

Master 2 – Probabilités et Finance
Sorbonne Université et Ecole Polytechnique

Convexity, Optimization and Stochastic Control
Session II

EXERCISE I. We consider a process X defined by the stochastic differential equation : $X_0 \in \mathbf{L}^2(\mathbb{R})$,

$$dX_t = (a + bX_t)dt + \sqrt{\sigma + \theta X_t}dW_t, \quad t \leq T$$

with W a scalar Brownian motion, and given scalar parameters a, b, σ, θ . The existence and uniqueness of a square integrable solution $X \in \mathbb{H}^2$ of this equation is admitted.

1. For each $t \in [0, T]$, justify that X_t is integrable and compute $\mathbb{E}[X_t]$.
2. Provide the stochastic differential equation satisfied by the process $(X_t^n, t \geq 0)$ for any positive integer n .
3. Compute $\mathbb{E}[X_t^2]$ (assuming that all local martingales appearing in the calculation are martingales).
4. We assume that $\mathbb{E}\left[e^{-\frac{\lambda^2}{2}X_T}\right] < \infty$. Justify that, for $t < T$ and $\lambda \in \mathbb{R}$,

$$\mathbb{E}\left[e^{-\frac{\lambda^2}{2}X_T} \mid \mathcal{F}_t\right] = \psi(t, X_t)$$

for some function ψ . Assuming that ψ is $C^{1,2}$, show that the calculation of $\mathbb{E}\left[e^{-\frac{\lambda^2}{2}X_T}\right]$ can be reduced to a partial differential equation.

5. Now, we assume that $\mathbb{E}\left[e^{-\frac{\lambda^2}{2}X_T - \mu \int_0^T X_s ds}\right] < \infty$. Show that the calculation of

$$\mathbb{E}\left[e^{-\frac{\lambda^2}{2}X_T - \mu \int_0^T X_s ds}\right]$$

can be reduced to a partial differential equation.

EXERCISE II. Let S be the price process of a risky security with dynamics

$$\frac{dS_t}{S_t} = (r - \delta)dt + \sigma dB_t,$$

where r is a constant interest rate, δ is a constant dividend rate paid by the security, and B is a Brownian motion (under the risk-neutral measure). Let $g : \mathbb{R}_+ \rightarrow \mathbb{R}_+$ be bounded measurable map. The price of a European option with payoff $g(S_T)$ is given by

$$V(t, S_t) := \mathbb{E}_t\left[e^{-r(T-t)}g(S_T)\right],$$

with \mathbb{E}_t denoting the conditional expectation on the information available at time t .

1. Justify that V is a smooth $C^{1,2}$ function.
2. Provide the partial differential equation satisfied by V .

EXERCISE III (BONUS). Let S be the price process of a risky security with dynamics

$$\frac{dS_t}{S_t} = rdt + \sigma dB_t,$$

where r is a constant interest rate, and B is a Brownian motion (under the risk-neutral measure). An Asian option is defined by the payoff $(Y_T - K)^+$ with $Y_T := \int_0^T S_u du$. Given the spot price S_t and the integral

$$Y_t := \int_0^t S_u du,$$

the price at time t of the Asian option is given by

$$V(t, S_t, Y_t) := \mathbb{E}_t \left[e^{-r(T-t)} (Y_T - K)^+ \right],$$

with \mathbb{E}_t denoting the conditional expectation on the information available at time t .

1. Derive the dynamics of the process Y , and justify that the pair process (S, Y) is Markovian.
2. Assuming V is smooth, provide the partial differential equation satisfied by V .
3. We introduce the guess that $V(t, s, y) = s\phi(t, z(s, y))$ with $z(s, y) = \frac{y-k}{s}$. By plugging this form into the PDE satisfied by V , show that ϕ satisfies a PDE in the variables (t, z) .
4. Provide a stochastic representation for the function ϕ .

