

2020-11-27

BERTSIMAS & LO EXECUTION PROBLEM

GENERAL SETUP

0: start time of execution

T: execution horizon

Time is discrete $t = 0, \dots, T$.

X_t : inventory at time t.

$-\Delta X_{t+1} = -X_{t+1} + X_t$ quantity to execute in $[t, t+1]$.

$F = F(t, s, \{X_u\}_{u=t}^T)$ expected execution cost at time t of the asset price at time t is $S_t = s$ and the inventory trajectory is $\{X_u\}_{u=t}^T$. Thus is defined as

$$F(t, s, \{X_u\}_{u=t}^T) = E_t \left[\sum_{u=t}^{T-1} (-\Delta X_{u+1}) S_{u+1} \mid S_t = s \right].$$

$C_t^* = C_t^*(x, s)$ value function at time t, i.e. the optimal execution cost. It depends on the current value x of the inventory at time t, and on the asset price s at time t. Thus is defined as

$$C_t^*(x, s) = \inf \left\{ F(t, s, \{X_u\}_{u=t}^T) : X_{u+1} \in \mathcal{I}_u \text{ for } u=t, \dots, T, \begin{array}{l} X_t = x, \\ X_T = 0 \end{array} \right\}.$$

BELLMAN EQUATION

For $0 \leq t \leq T-1$, it must hold

$$C_t^*(x_s) = \inf \left\{ \mathbb{E}_t \left[(-\Delta X_{t+1}) S_{t+1} + C_{t+1}^*(X_{t+1}, S_{t+1}) \right] : \begin{array}{l} X_{t+1} \in \Omega_t \\ X_t = x, X_T = 0 \end{array} \right\}.$$

LEMMA

Let $G_t = G_t(x, s, v)$ be defined as

$$\begin{aligned} G_t(x, s, v) = & \mathbb{E}_t \left[S_{t+1} \mid \Delta X_{t+1} = -v, S_t = s \right] \cdot v \\ & + \mathbb{E}_t \left[C_{t+1}^*(x - v, S_{t+1}) \mid \Delta X_{t+1} = -v, S_t = s \right]. \end{aligned}$$

Define

$$G_t^*(x, s) = \inf \left\{ G_t(x, s, v) : v \in \mathbb{R} \right\}.$$

Then

$$C_t^*(x, s) = G_t^*(x, s).$$

PROOF.

The inequality " \leq " follows from the fact that, on the one hand, X_{t+1} is Ω_t -measurable and, on the other hand, given S_t , S_{t+1} depends on $\{X_u\}_{u=0}^{T-1}$ only via ΔX_{t+1} .

The inequality " \geq " is clear. □

PERTINENT IMPACT WITH NO-INFORMATION

The asset price S_t is modelled as

$$S_{t+1} = S_t - \theta \Delta X_{t+1} + \sigma S_0 \Delta W_{t+1}.$$

PROPOSITION 1

It holds

$$C_t^*(x, s) = sx + \frac{\theta}{2} \frac{T-t+1}{T-t} x^2$$

and the optimal execution strategy is given by

$$-\Delta X_{t+1}^* = \frac{X_0}{T}.$$

PROOF.

We show by induction over $K=1 \dots T$ that

$$C_{T-K}^*(x, s) = sx + \frac{\theta}{2} \frac{K+1}{K} x^2.$$

For $K=1$, $C_{T-1}^*(x, s)$ is actually an infimum over the singleton $\Delta X_T = -x$. Hence

$$\begin{aligned} C_{T-1}^*(x, s) &= F(T-1, s, \{x, 0\}) \\ &= \mathbb{E}_{T-1} [S_T | S_{T-1} = s, \Delta X_{T-1} = -x] \cdot x \\ &= sx + \frac{\theta}{2} x^2. \end{aligned}$$

Hence we assume that the claim holds up to $K \in T$ and we argue for the induction step.

