

# Ein Martingalansatz zum optimalen Stoppen

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# Some Fundamentals

## Definition of SBM

A continuous stochastic process  $X_t$ ,  $t \geq 0$  is a standard Brownian motion with start in  $x$ , if

- i)  $X_0 = x$
- ii) For  $t_0 < t_1 < \dots < t_k$  the random variables  $X_{t_{i+1}} - X_{t_i}$ ,  $i = 0, \dots, k - 1$  are independent.
- iii) For  $s < t$   $X_t - X_s$  is distributed according to  $N(0, t - s)$ .

Note:  $E(X_t) = EX_0 = x$  and  $\text{Var}(X_t) = t$ .

## Definition of Brownian motion

A continuous stochastic process  $X_t$ ,  $t \geq 0$  is a Brownian motion with starting point  $x$  drift  $\mu$  and variance  $\sigma^2$  if there exists a standard Brownian motion  $B_t$ ,  $t \geq 0$  such that

- i)  $X_0 = x$
- ii)  $X_t = \sigma \cdot B_t + \mu \cdot t$

### Definition of a Martingale:

A stochastic process  $X_t$ ,  $t \geq 0$  is a martingale with respect to the filtration  $\mathcal{F}_t$ ,  $t \geq 0$  if

- i)  $X_t$  is  $\mathcal{F}_t$ -measurable
- ii) For  $s < t$   $E(X_t | \mathcal{F}_s) = X_s$

A consequence:

$$E(X_t) = E(X_0)$$

### Theorem (Lévy):

A continuous martingale  $X_t$ ,  $t \geq 0$  with  $E(X_t^2) < \infty$  for  $t \geq 0$  is a standard Brownian motion if  $E((X_t - X_s)^2 | \mathcal{F}_t) = t - s$  holds for all  $s < t$ .

Definition:

A continuous stochastic process  $(X_t, \mathcal{F}_t; t \geq 0)$  is called a diffusion with start in  $x_0$  if there exists a standard Brownian motion  $(B_t, \mathcal{F}_t; t \geq 0)$  such that

$$(+) \quad X_t = \int_0^t a(X_s) ds + \int_0^t \sigma(X_s) dB_s$$

with  $X_0 = x_0$  and  $a : \mathbb{R} \rightarrow \mathbb{R}$  and  $\sigma : \mathbb{R} \rightarrow \mathbb{R}_+$  measurable.

Remark:.

(+) is usually expressed as SDE:

$$dX_t = a(X_s)dt + \sigma(X_s)dB_s.$$

# Examples of Optimal Stopping

## a) Detection of a Trend Change

$B_t, t \geq 0$  standard Brownian motion

$\tau$  a random time

$$\text{Let } W_t = \begin{cases} B_t & \text{for } t < \tau \\ B_t + \theta(t - \tau) & \text{for } t \geq \tau \end{cases}$$

### Issue:

Find a stopping time  $T^*$  such that the expected delay  $E(T - \tau \mid T \geq \tau)$  is minimal given the false alarm probability  $P(T < \tau)$ .

## b) Stopping the Brownian Motion at the Maximum

$B_t, 0 \leq t \leq 1$  standard Brownian motion

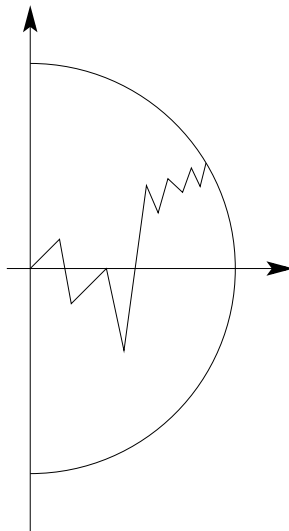
$$R(T) := E \left( B_T - \max_{0 \leq s \leq 1} B_s \right)^2$$

Here  $T$  denotes a stopping time of Brownian motion with  $0 \leq T \leq 1$ .