EXERCISE IV. Let $T > 0$ and W be a \mathbb{F} -Brownian motion. We denote by \mathcal{A} the set of \mathbb{F} -predictable processes $(\alpha_t)_{t \in [0, T]}$ satisfying $\|\alpha\|_\infty \leq 1$. For any $\alpha \in \mathcal{A}$, we introduce (Y^α, Z^α) two processes such that

$$Y_t^\alpha = Y_0 + \int_0^t \alpha_s dW_s \quad \text{and} \quad Z_t^\alpha = Z_0 + \int_0^t Y_s^\alpha dW_s, \quad \text{with } t \in [0, T].$$

Let λ be a positive parameter verifying $2\lambda T < 1$. We define the function $[0, T] \times \mathbb{R} \times \mathbb{R} \ni (t, y, z) \mapsto v(t, y, z) \in \mathbb{R}$ by

$$v(t, Y_t^1, Z_t^1) := \mathbb{E}[e^{2\lambda Z_T^1} | \mathcal{F}_t].$$

1. Provide the partial differential equation satisfied by v .
2. Compute explicitly $v(t, y, z)$ for any (t, y, z) .
3. Show that v is strictly convex in y and that $y v_{yz}(t, y, z) \geq 0$.
4. Show that

$$v(0, Y_0, Z_0) = \sup_{\alpha \in \mathcal{A}} \mathbb{E}[e^{2\lambda Z_T^\alpha}].$$

PROBLEM. We consider a continuous time financial market, containing a risk-free asset S^0 , with a price normalized to 1, and a risky asset S with a price process defined by the SDE :

$$\frac{dS_t}{S_t} = \sigma(Y_t) (\lambda(Y_t) dt + dW_t^1), \quad (1)$$

where Y is a state variable whose dynamics is governed by :

$$dY_t = \eta(Y_t) dt + \gamma(Y_t) \left[\rho dW_t^1 + \sqrt{1 - \rho^2} dW_t^2 \right]. \quad (2)$$

Here, $W = (W^1, W^2)$ denotes a \mathbb{R}^2 -valued Brownian motion on a probability space (Ω, \mathcal{F}, P) , et ρ is a constant in $]-1, 1[$. The coefficients $\eta(y), \gamma(y), s\lambda(y), s\sigma(y)$ satisfy the usual conditions for the existence and uniqueness of strong solution of two dimensional SDE (1)-(2). In addition, we assume that the maps $\lambda(\cdot), \sigma(\cdot)$ are bounded, and that $\inf_{y \in \mathbb{R}} \sigma(y)^2 + \gamma^2(y) > 0$. We will denote by $\mathbb{F} = \{\mathcal{F}_t, t \geq 0\}$ the canonical filtration of W .

A strategy θ is a \mathbb{F} predictable process. For any initial capital x and any strategy θ , one defines the wealth process by :

$$X_t^{x, \theta} = x + \int_0^t \theta_r \frac{dS_r}{S_r}, \quad t \geq 0.$$

We say that θ is an admissible strategy if $X^{0, \theta}$ is well-defined and is uniformly bounded by below by a constant. We use the notation \mathcal{A} for the set of admissible strategies.

Finally, consider a European option on the non-exchangeable variable Y :

$$G = g(Y_T) \quad \text{with} \quad g : \mathbb{R} \longrightarrow \mathbb{R} \text{ bounded continuous}$$

and we define the optimal investment problem by :

$$V^g(0, x, Y_0) := \sup_{\theta \in \mathcal{A}} \mathbb{E} \left[U \left(X_T^{x, \theta} - g(Y_T) \right) \right] \quad \text{where} \quad U(x) := -e^{-ax}, \quad a > 0, \quad x \in \mathbb{R}.$$

Our goal is to determine an explicit expression for :

$$p(0, x, y) := \inf \{ \pi : V^g(0, x + \pi, y) \geq V^0(0, x, y) \}.$$

In the following, we extend as usual the preceding quantities in the case where the initial time is t by noting $V^g(t, x, y)$ and $p(t, x, y)$. Besides, we suppose that the map V^g is $C^{1,2}([0, T], \mathbb{R} \times \mathbb{R}) \cap C([0, T] \times \mathbb{R} \times \mathbb{R})$, for any function g satisfying the previous conditions

