

## GAME THEORETIC ANALYSIS FOR AN OPTIMAL STOPPING PROBLEM BY MEANS OF MOMENTS OF A DISTRIBUTION FUNCTION

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*Abstract* Let  $X_1, X_2, \dots, X_n, \dots$  be mutually independent random variables with a common cdf  $F$ , which is unknown but belongs to some class  $\mathcal{F}$  of cdf's. The class  $\mathcal{F} = \mathcal{F}(\mu, \sigma^2, M)$  is the set of all cdf's whose mean, variance and domain are  $-\infty < \mu < \infty, 0 < \sigma^2 < \infty$ , and  $[\mu - M, \mu + M]$  respectively. It is assumed that they are known. Under an observation cost  $c, 0 < c < \infty$ , we consider a stopping problem  $\phi(x, F)$  as a two-person zero-sum game in which the player 1 decides his stopping set  $\{X > x\}, x \in R$ , and the player 2 chooses her cdf  $F$  in  $\mathcal{F}$ . We analyze the upper bound problem  $\phi^u = \sup_{x \in R} \sup_{F \in \mathcal{F}} \phi(x, F)$  and the game problem  $\phi^s = \text{value}_{x \in R, F \in \mathcal{F}} \phi(x, F)$  to derive a simple and meaningful solution with the parameters  $c, \mu, \sigma$  and  $M$ .

### 1. Introduction

#### 1.1. Preliminaries

Let  $X_1, X_2, \dots, X_n, \dots$  be mutually independent and identically distributed random variables with a common cdf  $F(t) = P\{X \leq t\}$  such that  $E[X^+] = \int_{R_+} t dF(t) < \infty$ , where  $R = (-\infty, \infty), R_+ = [0, \infty)$ . A positive observation cost  $c (\in R_{++} = (0, \infty))$  is incurred to the observation of each  $X_n, n \geq 1$ . If the observation process is stopped after  $X_n$  is observed, a reward  $X_n - nc$  is received.

When the cdf  $F$  is known precisely, an optimal stopping problem is to find a stopping time  $N$  which maximizes the expected reward  $E[X_N - cN]$ . An integer valued random variable  $N$  is called a stopping time if, for each  $n$ , the event  $\{N = n\}$  is independent of  $X_{n+1}, X_{n+2}, \dots$ . This is a typical example of the stationary stopping problem (cf. Chow, Robbins and Siegmund [1, p.56]), in which the optimal stopping time  $N$  is necessarily of the form: to stop at  $N = \min\{n \mid X_n \in S\}$  for some stopping set  $S \subset R$ , and  $S$  is stationary and of a control-limit-type  $\{X \geq x\}$  or  $\{X > x\}$  for some  $x \in R$ , where  $x$  is called a stopping level. For this, we define that a stopping level  $x$  (or  $x - 0$ ) means a stopping set  $\{X > x\}$  (or  $\{X \geq x\}$ ) respectively.

For any stopping level  $x$  and for any cdf  $F$ , we define an expected reward  $\phi(x, F) = E[X_N - cN]$  of the stopping problem by

$$(1.1) \quad \phi(x, F) = \frac{\int_{(x, \infty)} t dF(t) - c}{\bar{F}(x)} = x + \frac{\int_{(x, \infty)} (t - x) dF(t) - c}{\bar{F}(x)},$$

where  $\bar{F}(x) = 1 - F(x)$ . Note that  $\bar{F}(x) \rightarrow 0$  and  $\phi \rightarrow -\infty$  as  $x \rightarrow \infty$  and that  $\bar{F}(x) \rightarrow 1$  and  $\phi \rightarrow \mu_F - c$  as  $x \rightarrow -\infty$  where  $\mu_F = E[X] = \int_R t dF(t)$ . It means that to continue the observation process indefinitely gives us the reward  $-\infty$  and to stop the process immediately gives us the reward  $\mu_F - c$ .

By the assumption  $E[X^+] < \infty$ , using integration by parts, we have

$$\int_{(x,\infty)} (t-x)dF(t) = -\int_{(x,\infty)} (t-x)d\bar{F}(t) = \int_x^\infty \bar{F}(t)dt = \int_{[x,\infty)} (t-x)dF(t),$$

which is continuous in  $x$ . To handle this expectation, it is convenient to define  $T_F(x)$ ,

$$(1.2) \quad T_F(x) = \int_x^\infty (t-x)dF(t) = \int_x^\infty \bar{F}(t)dt.$$

It has some useful properties, which can be obtained by the elementary analytical technique. Then we give Lemma 1 without proof.

**Lemma 1.**  $T_F(x)$  is continuous, non-negative, convex and non-increasing function of  $x$ . It satisfies that  $T_F(x) \geq (\mu_F - x)^+$  for any  $x \in R$  and that  $T_F(x) \rightarrow +\infty$  as  $x \rightarrow -\infty$  and  $T_F(x) \rightarrow 0$  as  $x \rightarrow +\infty$ .  $T_F$  has a derivative a.e.. Moreover, if  $T_F(x)$  is positive at any point  $x$ , it is strictly decreasing at  $x$ .

Now, redefining the expected reward  $\phi(x, F)$  by (1.1') for any stopping level  $x$  and for any cdf  $F$ , we will have the optimal expected reward  $\phi^\circ(F)$  for any cdf  $F$ :

$$(1.1') \quad \phi(x, F) = x + \frac{T_F(x) - c}{\bar{F}(x)}.$$

$$(1.3) \quad \phi^\circ(F) \stackrel{\text{def}}{=} \sup_{x \in R} \phi(x, F).$$

$$(1.4) \quad \frac{d\phi(x, F)}{dF(x)} = \frac{T_F(x) - c}{\bar{F}^2(x)}.$$

The right hand side of (1.4) changes the sign from + to - at most one time as  $x$  goes from  $-\infty$  to  $+\infty$ . From Lemma 1, the equation  $T_F(x) = c$  for any fixed  $c (c > 0)$  has a unique solution  $x^\circ(F) \stackrel{\text{def}}{=} (T_F)^{-1}(c)$ , so that the set of optimal stopping levels  $\mathbf{x}^\circ(F)$  (which must contain the point  $x^\circ(F)$ ) of (1.3) is given by

$$(1.5) \quad \mathbf{x}^\circ(F) = \{x \mid F(x) = F(x^\circ(F))\}.$$

Since the cdf  $F$  is right-continuous, this set is an interval of the form  $[a, b)$ . If the cdf  $F$  has a positive density in the neighborhood of  $x^\circ(F)$ , the set  $\mathbf{x}^\circ(F)$  contains only one point  $x^\circ(F)$  i.e.,  $\mathbf{x}^\circ(F) = \{x^\circ(F)\}$ .

We have the optimal expected reward  $\phi^\circ(F)$ ,

$$(1.3') \quad \phi^\circ(F) = x^\circ(F) = \phi(\mathbf{x}^\circ(F), F),$$

where  $\phi(A, F)$  means  $\phi(x, F)$  for any  $x$  in a set  $A$ .

