

PDE for Finance, Spring 2000 – Homework 4

Distributed 3/7/00, due 3/21/00. Solutions will be distributed 3/28/00.

1) Problem 4 of HW3 considered the stochastic “linear quadratic regulator” problem in continuous time. Here is the analogous stochastic discrete-time problem. We label times by $k = 0, 1, \dots$. The state at time k is $y_k \in R^n$, and the control at time k is $\alpha_k \in R^n$. We place no restriction on the possible values of α_k . The state equation is

$$y_{k+1} = Ay_k + \alpha_k + e_k$$

where A is a (known) $n \times n$ matrix, and the e_k 's are independent, identically distributed random variables with mean value 0 and finite variance. We emphasize that e_k is independent of y_k and α_k . The initial condition is $y_0 = x$, and the goal is to minimize the expected cost

$$E_{y_0=x} \left\{ \sum_{k=0}^{N-1} [|y_k|^2 + |\alpha_k|^2] + |y_N|^2 \right\}.$$

The interpretation is the same as in the continuous case: we prefer $y = 0$. The system keeps getting perturbed away from this state by noise; the control must be chosen to bring it back, but there is also a cost associated to the control itself.

Let $J_k(x)$ be the minimum expected cost if the initial stage is k and the initial state is x . Observe that $J_N(x) = |x|^2$.

- (a) Write the dynamic programming relation connecting J_k to J_{k+1} .
- (b) Look for a solution of the form $J_k(x) = \langle K_k x, x \rangle + q_k$, where K_k is a symmetric matrix and q_k is a scalar. Show that K_k satisfies the following recurrence relation:

$$K_k = A^T [K_{k+1} - K_{k+1}(K_{k+1} + I)^{-1}K_{k+1}] A + I$$

with $K_N = I$. How is (the optimal) α_k related to y_k ? What is the value of q_k ?

(Remark: For much more about the discrete-time LQR problem see section 2.1 of Bertsekas.)

2) This problem develops a continuous-time analogue of the simple Bertsimas & Lo model of “Optimal control of execution costs” presented in the Section 4 notes. The state is (w, p) , where w is the number of shares yet to be purchased and p is the current price per share. The control $\alpha(s)$ is the rate at which shares are purchased. The state equation is:

$$\begin{aligned} dw &= -\alpha ds \text{ for } t < s < T, & w(t) &= w_0 \\ dp &= \theta\alpha ds + \sigma dz \text{ for } t < s < T, & p(t) &= p_0 \end{aligned}$$

where dz is Brownian motion and θ, σ are fixed constants. The goal is to minimize, among (nonanticipating) controls $\alpha(s)$, the expected cost

$$E \left\{ \int_t^T [p(s)\alpha(s) + \theta\alpha^2(s)] ds + [p(T)w(T) + \theta w^2(T)] \right\}.$$

The optimal expected cost is the value function $u(w_0, p_0, t)$.

(a) Show that the HJB equation for u is

$$u_t + H(u_w, u_p, p) + \frac{\sigma^2}{2} u_{pp} = 0$$

for $t < T$, with Hamiltonian

$$H(u_w, u_p, p) = -\frac{1}{4\theta}(p + \theta u_p - u_w)^2.$$

The final value is of course

$$u(w, p, T) = pw + \theta w^2.$$

(b) Look for a solution of the form $u(w, p, t) = pw + g(t)w^2$. Show that g solves

$$\dot{g} = \frac{1}{4\theta}(\theta - 2g)^2$$

for $t < T$, with $g(T) = \theta$. Notice that u does not depend on σ , i.e. setting $\sigma = 0$ gives the same value function.

(c) Solve for g . (Hint: start by rewriting the equation for g , “putting all the g ’s on the left and all the t ’s on the right”.)

(d) Show by direct examination of your solution that the optimal $\alpha(s)$ is constant.

(e) Give another proof that the optimal $\alpha(s)$ is constant, by examining the deterministic version of this control problem ($\sigma = 0$) and arguing roughly as we did for the Hopf-Lax solution formula (using the convexity of α^2).

(Remark: a better choice of objective would be

$E \left\{ \int_t^T [p(s)\alpha(s) + \theta' \alpha^2(s)] ds + [p(T)w(T) + \theta'' w^2(T)] \right\}$ for some constants θ', θ'' , since the state equation gives θ units of dollars/(share)², whereas the units of θ' and θ'' are different. Food for thought: what happens if one takes the running cost to be $\int_t^T p(s)\alpha(s) ds$ instead of $\int_t^T p(s)\alpha(s) + \theta\alpha^2(s) ds$?)