We can compute

$$\begin{aligned}
 G_{T-K-1}(x, s, v) &= (s + \theta v)v \\
 &\quad + \mathbb{E}_{T-K-1} \left[(x-v) S_{T-K} + \frac{\theta}{2} \frac{K+1}{K} (x-v)^2 \middle| \begin{array}{l} X = -v, \\ S_{T-K-1} = s \end{array} \right] \\
 &= (s + \theta v)v + (s + \theta v)(x-v) + \frac{\theta}{2} \frac{K+1}{K} (x-v)^2 \\
 &= (s + \theta v)x + \frac{\theta}{2} \frac{K+1}{K} (x-v)^2.
 \end{aligned}$$

Thus,

$$\underset{v \in \mathbb{R}}{\operatorname{argmin}} \quad G_{T-K-1}(x, s, v) = \frac{x}{K+1}$$

and

$$\begin{aligned}
 G_{T-K-1}^*(x, s) &= G_{T-K-1}\left(x, s, \frac{x}{K+1}\right) \\
 &= sx + \theta \frac{x^2}{K+1} + \frac{\theta}{2} \frac{K+1}{K} \left(\frac{Kx}{K+1}\right)^2 \\
 &= sx + \frac{\theta}{2} \frac{K+2}{K+1} x^2,
 \end{aligned}$$

proving the induction step.

We conclude by noting that

$$\begin{aligned}
 F(0, S_0, \left\{ \frac{T-t}{T} X_t \right\}_{t=0}^T) &= \frac{X_0}{T} \sum_{t=0}^{T-1} \left(s_0 + (t+1) \theta \frac{X_0}{T} \right) \\
 &= \frac{X_0}{T} \left(TS_0 + \theta \frac{X_0}{T} \frac{(T+1)T}{2} \right) \\
 &= X_0 S_0 + \frac{\theta}{2} \frac{T+1}{T} X_0^2 \\
 &= C_0^*(X_0, S_0).
 \end{aligned}$$

□

PERMANENT IMPACT WITH INFORMATION

The asset price is modelled as

$$\begin{cases} S_{t+1} = S_t + \gamma A_t - \delta \Delta X_{t+1} + \sigma S \Delta W_{t+1}, \\ A_{t+1} = \rho A_t + \eta \Delta \tilde{W}_{t+1}. \end{cases}$$

The AR(1) process $\{A_t\}_{t=0}^T$ represents information.

The value function accommodates conditioning with respect to the value $A_t = a$:

$$C_t^* = C_t^*(x, s, a)$$

$$= \inf \left\{ F(t, s, a, \{X_u\}_{u=t}^T) : \begin{array}{l} X_{u+1} \in \mathcal{F}_u \quad \forall t \leq u \leq T-1 \\ X_t = x, \quad X_T = 0 \end{array} \right\}$$

where

$$F(t, s, a, \{X_u\}_{u=t}^T)$$

$$= \mathbb{E}_c \left[\sum_{u=t}^{T-1} (-\Delta X_{u+1}) S_{u+1} \mid S_t = s, A_t = a \right].$$

PROPOSITION 2

It holds

$$C_t^*(x, \alpha) = Sx + c_{1,T-t-1} x^2 + c_{2,T-t-1} \alpha x + c_{3,T-t-1} \alpha^2 + c_{4,T-t-1}$$

where for $K=1-T$

$$c_{1,K} = \frac{\rho}{2} \frac{K+2}{K+1}$$

$$c_{2,K} = \gamma + \frac{\rho \beta c_{2,K-1}}{2 c_{1,K-1}}, \quad c_{2,0} = \gamma$$

$$c_{3,K} = \rho^2 c_{3,K-1} - \frac{\rho^2}{4} \frac{c_{3,K-1}^2}{c_{1,K-1}}, \quad c_{3,0} = 0$$

$$c_{4,K} = c_{4,K-1} + c_{3,K-1} \gamma^2 - c_{4,0} = 0.$$

Moreover the optimal execution strategy is given by

$$-\Delta X_{t+1}^* = \frac{1}{T-t} X_t + \frac{\rho}{2} \frac{c_{3,T-t-2}}{c_{1,T-t-2}} A_t .$$

PROOF.

We show by induction over $K=0 \dots T-1$ that

$$C_{T-K-1}^*(x, \underline{s}, \underline{a}) = sx + c_{1,K}x^2 + c_{2,K}ax + c_{3,K}^2 + c_{4,K}.$$

For $K=0$, $C_{T-1}^*(x, \underline{s}, \underline{a})$ is actually an optimum over the singleton $\Delta X_T = -x$. Hence,

$$\begin{aligned} C_{T-1}^*(x, \underline{s}, \underline{a}) &= F(T-1, \underline{s}, \{x_0\}) \\ &= E_{T-1} \left[xS_T | S_{T-1} = \underline{s}, A_{T-1} = \underline{a}, X_{T-1} = x \right] \\ &= sx + \theta x^2. \end{aligned}$$

Thus gives

$$c_{1,0} = \theta$$

$$c_{2,0} = \emptyset$$

$$c_{3,0} = 0$$

$$c_{4,0} = 0$$

as stated.

