{q+1}^f = \underline{M} \underline{P}_q^a \underline{M}^T$$

Kalman pour prévision

$x^f \leftarrow$ forecast
 $x^a \leftarrow$ analysis.





$$\dots \rightarrow \mathcal{W}(x_q^f, p_q^f) \rightarrow \mathcal{W}(x_q^a, p_q^a) \rightarrow \mathcal{W}(x_{q+1}^f, p_{q+1}^f) \rightarrow \dots$$

$$\ddot{x} + \omega^2 x = 0 \rightarrow x(t) = a \cos(\omega t + \varphi) \quad (a, \varphi) \text{ données à partir de } (x(\omega), \dot{x}(\omega)) \quad 1311-1$$

$$y \equiv \begin{pmatrix} x \\ \dot{x} \end{pmatrix} \quad \dot{y} = \begin{pmatrix} \frac{dy_1}{dt} = \dot{x} \equiv y_2 \\ \frac{dy_2}{dt} = -\omega^2 x \equiv -\omega^2 y_1 \end{pmatrix}$$

$$y = \begin{pmatrix} y_1 \\ y_2 \end{pmatrix} \quad \frac{dy}{dt}$$

$$\boxed{\frac{dy}{dt} = f(y)}$$

$$f(y) \quad \begin{cases} f_1(y) \equiv y_2 \\ f_2(y) \equiv -\omega^2 y_1 \end{cases}$$

mais comme f est linéaire ici
on peut écrire

$$\boxed{\frac{dy}{dt} = \begin{pmatrix} 0 & 1 \\ -\omega^2 & 0 \end{pmatrix} y}$$

$$\boxed{\frac{dy}{dt} = \underline{A} y}$$

← solution ?

$$\boxed{y(t) = y(0) e^{\underline{A} t}}$$

$$y(t) = \begin{pmatrix} a \cos(\omega t + \varphi) \\ -\omega a \sin(\omega t + \varphi) \end{pmatrix}$$

$$y(t) = \begin{pmatrix} a \cos(\omega t + \varphi) \\ -\omega a \sin(\omega t + \varphi) \end{pmatrix}$$

$$\boxed{\frac{dy}{dt} = \underline{A} y}$$

$$\boxed{M_{t \leftarrow 0} \equiv e^{\underline{A} t}} \text{ propagateur}$$

Solution: proposition 1: $y(t) = y(0) e^{\underline{A} t}$

proposition 2:

$$\boxed{y(t) = e^{\underline{A} t} y(0)}$$

$$\boxed{y(t) = M_{t \leftarrow 0} y(0)}$$

avec le formalisme de l'assimilation

$$\begin{aligned} x_{q+1} &= M_{q+1 \leftarrow q} x_q \\ &= M_{q+1 \leftarrow 0} x_0 \end{aligned}$$

cas scalaire:

$$\frac{dy}{dt} = a y \rightarrow y(t) = e^{at} y(0) = y(0) e^{at}$$

$$e^{\underline{A} t}$$

$$\underline{A} = \underline{P} \underline{D} \underline{P}^{-1} \text{ car } \underline{A} \text{ est diagonalisable}$$

$$\begin{aligned} e^{\underline{A} t} &= e^{\underline{P} \underline{D} \underline{P}^{-1} t} \\ &= \sum \frac{t^k}{k!} (\underline{P} \underline{D} \underline{P}^{-1})^k \\ &= \underline{P} \left(\sum \frac{t^k}{k!} \underline{D}^k \right) \underline{P}^{-1} \\ &= \underline{P} e^{\underline{D} t} \underline{P}^{-1} \end{aligned}$$

$$\begin{aligned} (\underline{P} \underline{D} \underline{P}^{-1})^2 &= (\underline{P} \underline{D} \underline{P}^{-1}) (\underline{P} \underline{D} \underline{P}^{-1}) \\ &= \underline{P} \underline{D} \underbrace{\underline{P}^{-1} \underline{P}}_{\underline{I}} \underline{D} \underline{P}^{-1} \\ &= \underline{P} \underline{D}^2 \underline{P}^{-1} \end{aligned}$$

$$\frac{dy}{dt} = \underline{A} y \quad \text{ou} \quad \underline{A} = \begin{pmatrix} 0 & 1 \\ -\omega^2 & 0 \end{pmatrix}$$

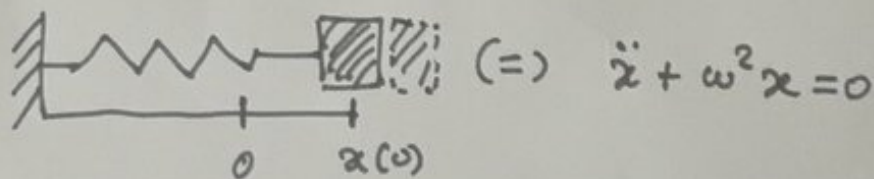
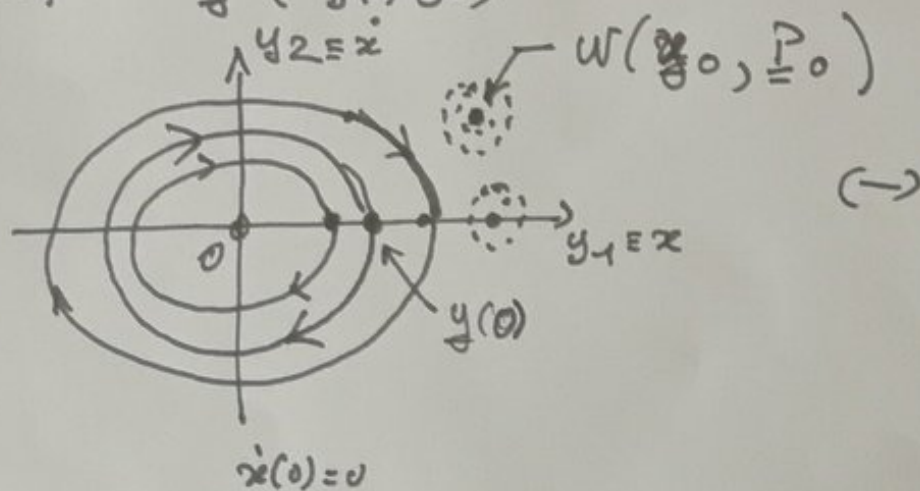
formellement $y(t) = e^{\underline{A}t} y(0)$

ie $y(t) = \underline{M}_{t \leftarrow 0} y(0)$

avec $\underline{M}_{t \leftarrow 0} = e^{\underline{A}t}$

Pour $x(t) = a \cos(\omega t + \varphi)$

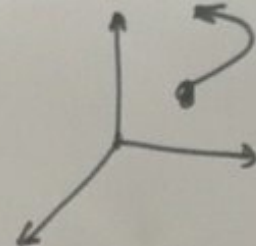
dans le plan $y = (y_1, y_2)$ on a



$$E = \omega^2 x^2 + \dot{x}^2$$

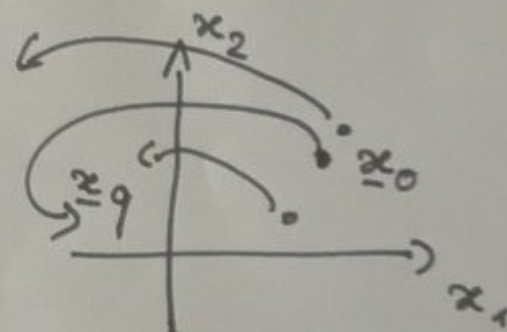
$$E(y) = \omega^2 y_1^2 + y_2^2 \equiv C \equiv \omega^2 x(0)^2 + \dot{x}(0)^2$$

$$\frac{dy}{dt} = f(y) \rightarrow$$



1311-3

Assimilation:



$$\frac{d\underline{x}}{dt} = \underline{A} \underline{x} \quad \underline{x} = \begin{pmatrix} x_1 \\ \dot{x} \end{pmatrix} \Rightarrow \begin{pmatrix} x_1 \\ x_2 \end{pmatrix}$$

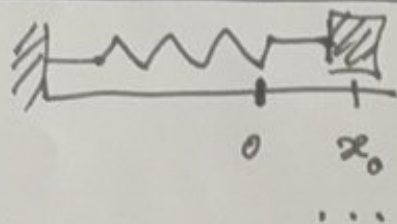
$$\underline{x}(t) = \underline{M}_{t \leftarrow 0} \underline{x}(0)$$