Let  $a = \min\{x \mid x \in \mathbf{x}^\circ(F)\}$  and  $b = \sup\{x \mid x \in \mathbf{x}^\circ(F)\}$ , then the set  $\mathbf{x}^\circ(F)$  of (1.5) is represented as the interval  $[a, b)$ . Since  $F$  has no probability mass in  $(a, b)$

$$\bar{F}(a) = P\{X > a\} = P\{X \geq b\} = \bar{F}(b-0) \stackrel{\text{def}}{=} \lim_{x \uparrow b} \bar{F}(x), \quad \int_{(a,\infty)} tdF(t) = \int_{[b,\infty)} tdF(t),$$

and by (1.1) it holds that,

$$(1.3'') \quad x^\circ(F) = \phi(a, F) = \lim_{x \uparrow b} \phi(x, F) \stackrel{\text{def}}{=} \phi(b - 0, F) .$$

Then, we have Lemma 2.

**Lemma 2.** For any given cdf  $F$ , the following stopping sets or stopping levels (i)(ii)(iii) are optimal, and the optimal expected reward is given by (1.3'');

- (i) the set  $\{X > a\}$  or level  $a$  where  $a = \min\{x \mid x \in x^\circ(F)\}$ ,
- (ii) the set  $\{X \geq b\}$  or level  $b - 0$  where  $b = \sup\{x \mid x \in x^\circ(F)\}$ ,
- (iii) the set  $\{X > x\}$  ( $\{X \geq x\}$ ) or level  $x$  ( $x - 0$ ) where  $\forall x \in (a, b)$ .

## 1.2. Statement of the Problem

The underlying premise is that some information is available about certain moments of an unknown cdf  $F$ . This determines some class  $\mathcal{F}$  of cdf's. This limited information is to be used in order to obtain an upper (or/and lower) bound for our stopping problem  $\phi(x, F)$  of (1.1'). In this paper, we consider the classes  $\mathcal{F}$  of all cdf's  $F$  which are unknown except for their first two moments and domain.

First, we shall consider the maximal bound  $\phi^u$  for  $\phi(x, F)$  on  $R \times \mathcal{F}$

$$(1.6) \quad \phi^u = \sup_{x \in R} \sup_{F \in \mathcal{F}} \phi(x, F) = \sup_{F \in \mathcal{F}} \phi^\circ(F) = \phi(x^\circ(F^u), F^u) = \phi(x^u, F^u) ,$$

where  $(x^u, F^u)$  is a joint maximizing point of  $\phi(x, F)$ .

Second, we shall consider  $\phi(x, F)$  as a two-person zero-sum game in which the player 1 (gambler) decides his level  $x$  in  $R$  and the player 2 (nature) chooses her cdf  $F$  in  $\mathcal{F}$ , before the observation of  $\{X_n; n \geq 1\}$ . Then the minimax value  $\phi^*$  and the maximin value  $\phi_*$  on  $R \times \mathcal{F}$ ,

$$(1.7) \quad \phi^* = \inf_{F \in \mathcal{F}} \sup_{x \in R} \phi(x, F) = \inf_{F \in \mathcal{F}} \phi^\circ(F) = \phi(x^\circ(F^*), F^*) = \phi(x^*, F^*) ,$$

$$(1.8) \quad \phi_* = \sup_{x \in R} \inf_{F \in \mathcal{F}} \phi(x, F) = \phi(x_*, F_*) ,$$

and the saddle value  $\phi^s$ , the saddle point  $(x^s, F^s)$  in  $R \times \mathcal{F}$ ,

$$(1.9) \quad \phi^s = \text{value}_{x \in R, F \in \mathcal{F}} \phi(x, F) = \phi(x^s, F^s) ,$$

will be derived for the following two classes  $\mathcal{F}(\mu, \sigma^2)$  and  $\mathcal{F}(\mu, \sigma^2, M)$  of cdf's.

The class  $\mathcal{F}(\mu, \sigma^2, M)$  is the set of cdf's whose mean  $\mu$ , variance  $\sigma^2$  and domain  $[\mu - M, \mu + M]$  are assumed to be known.

$$(1.10) \quad \mathcal{F}(\mu, \sigma^2, M) = \{F \mid \int_A dF(t) = 1, \int_A t dF(t) = \mu, \\ \int_A t^2 dF(t) = \mu^2 + \sigma^2 \text{ where } A =: [\mu - M, \mu + M], M \geq \sigma\}$$

The class  $\mathcal{F}(\mu, \sigma^2)$  is  $\mathcal{F}(\mu, \sigma^2, M)$  where  $M$  is arbitrary in  $[\sigma, \infty)$ , and  $\mathcal{F}(\mu)$  is  $\mathcal{F}(\mu, \sigma^2)$  where  $\sigma^2$  is arbitrary in  $R_{++}$ .

The organization of this paper is as follows. In Section 2, we study some basic results for our stopping problem  $\phi(x, F)$  and  $T_F(x)$  and properties of cdf's  $F$  in the class  $\mathcal{F}$ , which play fundamental roles in all that follows. Section 3 is a discussion about the existence and the

derivation of the maximizing point and the saddle point for  $\phi(x, F)$  in the class  $\mathcal{F} = \mathcal{F}(\mu, \sigma^2)$ . In fact, the class  $\mathcal{F}$  is so rich for the player 2 that the player 1 must stop immediately and may receive the reward of  $\mu - c$  as the saddle value. In this case, the information of the value  $\sigma^2$  is useless for the player 1.

To remove the non-interesting feature appearing in the game theoretic treatment in Section 3, we shall continue the discussion about the more interesting class  $\mathcal{F} = \mathcal{F}(\mu, \sigma^2, M)$  in Section 4. In this case, the information of the value  $\sigma^2$  and  $M$  is useful for the player 1. The player 1 can receive the reward of  $\mu + (\sigma^2/M - c)^+ - c$  as the saddle value which is greater than  $\mu - c$  in Section 3.

## 2. Some Fundamental Lemmas

The general theory of a duality theorem is presented in the textbook by Ekeland and Teman [2, Chapter 4]. It is hardly difficult to obtain the condition of the existence of a saddle point for our stopping problem  $\phi(x, F)$ . For an inventory problem where this condition is satisfied, we have derived a saddle point [4]. The following two propositions are used to check a candidate for a saddle point of  $\phi(x, F)$  on  $R \times \mathcal{F}$ .

**Proposition 1.** [2, p.166] *If  $\phi$  is a function defined on  $R \times \mathcal{F}$  with real values, then*

$$(2.1) \quad \phi_* = \sup_{x \in R} \inf_{F \in \mathcal{F}} \phi(x, F) \leq \phi^* = \inf_{F \in \mathcal{F}} \sup_{x \in R} \phi(x, F).$$

**Proposition 2.** [2, p.168] *If there exist  $x^s \in R, F^s \in \mathcal{F}$  and a real value  $\phi^s$  such that*

$$(2.2) \quad \begin{aligned} \phi(x^s, F) &\geq \phi^s \text{ for any } F \in \mathcal{F}, \\ \phi(x, F^s) &\leq \phi^s \text{ for any } x \in R, \end{aligned}$$

*then  $(x^s, F^s)$  is a saddle point of  $\phi$  and it holds that*

$$(2.3) \quad \phi^s = \text{value}_{x \in R, F \in \mathcal{F}} \phi(x, F) = \sup_{x \in R} \inf_{F \in \mathcal{F}} \phi(x, F) = \inf_{F \in \mathcal{F}} \sup_{x \in R} \phi(x, F).$$

*Moreover, the set of saddle points of  $\phi$  is of the form  $(\mathbf{x}^s, \mathcal{F}^s)$ , where  $\mathbf{x}^s \subset R$  and  $\mathcal{F}^s \subset \mathcal{F}$ .*

Before beginning our discussion, we shall establish some basic results for  $\phi(x, F), T_F(x)$  and the class  $\mathcal{F}$ .

