Weak Monotonicity and Bayes-Nash Incentive Compatibility

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COMSOC 2006



Introduction

Setting

- Set of agents: $N = \{1, \dots, n\}$
- Multi-dimensional type of agent $i: t^i \in T^i$ with $T^i \subseteq \mathbb{R}^k$
- Set of outcomes F
- Valuations $v(\alpha|t^i, t^{-i})$
- Types independently distributed
- T set of type profiles $t = (t^1, ..., t^n)$
- Allocation rule: f : T → Γ

Introduction

Goal

- Characterize allocation rules for which there is a
 P: T → ℝⁿ such that (f, P) is Bayes-Nash incentive
 compatible.
- Can we extend weak monotonicity characterization for dominant strategy i.c. (Bikhchandani, Chatterji, Sen, Lavi, Mu'alem, Nisan, Sen (2006), Gui, Müller, Vohra (2004), Saks, Yu (2005) to Bayes-Nash i.c.?

Notation

Bayes-Nash Incentive Compatibility

• f is Bayes-Nash i.c. if $\exists P$ s.t. $\forall i \in N$, $\forall r^i, \tilde{r}^i \in T^i$

$$\begin{split} &E_{-i}\left[v^{i}\left(f\left(r^{i},t^{-i}\right)\mid r^{i},t^{-i}\right)-v^{i}\left(f\left(\tilde{\boldsymbol{r}}^{i},t^{-i}\right)\mid r^{i},t^{-i}\right)\right]\\ &\geq &E_{-i}\left[P_{i}\left(r^{i},t^{-i}\right)-P_{i}\left(\tilde{\boldsymbol{r}}^{i},t^{-i}\right)\right] \end{split}$$

• Implies weak monotonicity: $\forall i \in N, \forall r^i, \tilde{r}^i \in T^i$

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Network approach

Network

- $\forall i \in N$ complete directed graph T_f^i
- Node associated with each type
- Length of edge from \tilde{r}^i to r^i (cost of manipulation):

$$I^{i}\left(\tilde{r}^{i}, r^{i}\right) = E_{-i}\left[v^{i}\left(f\left(r^{i}, t^{-i}\right) \mid r^{i}, t^{-i}\right) - v^{i}\left(f\left(\tilde{r}^{i}, t^{-i}\right) \mid r^{i}, t^{-i}\right)\right]$$

• weak-monotonicity becomes no-negative 2-cycle:

$$I^{i}\left(\mathbf{\tilde{r}}^{i},\mathbf{r}^{i}\right)+I^{i}\left(\mathbf{r}^{i},\mathbf{\tilde{r}}^{i}\right)\geq0$$

Network approach

Theorem

An allocation rule f is Bayes-Nash incentive compatible if and only if $\forall i \in N$, T_f^i has no negative cycle.

Proof

Similar to Rochet (1987), and infinite graph equivalent of "shortest path lengths exist if and only if no negative cycle".

Question

No negative 2-cycle (i.e., weak-monotonicity) if and only if no negative cycle?

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One-dimensional types

$T^i \subset \mathbb{R}$

• **Definition:** The costs of manipulation are decomposition monotone if $\forall \underline{r}^i, \overline{r}^i \in T^i$ and $\forall \alpha \in (0,1)$ we have

$$l^{i}\left(\underline{r}^{i}, \overline{r}^{i}\right) \geq l^{i}\left(\underline{r}^{i}, (1-\alpha)\underline{r}^{i} + \alpha\overline{r}^{i}\right) + l^{i}\left((1-\alpha)\underline{r}^{i} + \alpha\overline{r}^{i}, \overline{r}^{i}\right).$$

• **Theorem** If costs of manipulation are decomposition monotone, T^i convex, then f is Bayes-Nash i.c. if and only if for all $i \in N$, T^i_f has no negative 2-cycle. (Example: Myerson (1981) "Optimal Auction Design")

Additional Assumption

- $T^i \subseteq \mathbb{R}^k$ convex
- Valuations linear w.r.t. own type: $\forall \gamma \in \Gamma$

$$v^{i}\left(\gamma\mid t^{i}, t^{-i}\right) = \alpha^{i}\left(\gamma\mid t^{-i}\right) + \beta^{i}\left(\gamma\mid t^{-i}\right)t^{i}$$

- $\alpha^i : \Gamma \times T^{-i} \mapsto \mathbb{R}, \ \beta^i : \Gamma \times T^{-i} \mapsto \mathbb{R}^k$
- ullet Expected valuation: $E_{-i}\left[v^{i}\left(f\left(r^{i},t^{-i}
 ight)\mid t^{i},t^{-i}
 ight)
 ight]$

$$= E_{-i} \left[\alpha^{i} \left(f \left(r^{i}, t^{-i} \right) \mid t^{-i} \right) \right] + E_{-i} \left[\beta^{i} \left(f \left(r^{i}, t^{-i} \right) \mid t^{-i} \right) \right] t^{i}$$

Lemma

If v^i is linear in the own type and f satisfies weak monotonicity then the costs of manipulation are decomposition monotone.

Potential function and Path independence

- $E_{-i}\left[\beta^{i}\left(f\left(r^{i},t^{-i}\right)\mid t^{-i}\right)\right]$ is vector field $T^{i}\mapsto\mathbb{R}^{k}$
- A vector field $\psi \colon T^i \mapsto \mathbb{R}^k$ has a potential function $\varphi \colon T^i \mapsto \mathbb{R}$ if for any smooth path A joining $\underline{t}^i, \overline{t}^i \in T^i$

$$\int_{\mathbf{A}} \psi = \varphi\left(\overline{t}^{i}\right) - \varphi\left(\underline{t}^{i}\right).$$

 \bullet Equivalent: ψ is path-independent, that is for any closed path B

$$\int_{\mathcal{B}} \psi = 0.$$

Theorem

Suppose that $\forall i \in N$, T^i is convex and that agents have valuation functions that are linear w.r.t. their own true types then: f is Bayes-Nash incentive compatible if and only if for all $i \in N$

- (1) T_f^i has no negative 2-cycle and
- (2) $E_{-i}^{'} \left[\beta^{i} \left(f\left(r^{i}, t^{-i} \right) \mid t^{-i} \right) \right]$ is path independent.

Proof sketch

- Necessity of (2):
 - No-negative cycle $\Rightarrow E_{-i} \left[\beta^i \left(f \left(r^i, t^{-i} \right) \mid t^{-i} \right) \right]$ cyclically monotone (Rockafellar 1966) \Rightarrow is a selection of the sub-differential of a convex function (Rockafellar 1970) \Rightarrow path-independence (Krishna & Maenner 2001).
- Sufficiency:
 - Take a negative cycle. Decomposition monotonicity allows to bound edge lengths l(s,r) from below by integrals. Path-independence shows that the resulting integral is equal to 0.
- **Remark:** Neither of (1) or (2) implies the other, in particular this means that only (1) is not sufficient for B N I C

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