$$\underline{M}_{t \leftarrow 0} = e^{\underline{A}t}$$

$$\mathcal{W}(\underline{x}_0^a, \underline{p}_0^a)$$

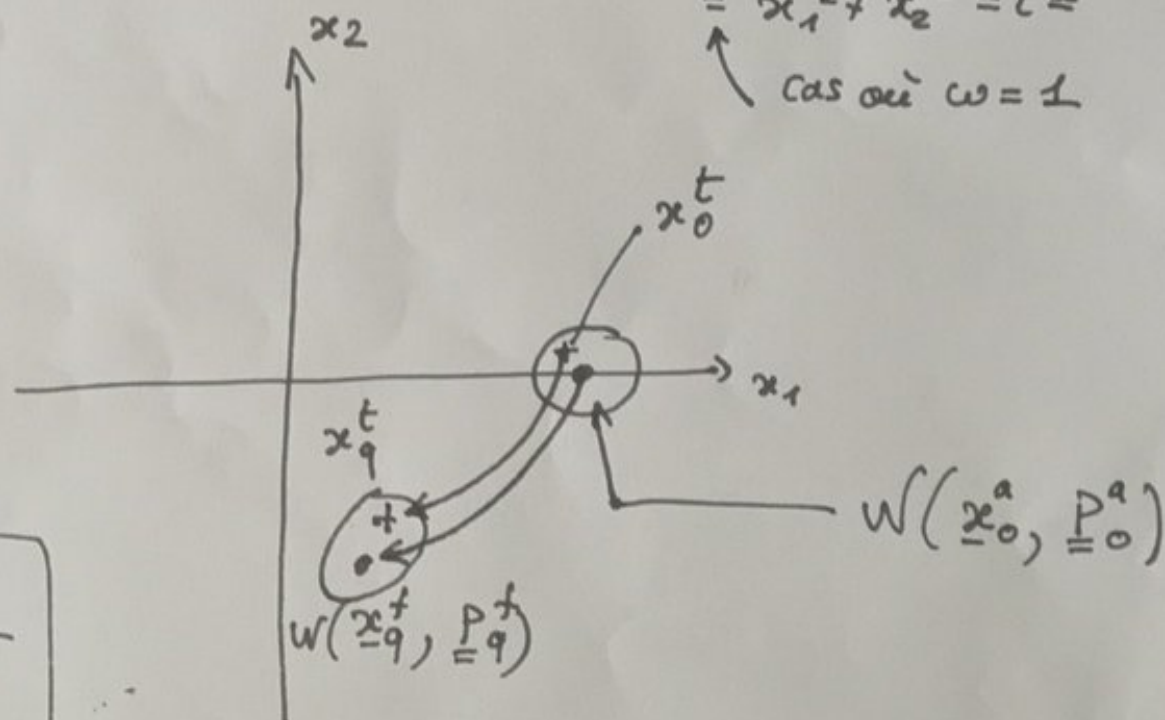
$t_q \leftarrow 0$

$$\begin{aligned} \underline{x}_q^f &= \underline{M}_{t_q \leftarrow 0} \underline{x}_0^a \\ \underline{p}_q^f &= \underline{M}_{t_q \leftarrow 0} \underline{p}_0^a (\underline{M}_{t_q \leftarrow 0})^T \end{aligned}$$



$t=0$

$$(\underline{x}_0^a, \underline{p}_0^a) \longrightarrow \dots$$



$$E = \frac{1}{2} \omega^2 x_1^2 + x_2^2$$

$$= x_1^2 + x_2^2 = C$$

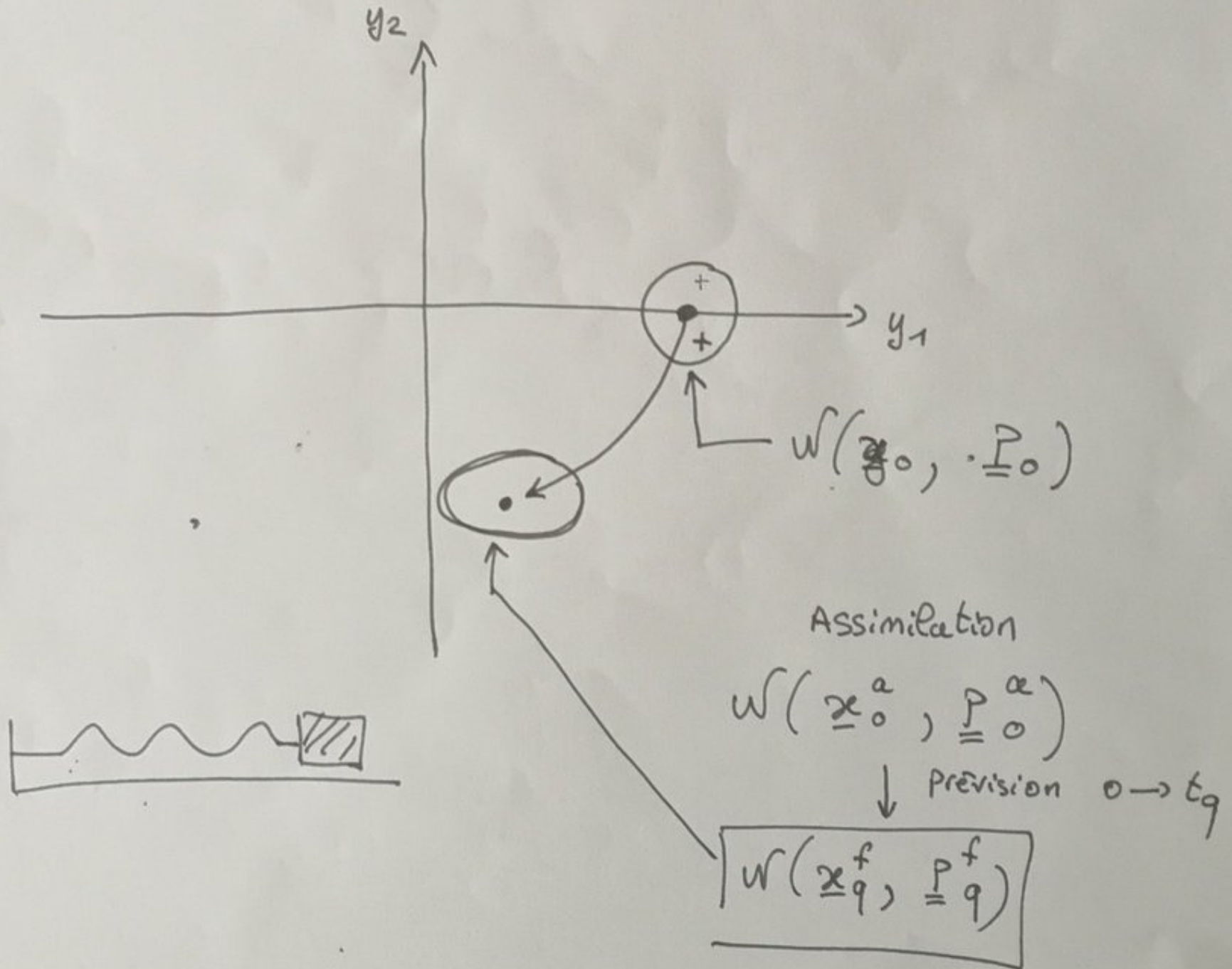
cas où $\omega = 1$

analyse

prévision

$$(\underline{x}_q^f, \underline{p}_q^f) \xrightarrow{\text{analyse}} (\underline{x}_q^a, \underline{p}_q^a) \xrightarrow{\text{prévision}} (\underline{x}_{q+1}^f, \underline{p}_{q+1}^f) \dots$$

y



1311-6

$$\ddot{x} + \omega^2 x = 0$$

$$\frac{d\underline{x}}{dt} = \underline{A} \underline{x} \quad \underline{A} = \begin{bmatrix} 0 & 1 \\ -\omega^2 & 0 \end{bmatrix}$$

$$\underline{x}(t) = \underbrace{e^{\underline{A}t}}_{\substack{M \\ t \leftarrow 0}} \underline{x}(0)$$

$$\boxed{\underline{P}^f(t) = e^{\underline{A}t} \underline{P}^f(0) (e^{\underline{A}t})^T}$$

$$p(x_q / y_{0:q}) \propto p(y_q / x_q) p(x_q / y_{0:q-1})$$

1311-8

$$\uparrow \quad \uparrow$$

$$W(\underline{x}_q^f, \underline{p}_q^f)$$

$$p(y_q / x_q) = \cancel{W(x_q^t)}$$

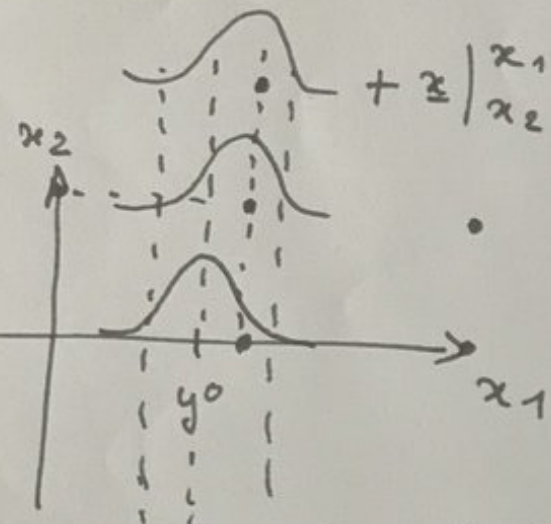
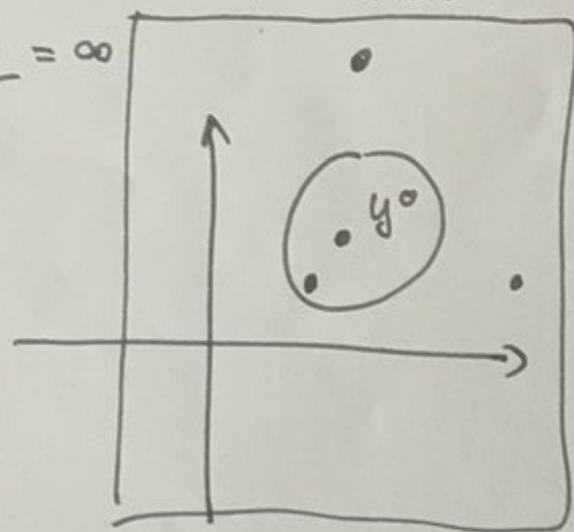
$$= W(\underline{H} \underline{x}_q^t, \underline{R}_q^o)$$

$$W((x_q^t)_1, (\sigma_o)^2)$$

$$\iint e^{-\frac{1}{2} \frac{1}{(\sigma_o)^2} (y_q^o - (x_q^t)_1)^2} dx_1 dx_2$$