Let a random variable  $X$  has a mean  $\mu$  with a cdf  $F_\mu(t)$ , then the new random variable  $X - \mu$  has the mean 0 with the cdf  $F_0(t) = F_\mu(t + \mu)$ . The following Lemma 3 follows immediately from the definition (1.1) of  $\phi(x, F)$ .

**Lemma 3.**

$$(2.4) \quad \phi(x, F_\mu) = \mu + \phi(x - \mu, F_0) \text{ for any } x \in R.$$

Therefore, we may assume without loss of generality that all the cdf's in  $F$  have the mean 0. So that, we shall analyze the stopping problem in only two classes  $\mathcal{F}(0, \sigma^2)$  and  $\mathcal{F}(0, \sigma^2, M)$ .

**Lemma 4.** *For cdf's  $F_i$  and non-negative numbers  $\lambda_i, i = 1, 2, \dots, n$ , such that  $\sum_{i=1}^n \lambda_i = 1$ , let  $F = \sum_{i=1}^n \lambda_i F_i$ . Then*

$$(2.5) \quad \phi(x, F) = \sum_{j=1}^n \lambda_j \phi(x, F_j) \text{ for any } x \in R, \text{ where } \lambda_j(x) = \frac{\lambda_j \bar{F}_j(x)}{\sum_{i=1}^n \lambda_i \bar{F}_i(x)}.$$

**Proof.** It follows at once from the definition (1.1) of  $\phi$ .  $\square$

Note, from Lemma 4, that we find  $\phi(x, F)$  is not necessarily convex in  $F$  for any fixed  $x \in R$ , and that the well-known sufficient condition for the existence of a saddle point is not satisfied.

Let  $G_n$  be a discrete cdf which has  $n$  probability masses  $p_i$ ,  $p_i > 0$ , at  $n$  points  $t_i$ ,  $i = 1, 2, \dots, n$ , respectively ( $\sum_{i=1}^n p_i = 1$ ), i.e., it is represented as

$$(2.6) \quad G_n(t) = \langle t_1, \dots, t_n \rangle \langle p_1, \dots, p_n \rangle ,$$

and  $\mathcal{G}_n(\mu, \sigma^2)$  be all discrete cdf's  $G_n$  in  $\mathcal{F}(\mu, \sigma^2)$ . Let

$$(2.7) \quad G_2(t; q) = \langle -\frac{\sigma}{q}, \sigma q \rangle \langle \frac{q^2}{1+q^2}, \frac{1}{1+q^2} \rangle$$

for any  $q, 0 < q < \infty$ . Then  $G_2(t; q)$  is the only two-point cdf which has the mean 0 and the variance  $\sigma^2$ .

**Lemma 5.** *The class  $\mathcal{G}_2(0, \sigma^2)$  of two-point cdf's is represented with a parameter  $q, 0 < q < \infty$ , as follows,*

$$\mathcal{G}_2(0, \sigma^2) = \{G_2(\cdot; q) \mid 0 < q < \infty\} .$$

Let us define

$$(2.8) \quad T_{\mathcal{F}}^u(x) = \sup_{F \in \mathcal{F}} T_F(x) , \quad T_{\mathcal{F}}^l(x) = \inf_{F \in \mathcal{F}} T_F(x) .$$

Then, from Lemma 1, we have the following lemma.

**Lemma 6.** *Suppose  $\mathcal{F} = \mathcal{F}(0)$  so that  $\mu_F = 0$  for all  $F \in \mathcal{F}$ , then  $T_{\mathcal{F}}^u(x)$  and  $T_{\mathcal{F}}^l(x)$  have the same property as  $T_F(x)$  in Lemma 1 with  $\mu_F$  replaced by 0, except that  $T_{\mathcal{F}}^l(x)$  is not always convex.*

From above Lemma 6,  $T_{\mathcal{F}}^u(x)$  and  $T_{\mathcal{F}}^l(x)$  have inverse functions  $(T_{\mathcal{F}}^u)^{-1}(c)$  and  $(T_{\mathcal{F}}^l)^{-1}(c)$  for all  $c, c > 0$ , respectively. Thus we have shown the existence of the values of  $\phi^u$  and  $\phi^*$ :

$$(2.9) \quad \phi^u = \sup_{F \in \mathcal{F}} \{x \mid T_F(x) = c\} = (T_{\mathcal{F}}^u)^{-1}(c) ,$$

$$(2.10) \quad \phi^* = \inf_{F \in \mathcal{F}} \{x \mid T_F(x) = c\} = (T_{\mathcal{F}}^l)^{-1}(c) .$$

### 3. The Class $\mathcal{F}(\mu, \sigma^2)$

In this section, we shall derive the maximal bound  $\phi^u$  and the saddle value  $\phi^s$  for  $\phi(x, F)$  in the class  $\mathcal{F} = \mathcal{F}(0, \sigma^2)$ .

$$(3.1) \quad \mathcal{F}(0, \sigma^2) = \{F \mid \int_R dF(t) = 1, \int_R t dF(t) = 0, \int_R t^2 dF(t) = \sigma^2\} .$$

#### 3.1 The maximal bound $\phi^u$

First, we prepare a useful proposition related to Schwartz inequalities.

**Proposition 3.** (Feller [3, p.151]) *If  $F$  is an arbitrary cdf, then*

$$(3.2) \quad \left( \int_A u(t)v(t)dF(t) \right)^2 \leq \left( \int_A u^2(t)dF(t) \right) \left( \int_A v^2(t)dF(t) \right)$$

for any set  $A$  and any functions  $u, v$  for which the integrals on the right exist. Furthermore, the equality sign holds if and only if

$$(3.3) \quad \int_A (au(t) + bv(t))^2 dF(t) = 0 \text{ for some } a, b \in R .$$

**Remark on Proposition 3.** If  $u$  and  $v$  are linearly dependent, i.e., for some  $a, b \in R$ ,  $au(t) + bv(t) = 0$ , the condition (3.3) is satisfied for all  $F \in \mathcal{F}$ , and that if  $u$  and  $v$  are linearly independent, the condition (3.3) is satisfied only when the cdf  $F$  is degenerated at one point in a set  $A$ .