Find a stopping time  $T^*$  with

$$R(T^*) = \min_T R(T).$$

Idea:



### c) Perpetual American Put Option

Samuelson (1965), McKean (1965)

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

Find a stopping time  $T^*$  which maximizes

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



# 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.

# 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:  $\tau$  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

$T^* = \min\{t > 0 \mid \pi_t \geq p^*\}$  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

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

$$\pi_t = \frac{\varphi_t}{e^{-\lambda t} + \varphi_t} \quad \text{posterior}$$

where

$$\varphi_t = \frac{p}{1-p} L_t + \int_0^t \frac{L_t}{L_s} \lambda e^{-\lambda s} ds$$

and

$$L_t = \exp(\theta W_t - \theta^2 t/2)$$

Case  $p = 0$ :

$$P(\tau \leq t) = 1 - e^{-\lambda t} \quad \text{prior}$$

$$R\pi_t = \frac{\pi_t}{1 - e^{-\lambda t}} - 1 \quad \text{relative posterior}$$

# Stopping the Brownian Motion at the Maximum

$B_t, 0 \leq t \leq 1$  standard Brownian motion

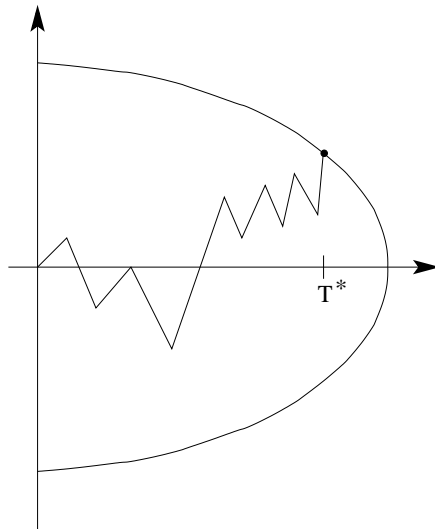
$$R(T) := E \left( B_T - \max_{0 \leq s \leq 1} B_s \right)^2$$

Here  $T$  denotes a stopping time of Brownian motion with  $0 \leq T \leq 1$ .

Find a stopping time  $T^*$  with

$$R(T^*) = \min_T R(T).$$

Idea:



# Graversen, Peskir, Shiryaev (2001)

$$T^* = \inf\{t \leq 1 \mid S_t - B_t \geq z_* \sqrt{1-t}\}$$

where  $S_t = \max_{0 \leq s \leq t} B_s$ .

$z_*$  is the unique solution of the equation

$$4\Phi(z_*) - 2z_*\varphi(z_*) - 3 = 0, \quad z_* \cong 1,12.$$

Note:  $\mathcal{L}(S - B) = \mathcal{L}(|B|)$

It holds:

$$ET^* = \frac{z_*^2}{1 + z_*^2} \cong 0,55, \quad \text{Var}T^* \cong 0,05$$

$$ET^* = EB_{T^*}^2 = z_*^2 E(1 - T^*)$$

Let  $V_* = R(T^*)$

$$\text{Then } V_* = 2 \inf_{\sigma} E \left( \int_0^{\sigma} e^{-2s} F(|Z_s|) ds \right) + 1$$

where  $F(x) = 4\Phi(x) - 3$  and  $Z_s$  is a diffusion process with  $dZ_t = Z_t dt + \sqrt{2} d\beta_t$  and  $\beta_t, t \geq 0$  is a SBM.

$$\text{Let } W_*(z) = \inf_{\sigma} E_z \left( \int_0^{\sigma} e^{-2s} F(|Z_s|) ds \right).$$

$$\text{Then } V_* = 2W_*(0) + 1$$

To determine  $W_*$  solve

$$\begin{aligned} \text{FBP: } (\mathcal{D} - 2)W(z) &= -F(|z|) \quad \text{for } -z_* \leq z \leq z_* \\ W(\pm z_*) &= 0 \\ W'(\pm z_*) &= 0 \end{aligned}$$