$= \infty$

$$= \int 1 dx_2 = \infty$$



\mathbb{I} cas où $\underline{H} = \underline{I}$

Si $\underline{y} = N W(\underline{H} \underline{x}^t, (\sigma_o)^2 \underline{I}_2)$

on observe à la fois la position et la vitesse

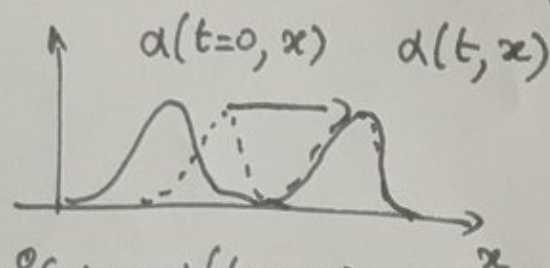
①

$$\partial_t \alpha + u \partial_x \alpha = 0$$

$u = u^0$ est constant
 $u^0 > 0$

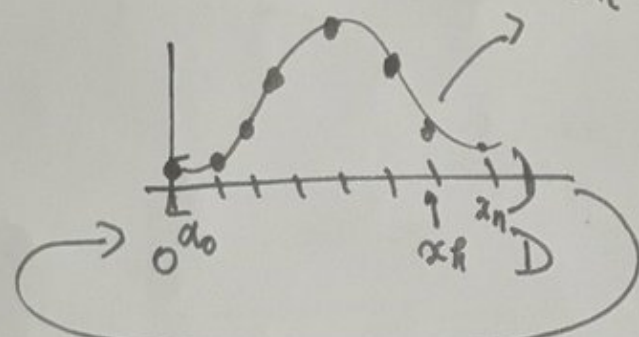
transport à la vitesse u^0

$$\alpha(t, x) = \alpha^0(x - ut)$$



$$\alpha^0(x) = \alpha(t=0, x)$$

Condition
initiale



$$\alpha(t_q, x_k) \equiv \alpha_k^q$$

discretisation
spatiale

soit 2 solutions de ①

$$\alpha(t, x)$$

$$\beta(t, x)$$

et $N \in \mathbb{R}$

$$\gamma = \alpha + N\beta$$

$\gamma(t, x)$ est aussi une solution de ①

\Rightarrow ① est linéaire.

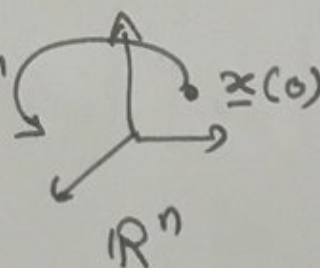
① (\Rightarrow)

$$\frac{d\underline{x}}{dt} = \underline{M} \underline{x}$$

$$\underline{x} = \begin{pmatrix} \alpha_0(t) \\ \vdots \\ \alpha_n(t) \end{pmatrix}$$

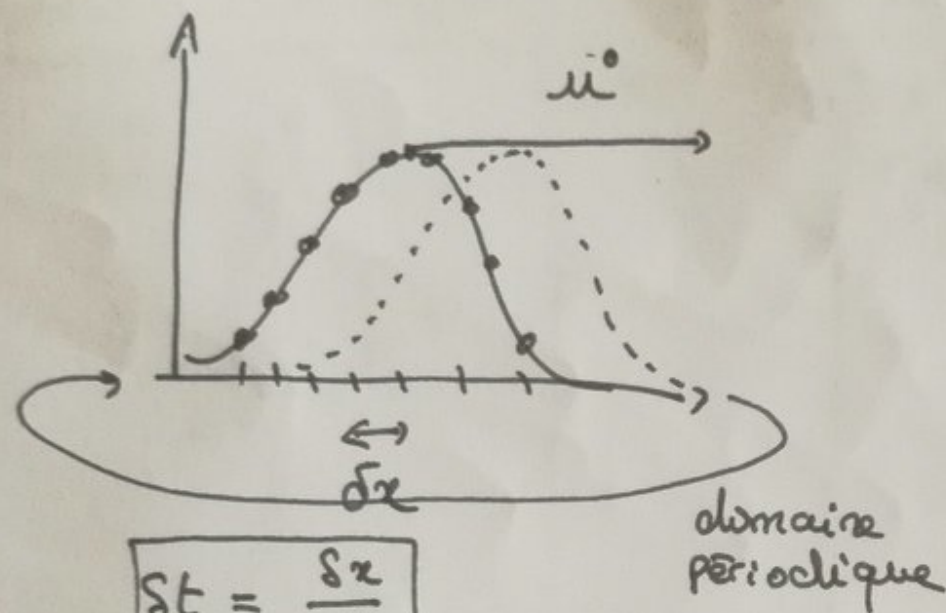
$$\underline{x}(t) = \underline{M}_{t \leftarrow 0} \underline{x}(0)$$

discretisation
temporelle



$$\frac{\alpha_k^{q+1} - \alpha_k^q}{\delta t} = -u \frac{\alpha_k^q - \alpha_{k-1}^q}{\delta x}$$

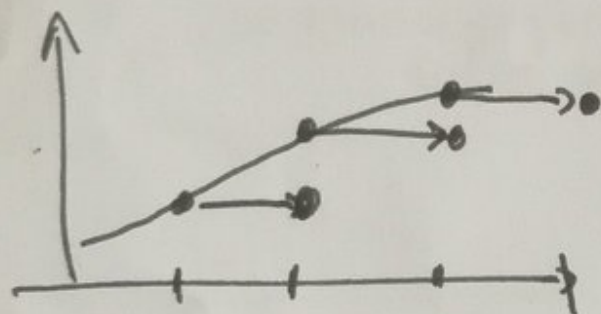
Euler + discretisation spatiale
de type difference finie



$$\partial_t \alpha + u \partial_x \alpha = 0$$

$$\delta t = \frac{\delta x}{u}$$

avec ce δt



$M \equiv$ Matrice de permutation

$$\begin{bmatrix} \alpha_n \\ \alpha_0 \\ \alpha_1 \\ \vdots \\ \alpha_{n-1} \end{bmatrix}_{t_{q+1}} \equiv \begin{bmatrix} 0 & 0 & \dots & 1 \\ 1 & 0 & \dots & 0 \\ & & (0) & \\ & & & (0) \\ & & & & 1 & 0 \end{bmatrix} \begin{bmatrix} \alpha_0 \\ \vdots \\ \alpha_n \end{bmatrix}_{t_q}$$

$t_{q+1} \leftarrow t_q + \delta t$

Construction d'une incertitude initiale

2011-1

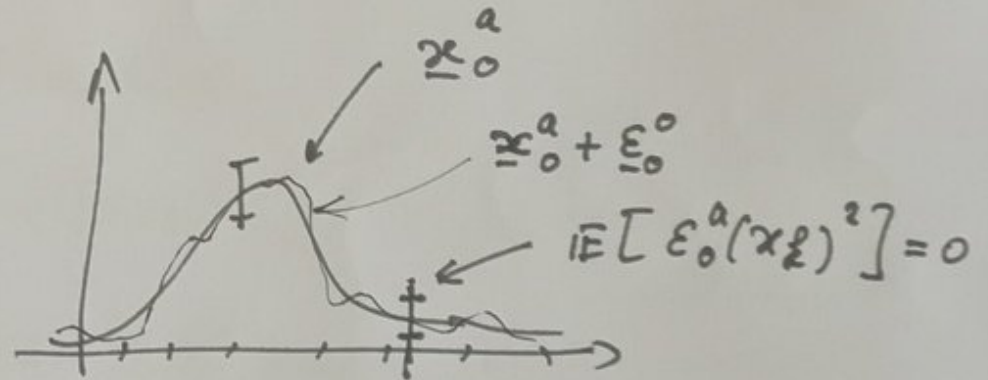
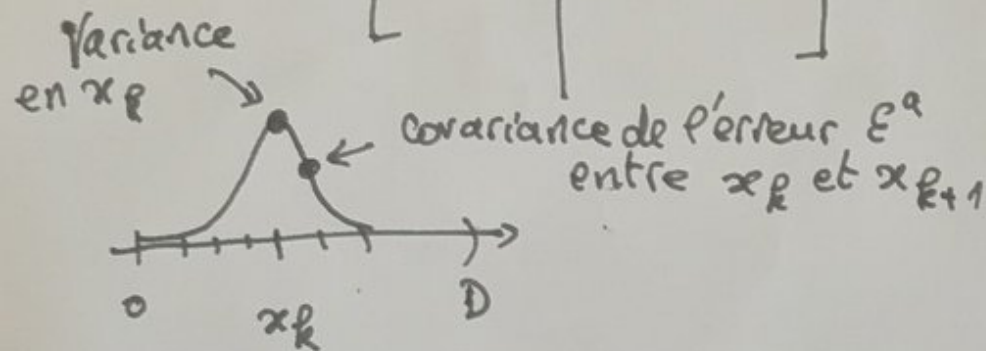
$$(\underline{x}_0^a, \underline{p}_0^a)$$

$k^{\text{ieme}} \equiv$ la k^{ieme} colonne est
la fonction de covariance
relative au point x_k

$$\text{Sous } \mathbb{E}[\varepsilon_0^a] = 0$$

$$\underline{p}_0^a =$$

$$p_0^a(x_k, x_{k+1}) = \mathbb{E}[\varepsilon_0^a(x_k) \cdot \varepsilon_0^a(x_{k+1})]$$