3) [from Bertsekas: chapter 2, problem 12]. A gambler plays a game in which he may at each time k stake any amount $u_k \geq 0$ that does not exceed his current fortune x_k (defined to be his initial capital plus his gain or minus his loss thus far). He wins his stake back and as much more with probability p , where $\frac{1}{2} < p < 1$, and he loses his stake with probability $(1 - p)$. His goal is to maximize $E\{\log x_N\}$, where x_N is his fortune after N plays. Let’s give two separate proofs that his optimal policy is to stake, at each play, $2p - 1$ times his current fortune (i.e. to choose $u_k = (2p - 1)x_k$).

(a) Let x_0 be the gambler’s initial capital, and let $q_k = u_k/x_k$ be the fraction of his wealth he stakes at time k . His *return* at time k is

$$R_k = \begin{cases} (1 + q_k) & \text{with probability } p \\ (1 - q_k) & \text{with probability } 1 - p \end{cases}$$

in the sense that $x_{k+1} = R_k x_k$. It follows that

$$\log x_N = \log x_0 + \log R_0 + \dots + \log R_{N-1},$$

whence

$$E[\log x_N] = \log x_0 + E[\log R_0] + \dots + E[\log R_{N-1}].$$

Show that $E[\log R_k]$ is maximized, for each k , by the choice $q_k = 2p - 1$.

- (b) Give an alternative analysis based on the principle of dynamic programming. Use $J_k(x_k) = E[\log x_N]$ as your value function, where k is the current time, x_k is the current wealth, and the expectation refers to all remaining uncertainty (the outcome of betting at times $k, \dots, N - 1$).

[Remark: the first approach works – i.e. the method of dynamic programming isn’t really needed here – because the optimal policy is “myopic,” i.e. it optimizes each time step separately. This is a special to the use of $\log x_N$ as the objective.]

4) [from Bertsekas: chapter 2, problem 19]. A driver is looking for a parking place on the way to his destination. Each parking place is free with probability p , independent of whether other parking spaces are free or not. The driver cannot observe whether a parking place is free until he reaches it. If he parks k places from his destination, he incurs a cost k . If he reaches the destination without having parked the cost is C .

- (a) Let F_k be the minimal expected cost if he is k parking places from his destination. Show that

$$\begin{aligned} F_0 &= C \\ F_k &= p \min[k, F_{k-1}] + q F_{k-1}, \quad k = 1, 2, \dots \end{aligned}$$

where $q = 1 - p$.

- (b) Show that an optimal policy is of the form: never park if $k \geq k^*$, but take the first free place if $k < k^*$, where k is the number of parking places from the destination, and k^* is the smallest integer i satisfying $q^{i-1} < (pC + q)^{-1}$.

5) The Section 4 notes discuss work by Bertsimas, Logan, and Lo involving least-square replication of a European option. The analysis there assumes all trades are *self-financing*, so the value of the portfolio at consecutive times is related by

$$V_j - V_{j-1} = \theta_{j-1}(P_j - P_{j-1}).$$

Let’s consider what happens if trades are permitted to be non-self-financing. This means we introduce an additional control g_j , the amount of cash added to (if $g_j > 0$) or removed from (if $g_j < 0$) the portfolio at time j , and the portfolio values now satisfy

$$V_j - V_{j-1} = \theta_{j-1}(P_j - P_{j-1}) + g_{j-1}.$$

It is natural to add a quadratic expression involving the g 's to the objective: now we seek to minimize

$$E \left[(V_N - F(P_N))^2 + \alpha \sum_{j=0}^{N-1} g_j^2 \right]$$

where α is a positive constant. The associated value function is

$$J_i(V, P) = \min_{\theta_i, g_i, \dots; \theta_{N-1}, g_{N-1}} E_{V_i=V, P_i=P} \left[(V_N - F(P_N))^2 + \alpha \sum_{j=i}^{N-1} g_j^2 \right].$$

The claim enunciated in the Section 4 notes remains true in this modified setting: J_i can be expressed as a quadratic polynomial

$$J_i(V_i, P_i) = \bar{a}_i(P_i) |V_i - \bar{b}_i(P_i)|^2 + \bar{c}_i(P_i)$$

where \bar{a}_i, \bar{b}_i , and \bar{c}_i are suitably-defined functions which can be constructed inductively. Demonstrate this assertion in the special case $i = N - 1$, and explain how $\bar{a}_{N-1}, \bar{b}_{N-1}, \bar{c}_{N-1}$ are related to the functions $a_{N-1}, b_{N-1}, c_{N-1}$ of the Section 4 notes.