

A Martingale Approach to Optimal Stopping

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Classical Theory

X_t diffusion with infinitesimal generator \mathcal{D}

$r(x, t)$ loss at (x, t)

$u(x, t) = \min_{S \geq t} E^{(x,t)} r(X_S, S)$, S stopping time

The optimal continuation region:

$$\mathcal{C}^* = \{(x, t) \mid r(x, t) > u(x, t)\}$$

The optimal stopping rule:

$$T^* = \inf\{t > 0 \mid (X_t, t) \notin \mathcal{C}^*\}.$$

Solution via free boundary problem (FBP):

$$\begin{aligned} u_t &= \mathcal{D}u && \text{in } \mathcal{C}^* \\ u &= r && \text{on } \partial\mathcal{C}^* \\ u_x &= r_x && \text{on } \partial\mathcal{C}^* \end{aligned}$$

See Shiryaev, Optimal Stopping Rules.

A stopping problem corresponds to a stationary FBP, if $\mathcal{D}u = 0$ or $\mathcal{D}u = ru$. The paper discusses the question of the structure of stopping problems with stationary FBP.

The Parking Problem

$$S_0 = -Q$$

$$S_n = \sum_{i=1}^n X_i - Q$$

X_i i.i.d. geometric (p)

p : probability of empty spot

Park as near as possible at "0"!

Find stopping time T^* of $S_i, i \geq 0$ with

$$E | S_{T^*} | = \min_T E | S_T | .$$

Solution: $T^* = \min\{n \geq 1 \mid S_n \geq -s_0\}$

with $s_0 = \min\{s \in \mathbb{N} \mid 1 - 2(1 - p)^s > 0\}$

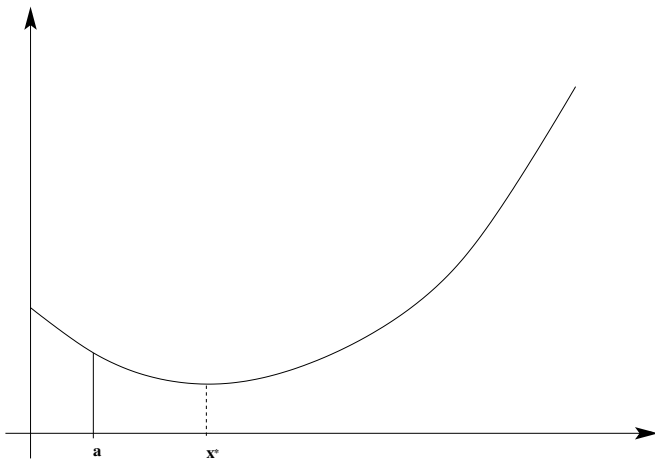
Generalized Parking Problem (GPP)

Let g be a convex function with a unique minimum at $x^* > 0$.

Assume X_i i.i.d. with $EX_i > 0$,

$$S_n = \sum_{i=1}^n X_i, \quad S_0 = 0.$$

Find a stopping time T^* with $Eg(S_{T^*}) = \min_T Eg(S_T)$



Solution (Keener, Lerche, Woodroffe '94):

$$T^* = \min\{n \geq 0 \mid S_n \geq a\} \text{ with } a < x^*.$$

The Main Idea: OS as GPP

Let $(Z_t, \mathcal{F}_t; t \geq 0)$ denote a continuous stochastic process.

Find a stopping time T^* with:

$$E(Z_{T^*} 1_{\{T^* < \infty\}}) = \max_T E(Z_T 1_{\{T < \infty\}})$$

Idea:

Find a process $(X_t, \mathcal{F}_t; t \geq 0)$, and a nonnegative martingale $(M_t, \mathcal{F}_t; t \geq 0)$ with $M_0 = 1$ and a (concave) function g with unique maximum at x^* such that

$$Z_t = g(X_t)M_t \text{ a.s.}$$

Then

$$\begin{aligned} EZ_T 1_{\{T < \infty\}} &= E(g(X_T)M_T 1_{\{T < \infty\}}) \\ &\leq g(x^*)E(M_T 1_{\{T < \infty\}}) \\ &\leq g(x^*) \end{aligned}$$

With $T^* = \min\{t \geq 0 \mid X_t = x^*\}$ the inequalities become equalities, if $E(M_{T^*} 1_{\{T^* < \infty\}}) = 1$.