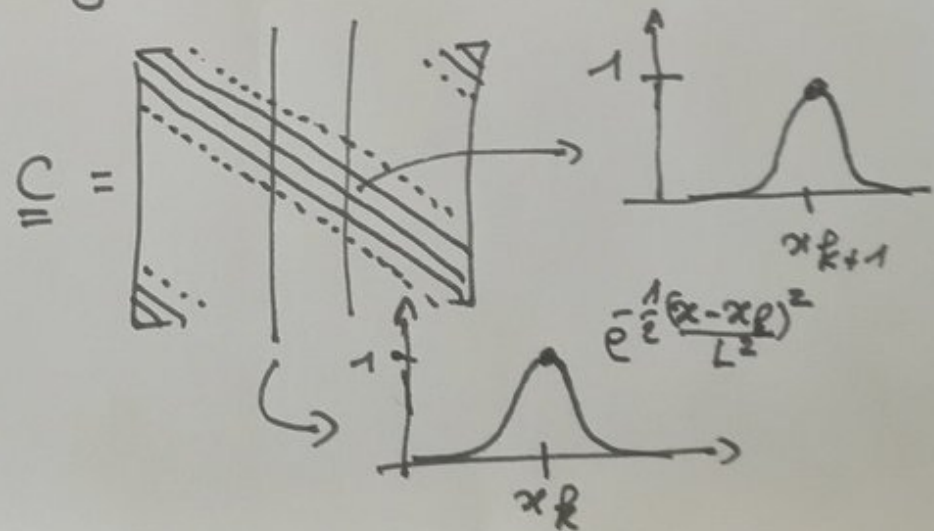


$$\underline{p}_0^a = \underline{\Sigma} \underline{C} \underline{\Sigma}^T$$

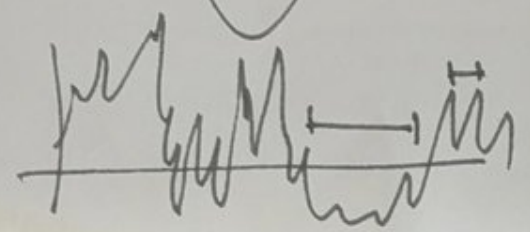
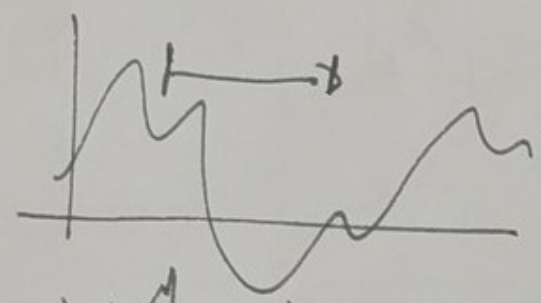
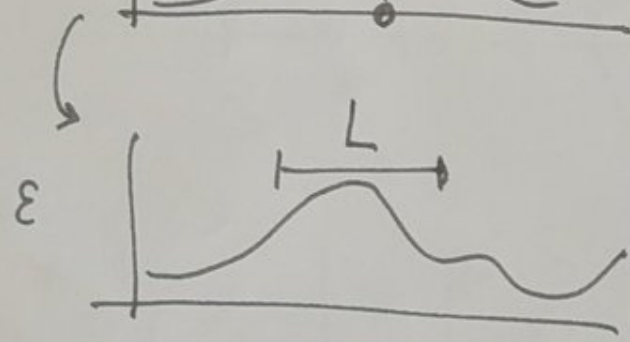
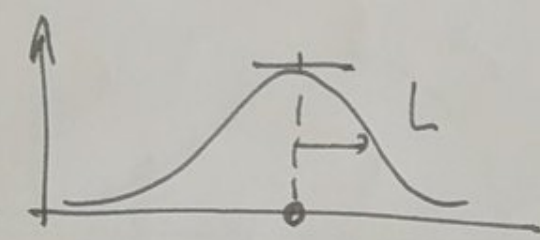
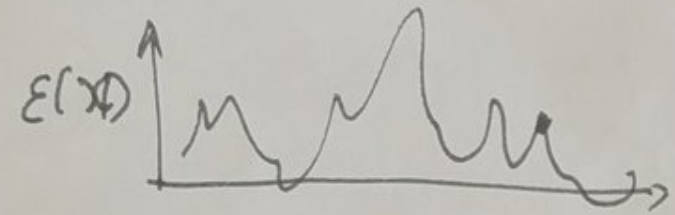
diagonale
des écart-type

matrice de
corrélation

la gaussienne est une fonction de covariance



$$e(x, y) = e^{-\frac{1}{L} |x-y|}$$

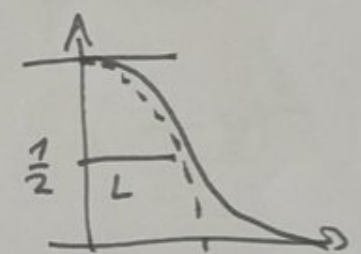


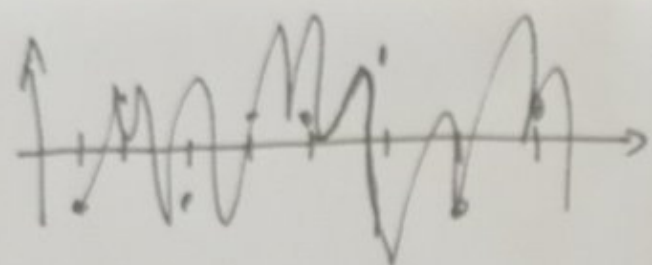
Pour corrélation lisse
à l'origine

$$e(x, y) = e^{-\frac{1}{2} (x-y)^2 \frac{1}{L^2}}$$

$$\simeq 1 - \frac{(x-y)^2}{2 L^2} + o(|x-y|^2)$$

$$p(x, x+\delta x) \simeq 1 - \frac{1}{2} \frac{\delta x^2}{L^2}$$

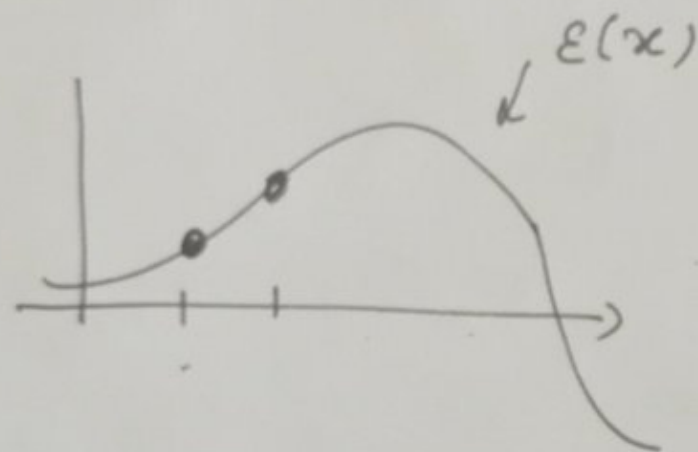
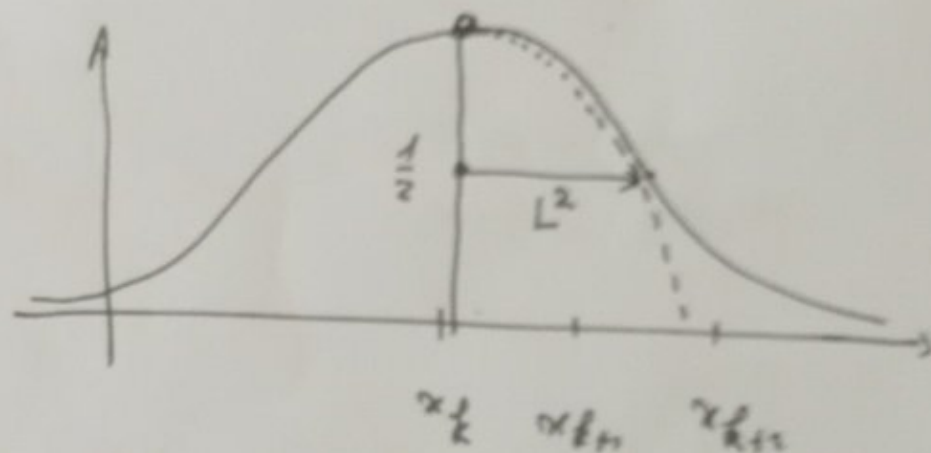




cas bruit blanc

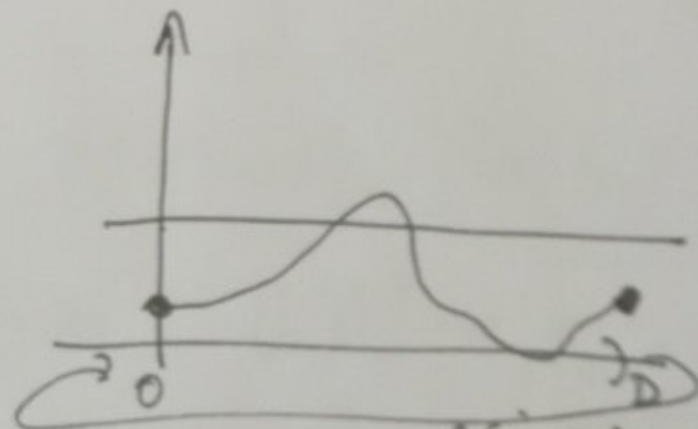
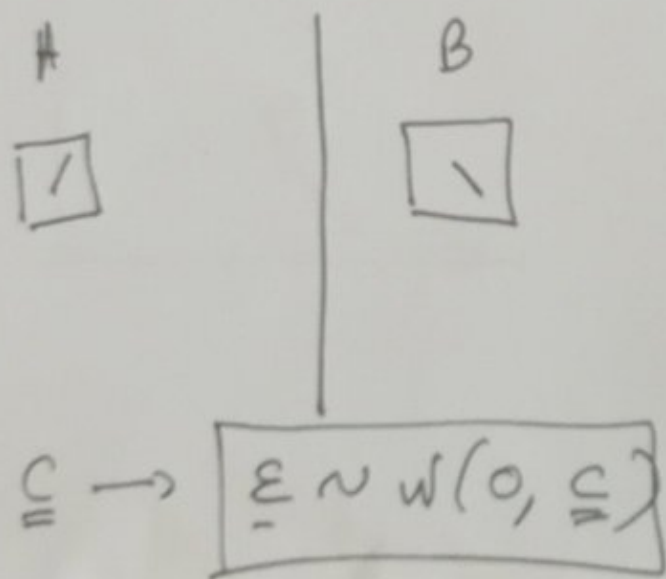
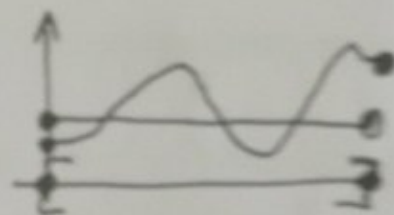
2011-3