We shall calculate  $\phi^u$  and the maximizing point  $(x^u, F^u)$  of the problem (2.9) by Proposition 3.

$$(3.4) \quad \left( \int_{(x, \infty)} (t-x)dF(t) \right)^2 \leq \left( \int_{(x, \infty)} dF(t) \right) \left( \int_{(x, \infty)} (t-x)^2 dF(t) \right),$$

$$(3.4') \quad \left( \int_{(-\infty, x]} (t-x)dF(t) \right)^2 \leq \left( \int_{(-\infty, x]} dF(t) \right) \left( \int_{(-\infty, x]} (t-x)^2 dF(t) \right).$$

For all  $F \in \mathcal{F}$ ,  $T_F(x) = \int_{(x, \infty)} (t-x)dF(t) = c$  from (2.9) and  $\int_R dF(t) = 1$ ,  $\int_R tdF(t) = 0$ ,  $\int_R t^2 dF(t) = \sigma^2$  from (3.1). Then, putting  $p = \int_{(x, \infty)} dF(t)$ , it holds that by adding (3.4) to (3.4'),

$$\frac{c^2}{p} + \frac{(x+c)^2}{1-p} \leq \sigma^2 + x^2, \quad 0 < p < 1,$$

$$(3.5) \quad -\frac{c}{p} - \sigma \sqrt{\frac{1-p}{p}} \leq x \leq -\frac{c}{p} + \sigma \sqrt{\frac{1-p}{p}}, \quad 0 < p < 1.$$

Putting  $q = \sqrt{(1-p)/p}$ ,  $0 < q < \infty$ , the upper bound of  $x$  (the right-hand side of (3.5)) is represented by the parameter  $q$ .

$$(3.6) \quad \sup_{0 < p < 1} \left( \sigma \sqrt{\frac{1-p}{p}} - \frac{c}{p} \right) = \sup_{0 < q < \infty} (\sigma q - c(1+q^2)) = \sup_{0 < q < \infty} \left[ -c \left( q - \frac{\sigma}{2c} \right)^2 + \frac{\sigma^2}{4c} - c \right] = \frac{\sigma^2}{4c} - c,$$

where the supremum is attained at  $q = \sigma/2c$  i.e.,  $p = 4c^2/(\sigma^2 + 4c^2)$ .

Then, we obtain the maximal bound  $\phi^u$ .

$$(3.7) \quad \phi^u = \sup_{F \in \mathcal{F}} \{x \mid T_F(x) = c\} = \frac{\sigma^2}{4c} - c.$$

Since the equality holds in two Schwartz inequalities (3.4) and (3.4'), from the remark of Proposition 3, the maximizing cdf  $F^u$  should be the two-point cdf. Then, we have

$$(3.8) \quad F^u(t) = G_2\left(t; \frac{\sigma}{2c}\right) = \left( < -2c, \frac{\sigma^2}{2c} > < \frac{\sigma^2}{\sigma^2 + 4c^2}, \frac{4c^2}{\sigma^2 + 4c^2} > \right),$$

$$(3.9) \quad x^u \in \mathbf{x}^u = \mathbf{x}^o(F^u) = \left[-2c, \frac{\sigma^2}{2c}\right].$$

**Theorem 1.** For a class  $\mathcal{F}(0, \sigma^2)$  of cdf's, the maximal bound  $\phi^u$  is  $\sigma^2/4c - c$  by (3.7) and all the maximizing points  $(x^u, F^u) \in (\mathbf{x}^u, \{F^u\})$  are given by  $F^u(t) = G_2(t; \sigma/2c)$  in (3.8) and  $\mathbf{x}^u = [-2c, \sigma^2/2c]$  in (3.9).

**Remark on Theorem 1.** From Lemma 2, the equation (3.9) means that the player 1 may decide a stopping level  $x^u$  for some  $x^u \in [-2c, \sigma^2/2c)$  or  $\sigma^2/2c - 0$ . If the player 1 decides any of the above stopping levels, he stops the process whenever  $X_n = \sigma^2/2c$  is observed because the player 2 chooses only one cdf given by (3.8).

**Corollary 1.** For a class  $\mathcal{F}(\mu, \sigma^2)$  of cdf's, the maximal bound  $\phi^u$  is  $\mu + \sigma^2/4c - c$  and all the maximizing points  $(x^u, F^u) \in (\mathbf{x}^u, \{F^u\})$  are given by  $F^u(t - \mu) = G_2(t; \sigma/2c)$  and  $\mathbf{x}^u = [\mu - 2c, \mu + \sigma^2/2c]$ .

In the theory of extreme order statistics, by letting  $Y = \max_{1 \leq n \leq \infty} [X_n - cn]$ , it holds that  $E[Y^+] < \infty$  if and only if  $E[X^+] < \infty$  (See Pickands III [5, Cor. 2.2]). Corollary 1 also says that the maximal bound of  $E[Y^+]$  is calculated by using  $\mu$  and  $\sigma^2$  if the cdf  $F$  is restricted in the class  $\mathcal{F}(\mu, \sigma^2)$ .

### 3.2 The minimax value $\phi^*$

Second, we shall calculate the minimax value  $\phi^*$  of (2.10) and the minimax-mizing point  $(x^*, F^*) \in (\mathbf{x}^*, \mathcal{F}^*)$ .

From Lemma 6,  $T_{\mathcal{F}}^{\ell}(x) \geq (-x)^+$  for all  $x \in R$ . Then it holds that  $T_{F^*}(x) = (-x)^+ \leq T_{\mathcal{F}}^{\ell}(x)$  for  $x \in (-\infty, -c]$  if a cdf  $F^*$ , which has all the mass on  $[-c, \infty)$ , is contained in  $\mathcal{F}$ . Since  $T_{F^*}(x) = (-x)^+$  is strictly decreasing on  $(-\infty, -c]$ , we have

$$(3.10) \quad \phi^* = \inf_{F \in \mathcal{F}} \{x \mid T_F(x) = c\} = \{x \mid T_{F^*}(x) = c\} = -c.$$

Such a class  $\mathcal{F}^*$  of cdf's  $F^*$  always exists in  $\mathcal{F}$  for all  $c, c > 0$ .

$$(3.11) \quad \mathcal{F}^* = \left\{F \mid \int_{[-c, \infty)} dF(t) = 1, F \in \mathcal{F}\right\}.$$

In particular, we can find the class  $\mathcal{G}_2^* = \mathcal{G}_2^*(0, \sigma^2)$  of two-point cdf's in  $\mathcal{F}^*$  from Lemma 5.

$$(3.11') \quad \mathcal{G}_2^* = \left\{G_2(\cdot; q) \mid q \geq \frac{\sigma}{c}\right\}.$$

It is easily shown that for any  $F^* \in \mathcal{F}^*$  it is optimal for the player 1 to stop the process immediately. That is,

$$(3.12) \quad \mathbf{x}^* = \mathbf{x}^o(F^*) = (-\infty, -c) \text{ for all } F^* \in \mathcal{F}^*.$$

**Theorem 2.** For a class  $\mathcal{F}(0, \sigma^2)$  of cdf's, the minimax value  $\phi^*$  is  $-c$  by (3.10) and all the minimax-mizing points  $(x^*, F^*) \in (\mathbf{x}^*, \mathcal{F}^*)$  are given by (3.11) and (3.12). In particular, there exists the class  $\mathcal{G}_2^*$  of two-point cdf's in  $\mathcal{F}^*$  by (3.11').

