

Lecture 11: The Valuation and Pricing of Information

I. Economic Foundations of Value of Information

		Coin state ω		Prior belief $q(\omega)$
		1/2 tail	1/2 head	
action	0	2t	0	
	1	0	2t	

$u(a, \omega)$

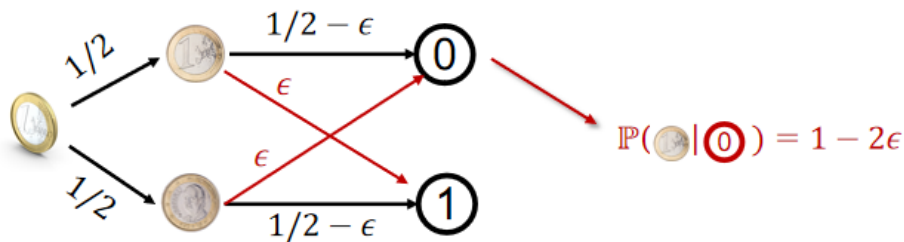
Without information, decision maker(DM) gets $\max_a [\mathbb{E}_{\omega \sim q} u(a, \omega)] = t$

With my (full) information, DM gets $\mathbb{E}_{\omega \sim q} [\max_a u(a, \omega)] = 2t$

Value of (full) info = $\mathbb{E}_{\omega \sim q} [\max_a u(a, \omega)] - \max_a [\mathbb{E}_{\omega \sim q} u(a, \omega)]$

		1 - 2ε	2ε	Posterior belief $p(\omega)$, given ①
		1/2 tail	1/2 head	
action	0	t	0	Prior belief $q(\omega)$
	1	0	3t	

$u(a, \omega)$



Noisy information revelation

Realistically, can think of 0 as noisy prediction of state ω (e.g., stock trend, purchase prob)

Question: What is the value of this noisy signal 0?

- Without knowing this signal, DM takes action 1
- With this signal 0, DM takes action 0 (assuming ϵ very small)
- However, true distribution is the posterior p regardless

$$\text{Value of knowing } 0 = \mathbb{E}_{\omega \sim p}[u(0, \omega)] - \mathbb{E}_{\omega \sim p} u(1, \omega)$$

Definition(FK'19): Consider an arbitrary decision making problem $u(a, \omega)$, suppose a signal updates the DM's belief about state ω from $q \in \Delta(\Omega)$ to $p \in \Delta(\Omega)$, the value of this signal is defined as

$$D^u(p; q) = \mathbb{E}_{\omega \sim p}[u(a^*(p), \omega)] - \mathbb{E}_{\omega \sim p} u(a^*(q), \omega)$$

Example 1:

- $a \in A = \Delta(\Omega) \rightarrow$ action is to pick a distribution over states
- $u(a, \omega) = \log a_\omega$
- Which action $a \in \Delta(\Omega)$ maximizes expected utility $\mathbb{E}_{\omega \sim p}[u(a, \omega)]$?

$$a^*(p) = p$$

$$D^u(p; q) = \sum_{\omega} p_{\omega} \log \frac{p_{\omega}}{q_{\omega}} \quad \text{KL-divergence}$$

Example 2:

- $a \in A = \Delta(A) \rightarrow$ action is to pick a distribution over states
- $u(a, \omega) = -\|a - e_{\omega}\|^2$

$$a^*(p) = p$$

$$D^u(p; q) = \|p - q\|^2 \quad \text{Squared distance}$$

Some obvious properties

- Non-negativity: $D^u(p; q) \geq 0$
- Null information has no value: $D^u(q; q) = 0$
- Order-invariant: if DM receives signal σ_1, σ_2 , the order of receiving them does not affect final expected total value

In this case, we say $D(p; q)$ is a valid measure for value of information

Theorem 1(FK'19): Consider any $D(p; q)$ function. There exists a decision problem $u(a, \omega)$ such that

$$D^u(p; q) = \mathbb{E}_{\omega \sim p}[u(a^*(p), \omega)] - \mathbb{E}_{\omega \sim p} u(a^*(q), \omega)$$

if and only if $D(p; q)$ satisfies

- Non-negativity: $D^u(p; q) \geq 0$
- Null information has no value: $D^u(q; q) = 0$
- Order-invariant: if DM receives signal σ_1, σ_2 , the order of receiving them does not affect final expected total value

Theorem 2(FK'19):

1. For any concave function H , its Bregman divergence is a valid measure for value of information.
2. Conversely, for any valid measure $D(p; q)$ for value of information,

$$H(q) = \sum_{\omega} q^{\omega} D(e_{\omega}, q)$$

is a concave function whose Bregman divergence is $D(p; q)$

Why useful?

- Many functions - even natural ones like l_2 distance $\|p - q\|$ - are not valid measures

- In fact, any metric is not valid, since metric cannot be a Bregman divergence
- There are efficient ways to tell whether a $D(p, q)$ is valid



II. Optimal Pricing of Information

1. Plans

- Vignette 1: closed-form optimal mechanism for structured setups
- Vignette 2: algorithmic solution for general setups
- Vignette 3: from distilled data (i.e. information) to raw data

2. A Model of Information Pricing

- One seller, one buyer
- Buyer is a decision maker who faces a binary choice: an active action 1 and a passive action 0: Active action: come to talk, approve loan, invest stock X, etc.
- Payoff of passive action $\equiv 0$
- Payoff of active action $= v(\omega, t) = v_1(\omega)[t + \rho(\omega)]$
 - ω is a state of nature, t is buyer type
 - Assume $v(\omega, t)$ is linear and non-decreasing in $t \in [t_1, t_2]$
- Information structure:
 - Seller observes ω , and buyer knows t

Mechanism design question: How can seller optimally sell her information about ω to the buyer?