$$\underline{\varepsilon}^a \sim \mathcal{N}(\underline{0}, \underline{I})$$



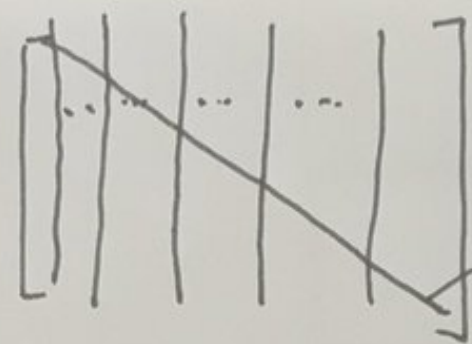
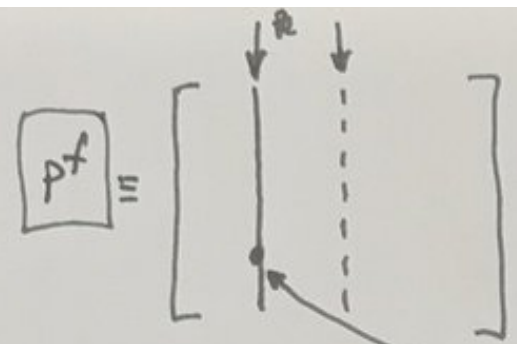
$$p(x, y) = \exp\left(-\frac{1}{2} \frac{(x-y)^2}{L^2}\right)$$

$$\mathbb{E}[\varepsilon^a(x) \varepsilon^a(y)]$$



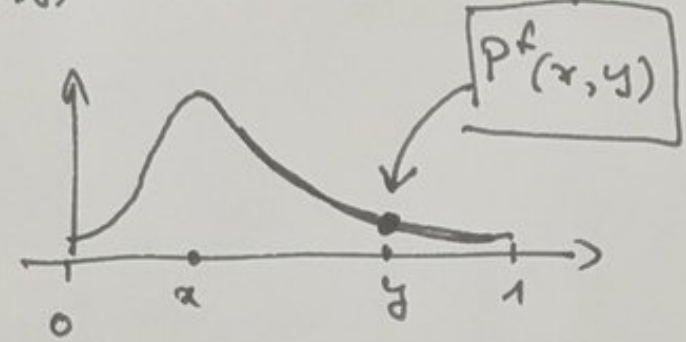
cas où $L = \infty$

$$\underline{\varepsilon} = \underline{C}^{1/2} \underline{\xi} \rightarrow \mathcal{N}(\underline{0}, \underline{I}) \quad \mathbb{E}[\underline{\varepsilon} \underline{\varepsilon}^T] = \underline{C}^{1/2} \underline{I} \underline{C}^{1/2} = \underline{C}$$

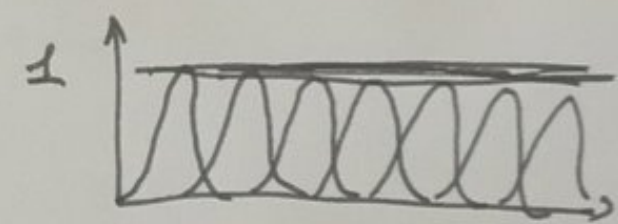
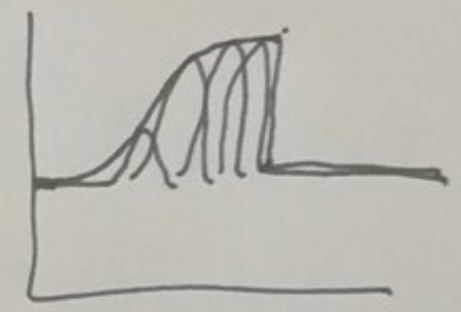
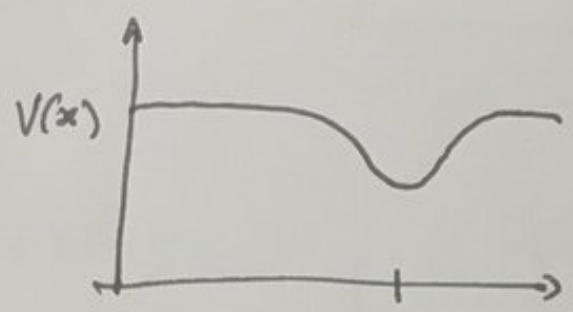
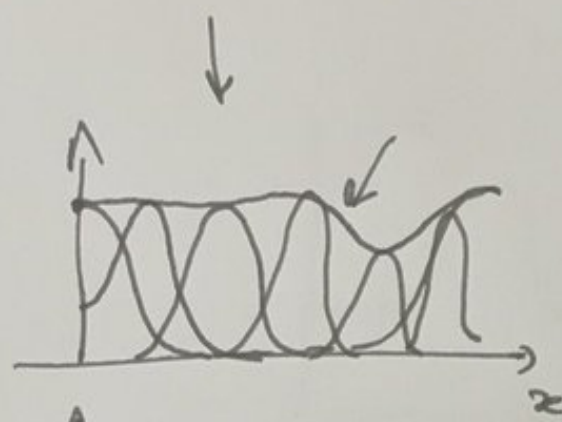
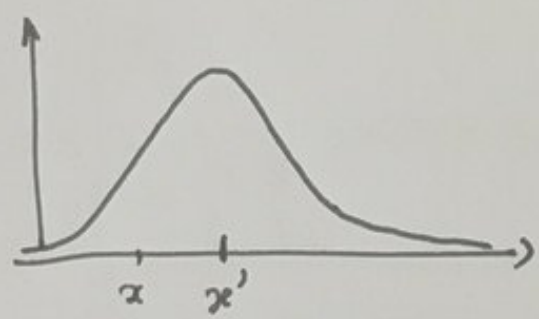


Carte de variance
 $V(x) = \mathbb{E}[\varepsilon^f(x)^2]$

$$p_{(x,y)}^f = \mathbb{E}[\varepsilon^f(x) \varepsilon^f(y)]$$



$x_0 \quad x_\ell \quad \dots \quad x_{k'} \quad \dots \quad x_{n-1}$

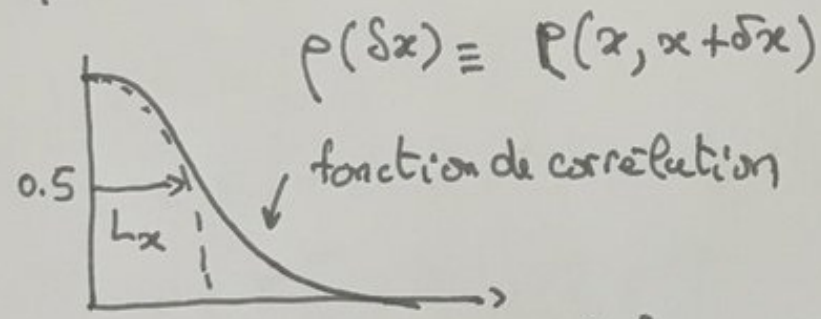
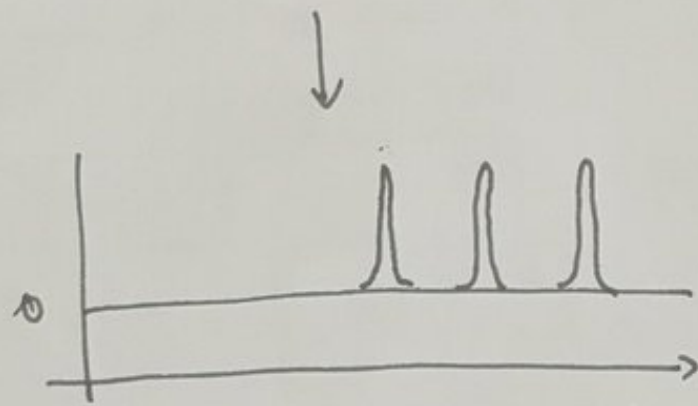
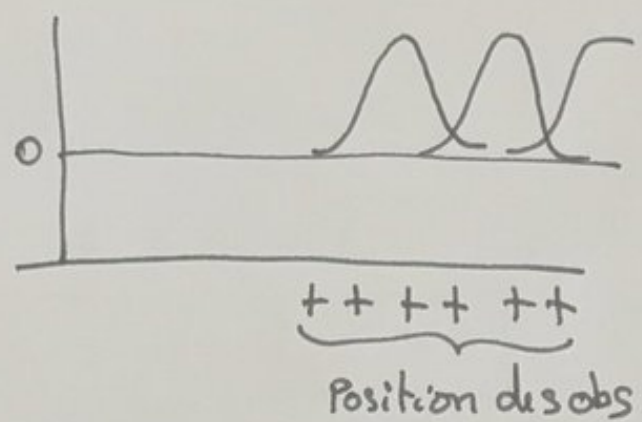


$$p_{(x,y)}^f = \mathbb{E}[\varepsilon^f(x) \varepsilon^f(y)] \rightarrow$$

$$C_{(x,y)}^f = \frac{p_{(x,y)}^f}{\sqrt{V(x)} \sqrt{V(y)}}$$

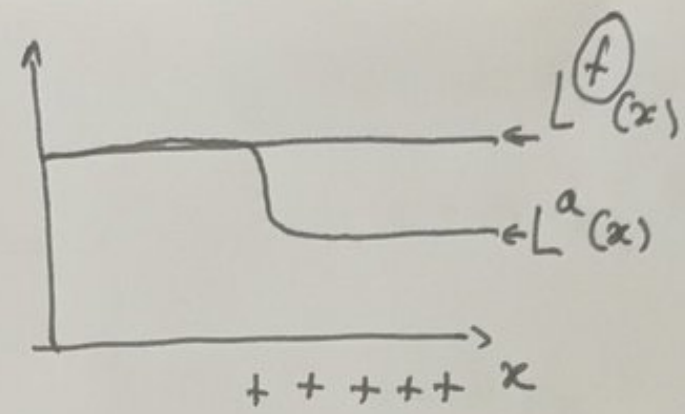
$$\underline{P}^f = \mathbb{E}[\underline{\varepsilon}^f \cdot (\underline{\varepsilon}^f)^T] \rightarrow$$

$$\underline{C}^f = \underline{\Sigma}^{-1} \underline{P}^f \underline{\Sigma}^{-T}$$