**Corollary 2.** For a class  $\mathcal{F}(\mu, \sigma^2)$  of cdf's, the minimax value  $\phi^*$  is  $\mu - c$ , and all the minimax-mizing points  $(x^*, F^*) \in (\mathbf{x}^*, \mathcal{F}^*)$  are given by

$$\mathcal{F}^* = \left\{F \mid \int_{[\mu-c, \infty)} dF(t) = 1, F \in \mathcal{F}(\mu, \sigma^2)\right\}, \mathbf{x}^* = (-\infty, \mu - c).$$

### 3.3 The saddle value $\phi^s$

Now, we shall derive the saddle value  $\phi^s$  for  $\phi(x, F)$  in  $\mathcal{F} = \mathcal{F}(\mu, \sigma^2)$ . We have a candidate  $(\mathbf{x}^*, \mathcal{F}^*)$  for a set of saddle points  $(\mathbf{x}^s, \mathcal{F}^s)$  to be checked by Proposition 2. Since  $(\mathbf{x}^*, \mathcal{F}^*)$  includes  $(\mathbf{x}^s, \mathcal{F}^s)$  in general, we shall make an attempt to prove the inverse. From Theorem 2 it holds that  $\phi(x, F) = -c$  for all  $x \in \mathbf{x}^*$  and all  $F \in \mathcal{F}^*$ . Moreover, from (3.12), it holds that for any fixed  $x \notin \mathbf{x}^*$ ,  $\phi(x, F) \leq -c$  for all  $F \in \mathcal{F}^*$ . It suffices to prove for any fixed  $F \in \mathcal{F}$ ,

$$(3.13) \quad \phi(x, F) \geq -c \text{ for all } x \in \mathbf{x}^* .$$

**Proof of (3.13).** For any fixed  $F$ , it holds that  $\phi(-\infty, F) = -c$  and  $\phi(x, F)$  is a unimodal function of  $x$  and maximized at the point  $x^o(F)$  from the remark of (1.1). When (i)  $x^o(F) \geq -c$ ,  $\phi(x, F) \geq -c$  for  $x \in (-\infty, -c]$ , i.e. (3.13) is true in the case (i). When (ii)  $x^o(F) \leq -c$ ,  $\phi(x, F) \geq \phi(-c, F)$  for  $x \in [x^o(F), -c]$ , so that (3.13) is true in the case (ii) if we can prove  $\phi(-c, F) \geq -c$ .

For  $F \in \mathcal{F}$ ,  $F$  has the mean 0, so that  $\bar{F}(-c) > 0$  and

$$\int_{(-c, \infty)} t dF(t) = - \int_{(-\infty, -c]} t dF(t) \geq c(1 - \bar{F}(-c)) .$$

Thus, we have from (1.1),

$$(3.14) \quad \phi(-c, F) = \frac{\int_{(-c, \infty)} t dF(t) - c}{\bar{F}(-c)} \geq \frac{c(1 - \bar{F}(-c)) - c}{\bar{F}(-c)} = -c .$$

This completes the proof.  $\square$

Hence, we have the main theorem in this chapter.

**Theorem 3.** For a class  $\mathcal{F}(0, \sigma^2)$  of cdf's, the saddle value  $\phi^s$  is  $-c$  and all the saddle points  $(x^s, F^s) \in (\mathbf{x}^s, \mathcal{F}^s)$  are given by  $\mathbf{x}^s = \mathbf{x}^*$ ,  $\mathcal{F}^s = \mathcal{F}^*$  and  $\mathcal{G}_2^s = \mathcal{G}_2^* \subset \mathcal{F}^s$  defined in Theorem 2.

**Corollary 3.** For a class  $\mathcal{F}(\mu, \sigma^2)$  of cdf's, the saddle value  $\phi^s$  is  $\mu - c$  and all the saddle points  $(x^s, F^s) \in (\mathbf{x}^s, \mathcal{F}^s)$  are given by  $\mathbf{x}^s = \mathbf{x}^*$ ,  $\mathcal{F}^s = \mathcal{F}^*$  defined in Corollary 2.

Theorem 3 says the class  $\mathcal{F}(\mu, \sigma^2)$  is so rich for the player 2 that the player 1 must stop immediately. In this case, the information of the value  $\sigma^2$  is useless for the player 1.

If we consider the problem in the class

$$(3.15) \quad \mathcal{F}(\mu, \cdot, M) = \{F \mid \int_A dF(t) = 1, \int_A t dF(t) = \mu, A = [\mu - M, \mu + M]\} ,$$

the player 2 may choose the cdf which is degenerated at the point  $\mu$  and the player 1 receives the reward of  $\mu - c$ , in which the information of the value  $M$  is useless for the player 1.

To remove the non-interesting strategies for the player 1 in the above two cases  $\mathcal{F}(\mu, \sigma^2)$  and  $\mathcal{F}(\mu, \cdot, M)$ , we shall analyze the problem in the more restrictive class  $\mathcal{F}(\mu, \sigma^2, M)$  of (1.10) in the next section.

## 4. The Class $\mathcal{F}(\mu, \sigma^2, M)$

In this section, we shall derive the maximal bound  $\phi^u$  and the saddle value  $\phi^s$  in the more restrictive and interesting class  $\mathcal{F} = \mathcal{F}(0, \sigma^2, M)$  (see (1.10)).

$$\mathcal{F}(0, \sigma^2, M) = \{F \mid \int_A dF(t) = 1, \int_A t dF(t) = 0, \int_A t^2 dF(t) = \sigma^2, A = [-M, M], \sigma \leq M\} .$$



If  $\sigma = M > 0$ , the class  $\mathcal{F}$  contains only one cdf  $G_2(t; 1) = (< -M, M > < 1/2, 1/2 >)$ . So, it is assumed that  $\sigma < M$ .

We calculate  $\phi^u$  and the maximizing point  $(x^u, F^u)$  in the same fashion as (3.6) with the additional constraint  $\sigma/M \leq q \leq M/\sigma$ ,

$$(4.1) \quad \phi^u = \max_{\sigma/M \leq q \leq M/\sigma} [\sigma q - c(1 + q^2)] .$$

**Theorem 4.** For a class  $\mathcal{F}(0, \sigma^2, M)$  of cdf's,  $\sigma < M$ , the maximal bound  $\phi^u$  and all the maximizing points  $(x^u, F^u) \in (\mathbf{x}^u, \mathcal{F}^u)$  are as follows:

(i) When  $0 \leq c \leq \sigma^2/2M$ ,

$$\begin{aligned} \phi^u &= M - c(1 + \frac{M^2}{\sigma^2}) , \quad \mathbf{x}^u = [-\frac{\sigma^2}{M}, M) , \\ F^u(t) &= G_2(t; \frac{M}{\sigma}) = (< -\frac{\sigma^2}{M}, M > < \frac{M^2}{\sigma^2 + M^2}, \frac{\sigma^2}{\sigma^2 + M^2} > ) . \end{aligned}$$

(ii) When  $\sigma^2/2M \leq c \leq M/2$ , the same result as Theorem 1 holds, i.e.,

$$\begin{aligned} \phi^u &= \frac{\sigma^2}{4c} - c , \quad \mathbf{x}^u = [-2c, \frac{\sigma^2}{2c}) , \\ F^u(t) &= G_2(t; \frac{\sigma}{2c}) = (< -2c, \frac{\sigma^2}{2c} > < \frac{\sigma^2}{\sigma^2 + 4c^2}, \frac{4c^2}{\sigma^2 + 4c^2} > ) . \end{aligned}$$

(iii) When  $M/2 \leq c \leq M$ ,

$$\begin{aligned} \phi^u &= \frac{\sigma^2}{M} - c(1 + \frac{\sigma^2}{M^2}) , \quad \mathbf{x}^u = [-M, \frac{\sigma^2}{M}) , \\ F^u(t) &= G_2(t; \frac{\sigma}{M}) = (< -M, \frac{\sigma^2}{M} > < \frac{\sigma^2}{\sigma^2 + M^2}, \frac{M^2}{\sigma^2 + M^2} > ) . \end{aligned}$$

**Remark on Theorem 4.** When  $c > M$ , i.e. the observation cost is larger than the maximal value of the observation, it is natural for the player 1 to stop immediately, i.e.,  $\phi^u = -c$ ,  $\mathcal{F}^u = \mathcal{F}$  and  $\mathbf{x}^u = (-\infty, -M)$ . The shape of  $\phi^u$  as the function of  $c$  is illustrated in Figure 1 at the end of this paper. Furthermore, if the results for the class  $\mathcal{F}(\mu, \sigma^2, M)$  are required, Lemma 2 is useful for the theorems in this section.