3. Design Space

Standard revelation principle implies optimal mechanism can w.l.o.g be a menu $\{\pi_t, p_t\}_{t \in T}$

- $\pi_t : \Omega \rightarrow S$ is an experiment (which generates signals) for type i
- $p_t \in \mathbb{R}$ is t 's payment
- Each type is incentivized to report type truthfully

Concrete design question: design IC $\{\pi_t, p_t\}_{t \in T}$ to maximize seller's revenue

4. How Does It Differ from Selling Goods?

- Each experiment is like an item
 - In this sense, we are selling infinitely many goods
 - In fact, we are even “designing the goods”
- Participation constraint is different
 - Without any information, type t 's utility is $\max\{\bar{v}(t), 0\}$

$$\bar{v}(t) = \int_{\omega \in \Omega} v(\omega, t) g(\omega) d\omega$$

Ex-ante expected utility of action 1

5. Threshold experiments turn out to suffice

Recall $v(\omega, t) = v_1(\omega)[t + \rho(\omega)]$

Def. π_t is a threshold experiment if π_t simply reveals $\rho(\omega) \geq \theta(t)$ or not some buyer-type-dependent threshold $\theta(t)$

Threshold is on $\rho(\omega)$

6.Virtual Value Functions

Recall virtual value function in [Myerson'81]: $\varphi(t) = t - \frac{1-F(t)}{f(t)}$

Def.

- Lower virtual value function: $\varphi(t) = t - \frac{1-F(t)}{f(t)}$
- Upper virtual value function: $\bar{\varphi}(t) = t + \frac{F(t)}{f(t)}$
- Mixed virtual value function: $\varphi_c(t) = c\underline{\varphi}(t) + (1-c)\bar{\varphi}(t)$

Note:"upper" or "lower" is due to:

$$\underline{\varphi}(t) \leq t \leq \bar{\varphi}(t)$$

7.The Optimal Mechanism

Depend on two problem-related constants:

$$V_L = \max\{v(t_1), 0\} + \int_{t_1}^{t_2} \int_{q:\rho(q) \geq -\underline{\varphi}^+(x)} g(q)v_1(q)dqdx$$

$$V_H = \max\{v(t_1), 0\} + \int_{t_1}^{t_2} \int_{q:\rho(q) \geq -\bar{\varphi}^+(x)} g(q)v_1(q)dqdx$$

Note:

$$V_L < V_H$$

Theorem([LSX'21])

1. If $\bar{v}(t_2) \leq V_L$, the mechanism with threshold experiments $\theta^*(t) = -\underline{\varphi}(t)$ and following payment function represents an optimal mechanism:

$$p^*(t) = \int_{\omega \in \Omega} \pi^*(\omega, t)g(\omega)v(\omega, t)d\omega - \int_{t_1}^t \int_{\omega \in \Omega} \pi^*(\omega, x)g(\omega)v_1(\omega)d\omega dx$$

2. If $\bar{v}(t_2) \geq V_H$, the mechanism with threshold experiments $\theta^*(t) = -\bar{\varphi}(t)$ and following payment function represents an optimal mechanism:

$$p^*(t) = \int_{\omega \in \Omega} \pi^*(\omega, t)g(\omega)v(\omega, t)d\omega + \int_t^{t_2} \int_{\omega \in \Omega} \pi^*(\omega, x)g(\omega)v_1(\omega)d\omega dx - \bar{v}(t_2)$$

3. If $V_L \leq \bar{v}(t_2) \leq V_H$, the mechanism with threshold experiments $\theta^*(t) = -\varphi_c(t)$ and following payment function represents an optimal mechanism

$$p^*(t) = \int_{\omega \in \Omega} \pi^*(\omega, t)g(\omega)v(\omega, t)d\omega - \int_{t_1}^{t_2} \int_{\omega \in \Omega} \pi^*(\omega, x)g(\omega)v_1(\omega)d\omega dx$$

where constant c is chosen such that

$$\int_{t_1}^{t_2} \int_{\omega:\rho(\omega) \geq \varphi_c^+(x)} g(\omega)v_1(\omega)d\omega dx = \bar{v}(t_2)$$

8.Remarks

- Threshold mechanisms are common in real life:House/car inspections, stock recommendations: information seller only need to reveal it "passed" or "deserves a buy" or not

- Optimal mechanism has personalized thresholds and payments, tailored to accommodate different level of risk each buyer type can take: Different from optimal pricing of physical goods

What if seller is restricted to sell the same information to every buyer (e.g., due to regulation)? How will revenue change?

- This is the optimal price (Merson reserve) in previous example
- Revenue can be arbitrarily worse
- $\frac{1}{e}$ - approximation of optimal revenue if the value of full information as a function of t has monotone hazard rate

9. Additional Properties of Optimal Mechanism



III. Summary and Open Problems