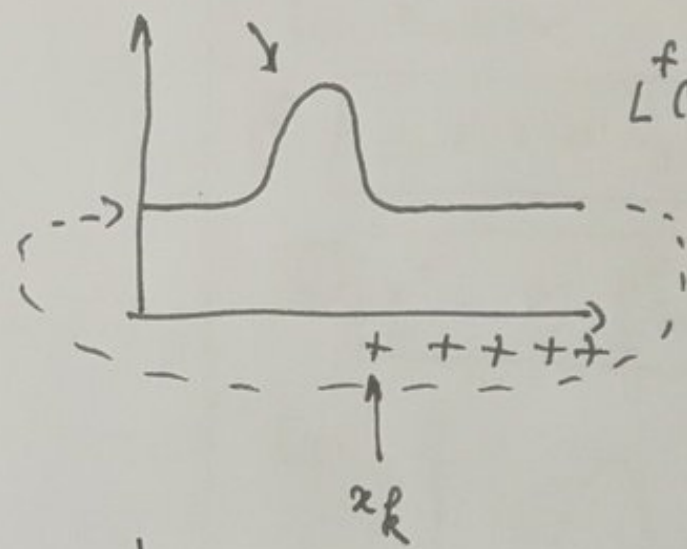


$$\rho(\delta x) = 1 - \frac{\delta x^2}{2L_x^2} + o(\delta x^2)$$

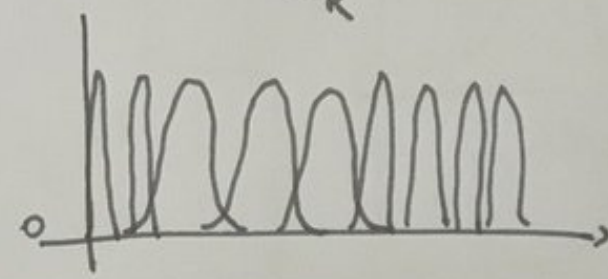
↑
longueur de portée



$t=0$



$t=T$



$$\textcircled{1} \quad \partial_t \alpha + \mu \partial_x \alpha = 0$$

$$\textcircled{2} \quad \alpha = \mathbb{E}[\alpha] + \alpha'$$

$$\alpha' = \alpha - \mathbb{E}[\alpha]$$

dynamique de l'erreur
de prévision.

$$\textcircled{3} \quad \partial_t \varepsilon^f + \mu \partial_x \varepsilon^f = 0 \quad \varepsilon^f(t, x)$$

on peut montrer que la variance
vérifie une dynamique:

$$\textcircled{4} \quad V(x) = \mathbb{E}[(\varepsilon^f(x))^2] \quad V(t, x)$$

$$\partial_t V(x) = \partial_t \mathbb{E}[(\varepsilon^f)^2]$$

$$= \mathbb{E}[\partial_t (\varepsilon^f)^2]$$

$$= \mathbb{E}[2 \varepsilon^f \partial_t \varepsilon^f] \text{ or } \partial_t \varepsilon^f = -\mu \partial_x \varepsilon^f$$

$$= 2 \mathbb{E}[\varepsilon^f (-\mu) \partial_x \varepsilon^f]$$

$$= -2\mu \mathbb{E}[\varepsilon^f \partial_x \varepsilon^f] \quad \partial_x (\varepsilon^f)^2 = 2 \varepsilon^f \partial_x \varepsilon^f$$

$$= -\mu \mathbb{E}[\partial_x (\varepsilon^f)^2]$$

(Suite)

2011-6

$$\partial_t V(x) = -\mu \mathbb{E}[\partial_x (\varepsilon^f)^2]$$

$$= -\mu \partial_x [\mathbb{E}[(\varepsilon^f)^2]]$$

↑ c'est $V(t, x)$

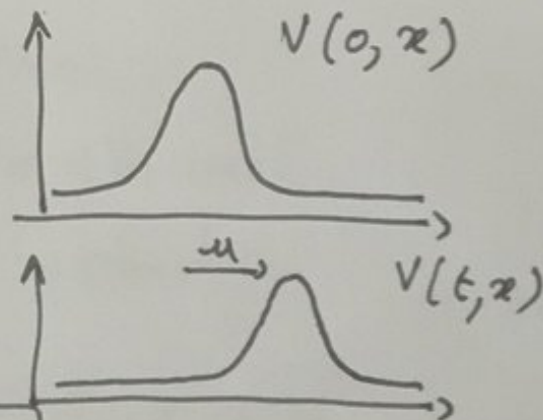
$$= -\mu \partial_x V$$

Conclusion

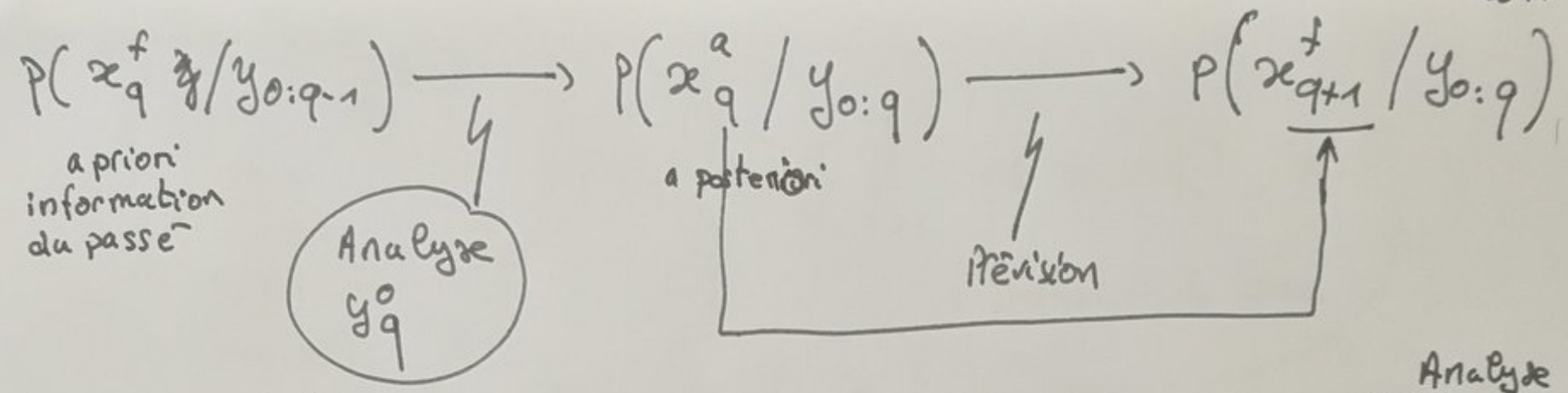
$$\textcircled{5} \quad \partial_t V + \mu \partial_x V = 0$$

$$\textcircled{6} \quad \underline{P}^f = \underline{M} \underline{P}_{(0)}^f \underline{M}^T = \underline{M} (\underline{M} \underline{P}_{(0)}^f)^T$$

Ex:



$$(\underline{P}^f)^T = \underline{P}^f$$



≡ Formule de Bayes

$$P(x_q^a / y_{0:q}) \propto P(y_q^o / x_q) P(x_q / y_{0:q-1})$$

Analyse

$$\begin{cases} x^a = x^f + K(y^o - Hx^f) \\ P^a = (I - KF) P^f \end{cases}$$

Prévision

$$\begin{cases} x^f = \Gamma x^a \\ P^f = \Gamma P^a \Gamma^T \end{cases}$$

Cas linéaire Gaussien \Rightarrow Filtre de Kalman.

Filtre de Kalman d'ensemble

$n \sim 10^3$

$\propto w(x_q^f, P_q^f)$

$$P_q^f = \frac{1}{N} \sum_{k=1}^N P_q^k$$

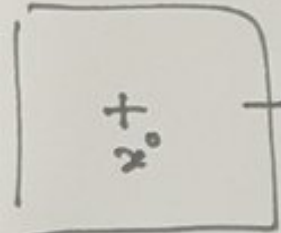
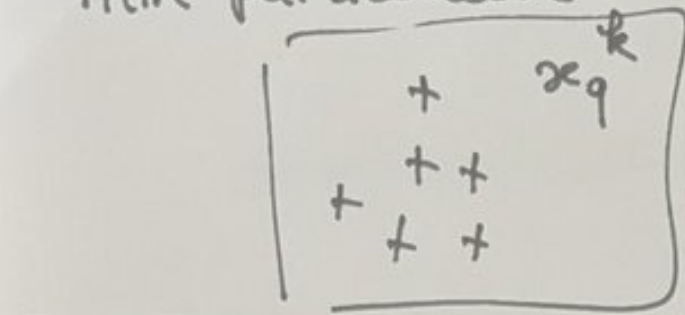
2 n intégration

N échantillon

N intégration $\sim 20 \text{ à } 30 \text{ à } 100$

$$\bar{x}_q^f = \frac{1}{N} \sum_{k=1}^N x_q^k = \begin{bmatrix} 1 \\ \bar{x}_q \end{bmatrix}$$

$$P_q^f = \frac{1}{N} \sum_{k=1}^N (x_q^k - \bar{x}_q^f)(x_q^k - \bar{x}_q^f)^T$$



$\rightarrow \delta(x - x^0)$

$$P(x_q) \stackrel{N}{=} \frac{1}{N} \sum_{k=1}^N \delta(x_q - x_q^k) = \bar{P}$$

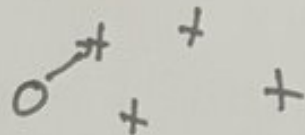
distribution de Dirac

au sens faible ie

$$\mathbb{E}_P[f(x_q)] \approx \mathbb{E}_{\bar{P}}[f(x_q)] \quad \forall f \text{ bornée}$$