Optimality of Parabolic Boundaries

Let $X_t = B_t + x_0$, $t \geq 0$ B_t standard Brownian motion. For a measurable function h find a stopping time T that maximizes

$$E \left((T + 1)^{-\beta} h \left(\frac{X_T}{\sqrt{T + 1}} \right) \right) !$$

(Moerbeke(1974))

Let $H(x) = \int_0^\infty e^{ux - u^2/2} u^{2\beta-1} du$ with $\beta > 0$ and assume that there exists a unique point x^* with

$$\sup_{x \in \mathbb{R}} \frac{h(x)}{H(x)} = \frac{h(x^*)}{H(x^*)} = C^* \quad \text{and } 0 < C^* < \infty$$

Theorem 1:

Let $x_0 < x^*$. Then

$$\begin{aligned} \sup_T E \left\{ (T + 1)^{-\beta} h \left(\frac{X_T}{\sqrt{T + 1}} \right) \right\} \\ = E \left\{ (T^* + 1)^{-\beta} h \left(\frac{X_{T^*}}{\sqrt{T^* + 1}} \right) \right\} \\ = H(x_0) C^* \end{aligned}$$

where $T^* = \inf \left\{ t > 0 \mid \frac{X_t}{\sqrt{t+1}} = x^* \right\}$.

$$(t + 1)^{-\beta} H \left(\frac{X_t}{\sqrt{t + 1}} \right) = \int_0^\infty e^{uX_t - \frac{u^2}{2}t} e^{-\frac{u^2}{2}} u^{2\beta-1} du$$

is a positive martingale with starting value $H(x_0)$.

Then $M_t = (t + 1)^{-\beta} H(X_t/\sqrt{t + 1})/H(x_0)$ is a positive martingale with $EM_0 = 1$.

Then

$$\begin{aligned} (t + 1)^{-\beta} h \left(\frac{X_t}{\sqrt{t + 1}} \right) &= H(x_0) \frac{h \left(\frac{X_t}{\sqrt{t + 1}} \right)}{H \left(\frac{X_t}{\sqrt{t + 1}} \right)} M_t \\ &\leq H(x_0) C^* M_t \end{aligned}$$

Then

$$E \left((T + 1)^{-\beta} h \left(\frac{X_T}{\sqrt{T + 1}} \right) \right) \leq H(x_0) C^*$$

But $EM_{T^*} = 1$ and $P(T^* < \infty) = 1$ for

$$T^* = \inf \left\{ t > 0 \mid \frac{X_t}{\sqrt{t+1}} = x^* \right\}.$$

Special case: Dvoretzky(1965), Chow-Robbins(1965)

$$h(x) = x, \quad x_0 = 0, \quad \beta = \frac{1}{2}$$

$$E(X_T/(T + 1)) = \max \text{ with}$$

$$T^* = \min \left\{ t > 0 \mid \frac{X_t}{\sqrt{t + 1}} = x^* \right\}$$

x^* is solution of $x = (1 - x^2) \int_0^\infty e^{ux - u^2/2} du$ (Shepp 1969)

Perpetual Put Option

Samuelson(1965), McKean(1965)

$X_t = \sigma B_t + \mu t$ Brownian Motion with drift μ
and variance σ^2 .

Find stopping time T^* which maximizes

$$E_P e^{-rT} (K - e^{X_T})^+ 1_{\{T < \infty\}}.$$

Idea:

Find Q and g with $E_P e^{-rT} (K - e^{X_T})^+ = E_Q g(X_T)$,
where $Q \ll P$ and g has a unique maximum at x^* .

Then $T^* = \min\{t \geq 0 \mid X(t) = x^*\}$, if $Q(T^* < \infty) = 1$.