1. Give a financial interpretation of the map p . Let $\hat{\pi} \in \mathbb{R}$ and $\hat{\theta} \in \mathcal{A}$ such that $X_T^{\hat{\pi}, \hat{\theta}} \geq G$ a.s. and $X_T^{\hat{\pi}, \hat{\theta}}$ is bounded. Show that $p(0, x, y) \leq \hat{\pi}$, and interpret this result.
2. Show that there exists a non-negative function $F^g(t, y)$ satisfying :

$$V^g(t, x, y) = -e^{-ax} F^g(t, y) \quad \text{for all } t \leq T, \quad (x, y) \in \mathbb{R}^2,$$

and deduce that

$$p(t, x, y) = p(t, y) = \frac{1}{a} \ln \left(\frac{F^g(t, y)}{F^0(t, y)} \right), \quad (t, x, y) \in [0, T] \times \mathbb{R}^2.$$

3. We assume that the map $V^g(t, x, y)$ is a classic solution of the equation

$$\inf_{\theta \in \mathbb{R}} -\mathcal{L}^\theta V^g(t, x, y) = 0, \quad V^g(T, x, y) = U(x - g(y))$$

where

$$\mathcal{L}^\theta V^g := V_t^g + \eta V_y^g + \frac{1}{2} \gamma^2 V_{yy}^g + \lambda \sigma \theta V_x^g + \frac{1}{2} \sigma^2 \theta^2 V_{xx}^g + \theta \rho \sigma \gamma V_{xy}^g$$

Show that $F^g(t, y)$ verifies :

$$F_t^g + \eta F_y^g + \frac{1}{2} \gamma^2 F_{yy}^g - \frac{(\lambda F^g + \rho \gamma F_y^g)^2}{2 F^g} = 0, \quad F^g(T, y) = e^{ag(y)}.$$

4. Find a parameter δ such that the function $f^g(t, y) := [F^g(t, y)]^{1/\delta}$ is the solution of a **linear** partial differential equation.
5. Deduce that

$$f^g(t, y) = \mathbb{E} \left[e^{(1-\rho^2)(ag(\widehat{Y}_T) - \frac{1}{2} \int_t^T \lambda^2(\widehat{Y}_u) du)} \right]$$

where \widehat{Y} is the solution of an SDE to be specified.

6. Give a probability measure $\widehat{\mathbb{Q}}$ equivalent to \mathbb{P} so that p is written as

$$p(t, y) = \frac{1}{a(1-\rho^2)} \ln \left(\mathbb{E}^{\widehat{\mathbb{Q}}} \left[e^{a(1-\rho^2)g(\widehat{Y}_T)} \right] \right).$$

7. Find a random variable \mathcal{F}_T -measurable H s.t. for any function with payoff g :

$$\frac{\partial p}{\partial y}(t, y) = \frac{1}{a(1-\rho^2)} \frac{\mathbb{E}^{\widehat{\mathbb{Q}}} \left[H e^{a(1-\rho^2)g(\widehat{Y}_T)} \right]}{\mathbb{E}^{\widehat{\mathbb{Q}}} \left[e^{a(1-\rho^2)g(\widehat{Y}_T)} \right]}.$$

Exercice 1. $X_0 \in \mathcal{L}^2(\mathbb{R})$

$dX_t = (a+bX_s)dt + \sqrt{\tau + \delta X_s} dW_t \quad \forall t \leq T$

 (a, b, τ, δ) sont pris de telle sorte que X est bien défini et $X \in \mathbb{H}^2$ i.e. $\mathbb{E}[\int_0^T X_s^2 dt] < \infty$ 1) $\forall t \leq T, X_t \in \mathcal{L}^2(\mathbb{R})$ et $\mathbb{E}[X_t] = ?$

$$\text{On sait que } X_t = \underbrace{X_0}_{\text{①}} + \underbrace{\int_0^t (a+bX_s) ds}_{\text{②}} + \underbrace{\int_0^t \sqrt{\tau + \delta X_s} dW_s}_{\text{③}} \quad \forall t \leq T$$

$$\begin{aligned} \text{①} \in \mathcal{L}^2 \text{ car } \mathbb{E}[\int_0^t (a+bX_s) ds] &\leq \mathbb{E}[\int_0^t |a| + |b||X_s| ds] \\ &\stackrel{\text{CS}}{\leq} C(|a|t + |b| \mathbb{E}[\int_0^t |X_s|^2 ds]^{\frac{1}{2}}) \quad C > 0 \\ &\stackrel{\text{car } X \in \mathbb{H}^2}{\leq} \infty \end{aligned}$$