$P(y_q^0 / x_q^k) \rightarrow$ poids \equiv vraisemblance

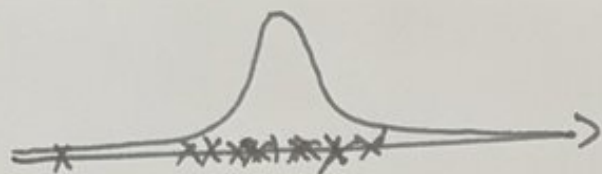
Formule de Bayes : au sens faible



+

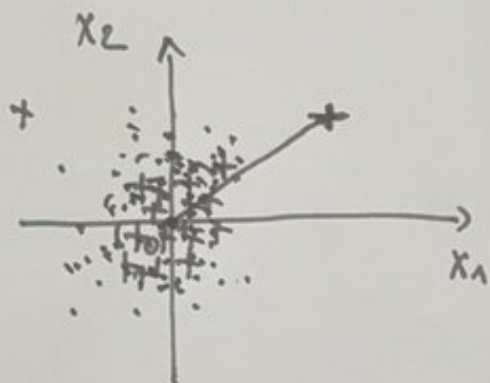
$$P(x_q / y_{0:q}) \approx \sum w_k \delta(x_q - x_q^k)$$

$$w_k = \frac{P(y_q^0 / x_q^k)}{\sum_i P(y_q^0 / x_q^i)}$$



0

$$X \sim \mathcal{N}(0, 1)$$



$$X \sim \mathcal{N}(0, \mathbb{I}_2)$$

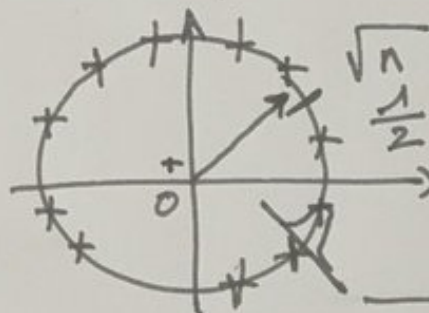
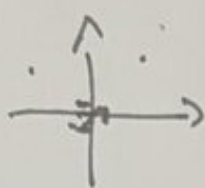
$$X = (X_1, X_2)$$

$$X_i \sim \mathcal{N}(0, 1)$$

$$\|X\|^2 = \sum X_i^2$$

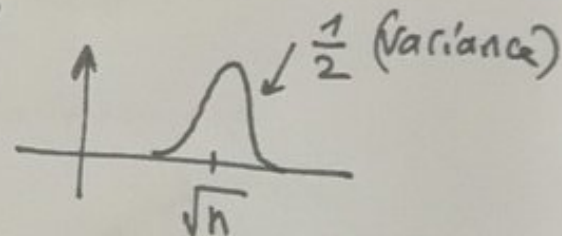
$$X \sim \mathcal{N}(0, \mathbb{I}_n)$$

$n=30$ ou 1000 ?

 \mathbb{R}^{30}

$$\underline{X} = (X_1, \dots, X_{30})$$

$$X_i \sim \mathcal{N}(0, 1)$$

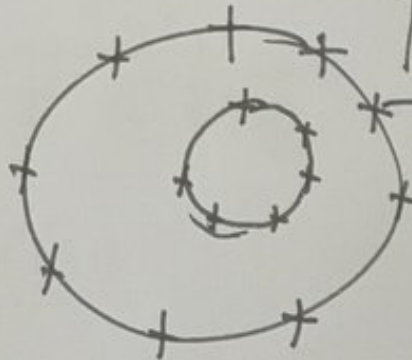


~~$M_n \sim \mathcal{N}(\sqrt{n}, 1)$~~

$$\|\underline{X}(\omega)\|^2 = \sum X_i^2 = \boxed{n}$$

$\Omega \dots$ $\mathbb{E}[\|X\|^2] = \sum_{i=1}^n \underbrace{\mathbb{E}[X_i^2]}_{=1} = n$

$$\underline{X} = (0, \dots, 0)$$



$$M_n = \frac{1}{n} \sum_{i=1}^n Z_i$$

Estimateur d'une moyenne

va.

Z_i va iid

loi des grands nombres.

$$\lim_n M_n = \mathbb{E}[Z] = \int P_Z(z) z dz$$

$$M_n = \frac{1}{n} \sum_{i=1}^n Z_i$$

$$M_n \sim \mathcal{W}\left(\mathbb{E}[Z], \frac{V(Z)}{n}\right)$$

↑
les fluctuations
autour de la
moyenne

$$\|X\|^2 = \sum_{i=1}^n X_i^2 \equiv n$$

$$\frac{1}{n} \sum_{i=1}^n X_i^2 \sim \mathcal{W}\left(1, \frac{V[X_i^2]}{n}\right)$$

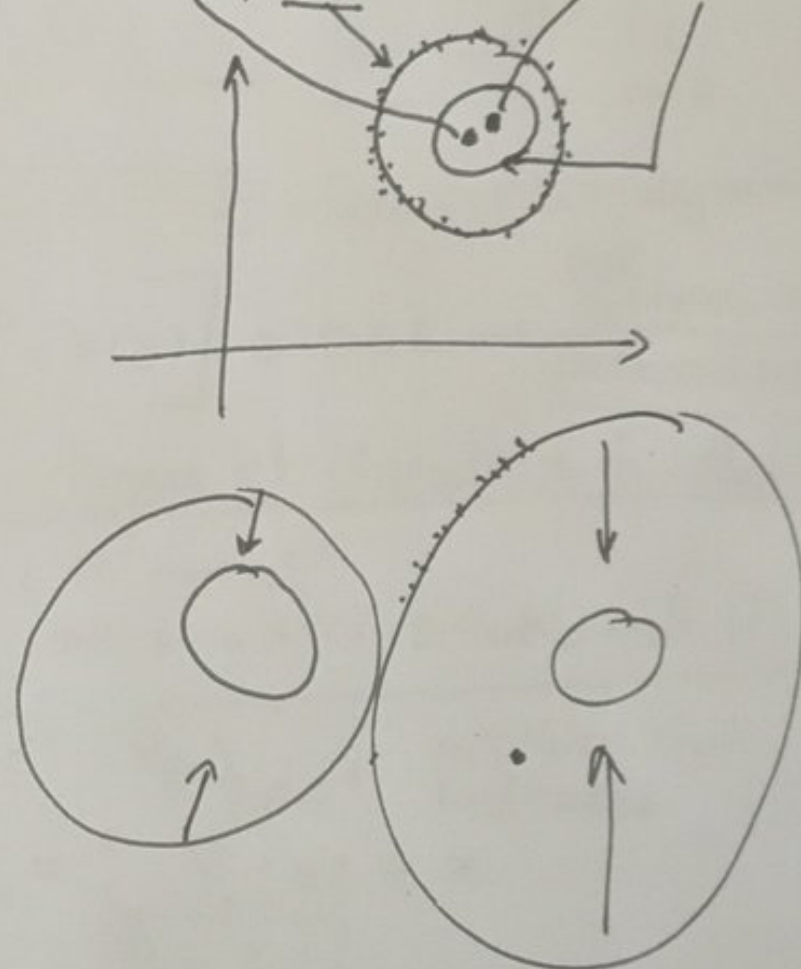
$$\sum_{i=1}^n X_i^2 \sim \mathcal{W}\left(n, n^2 \frac{V(X^2)}{n}\right)$$

$$N_n = n + \sum \sqrt{n} \sqrt{V(X^2)}$$

↑
 $\mathcal{W}(2, 1)$

$$\boxed{\|X\| \sim \mathcal{W}\left(\sqrt{n}, \frac{1}{2}\right)}$$

$$\mathcal{W}(x_q^f, p_q^f) \rightarrow \mathcal{W}(x_q^a, p_q^a)$$



Comparaison des filtres : étape d'analyse

Filtre "non linéaire"
Formule de Bayes

Linéaire
Gaussien
→

Filtre de Kalman

$$P(x_q/y_q) \propto \underbrace{P(y_q/x_q)}_{\text{pondération via vraisemblance}} P(x_q/y_{q-1})$$