Let

$$f(x) = (K - e^x)^+ \text{ and } M_t = \frac{dQ_t}{dP_t}.$$

Then

$$Ee^{-rT} f(X_T) = Ef(X_T)(e^{X_T})^{-\alpha}(e^{X_T})^{\alpha}e^{-rT}.$$

Choose $g(x) = f(x)e^{-\alpha x}$ and α such that $M_t = e^{\alpha X_T}e^{-rt}$ is a martingale. With

$$\begin{aligned} M_t &= \exp[\alpha(\sigma B_t) + \alpha\mu t - rt] \\ &= \exp[(\alpha\sigma)B_t - t(\alpha\sigma)^2/2] \end{aligned}$$

$M_0 = 1$ and M_t is a positive martingale. Then

$$\alpha^{\pm} = -\frac{\mu}{\sigma^2} \pm \sqrt{\frac{\mu^2}{\sigma^4} + \frac{2r}{\sigma^2}}.$$

Let $K < 1 + (-\alpha^-)^{-1}$. Then g has a unique maximum at $x^* = \log \frac{\alpha^- K}{\alpha^- - 1} < 0$. Under Q X_t has drift

$$\alpha^- \sigma^2 + \mu = -\sigma^2 \sqrt{\frac{\mu^2}{\sigma^4} + \frac{2r}{\sigma^2}} < 0.$$

This yields $Q(T^* < \infty) = 1$, if $x^* < 0$.

If $\mu < 0$ then $P(T^* < \infty) = 1$ and

$$\sup_T E_P e^{-rT} (K - e^{X_T})^+ = E_P e^{-rT^*} (K - e^{X_{T^*}})^+$$

The Repeated Significance Test is a Bayes-Test

$W(t), t \geq 0$ Brownian motion with drift θ

Testing sequentially: $H_0 : \theta < 0$ versus $H_1 : \theta > 0$

Prior: $G(d\theta) = \varphi(\tau\theta)\sqrt{\tau}d\theta$

$$R(T, \delta) = \int_{-\infty}^0 \left(P_{\theta}\{\delta \text{ rejects } H_0\} + \frac{c}{2}\theta^2 E_{\theta}T \right) G(d\theta) \\ + \int_0^{\infty} \left(P_{\theta}\{\delta \text{ rejects } H_1\} + \frac{c}{2}\theta^2 E_{\theta}T \right) G(d\theta)$$

Find (T^*, δ^*) with $R(T^*, \delta^*) = \min_{(T, \delta)} R(T, \delta)$.

$$\delta^* = \delta_T^* = 1_{\{W(T) > 0\}} \quad T^* = ?$$

PNAS, 83 (1986)

$$\begin{aligned}
& \int_{-\infty}^0 P_\theta \{ \delta \text{ rejects } H_0 \} G(d\theta) + \int_0^\infty \{ \delta \text{ rejects } H_1 \} G(d\theta) \\
&= \int G_{x,T}(-\infty, 0] 1_{\{\delta > 0\}} \bar{P}(dx) \\
&\quad + \int G_{x,T}(0, \infty] 1_{\{\delta < 0\}} \bar{P}(dx) \\
&\geq \int \min_x (G_{x,T}(-\infty, 0], G_{x,T}(0, \infty]) \bar{P}(dx) \\
&= \int \Phi \left(-\frac{|W(T)|}{\sqrt{T+r}} \right) d\bar{P}
\end{aligned}$$

$$G = N(0, r^{-1}), \quad \bar{P} = \int P_\theta G(d\theta)$$

$$\begin{aligned}
& \int \theta^2 E_\theta T G(d\theta) \\
&= \int T \int \theta^2 G_{W(T),T}(d\theta) d\bar{P} \\
&= \int T \left(\frac{W(T)^2}{(T+r)^2} + \frac{1}{T+r} \right) d\bar{P} \\
&= \int (T+r) \left(\frac{W(T)^2}{(T+r)^2} + \frac{1}{T+r} \right) d\bar{P} - 1 \\
&= \int \frac{W(T)^2}{T+r} d\bar{P}
\end{aligned}$$

$$G_{W(T),T} = N \left(\frac{W(T)}{T+r}, \frac{1}{T+r} \right)$$

Representation of the risk:

$$R(T, \delta_T^*) = \int g\left(\frac{W(T)^2}{T+r}\right) d\bar{P}$$

with $g(x) = \Phi(-\sqrt{x}) + cx/2$

g is convex with unique minimum x^*

$$R(T, \delta_T^*) = \int g\left(\frac{W(T)^2}{T+r}\right) d\bar{P} \geq g(x^*)$$

