PROBLEM OVERVIEW

Abstract.

1. Optimization Problems

Suppose we have the following problem on $(\Omega, \mathcal{F}, \mathbb{F}, \mathbb{P})$ where \mathbb{F} is the filtration generated by a Brownian motion $W = (W_t)_{t \geq 0}$:

$$J(x) := \inf_{a \in \mathcal{A}} \mathbb{E} \left[\log_{a} \mathbb{E} \left(X_{T}^{0,x} \right) \right].$$

This optimization is over $\mathcal{A} := \{a = (a_t)_{t \in [0,T]} \text{ such that } a \text{ is adapted to } \mathbb{F} \}$. For simplicity we let

$$X_t = x + \int_0^t a_s ds + \sigma W_t.$$

and assume that g is continuously differentiable.

Our control is the "drift" of X. For a fixed control a we can consider another adapted process $\eta = (\eta_t)_{t\geq 0}$ and perturb a by $\epsilon > 0$ in the direction of η :

$$a + \epsilon \eta$$
.

Naively, we can "differentiate" the objective function

$$F(a,x) = \mathbb{E}\left[\frac{1}{2} \int_0^T a_s^2 ds + g(X_T^{0,x})\right]$$

in an arbitrary perturbation direction η :

$$\delta_{\eta}F(a,x) := \lim_{\epsilon \downarrow 0} \frac{F(a+\epsilon\eta,x) - F(a,x)}{\epsilon}.$$

Note that:

$$\delta_{\eta} X_t = \int_0^t \eta_s ds$$

and under some integrability assumptions (so that we can naively pass limits under the integrals/expectations):

$$\delta_{\eta} F(a, x) = \mathbb{E} \left[\int_0^T a_s \eta_s ds + g'(X_T^{0, x}) \int_0^T \eta_s ds \right]$$
$$= \mathbb{E} \left[\int_0^T \left[a_s + g'(X_T^{0, x}) \right] \eta_s ds \right].$$

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By Fubini's Theorem and Iterated Conditioning:

$$\begin{split} \mathbb{E}\left[\int_0^T \left[a_s + g'(X_T^{0,x})\right] \eta_s ds\right] &= \int_0^T \mathbb{E}\left[(a_s + g'(X_T^{0,x})) \eta_s\right] ds \\ &= \int_0^T \mathbb{E}\left[\mathbb{E}\left[(a_s + g'(X_T^{0,x})) \eta_s | \mathcal{F}_s\right]\right] ds \\ &= \mathbb{E}\left[\int_0^T \mathbb{E}\left[(a_s + g'(X_T^{0,x})) \eta_s | \mathcal{F}_s\right] ds\right]. \end{split}$$

Taking out what is known:

$$\mathbb{E}\left[\int_0^T \mathbb{E}\left[(a_s+g'(X_T^{0,x}))\eta_s|\mathcal{F}_s\right]ds\right] = \mathbb{E}\left[\int_0^T \left[a_s+\mathbb{E}\left[g'(X_T^{0,x})|\mathcal{F}_s\right]\right]\eta_sds\right].$$

Taken together we have:

$$\delta_{\eta} F(a, x) = \mathbb{E}\left[\int_{0}^{T} \left[a_{s} + \mathbb{E}\left[g'(X_{T}^{0, x}) | \mathcal{F}_{s}\right]\right] \eta_{s} ds\right].$$

Like in calculus, to minimize F over adapted a, we solve for a satisfying the following first order condition for all adapted η :

$$\delta_{\eta}F(a,x) = \mathbb{E}\left[\int_{0}^{T}\left[a_{s} + \mathbb{E}\left[g'(X_{T}^{0,x})|\mathcal{F}_{s}\right]\right]\eta_{s}ds\right] = 0.$$

It is possible to show that this holds if and only if

$$a_s = -\mathbb{E}\left[g'(X_T^{0,x})|\mathcal{F}_s\right]$$

almost surely for almost every $t \in (0,T)$. If we apply the Martingale Representation Theorem we get that there exists an $a_0 = -\mathbb{E}[g'(X_T^{0,x})]$ and adapted $Z = (Z_t)_{t \geq 0}$ such that

$$a_t = a_0 + \int_0^t Z_s dW_s$$

and $a_T = -g'(X_T^{0,x})$. Putting this together with the dynamics of X (which depend on a) we arrive at the following Forward-Backward Stochastic Differential Equation (FBSDE):

$$\begin{cases} dX_t = a_t dt + \sigma dW_t, & X_0 = x \\ da_t = Z_t dW_t, & a_T = -g'(X_T^{0,x}). \end{cases}$$

This characterizes the first order condition. We can search for a solution of the optimization problem by searching over measurable initial conditions a_0 and adapted volatilities $Z=(Z_t)_{t\geq 0}$ so that we match the terminal condition of the FBSDE over all starting values x of X and paths of $W=(W_t)_{t\geq 0}$. To solve this numerically, we can discretize the FBSDE and parameterize a_0 and Z_t (on the discrete grid $0=t_0< t_1< \cdots < t_N=T$) by neural networks that take as inputs X_0 and X_t , respectively. Using this approximation we can try to minimize the loss:

$$\frac{1}{N} \sum_{i=1}^{N} (a_{\mathbf{T}}(\omega_i) + g'(X_T^{0,x}(\omega_i)))^2$$

over N samples $\omega_i \in \Omega$, i = 1, ..., N that define a trajectory of the Brownian Motion W.