Now, we shall derive the saddle value  $\phi^s$ . By calculating  $T_{\mathcal{F}}(x)$  of (1.2) for the cdf's  $G_2(\cdot; M/\sigma)$  and  $G_2(\cdot; \sigma/M)$ , we have, from (2.8) and Lemma 6,

$$(4.2) \quad T_{\mathcal{F}}^{\ell}(x) \geq (-x)^+ = -x = T_{G_2(\cdot; M/\sigma)}(x) \text{ for } x \in [-M, -\sigma^2/M] ,$$

$$(4.3) \quad T_{\mathcal{F}}^{\ell}(x) \geq (-x)^+ = 0 = T_{G_2(\cdot; \sigma/M)}(x) \text{ for } x \in [\sigma^2/M, M] .$$

If the observation cost  $c$  is a constant such that  $M \geq c \geq \sigma^2/M$ , the equality  $\phi^* = (T_{\mathcal{F}}^{\ell})^{-1}(c) = -c$  is satisfied from (4.2). In this case, the saddle value  $\phi^s$  and the saddle point  $(x^s, F^s)$  are the same ones given in Theorem 3, because the player 2 can choose a cdf  $G_2(\cdot, M/\sigma)$  in this restrictive class  $\mathcal{F} = \mathcal{F}(0, \sigma^2, M)$ , i.e.,  $G_2(\cdot; M/\sigma) \in \mathcal{F}(0, \sigma^2, M) \subset \mathcal{F}(0, \sigma^2)$ . So that we confine our consideration to the case:

$$(4.4) \quad 0 < c < \sigma^2/M .$$

On the other hand, from (4.2) and (4.3), it holds that

$$(4.2') \quad \inf_{F \in \mathcal{F}} \phi(x, F) \leq \phi(x, G_2(\cdot; M/\sigma)) = -c \text{ for } x \in [-M, -\sigma^2/M],$$

$$(4.3') \quad \inf_{F \in \mathcal{F}} \phi(x, F) \leq \phi(x, G_2(\cdot; \sigma/M)) = -\infty \text{ for } x \in [\sigma^2/M, M],$$

because the player 1 stops immediately in the case of (4.2') or he cannot stop in the case of (4.3'). Then, the player 1 must decide his stopping level  $x$  in the interval

$$(4.5) \quad \mathbf{x}^M \stackrel{\text{def}}{=} \left[-\frac{\sigma^2}{M}, \frac{\sigma^2}{M}\right],$$

in order not to make his reward  $\inf_{F \in \mathcal{F}} \phi(x, F) \leq -c$ , where  $-c$  is the reward of immediately stopping or the saddle value  $\phi^s = -c$  in Section 3.

Hereafter, we consider the stopping problem  $\phi(x, F)$  under the restriction of (4.4) and (4.5). To begin with, we prepare the following three lemmas.

**Lemma 7.** *If  $F$  is an arbitrary cdf defined on a finite interval  $[a, b]$  with the mean  $\mu$  ( $a \leq \mu \leq b$ ,  $a < b$ ), then*

$$\int_{[a,b]} (t - \mu)^2 dF(t) \leq (\mu - a)(b - a).$$

Furthermore, the equality holds if and only if

$$(4.6) \quad F = \left(\langle a, b \rangle \langle \frac{b - \mu}{b - a}, \frac{\mu - a}{b - a} \rangle\right).$$

**Proof.** Since  $f(t) = (t - \mu)^2$  is strictly convex, we have

$$\int_{[a,b]} (t - \mu)^2 dF(t) \leq (a - \mu)^2 \int_{[a,\mu]} dF(t) + (b - \mu)^2 \int_{(\mu,b]} dF(t).$$

The equality holds iff  $F$  satisfies  $\int_{[a,\mu]} dF(t) = \int_{\{a\}} dF(t)$  and  $\int_{(\mu,b]} dF(t) = \int_{\{b\}} dF(t)$ . Such a cdf is uniquely determined by (4.6). This completes the proof.  $\square$

**Lemma 8.** *For any strategy  $(x, F) \in (\mathbf{x}^M, \mathcal{F})$ , if  $F$  has a positive probability on the interval  $(x, M)$  and satisfies  $\phi(x, F) \geq -c$ , then there exists a cdf  $F'' \in \mathcal{F}$  such that  $F''$  has no probability on the interval  $(x + \varepsilon, M)$  for an arbitrary small  $\varepsilon > 0$ , and it satisfies  $\phi(x, F'') \leq \phi(x, F)$ .*

**Proof.** Let  $x' = x + \varepsilon$ ,  $p = \int_{(x',M)} dF(t) > 0$  and  $y = p^{-1} \int_{(x',M)} t dF(t)$ ,  $x' < y < M$ . From Lemma 7, the probability  $p$  of  $F$  is allotted to the points  $x'$  and  $M$  without changing its mean 0. Let a cdf  $F'$  be

$$(4.7) \quad F'(t) = \begin{cases} F(t) & , \quad t < x' \\ F(x') + \langle x', M \rangle \langle p \frac{M-y}{M-x'}, p \frac{y-x'}{M-x'} \rangle & , \quad x' \leq t < M \\ 1 & , \quad M \leq t \end{cases}$$

which has the variance greater than  $\sigma^2$ . The difference  $\gamma^2$  of the variances is given by

$$\begin{aligned} \gamma^2 &= \int_A t^2 dF'(t) - \int_A t^2 dF(t) \\ &= p \left[ (x')^2 \frac{M-y}{M-x'} + M^2 \frac{y-x'}{M-x'} \right] - \int_{(x',M)} t^2 dF(t) > 0. \end{aligned}$$

Putting  $\lambda = \sigma^2/(\sigma^2 + \gamma^2)$ , let us define

$$(4.8) \quad F''(t) = \lambda F'(t) + (1 - \lambda)G_1(t), \quad 0 < \lambda < 1,$$

where  $G_1$  is the cdf degenerated at the origin 0. Then we find  $F''$  is in  $\mathcal{F}$ , i.e.,  $F''$  has the mean 0 and the variance  $\sigma^2$ . From Lemma 4 and (4.8) it holds that

$$(4.9) \quad \phi(x, F'') = \frac{\lambda \bar{F}'(x)}{\bar{F}''(x)} \phi(x, F') + \frac{(1 - \lambda) \bar{G}_1(x)}{\bar{F}''(x)} \phi(x, G_1),$$

where  $\bar{G}_1(x) = 1$  and  $\phi(x, G_1) = -c$  for  $x < 0$ ,  $\bar{G}_1(x) = 0$  for  $x \geq 0$ . Since  $\bar{F}'(x) = \bar{F}(x)$  and  $\phi(x, F') = \phi(x, F)$  from (4.7) and (1.1), we have  $\phi(x, F'') \leq \phi(x, F)$  because  $\phi(x, F'')$  in (4.9) is a convex combination of  $\phi(x, F)(\geq -c)$  and  $-c$ .

Now, we shall redefine the cdf  $F''$  which has no probability on the interval  $(x', M)$ .