$$\begin{aligned} \text{③} \in \mathcal{L}^2 \text{ car } \mathbb{E}[\int_0^t \sqrt{\tau + \delta X_s} dW_s] &\leq \mathbb{E}[\int_0^t \sqrt{\tau + \delta X_s} dW_s]^2 = \mathbb{E}[\int_0^t \tau + \delta X_s ds]^{\frac{1}{2}} \\ &\stackrel{\text{Isométrie d'Ito}}{\leq} \mathbb{E}[\int_0^t |a|t + |b||X_s| ds]^{\frac{1}{2}} \\ &\stackrel{\text{car } (X_s)_{s \in [0,T]} \in \mathbb{H}^2 \text{ et } X \in \mathbb{H}^2}{\leq} C(\sqrt{T} + |b| \mathbb{E}[\int_0^T |X_s|^2 ds]^{\frac{1}{2}}) < \infty \end{aligned}$$

$\Rightarrow X_t \in \mathcal{L}^2 \quad \forall t$

$$\begin{aligned} \Rightarrow \mathbb{E}[X_t] &= \mathbb{E}[X_0 + \int_0^t a+bX_s ds + \int_0^t \sqrt{\tau + \delta X_s} dW_s] \\ &= X_0 + at + b \int_0^t \mathbb{E}[X_s] ds \quad \text{Fubini car } \mathcal{L}^1 \end{aligned}$$

$$\begin{cases} m_0 = X_0 \\ m_r = C(r)e^{br} \quad (c(0) = X_0) \\ \dot{c}(r)e^{br} = a \Rightarrow \dot{c}(r) = ae^{-br} \\ \Rightarrow c(r) = X_0 + \int_0^r ae^{-bs} ds = X_0 + \frac{a}{b}(1 - e^{-br}) \\ \Rightarrow m_r = X_0 e^{br} + \frac{a}{b}(e^{br} - 1) = (X_0 + \frac{a}{b})e^{br} - \frac{a}{b} \end{cases}$$

$\text{Donc } \mathbb{E}[X_t] = (X_0 + \frac{a}{b})e^{br} - \frac{a}{b}$

2) Donner l'EDS qui satisfait le processus $(X_t^m, t \geq 0) \quad \forall m > 0$ On applique Ito car $x \mapsto x^m \in C^2$

$$\begin{aligned} \Rightarrow dX_t^m &= m X_t^{m-1} dX_t + \frac{1}{2} m(m-1) X_t^{m-2} d\langle X \rangle_t \\ &= m X_t^{m-1} ((a+bX_t) dt + \sqrt{\tau + \delta X_t} dW_t) + \frac{1}{2} m(m-1) X_t^{m-2} (\tau + \delta X_t) dt \\ &= (am X_t^{m-1} + bm X_t^m + \frac{1}{2} m(m-1) X_t^{m-2} \delta m(m-1) X_t^{m-1}) dt + m X_t^{m-1} \sqrt{\tau + \delta X_t} dW_t \end{aligned}$$

3) Calculer $\mathbb{E}[X_t^2]$ (à supposer que toutes les martingales du champ sont des martingales).

$X_t^2 = X_0^2 + \int_0^t 2X_s \{(a+bX_s)ds + \sqrt{\tau + \delta X_s} dW_s\} + \int_0^t (\tau + \delta X_s) ds$

$$\Rightarrow \mathbb{E}[X_t^2] = \mathbb{E}[X_0^2 + \int_0^t \underbrace{(a+2a+\delta)X_s + 2bX_s^2}_{\text{On admet que } f \text{ est une martingale}} ds + \int_0^t 2X_s \sqrt{\tau + \delta X_s} dW_s]$$