$$\text{with } \mathcal{D} = z \frac{d}{dz} + \frac{d^2}{dz^2}.$$

With Ito's formula

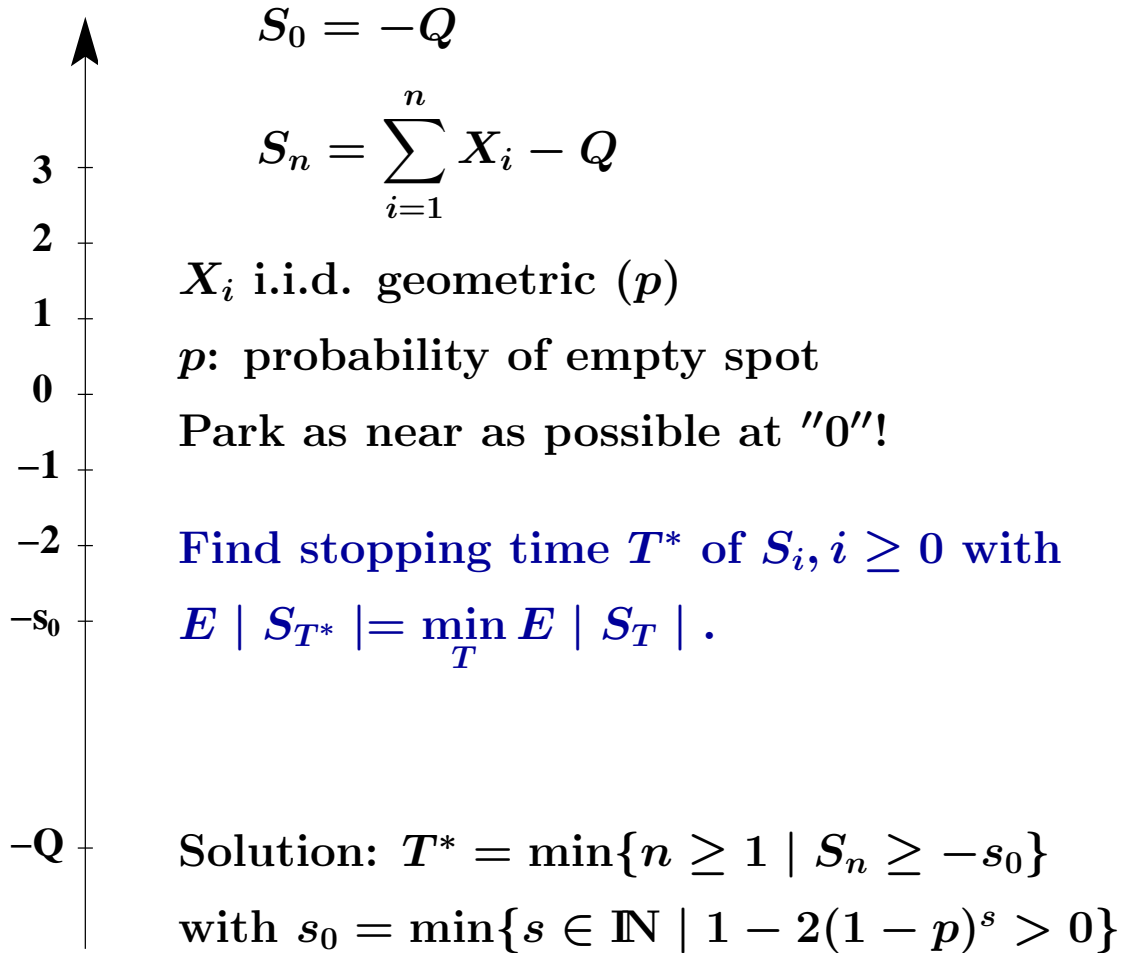
$$E_z (e^{-2\tau} W(|Z_{\tau}|) - W(z)) = -E_z \int_0^{\tau} e^{-2t} F(|Z_t|) dt$$

Find a stopping time  $\sigma^*$  with

$$E_z \left( e^{-2\sigma^*} W(|Z_{\sigma^*}|) \right) = \max_{\tau} E (e^{-2\tau} W(|Z_{\tau}|))$$

$$\text{Solution: } \sigma^* = \inf\{t \geq 0 \mid |Z_t| = z_*\}$$

# The Parking Problem



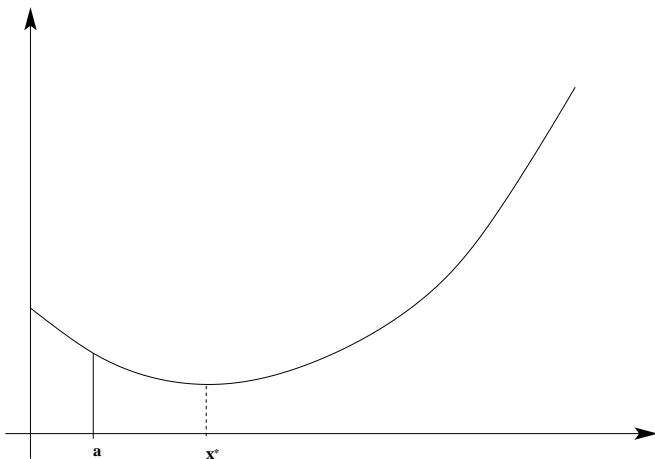
# Generalized Parking Problem (GPP)

