

Stochastic Filtering

Consider SDE:

$$dX_t = B(X_t)dt + C(X_t)dW_t \in \mathbb{R}^d. \quad (\text{system})$$

with B, C global Lip. conti. W_t is BM.

And the info. on X_t is provided by

$$dY_t = H(X_t)dt + \Gamma dV_t \in \mathbb{R}^p. \quad Y_0 = 0 \quad (\text{observation})$$

with H global Lip. V_t is p -dim BM indept

of W . $R = \Gamma\Gamma^T > 0$.

Denote $\mathcal{Y}_{0:t} := \sigma(Y_s, s \leq t)$. We want to compute

prob / approxi. $\eta_t(A) := \mathbb{P}(X_t \in A | \mathcal{Y}_{0:t})$. $A \in \mathcal{B}_{\mathbb{R}^d}$.

(1) Kallianpur - Striebel formula:

Note that $\int_0^t \langle R^{-1}H(X_s), dY_s \rangle$ is well-def

by $\mathbb{E} \left(\int_0^T \|X_s\|^2 ds \right) < \infty$ (sol. for SDE)

$$\text{Denote } Z_t(X, Y) := \exp \left(\int_0^t \langle R^{-1}H(X_s), dY_s \rangle - \frac{1}{2} \int_0^t \langle R^{-1}H(X_s), H(X_s) \rangle ds \right)$$

Thm. (\bar{X}_t) is copy of X_t , st. indept of (X, V) . Then:

$$\eta_t(A) = E(I_A(X_t) | \mathcal{Y}_{0:t})$$

$$= \frac{E_{\bar{x}}(I_A(\bar{X}_t) Z_t(\bar{x}, Y))}{E_{\bar{x}}(Z_t(\bar{x}, Y))}$$

Prmk: We see $Y_t \mapsto \eta_t(A)$ isn't const.

w.r.t. $\|\cdot\|_{\infty}$ if $\lambda > 1$. \Rightarrow Z_t 's not

robust. \Rightarrow Rough path comes in.

Pf: $P_{(x,y)} \ll P_{(x,v)} = P_x \otimes P_v$ with Radon-Nikodym deriv. $Z_t(x, Y)$.

Since $P_{Y|x} = Z_t(x, Y) P_v$ by Girsanov:

$Y_{0:t} | X_{0:t}$ is BM with drift $H(x_t)$.

Then we can compute $E(I_A(X_t) H(Y_{0:t}))$

\Rightarrow We can use the Malliavin-Stribel formula to obtain a SPDE for unnormalized

conditional risk. $\tilde{\eta}_t(A) := E_{\bar{x}}(I_A(\bar{X}_t) Z_t(\bar{x}, Y))$:

For $f \in C^{\infty}(R^d)$. by Itô's, we have

$$L E_{\bar{x}}(f(\bar{X}_t) Z_t(\bar{x}, Y))$$

$$= E_{\bar{x}}(Z_t(\bar{x}, Y) (L f(\bar{X}_t) dt + f(\bar{X}_t) \langle R^{-1} H(\bar{X}_t), dY_t \rangle))$$

$$\Rightarrow L \tilde{\eta}_t(f) = \tilde{\eta}_t(L f) dt + \tilde{\eta}_t(f \cdot H) R^{-1} dY_t \quad \text{where}$$

L is generator for \bar{X}_t . It's called Zakai-equation in weak form.

If $\tilde{\eta}_t(x) = \tilde{\eta}_t(x) \mu_x$, $\tilde{\eta}_t$ is smooth density

$$\Rightarrow \partial_t \tilde{\eta}_t(x) = L^* \tilde{\eta}_t(x) \mu_t + \tilde{\eta}_t(x) M(x) R^{-1} \mu Y_t.$$

Rmk: To get SPDE for η_t , we can apply

Itô's with $\mu(x, \eta) = x/\eta$ ($\eta > 0$).

$$\Rightarrow \mu \eta_t(f) = \eta_t(Lf) \mu_t - (\eta_t(Lf) - \eta_t(f) \eta_t(M)) \cdot$$

$$R^{-1} (\mu Y_t - \eta_t(M) \mu_t)$$

It's called Kushner - Stratonovich eq.

If $\eta_t(x) = \eta_t(x) \mu_x$, then

$$\partial_t \eta_t(x) = L^* \eta_t(x) \mu_t + (M(x) - \eta_t(M)) \eta_t(x) R^{-1} \cdot (\mu Y_t - \eta_t(M) \mu_t)$$

2) Kalman - Bucy Filter:

For $B(x) = Bx$, $M(x) = Mx$ are linear, $C(x) = C \cdot \text{const.}$ and $x_0 \sim N(m, P_0)$, i.e.

$$\mu \begin{pmatrix} x_t \\ Y_t \end{pmatrix} = \begin{pmatrix} B & 0 \\ M & 0 \end{pmatrix} \begin{pmatrix} x_t \\ Y_t \end{pmatrix} \mu_t + \begin{pmatrix} C & 0 \\ 0 & \Gamma \end{pmatrix} \begin{pmatrix} \mu W_t \\ \mu V_t \end{pmatrix}$$

Rmk: Note it's a Gaussian process $\Rightarrow \eta_t = N(m_t, P_t)$ is again normal dist. since

$$(X, Y) \sim N(m, \sigma) \Rightarrow X|Y \sim N(m_X, \sigma_X)$$

By Itô's, we have Kalman - Bucy filter eq.

for m_t, P_t :

$$\dot{m}_t = B m_t + P_t H^T R^{-1} (A Y_t - H m_t)$$

$$\frac{d}{dt} P_t = B P_t + P_t B^T + C C^T - P_t H^T R^{-1} H P_t.$$

Prop: Sol. m_t of the SDE is $E(X_t | Y_{0,t})$.