$\Rightarrow \text{Par Fubini, } \mathbb{E}[X_t^2] = \mathbb{E}[X_0^2] + \int_0^t (2a+\delta) \mathbb{E}[X_s] + 2b \mathbb{E}[X_s^2] ds$

$$\Rightarrow \begin{cases} f'(t) = m_r (2a+\delta) + 2b f(s) & t \leq T \\ f(0) = \mathbb{E}[X_0^2] \end{cases}$$

$$\begin{cases} f(t) = C(t) e^{2bt} \\ f(0) = X_0^2 \end{cases} \Rightarrow C(t) = X_0^2 e^{2bt} (\tau + (2a+\delta)m(s)) ds$$

$\Rightarrow f(t) = X_0^2 e^{2bt} + \int_0^t e^{2b(t-s)} (\tau + (2a+\delta)m(s)) ds$

4) $\mathbb{E}[e^{\frac{1}{2}X_T} | \mathcal{F}_t] = \psi(t, X_t)$? pour un certain ψ ?
 On a que $\mathbb{E}[e^{\frac{1}{2}X_T} | \mathcal{F}_t] = \mathbb{E}[e^{\frac{1}{2}(X_t + \int_t^T \mu_s ds + \frac{1}{2}\int_t^T \sigma_s^2 ds)} | \mathcal{F}_t]$
 $= e^{-\frac{1}{2}X_t} \mathbb{E}[e^{\frac{1}{2}(X_t + \int_t^T \mu_s ds)} | \mathcal{F}_t]$

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On observe que $X_t = X_0^{w_k} = X_t^{w_k} \quad \forall s \leq t$ (Propriété de Markov)

où $X_t^{w_k} = X_0 + \int_0^t (a + bX_s^{w_k}) ds + \int_0^t \sqrt{\sigma_s^2} dW_s$
 et $X_t^{w_k} = F(t, X_0, (W_s - W_0)_{s \leq t})$

$$\begin{aligned} \rightarrow \mathbb{E}[e^{\frac{1}{2}X_T} | \mathcal{F}_t] &= e^{-\frac{1}{2}X_t} \mathbb{E}[e^{\frac{1}{2}(X_t^{w_k} - X_t)} | \mathcal{F}_t] \\ &= \mathbb{E}[e^{\frac{1}{2}(F(t, X_0, (W_s - W_0)_{s \leq t}) - X_t)} | \mathcal{F}_t] \\ &\quad \text{Car } X_t \text{ est } \mathcal{F}_t \text{-mesuré} \end{aligned}$$

$$\Rightarrow \psi(t, X_0) = \mathbb{E}[e^{\frac{1}{2}(F(t, X_0, (W_s - W_0)_{s \leq t}) - X_t)}]$$

$$= \mathbb{E}[e^{\frac{1}{2}X_T}]$$

Rappel: si Z est G -mesuré et $Y \perp\!\!\!\perp G$ alors $\mathbb{E}[H(z, Y)|G] = h(z)$
 où $h(z) = \mathbb{E}[H(z, Y)]$

En supposant que ψ est $C^{1,2}$ on peut calculer $\mathbb{E}[e^{\frac{1}{2}X_T}]$ pour être réduit à une EDP
 L'idée est de trouver une méthode par EDP pour calculer $\mathbb{E}[e^{\frac{1}{2}X_T}]$

Dans le cours de Probab Num, on voit qu'on peut le faire par Monte Carlo

On sait que $\psi: [0, T] \times \mathbb{R} \rightarrow \mathbb{R}$ de classe $C^{1,2}(G, T \times \mathbb{R}) \cap C([0, T] \times \mathbb{R})$ est solution de :

$$\begin{cases} \text{FEYNMANN-KAC} \quad \partial_t V(t, X) + (a + bX) \partial_X V(t, X) + \frac{1}{2} (\sigma^2 + \sigma^2 X) \partial_{XX}^2 V(t, X) = 0 & t \in [0, T] \\ V(T, X) = e^{-\frac{1}{2}X} & \end{cases} \quad) \text{ A absolument connaitre pour cœur.}$$