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):

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

with  $a = \sup\{x \mid H^+g(x) < g(x)\}$  where  $H^+$  is the ladder-height distribution of  $S_n$ ;  $n \geq 1$ .



# The Main Idea: OS as GPP

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

Find a stopping time  $T^*$  with:

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

Idea:

Find a process  $(X_t, \mathcal{F}_t; t \geq 0)$ , a measure  $Q(Q \ll P)$  and a function  $g$  with unique maximum at  $x^*$  such that

$$Z_t = g(X_t) \frac{dQ}{dP} \Big|_{\mathcal{F}_t}$$

Then

$$\begin{aligned} E Z_T 1_{\{T < \infty\}} &= E \left( g(X_T) \frac{dQ}{dP} \Big|_{\mathcal{F}_T} \right) \\ &= E_Q (g(X_T) 1_{\{T < \infty\}}) \\ &\leq g(x^*) Q(T < \infty) \\ &\leq g(x^*) \end{aligned}$$

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

# The RN-Densities as Martingales

Let  $M_t = \frac{dQ}{dP} \Big|_{\mathcal{F}_t}$  where  $Q \ll P$ .

Then for all  $t \geq 0$  :

$$1) E_P M_t = E_P \frac{dQ}{dP} \Big|_{\mathcal{F}_t} = E_Q 1 = 1$$

For  $s < t$  it holds:

$$2) E(M_t | \mathcal{F}_s) = M_s, \text{ the martingale property.}$$

Of course

$$3) M_t \text{ is nonnegative and } \mathcal{F}_t\text{-measurable.}$$

Conversely:

Given a stochastic process  $M_t$ ;  $t \geq 0$  with properties 1) – 3). It defines a measure  $Q$  by

$$Q_t(A) = \int_A M_t dP \quad \text{for } A \in \mathcal{F}_t.$$

# The Repeated Significance Test is a Bayes-Test

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

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

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

PNAS, 83 (1986)

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

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

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

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

Representation of the risk:

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

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

$g$  is convex with unique minimum  $x^*$

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

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: The Representation

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

$\pi_t$  is a diffusion with

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

where  $\overline{W}_t$  is a standard Brownian motion.

Ito's formula yields:

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

If  $G$  satisfies the equation

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

then

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

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

Then with  $g(x) = (1 - x) + cG(x)$  yields

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

$g$  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).

# Perpetual American Put Option

Samuelson(1965), McKean(1965)

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

Find a 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  $\alpha$  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

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

# One-Sided Boundaries

Let  $h$  be measurable,  $X_t = \sigma B_t + \mu t$  Brownian motion with drift  $\mu$  and variance  $\sigma^2$ . Find a stopping time  $T^*$  which maximizes

$$Ee^{-rT}h(X_T)1_{\{T<\infty\}}.$$

Let  $\alpha_{1,2} = -\frac{\mu}{\sigma^2} \pm \sqrt{\frac{\mu^2}{\sigma^4} + \frac{2r}{\sigma^2}}$ . Then  $M_t^{(i)} = e^{-rt}e^{\alpha_i X_t}$ ,  $i = 1, 2$  are positive martingales.