Let $T^* = \min\{t > 0 \mid W(t)^2/(t+r) = x^*\}$

Since $\bar{P}\{T^* < \infty\} = 1$ it follows

$$R(T^*, \delta_{T^*}^*) = g(x^*).$$

The same type of argument holds for the SPRT.

The representation is $R(T, \delta_T^*) = \int g(|\theta| |W(T)|) d\bar{Q}$

with $\bar{Q} = \frac{1}{2}(P_\theta + P_{-\theta})$, $\theta > 0$.

Disruption Problem

Dissertation of Shiryaev (1961)

Observations: $W(t) = B(t) + \theta(t - \tau)^+$ with
 $B(t), t \geq 0$ standard Brownian motion,
 $\theta > 0$ fixed

Filtration: $\mathcal{F}_t = \sigma(W(s); 0 \leq s \leq t)$

Change-point: τ random time,
with distribution $\pi = p\delta_0 + (1-p)F$,
where $F(t) = 1 - e^{-\lambda t}$

Risk: $R(T) = P_\pi(T < \tau) + cE_\pi(T - \tau)^+$

Find T^* with $R(T^*) = \min_T R(T)$

Theorem 2:

$T^* = \min\{t > 0 \mid \pi_t \geq p^*\}$ with $\pi_t = P(\tau \leq t \mid \mathcal{F}_t)$

Here p^* is the unique solution of $G(p) = p$ and
 $G'(p) = -1$, where G is the positive (and finite at
0) solution of

$$\frac{\theta}{2}x^2(1-x^2)G''(x) + \lambda(1-x)G'(x) = -x$$

$$\begin{aligned}
R(T) &= P(T < \tau) + cE(T - \tau)^+ \\
&= E \left[(1 - \pi_T) + c \int_0^T \pi_s ds \right]
\end{aligned}$$

Find f with

$$E \left(\int_0^T \pi_s ds \right) = Ef(\pi_T) - f(p)$$

Then $g(x) = (1 - x) + cf(x)$ yields

$$R(T) = \int g(\pi_T) dP$$

But this holds with $f = G$!

g is convex with a unique minimum at p^* .

This insight opens a new direction to Bayes tests of power one for change point problems. Cusum and Mixture stopping rules can be derived as Bayes tests. (Beibel 1996, 1997), (Beibel - Lerche 2003).

Disruption Problem: The Representation

Let $\pi_t = P(\tau < t \mid \mathcal{F}_t)$.

π_t is a diffusion with

$$d\pi_t = \lambda(1 - \pi_t)dt + \theta\pi_t(1 - \pi_t)d\bar{W}_t$$

where \bar{W}_t is a Standard Brownian motion.

Ito's formula yields:

$$\begin{aligned} dG(\pi_t) &= G'(\pi_t)d\pi_t + \frac{1}{2}G''(\pi_t)(d\pi_t)^2 \\ &= G'(\pi_t)\lambda(1 - \pi_t)dt + \theta\pi_t(1 - \pi_t)d\bar{W}_t \\ &\quad + \frac{1}{2}G''(\pi_t)\theta^2\pi_t^2(1 - \pi_t)^2dt \end{aligned}$$

If G satisfies the equation

$$\frac{\theta^2}{2}x^2(1 - x)^2G''(x) + \lambda(1 - x)G'(x) = x$$

then

$$\begin{aligned} G(\pi_t) - G(\pi_0) &= \int_0^t \pi_s ds + \int_0^t \theta\pi_s(1 - \pi_s)d\bar{W}_s \\ \Rightarrow E[G(\pi_T) - G(\pi_0)] &= E \int_0^T \pi_s ds \end{aligned}$$