Si l'EDP (*) admet une solution $V: [0, T] \times \mathbb{R} \rightarrow \mathbb{R}$

$$\mathbb{E}[e^{\frac{1}{2}X_T}] = \mathbb{E}[V(0, X_0)]$$

$\in \mathcal{C}^2(X_0)$ connue

On peut approximer une solution de (*) par différence finie

5) On suppose $\mathbb{E}[e^{-\frac{1}{2}X_T - \mu \int_0^T X_s ds}] < \infty$

Mais le calcul de $\mathbb{E}[e^{-\frac{1}{2}X_T - \mu \int_0^T X_s ds}]$ peut être réduit à une EDP

$$\begin{cases} FK \quad \partial_t V(t, X) + \gamma(t, X) \mu X + \partial_X V(t, X) (a + bX) + \frac{1}{2} (\sigma^2 + \sigma^2 X) \partial_{XX}^2 V(t, X) = 0 \\ (*) \quad V(T, X) = e^{-\frac{1}{2}X} \end{cases}$$

$$\begin{aligned} 5 - \mathbb{E} \left[e^{\frac{1}{2}X_T - \mu \int_0^T X_s ds} \right] &= 0 \\ FK \quad \begin{cases} \partial_t V(t, X) + \gamma(t, X) \mu X + \partial_X V(t, X) (a + bX) + \frac{1}{2} (\sigma^2 + \sigma^2 X) \partial_{XX}^2 V(t, X) = 0 \\ V(T, X) = e^{-\frac{1}{2}X} \end{cases} \\ \left(\begin{aligned} & \mathbb{E} \left[e^{\frac{1}{2}X_T - \mu \int_0^T X_s ds} \right] - V(t, X_t) = \mathbb{E} \left[e^{\frac{1}{2}X_T - \mu \int_0^T X_s ds} \right] - e^{-\frac{1}{2}X_t} \\ & \mathbb{E} \left[e^{\frac{1}{2}X_T - \mu \int_0^T X_s ds} \right] = e^{-\frac{1}{2}X_t} H(t, X_t) \end{aligned} \right) \end{aligned}$$

La vers° du dynamique seraient

$$V(t, X_t) = \mathbb{E}[e^{\frac{1}{2}X_T - \mu \int_0^T X_s ds} | \mathcal{F}_t]$$

$$\begin{cases} FK \quad \partial_t V - \gamma \partial_X V + b \partial_{XX} V + \frac{1}{2} \sigma^2 \partial_{XXX}^2 V = 0 \\ V(T, X_T) = e^{-\frac{1}{2}X_T} \end{cases}$$

Donc si V solution de (*), alors on a que $\mathbb{E}[e^{-\frac{1}{2}X_T - \mu \int_0^T X_s ds}] = \mathbb{E}[V(0, X_0)]$

Exercice 2 :

$$\frac{dS_t}{S_t} = (\mu - \delta)dt + \sigma dB_t$$

$$V(t, S_t) := \mathbb{E}_t [e^{r(T-t)} g(S_T)] = \mathbb{E}_{\mathcal{F}_t} [e^{r(T-t)} g(S_T) | \mathcal{F}_t]$$

\mathcal{F}_t d'obligatoirement

1) Montrer V est une fct de $C^{\infty}(C_0 T \times \mathbb{R})$

$$\text{On sait que } V(t, x) = \mathbb{E}[e^{r(T-t)} g(S_T^x)]$$

Si g est régulière, on dérive sous l'espérance pour vérifier la régularité de V .

$$\begin{aligned} S_T^x &= X e^{(r-\delta)(T-t) - \frac{\sigma^2}{2}(T-t) + \sigma(W_T - W_t)} \\ &\sim_{XG, T-t} \end{aligned}$$

$$\Rightarrow Y(t, x) = \mathbb{E}[e^{r(T-t)} g(x e^{(r-\delta) - \frac{\sigma^2}{2}(T-t) + \sigma(W_T - W_t)})] \text{ par chgt de variable}$$

$$= \int_{\mathbb{R}} e^{-r(T-t)} g(e^{(r-\delta) - \frac{\sigma^2}{2}(T-t) + \sigma(W_T - W_t)}) \frac{1}{\sqrt{\pi}} e^{-\frac{y^2}{2}} dy$$

Par chgt de variable et en dérivant sous l'intégrale, on vérifie que $V \in C^{\infty}(C_0 T \times \mathbb{R})$