Hence, we assume that the claim holds up to $K-1 < T-2$ and we argue for the induction step.

$$\begin{aligned}
G_{T-K-1}(x, s, a, v) &= E_{T-K-1} \left[S_{T-K} \mid \Delta X_{T-K} = -v, S_{T-K-1} = s, A_{T-K-1} = a \right] \cdot v \\
&\quad + E_{T-K-1} \left[C_{T-K}^*(x-v, S_{T-K}, A_{T-K}) \mid \Delta X_{T-K} = -v, S_{T-K-1} = s, A_{T-K-1} = a \right] \\
&= (s + \delta_a + \theta v) v \\
&\quad + E_{T-K-1} \left[(x-v) S_{T-K} + C_{2,K-1}(x-v)^2 \right. \\
&\quad \quad \left. + C_{2,K-1} A_{T-K}(x-v) \right. \\
&\quad \quad \left. + C_{3,K-1} A_{T-K}^2 + C_{3,K-1} \mid \Delta X_{T-K} = v, S_{T-K-1} = s, A_{T-K-1} = a \right] \\
&= (s + \delta_a + \theta v) x \\
&\quad + C_{2,K-1}(x-v)^2 + C_{3,K-1}(x-v)\rho a \\
&\quad + C_{3,K-1}(\rho^2 a^2 + \gamma^2) + C_{3,K-1}.
\end{aligned}$$

thus

$$\underset{v \in \mathbb{R}}{\operatorname{argmin}} \quad G_{T-K-1}(x, s, a, v) = \left(1 - \frac{\theta}{2C_{3,K-1}} \right) x + \frac{\rho C_{2,K-1}}{2C_{3,K-1}} a$$

and

$$\begin{aligned}
G_{T-K-1}^*(x, s, a) &= sx + \theta \left(1 - \frac{\theta}{4C_{3,K-1}} \right) x^2 \\
&\quad - \left(\theta + \frac{\theta \rho C_{2,K-1}}{2C_{1,K-1}} \right) ax + \left(\rho^2 C_{3,K-1} - \frac{\rho^2 C_{2,K-1}^2}{4C_{3,K-1}} \right) a^2 \\
&\quad + C_{3,K-1} + C_{3,K-1}\gamma^2.
\end{aligned}$$

Finally, the optimal execution strategy is given by

$$\begin{aligned}-\Delta X_{T-K}^* &= \underset{v \in \mathbb{R}}{\operatorname{argmin}} G_{T-K-1}(X_{T-K-1}, S_{T-K-1}, A_{T-K-1}, v) \\&= \left(1 - \frac{\theta}{2c_{2,K-1}}\right) X_{T-K-1} + \frac{\rho c_{2,K-1}}{2c_{1,K-1}} A_{T-K-1} \\&= \frac{1}{K+1} X_{T-K-1} + \frac{\rho}{2} \frac{c_{2,K-1}}{c_{1,K-1}} A_{T-K-1}.\end{aligned}$$

□

PERMANENT IMPACT WITH RISK ADJUSTMENT

The asset price is modelled as

$$S_{t+1} = S_t - \theta \Delta X_{t+1} + \sigma S_0 \Delta W_{t+1}.$$

We define the "unimpaired" price as

$$\tilde{S}_{t+1} = \tilde{S}_t + \tilde{\sigma} \Delta W_{t+1}, \quad \tilde{S}_0 = S_0$$

where $\tilde{\sigma} = \sigma \sqrt{s}$.

We consider the following risk-adjusted expected execution cost

$$\begin{aligned} F(t, \mathbb{E} \{ X_u \}_{u=t}^T) \\ = \mathbb{E}_t \left[\sum_{u=t}^{T-1} (-\Delta X_{u+1}) \tilde{S}_{u+1} + 2\alpha \Delta \tilde{S}_{u+1}^2 X_{u+1} \mid S_t = s \right]. \end{aligned}$$

PROPOSITION 3

It holds

$$C_t^*(x, s) = sx + \frac{\theta}{2} \frac{T-t+1}{T-t} x^2 + \alpha \sigma^2 (T-t-1) x$$

and the optimal execution strategy is given by

$$-\Delta X_{t+1}^* = \frac{X_t^*}{T-t} + (T-t-1) \alpha \frac{\sigma^2}{\theta}.$$

PROOF.