Stopping of Diffusions with Random Discounting

$B_t, t \geq 0$ SBM

X_t diffusion with $X_0 = x$ and

$$dX_t = \mu(X_t)dt + \sigma(X_t)dB_t$$

Find stopping time T^* of X with

$$E\left(e^{-A(T)}h(X_T)1_{\{T<\infty\}}\right) = \max$$

$A(s)$: additive stochastic process adapted to \mathcal{F}^X

$$A(s+t) = A(s) + A(t) \circ \theta_s$$

Example: $r(x) \geq 0, \alpha > 0$

$$E\left(\exp\left\{-\int_0^T r(B_t)dt\right\}(B_T)^\alpha 1_{\{T<\infty\}}\right) = \max$$

How to choose the martingales?

$$\psi_+(x) = \begin{cases} E_x \left(e^{-A(T_{x_0})} \mathbf{1}_{\{T_{x_0} < \infty\}} \right) & \text{for } x \leq x_0 \\ \left[E_{x_0} \left(e^{-A(T_x)} \mathbf{1}_{\{T_x < \infty\}} \right) \right]^{-1} & \text{for } x \geq x_0 \end{cases}$$

$$\psi_-(x) = \begin{cases} \left[E_{x_0} \left(e^{-A(T_x)} \mathbf{1}_{\{T_x < \infty\}} \right) \right]^{-1} & \text{for } x \leq x_0 \\ E_x \left(e^{-A(T_{x_0})} \mathbf{1}_{\{T_{x_0} < \infty\}} \right) & \text{for } x \geq x_0 \end{cases}$$

$$\begin{aligned} M_t^{(+)} &= e^{-A(t)} \psi_+(X_t) \\ M_t^{(-)} &= e^{-A(t)} \psi_-(X_t) \end{aligned} \quad \text{are u.i. martingales with}$$

$$E_x(M_{T_b}^{(+)} \mathbf{1}_{\{T_b < \infty\}}) = \psi_+(x) \quad \text{for } b \geq x$$

$$E_x(M_{T_a}^{(-)} \mathbf{1}_{\{T_a < \infty\}}) = \psi_-(x) \quad \text{for } x \geq a$$

Play the trick with $h(x)/\psi_+(x)$, where $\psi_+(x_0) = 1$

$$X(0) = x_0, \quad x_0 \in I$$

Assume $\psi_+(x_0) = \psi_-(x_0) = 1$

Then

$$e^{-At}h(X_t) = M_t \frac{h(X_t)}{p\psi_+(X_t) + (1-p)\psi_-(X_t)}$$

with $M_t = e^{-At} (p\psi_+(X_t) + (1-p)\psi_-(X_t))$.

M_t is a positive local martingale hence

$$E(M_T 1_{\{T < \infty\}}) \leq 1$$

Problem:

Maximize $\frac{h(x)}{p\psi_+(x) + (1-p)\psi_-(x)}$ over all $x \in I$ with proper p .

Distinguish the following Cases

$$1) \quad \sup_{x \geq x_0, x \in I} (h(x)/\psi_+(x)) = \infty$$

$$2) \quad \sup_{x \leq x_0, x \in I} (h(x)/\psi_-(x)) = \infty$$

$$3) \quad 0 < C^* = \sup_{x \in I} \frac{h(x)}{\psi_+(x)} = \sup_{x \geq x_0} \frac{h(x)}{\psi_+(x)}$$

$$4) \quad 0 < C^* = \sup_{x \in I} \frac{h(x)}{\psi_-(x)} = \sup_{x \leq x_0, x \in I} \frac{h(x)}{\psi_-(x)}$$

$$5) \quad 0 < \sup_{x \geq x_0, x \in I} (h(x)/\psi_+(x)) < \infty$$

$$0 < \sup_{x \leq x_0} (h(x)/\psi_-(x)) < \infty$$

and

$$\sup_{x \leq x_0} \frac{h(x)}{\psi_+(x)} > \sup_{x \geq x_0} \frac{h(x)}{\psi_+(x)} \quad \text{and}$$

$$\sup_{x \geq x_0} \frac{h(x)}{\psi_-(x)} > \sup_{x \leq x_0} \frac{h(x)}{\psi_-(x)}$$