pondération via vraisemblance

~~description "particulière"~~

$$x_q^a = x_q^f + K(y_q - H x_q^f)$$

correction de x^f via les obs

$$P_q^a = (I - K H) P_q^f$$

mise à jour mat. covariance

discretisation

Filtre Particulaire

$$P^f(x_q) = \frac{1}{N} \sum_k \delta(x - x_q^k)$$

où $(x_q^k)_{k \in [1, N]}$ un échantillon

Filtre de Kalman d'ensemble

$$(x_q^k) \text{ discretisation de } \mathcal{U}(x_q^f, P_q^f)$$

avec

$$\bar{x}_q = \frac{1}{N} \sum_k x_q^k \approx x_q^f$$

$$\bar{P}_q^f = \frac{1}{N} \sum_k (x_q^k - \bar{x})(x_q^k - \bar{x})^T$$

$$\text{tq } \bar{P}_q^f \approx P_q^f$$

Analyse

$$w_q^k = \frac{P(y_q/x_q^k)}{\sum_j P(y_q/x_q^j)}$$

$$P^a(x_q) = \sum_k w_q^k \delta(x - x_q^k)$$

ce sont les mêmes x_q^k que pour P_q^f

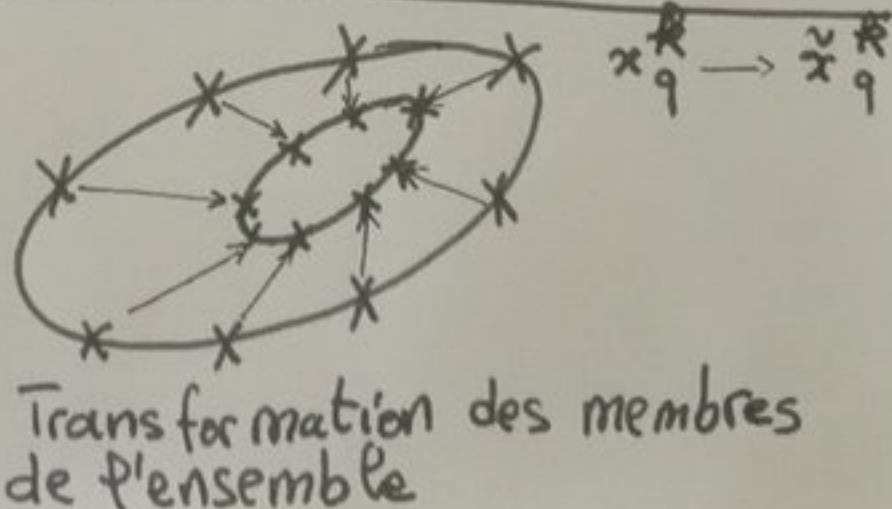
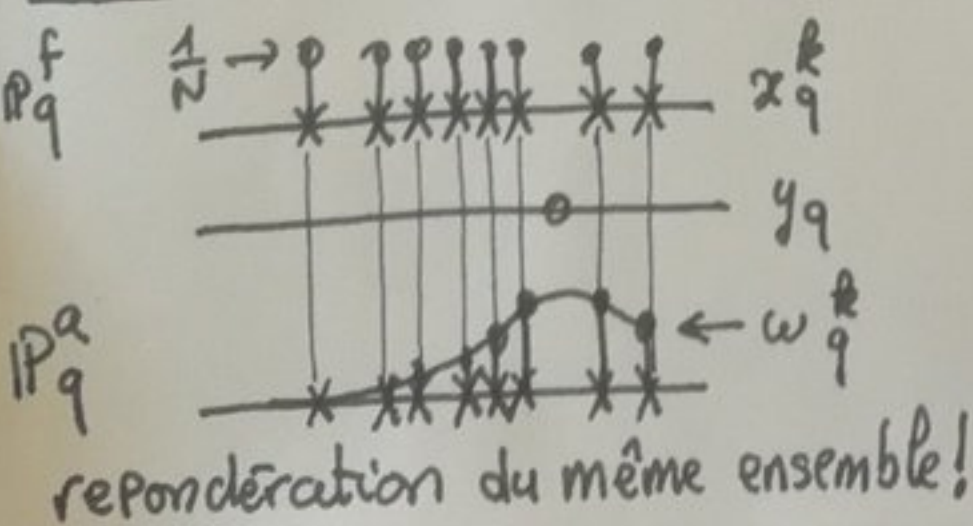
$$\tilde{x}_q^k = x_q^k + K(y_q^k - H x_q^k)$$

avec $y_q^k = y_q + R_q^{1/2} \xi^k$
ensemble d'analyse tel que

$$x_q^a \approx \frac{1}{N} \sum_k \tilde{x}_q^k = \bar{x}_q^a$$

$$P_q^a \approx \frac{1}{N} \sum_k (\tilde{x}_q^k - \bar{x}_q^a)(\tilde{x}_q^k - \bar{x}_q^a)^T$$

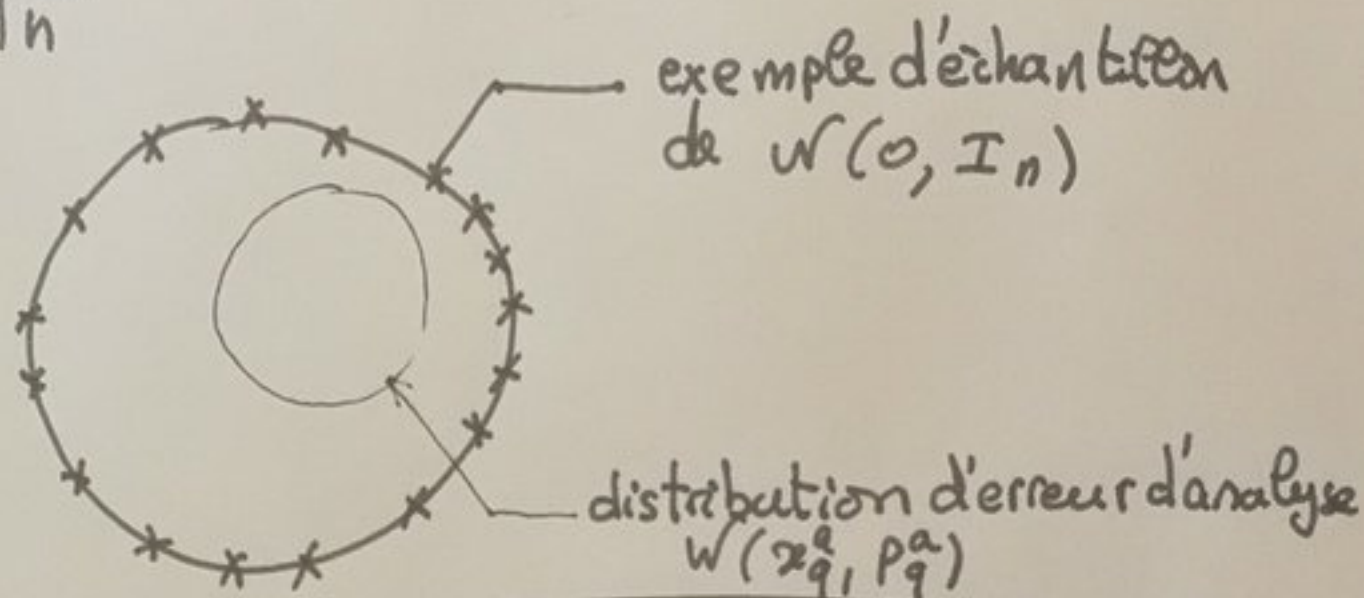
Schéma



Problématique de la grande dimension

on considère $x_q \sim \mathcal{W}(x_q^f, P_q^f)$ cas gaussien, $x \in \mathbb{R}^n$
avec $x_q^f = 0$ et $P_q^f = I$ $n \geq 30$

Avec une méthode de discrétisation touche (pour un ensemble fini de taille raisonnable) les échantillons se trouvent sur la sphère de rayon \sqrt{n}



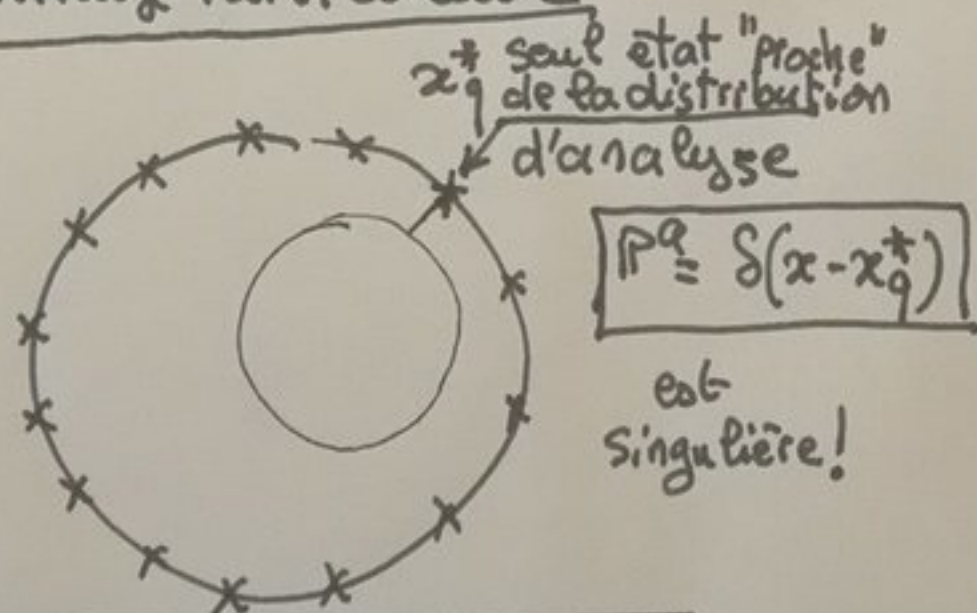
Si tous les points sont observés,

$$P_q^a = (I - KH) P_q^f \approx \frac{1}{2} P_q^f$$

or dans cas gaussien

Formule de Bayes \equiv Filtre de Kalman

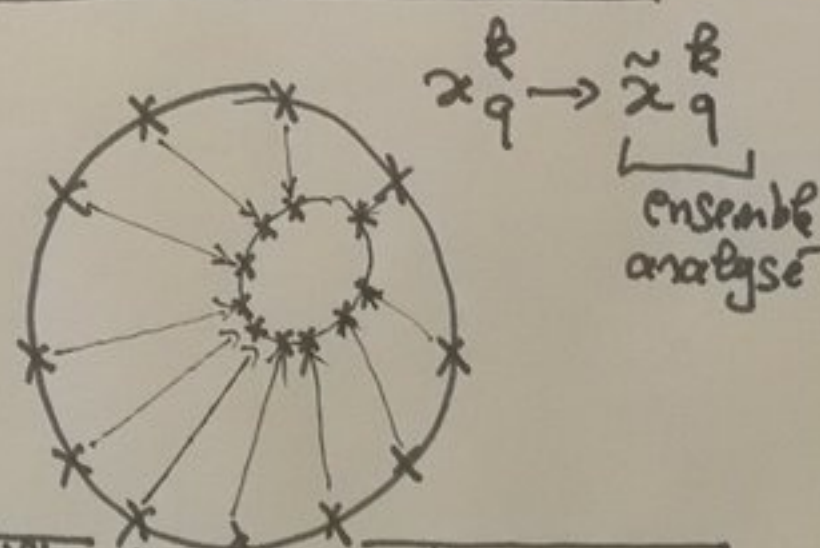
Filtrage Particulaire



Aucun échantillon ne se trouve sur la distribution d'analyse

$P_q^a \equiv$ rep pondération des échantillon x_q^k

Filtre de Kalman d'ensemble



Le filtre de Kalman transforme l'échantillon de prévision en un échantillon d'analyse

\Rightarrow Le Filtre de Kalman / EnKF ne souffre pas de la malédiction de la dimension car la solution analytique du cas Linéaire - Gaussien