## Theorem 1:

If  $0 < C_1 = \sup_{x \in \mathbb{R}}(e^{-\alpha_1 x} h(x)) < \infty$  and  $C_1 = e^{-\alpha_1 x_1} h(x_1)$  for some  $x_1 > 0$ , then

$$\sup_T Ee^{-rT}h(x_T)1_{\{T<\infty\}} = C_1,$$

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

## Theorem 2:

If  $0 < C_2 = \sup_{x \in \mathbb{R}}(e^{-\alpha_2 x} h(x)) < \infty$  and  $C_2 = e^{-\alpha_2 x_2} h(x_2)$  for some  $x_2 > 0$ , then

$$\sup_T Ee^{-rT}h(x_T)1_{\{T<\infty\}} = C_2,$$

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

# Two-Sided Boundaries

Let  $h(x)$  be nonnegative and measurable with

$$\text{a) } \sup_{x \leq 0} (e^{-\alpha_1 x} h(x)) > \sup_{x \geq 0} (e^{-\alpha_1 x} h(x)) > 0 \text{ and}$$

$$\text{b) } \sup_{x \geq 0} (e^{-\alpha_2 x} h(x)) > \sup_{x \leq 0} (e^{-\alpha_2 x} h(x)) > 0.$$

Examples:

$$1.) \quad h(x) = x^2$$

$$2.) \quad h(x) = \max\{(L - e^x)^+, (e^{-x} - K)^+\}$$

Let  $p \in [0, 1]$ . Let  $M_t = pM_t^{(1)} + (1-p)M_t^{(2)}$ . Then

$$Ee^{-rT} h(X_t) = EM_T \frac{h(X_T)}{pe^{\alpha_1 X_T} + (1-p)e^{\alpha_2 X_T}}.$$

Lemma: If a) and b) holds, there exists a  $p^* \in (0, 1)$

with  $\sup_{x \geq 0} G_{p^*}(x) = \sup_{x \leq 0} G_{p^*}(x)$ , where

$$G_p(x) = \frac{h(x)}{pe^{\alpha_1 x} + (1-p)e^{\alpha_2 x}}.$$

Theorem 3:

Let  $C^* = \sup_{x \in \mathbb{R}} G_{p^*}(x)$ . If there exists points  $x_1 > 0$  and  $x_2 < 0$  with  $G_{p^*}(x_1) = C^* = G_{p^*}(x_2)$ , then

$$\sup_T Ee^{-rT} h(X_T) 1_{\{T < \infty\}} = C^*$$

and

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

# Stopping of Diffusions with Random Exponential Discounting

$B_t, t \geq 0$  SBM

$X_t$  diffusion with  $X_0 = x$  and

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

$h : \mathbb{R} \rightarrow \mathbb{R}_+$  a continuous function

Find a stopping time  $T^*$  of  $X$  with

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

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

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

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

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

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

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

for any  $p \in [0, 1]$  and  $0 \leq t < \infty$ .

$M_t$  is a positive local martingale and 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 a proper  $p$ .

## How to choose the martingales?

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

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

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

$$E_x(M_{T_b}^{(+)} \mathbf{1}_{\{T_b < \infty\}}) = \psi_+(x) \quad \text{for } b \geq x \text{ on } 0 \leq t \leq T_b$$

$$E_x(M_{T_a}^{(-)} \mathbf{1}_{\{T_a < \infty\}}) = \psi_-(x) \quad \text{for } x \geq a \text{ on } 0 \leq t \leq T_a.$$

### Note:

If  $A(t) = \int_0^t r(X_s) ds$  with  $r(x) \geq 0$ , then  $\psi_{\pm}(x)$  are the solutions of  $\mathcal{D}\psi = r \cdot \psi$  with appropriate boundary conditions.

$$\mathcal{D} = \mu(x) \frac{\partial}{\partial x} + \frac{1}{2} \sigma(x) \frac{\partial^2}{\partial x^2}.$$

# Distinguish the following Cases

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

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

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

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

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

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

and

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

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

In case 5) there exists a  $p^* \in (0, 1)$  such that

$$\sup_{x \geq x_0, x \in I} \frac{h(x)}{p^*\psi_+(x) + (1-p^*)\psi_-(x)} = \sup_{x \leq x_0, x \in I} \frac{h(x)}{p^*\psi_+(x) + (1-p^*)\psi_-(x)}.$$

## Case 3

Theorem “3”:

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

Then

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

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

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

This holds since

$$E_{x_0} e^{-A_{T^*}} h(X_{T^*}) = E_{x_0} \frac{h(X_{T^*})}{\psi_+(x)} M_{T^*} = C^*.$$



## Case 5

Theorem “5”:

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, Details

$X_1, X_2, \dots$  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  $S_\eta$ .

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

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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