When  $x \geq 0$ ,  $F''$  in (4.8) has no probability on  $(x', M)$  and the result holds. When  $x < 0$ , let  $x' = x + \varepsilon < 0$  and  $F''_{(1)} \stackrel{\text{def}}{=} F''$  in (4.8) has a probability mass  $p_{(1)} = F''_{(1)}(0) - F''_{(1)}(0 - 0)$  at the origin 0 on  $(x', M)$ . If the mass  $p_{(1)}$  of  $F''_{(1)}$  is allotted to the points  $x'$  and  $M$ , then we can define  $F'_{(2)}$  and  $F''_{(2)}$  similarly as (4.7) and (4.8):

$$(4.7') \quad F'_{(2)}(t) = F''_{(1)}(t) + (\langle x', 0, M \rangle \langle p_{(1)} \frac{M}{M + |x'|}, -p_{(1)}, p_{(1)} \frac{|x'|}{M + |x'|} \rangle),$$

$$(4.8') \quad F''_{(2)}(t) = \lambda_{(2)} F'_{(2)}(t) + (1 - \lambda_{(2)}) G_1(t), \quad \text{where } \lambda_{(2)} = \frac{\sigma^2}{\sigma^2 + p_{(1)} M |x'|}.$$

Let us define  $F'_{(n+1)} \in \mathcal{F}$  and  $F''_{(n+1)} \in \mathcal{F}$  recursively by (4.7') and (4.8') with the subindexes (2) and (1) replaced by  $(n + 1)$  and  $(n)$  respectively ( $n \geq 1$ ). The mass  $p_{(n+1)}$  of  $F''_{n+1}$  is given successively by

$$(4.10) \quad p_{(n+1)} = \frac{p_{(n)}}{k + p_{(n)}}, \quad k = \frac{\sigma^2}{M |x'|} > 0, \quad n \geq 1,$$

where  $\lim_{n \rightarrow \infty} p_{(n)} = 0$  for any  $p_{(1)}$ . By the similar argument about  $F'' = F''_{(1)}$  in (4.9),  $F''_{(n)} \in \mathcal{F}$ ,  $n \geq 1$ ,  $F'' \stackrel{\text{def}}{=} \lim_{n \rightarrow \infty} F''_{(n)} \in \mathcal{F}$  and  $\phi(x, F'') \leq \phi(x, F''_{(n)}) \leq \phi(x, F)$ ,  $n \geq 1$ . This completes the proof.  $\square$

**Lemma 9.** For any strategy  $(x, F) \in (\mathbf{x}^M, \mathcal{F})$ , if  $F$  has a positive probability on the interval  $(-M, x)$  and it satisfies  $\phi(x, F) \geq -c$ , then there exists a cdf  $F'' \in \mathcal{F}$  such that  $F''$  has no probability on the interval  $(-M, x)$ , and it satisfies  $\phi(x, F'') \leq \phi(x, F)$ .

**Proof.** Let  $p = \int_{(-M, x)} dF(t) > 0$  and  $y = p^{-1} \int_{(-M, x)} t dF(t)$ ,  $-M < y < x$ . From Lemma 7, the probability  $p$  of  $F$  is allotted to the point  $-M$  and  $x$  without changing its mean 0. Let a cdf  $F'$  be

$$F'(t) = \begin{cases} F(-M) + (\langle -M, x \rangle \langle p \frac{x-y}{M+x}, p \frac{M+y}{M+x} \rangle) & , \quad -M \leq t \leq x \\ F(t) & , \quad x < t \end{cases}$$

which has the variance greater than  $\sigma^2$ . The difference  $\gamma^2$  of the variances is given by

$$\gamma^2 = p[x^2 \frac{M+y}{M+x} + M^2 \frac{x-y}{M+x}] - \int_{(-M, x)} t^2 dF(t) > 0.$$

Putting  $\lambda = \sigma^2/(\sigma^2 + \gamma^2)$ , let a cdf  $F''$  be defined similarly by (4.8). Then, in the same fashion as in Lemma 8, the result holds.  $\square$

Let us define for any  $x \in [-\sigma^2/M, \sigma^2/M]$ , a three-point cdf  $G_3^M(\cdot; x) \in \mathcal{F}$  which has all the mass at three points  $-M, x, M$  with the mean 0 and the variance  $\sigma^2$ . This cdf is uniquely determined by

$$(4.11) \quad G_3^M(t; x) = \langle -M, x, M \rangle \langle \frac{Mx + \sigma^2}{2M(M+x)}, \frac{M^2 - \sigma^2}{M^2 - x^2}, \frac{\sigma^2 - Mx}{2M(M-x)} \rangle,$$

and let  $\mathcal{G}_3^M = \{G_3^M(t; x) \mid -\sigma^2/M \leq x \leq \sigma^2/M\}$ . Note that if  $x = \sigma^2/M$  or  $-\sigma^2/M$ ,  $G_3^M(t; x)$  becomes the two-point cdf  $G_2(t; \sigma/M)$  or  $G_2(t; M/\sigma)$  respectively.

Now, we shall derive a saddle point. It holds, from Theorem 3, that

$$(4.12) \quad -c = \sup_{x \in \mathbb{R}} \inf_{F \in \mathcal{F}(0, \sigma^2)} \phi(x, F) \leq \sup_{x \in \mathbb{R}} \inf_{F \in \mathcal{F}} \phi(x, F).$$

Then the player 1 would decide a stopping level  $x$  in the following set

$$(4.13) \quad \{x \mid \phi(x, F) \geq -c \text{ for all } F \in \mathcal{F}\} \cap \mathbf{x}^M \stackrel{\text{def}}{=} \mathbf{x}_c^M.$$

This set is not empty because  $x = -c$  is contained in it.

**Remark on Lemmas 8 and 9.** Lemmas mean the following : for any  $x \in \mathbf{x}_c^M$ , if the player 1(he) decides his stopping level  $x$ , the player 2(she) may choose her cdf which has no probability on the interval  $(-M, x) \cup (x + \varepsilon, M)$  for an arbitrary small  $\varepsilon > 0$ , where her cdf converges to  $G_3^M(\cdot; x)$  of (4.11) as  $\varepsilon$  goes to 0. In this situation, his stopping set becomes  $\{X \in (x, x + \varepsilon] \cup \{M\}\}$  for an arbitrary small  $\varepsilon > 0$ , i.e.,  $\{X \in \{M\}\}$  or  $\{X \in \{x\} \cup \{M\}\}$ .