We show by induction over $K=1 \dots T$ that

$$C_{T-K}^*(x-s) = sx + \frac{\theta}{2} \frac{K+1}{K} x^2 + \alpha \sigma^2(K-1)x.$$

For $K=1$, $C_{T-1}^*(x-s)$ is actually an infimum over the singleton $-\Delta X_T = x$. Hence,

$$\begin{aligned} C_{T-1}^*(x-s) &= F(T-1, \leq \{x\}) \\ &= E_{T-1} \left[x S_{T-1} + 2\alpha \tilde{\sigma}^2 \Delta W_T^2 \cdot 0 \mid S_{T-1} = s, X_{T-1} = x \right] \\ &= sx + \theta x^2. \end{aligned}$$

Now we assume that the claim holds up to $K < T$ and we argue for the induction step.

$$\begin{aligned} G_{T-K-1}(x, s, v) &= E_{T-K-1} \left[v S_{T-K} + 2\alpha \tilde{\sigma}^2 \Delta W_{T-K}^2(x-v) \mid S_{T-K-1} = s, \right. \\ &\quad \left. X_{T-K-1} = x, -\Delta X_{T-K} = v \right] \\ &\quad + E_{T-K-1} \left[C_{T-K}^*(x-v, S_{T-K}) \mid \Delta X_{T-K} = -v, S_{T-K-1} = s \right] \\ &= (s+\theta v)v + 2\alpha \tilde{\sigma}^2(x-v) \\ &\quad + E_{T-K-1} \left[(x-v)S_{T-K} + \frac{\theta}{2} \frac{K+1}{K} (x-v)^2 + \alpha \sigma^2(K-1)(x-v) \right] \end{aligned}$$

$$= (s + \theta v)x + \frac{\theta}{2} \frac{k+1}{k} (x-v)^2 + \alpha \tilde{\sigma}^2 (k+1)(x-v).$$

Therefore,

$$\underset{v \in \mathbb{R}}{\operatorname{argmin}} G_{T-k-1}(x, s, v) = \frac{x}{k+1} + \alpha \frac{\tilde{\sigma}^2}{\theta} k$$

and

$$G_{T-k-1}^*(x, s) = sx + \frac{\theta}{2} \frac{k+2}{k+1} x^2 + \alpha \tilde{\sigma}^2 K x,$$

proving the induction step.

Finally

$$\begin{aligned} -\Delta X_{T-k}^* &= \underset{v \in \mathbb{R}}{\operatorname{argmin}} G_{T-k-1}\left(X_{T-k-1}^*, S_{T-k-1}, v\right) \\ &= \frac{X_{T-k-1}^*}{k+1} + \alpha \frac{\tilde{\sigma}^2}{\theta} k. \end{aligned}$$

□

PROBLEM SET 1 - SOLUTIONS

EXERCISE 1.1.

From PROPOSITION 1 above we know that

$$E \left[\sum_{t=0}^{T-1} (-\Delta X_{t+1}) S_{t+1} \right] = S_0 X_0 + \frac{\theta}{2} \left(1 + \frac{1}{T} \right) X_0^2.$$

Moreover, we can compute

$$2\alpha\tilde{\sigma}^2 \sum_{t=0}^{T-1} X_{t+1} = 2\alpha\tilde{\sigma} \frac{X_0}{T} \sum_{t=1}^T (T-t) = \alpha\tilde{\sigma}^2 X_0 (T-1).$$

Hence the optimal horizon is given by the minimizer of

$$T \mapsto \frac{\theta}{2} X_0^2 \cdot \frac{1}{T} + \alpha\tilde{\sigma}^2 X_0 T.$$

This is

$$T^* = \sqrt{\frac{\theta}{2} \frac{X_0}{\alpha\tilde{\sigma}^2}}.$$

EXERCISE 1.2

This is Proposition 3 above.

EXERCISE 2

This is Proposition 2 above.