Case 3/4

Theorem 3:

If $0 < C^* = \sup_{x \in I} \frac{h(x)}{\psi_{\pm}(x)} = \sup_{x \geq x_0, x \in I} \frac{h(x)}{\psi_{\pm}(x)} < \infty$

Then

$$\sup_T E_{x_0} \{ e^{-A_T} h(X_T) 1_{\{T < \infty\}} \} = C^* \quad (+)$$

If there exists a point $x^* \underset{\leq}{\geq} x_0$ with $C^* = h(x^*)/\psi_{\pm}(x^*)$, then the supremum in (+) is attained by

$$T^* = \inf \{ t \geq 0 \mid X_t = x^* \}.$$

Of course

$$E_{x_0} e^{-A_{T^*}} h(X_{T^*}) = E_{x_0} g(X_{T^*}) M_{T^*} = C^*.$$

Theorem 4:

Let p^* be such that

$$\begin{aligned} 0 &< \sup_{x \geq x_0, x \in I} \frac{h(x)}{p^* \psi_+(x) + (1 - p^*) \psi_-(x)} \\ &= \sup_{x \leq x_0, x \in I} \frac{h(x)}{p^* \psi_+(x) + (1 - p^*) \psi_-(x)} \end{aligned}$$

then $\sup_T E_{x_0} (e^{-A_T} h(X_T) \mathbf{1}_{\{T < \alpha\}}) = C^*$.

If there exist points $x_1 > x_0$ and $x_2 < x_0$ such that

$$\begin{aligned} &\frac{h(x_1)}{p^* \psi_+(x) + (1 - p^*) \psi_-(x)} \\ &= \frac{h(x_2)}{p^* \psi_+(x) + (1 - p^*) \psi_-(x)} = C^*, \end{aligned}$$

then the supremum is attained for

$$T^* = \inf\{t > 0 \mid X_t = x_1, X_2 = x_2\}.$$

Generalized Parking Problem: Discrete Case

X_1, X_2, \dots i.i.d. with $EX_i > 0$,

$$S_n = \sum_{i=1}^n X_i, \quad S_0 = 0.$$

Find stopping time T^* with $Eg(S_{T^*}) = \min_T Eg(S_T)$

Solution: $T^* = \min\{n \geq 0 \mid S_n \geq a\}$

with

$$a = \sup\{x \mid H^+g(x) < g(x)\}$$

$$H^+g(x) := \int g(x+y)H^+(dy)$$

$$H^+(y) := P(S_\eta \leq y)$$

$$\eta := \min\{n > 0 \mid S_n > 0\}$$

H^+ : the distribution of the first ladder height S_η .

Let $K(x) = \int_0^x \frac{1 - H^+(y)}{\gamma_1} dy$
 with $\gamma_i = \int y^i dH^+(y)$, $i \in \mathbb{N}$.

Theorem 5:

If $Kg(x) < \infty$ for all $0 \leq x < \infty$, then $Kg(x)$ is minimized at $x = a$.

Example 1:

If $g(x) = |x - b| \forall x \in \mathbb{R} \Rightarrow b - a = \text{med}(K)$

Example 2:

If $g(x) = (x - b)^2 \forall x \in \mathbb{R}$
 $\Rightarrow b - a = \text{mean}(K) = \gamma_2/\gamma_1$

Example 3:

If $g(x) = e^{-x} + cx \forall x \in \mathbb{R}$, $0 < c < 1$
 $\Rightarrow b = \log(1/c)$.

If $\int x^2 H^+(dx) < \infty$ and if $\kappa := \int_0^\infty e^{-x} K(dx)$
 $\Rightarrow Kg(x) = \kappa e^{-x} + c(x + \frac{\gamma_2}{2\gamma_1})$ and is minimized
 when $x = \log(\kappa/c)$.

Related Literature

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