From the above remark, we have for any  $x \in \mathbf{x}_c^M$ ,

$$(4.14) \quad \inf_{F \in \mathcal{F}} \phi(x, F) = \min[\phi(x, G_3^M(\cdot; x)), \phi(x - 0, G_3^M(\cdot; x))].$$

If there exists a point  $x^s \in \mathbf{x}_c^M$  such that

$$(4.15) \quad \phi(x^s, G_3^M(\cdot; x^s)) = (T_{\mathcal{G}_3^M}^t)^{-1}(c) (= \phi(x^s - 0, G_3^M(\cdot; x^s))) \geq -c,$$

the strategy  $(x^s, G_3^M(\cdot; x^s))$ ,  $x \in \mathbf{x}_c^M$ ,  $G_3^M(\cdot; x^s) \in \mathcal{G}_3^M \subset \mathcal{F}$ , is the saddle point and  $\phi^s = (T_{\mathcal{G}_3^M}^t)^{-1}(c)$  is the saddle value. Because, from (4.14) and (2.10), the following relation is satisfied.

$$\begin{aligned} & \min[\phi(x^s, G_3^M(\cdot; x^s)), \phi(x^s - 0, G_3^M(\cdot; x^s))] \leq \sup_{x \in \mathbf{x}_c^M} \inf_{F \in \mathcal{F}} \phi(x, F) \\ & \leq \inf_{F \in \mathcal{F}} \sup_{x \in \mathbf{x}_c^M} \phi(x, F) \leq \inf_{F \in \mathcal{G}_3^M} \sup_{x \in \mathbf{x}_c^M} \phi(x, F) = (T_{\mathcal{G}_3^M}^t)^{-1}(c) = \phi(x^s, G_3^M(\cdot; x^s)). \end{aligned}$$

For any  $x, y \in [-\sigma^2/M, \sigma^2/M]$ , it is shown, by the graph of  $T_{\mathcal{G}_3^M(\cdot; y)}(x)$ , that

$$(4.16) \quad T_{\mathcal{G}_3^M(\cdot; y)}(x) = \int_x^M [1 - G_3^M(t; y)] dt \geq T_{\mathcal{G}_3^M(\cdot; x)}(x) = \int_x^M [1 - G_3^M(t; x)] dt = \frac{\sigma^2 - Mx}{2M}.$$

This line segment  $T = (\sigma^2 - Mx)/2M$  connects the points  $(-\sigma^2/M, \sigma^2/M)$  and  $(\sigma^2/M, 0)$  in  $(x, T)$ -plane, and the equality in (4.16) holds only when  $y = x$ .

Then, we have proved (4.15).

$$(4.17) \quad (T_{G_3^M}^t)^{-1}(c) = \frac{\sigma^2}{M} - 2c = \left(\frac{\sigma^2}{M} - c\right)^+ - c \geq -c .$$

$$(4.18) \quad x^s = \left(\frac{\sigma^2}{M} - c\right)^+ - c, \quad F^s = G_3^M(\cdot; x^s) .$$

Hence, we have the main theorem of our problem.

**Theorem 5.** For a class  $\mathcal{F}(0, \sigma^2, M)$  of cdf's,  $\sigma \leq M$ , we have the following solution:

(i) When  $\sigma^2/M \leq c \leq M$ , the same result as Theorem 3 holds, that is, the saddle value  $\phi^s$  and all the saddle points  $(x^s, F^s) \in (\mathbf{x}^s, \mathcal{F}^s)$  are given by

$$\phi^s = -c, \quad \mathbf{x}^s = [-M, -c] \text{ and } \mathcal{F}^s = \left\{ F \mid \int_{[-c, M]} dF(t) = 1, F \in \mathcal{F}(0, \sigma^2, M) \right\} .$$

(ii) When  $0 < c < \sigma^2/M$ , the saddle value  $\phi^s$  and the saddle point  $(x^s, F^s)$  are given by

$$\phi^s = (\sigma^2/M - c)^+ - c, \quad x^s = (\sigma^2/M - c)^+ - c \text{ and } F^s(t) = G_3^M(t; x^s) \text{ defined by (4.11).}$$

Unfortunately, we could not show the uniqueness of the saddle point  $(x^s, F^s)$  in Case (ii). Finally, we conclude this paper by illustrating  $\phi^u$  of Theorem 4 and  $\phi^s$  of Theorem 5 in Figure 1.

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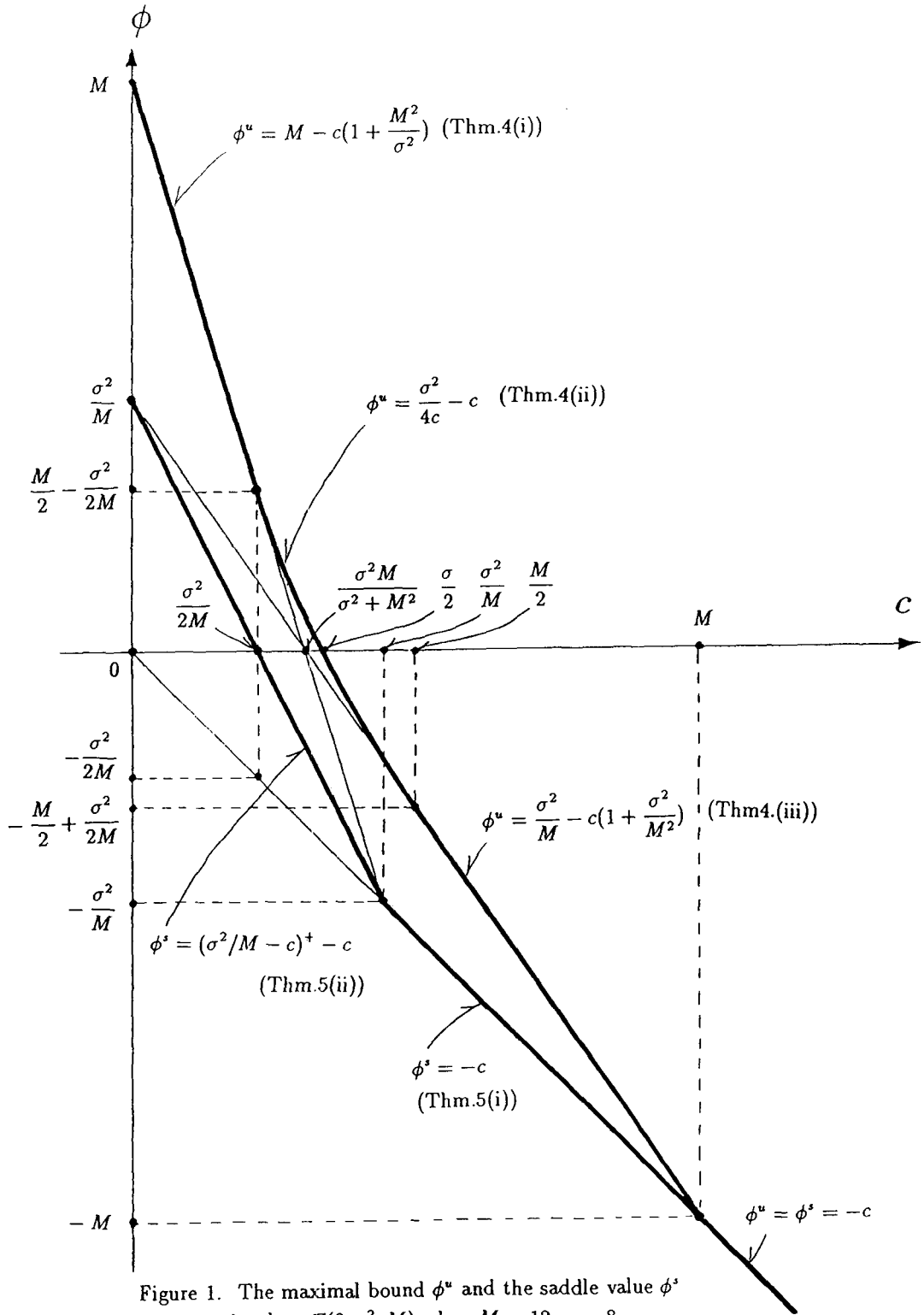


Figure 1. The maximal bound  $\phi^u$  and the saddle value  $\phi^s$  in the class  $\mathcal{F}(0, \sigma^2, M)$  when  $M = 12, \sigma = 8$ .