2) Donner l'EDP satisfaite par V

$$V \in C^{\infty} NC$$

$$\begin{cases} \partial_t V(t, x) - r V(t, x) + (\mu - \delta) x \partial_x V(t, x) + \sigma^2 x^2 \partial_{xx}^2 V(t, x) = 0 \\ V(T, x) = g(x) \end{cases}$$

Exercice 4 : $\|\alpha\|_{\infty} \leq 1$

$$Y_t^\alpha = Y_0 + \int_0^t \alpha_s dW_s \text{ et } Z_t^\alpha = Z_0 + \int_0^t Y_s^\alpha dW_s \quad t \in [0, T]$$

$$\lambda > 0, b_T > 2\lambda T < 1 \text{ et } v: C_0 T \times \mathbb{R} \times \mathbb{R} \rightarrow \mathbb{R} \quad \text{tg } V(t, Y_t^\alpha, Z_t^\alpha) := \mathbb{E}[e^{2\lambda Z_T^\alpha} | \mathcal{F}_t] \quad |_{Y_t^\alpha, Z_t^\alpha}$$

$$d\begin{pmatrix} Y_t^\alpha \\ Z_t^\alpha \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \end{pmatrix} dt + \begin{pmatrix} 1 & 0 \\ Y_t^\alpha & 0 \end{pmatrix} \begin{pmatrix} dW_t \\ dW_t \end{pmatrix}$$

$$P_t \in \mathbb{R}^d \quad dP_t = b_t dt + \sigma_t dW_t \Leftrightarrow$$

$$b_t \in \mathbb{R}^d, \sigma_t \in \mathbb{R}^{d \times q}, W \in \mathbb{R}^q$$

(Y_t^α, Z_t^α) vérifie l'EDS, la déf se justifie par la prop de Markov

1- (EDP) :

$$\begin{cases} \partial_t v + 0x \partial_x v + 0x \partial_y v + 0x \partial_z v + \frac{1}{2} \sigma^2 \partial_{yy}^2 v + \frac{1}{2} y^2 \partial_{zz}^2 v + yx \partial_{yz}^2 v \\ v(T, y, z) = e^{2\lambda z} \end{cases}$$

$$\star \quad \text{Si } Y_t^\alpha = Y_0 + \int_0^t \alpha_s d\tilde{W}_s \text{ avec } \tilde{W} \perp\!\!\!\perp W$$

$$\Rightarrow \star = 0$$

$$\text{Si } Y_t^\alpha = Y_0 + \int_0^t \alpha_s d\tilde{W}_s + c dB_s \text{ avec } B \perp\!\!\!\perp W$$

$$\Rightarrow \frac{1}{2} \sigma^2 \partial_{yy}^2 v \text{ devient } \frac{1}{2} (1 + c^2) \partial_{yy}^2 v$$

EXERCICE IV. Let $T > 0$ and W be a \mathbb{F} -Brownian motion. We denote by \mathcal{A} the set of \mathbb{F} -predictable processes $(\alpha_t)_{t \in [0, T]}$ satisfying $\|\alpha\|_{\infty} \leq 1$. For any $\alpha \in \mathcal{A}$, we introduce (Y^α, Z^α) two processes such that

$$Y_t^\alpha = Y_0 + \int_0^t \alpha_s dW_s \text{ and } Z_t^\alpha = Z_0 + \int_0^t Y_s^\alpha dW_s, \text{ with } t \in [0, T].$$

Let λ be a positive parameter verifying $2\lambda T < 1$. We define the function $[0, T] \times \mathbb{R} \times \mathbb{R} \ni (t, y, z) \mapsto v(t, y, z) \in \mathbb{R}$ by

$$v(t, Y_t^\alpha, Z_t^\alpha) := \mathbb{E}[e^{2\lambda Z_T^\alpha} | \mathcal{F}_t].$$

1. Provide the partial differential equation satisfied by v .

2. Compute explicitly $v(t, y, z)$ for any (t, y, z) .

3. Show that v is strictly convex in y and that $y v_{yz}(t, y, z) \geq 0$.

4. Show that

$$v(0, Y_0, Z_0) = \sup_{\alpha \in \mathcal{A}} \mathbb{E}[e^{2\lambda Z_T^\alpha}].$$

Retenir Feynmann KAC et HJB pour exam !!!