

Algorithms for 2-player Nash Equilibrium

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Nash Equilibrium

Two-player version

- A pair of strategies (\mathbf{x}, \mathbf{y}) is **NE** iff neither can increase her payoff by deviating from her strategy **unilaterally**. That is

$$\mathbf{x}^T R \mathbf{y} \geq \mathbf{x}'^T R \mathbf{y}, \quad \forall \mathbf{x}' \in \Delta_m;$$

$$\mathbf{x}^T C \mathbf{y} \geq \mathbf{x}^T C \mathbf{y}', \quad \forall \mathbf{y}' \in \Delta_n.$$

- Or an equivalent definition
- Support** of \mathbf{x} : $\text{supp}(\mathbf{x}) := \{i \in [n] \mid x_i \neq 0\}$.
- Each action in the support of \mathbf{x} (or \mathbf{y}) should be the best response to the other.

$$x_i > 0 \Rightarrow \mathbf{e}_i^T R \mathbf{y} \geq \mathbf{e}_k^T R \mathbf{y}, \quad \forall k \in [m]$$

$$y_j > 0 \Rightarrow \mathbf{x}^T C \mathbf{e}_j \geq \mathbf{x}^T C \mathbf{e}_k, \quad \forall k \in [n]$$

Normal Form Games

- NFG: $\langle n, (S_p)_{p \in [n]}, (u_p)_{p \in [n]} \rangle$
 - # of players in the game, $[n] = \{1, \dots, n\}$
 - A set S_p of **pure strategies** of player $p \in [n]$
 - A utility function $u_p : \times_{p \in [n]} S_p \rightarrow \mathbb{R}$
- Recall RSP game...

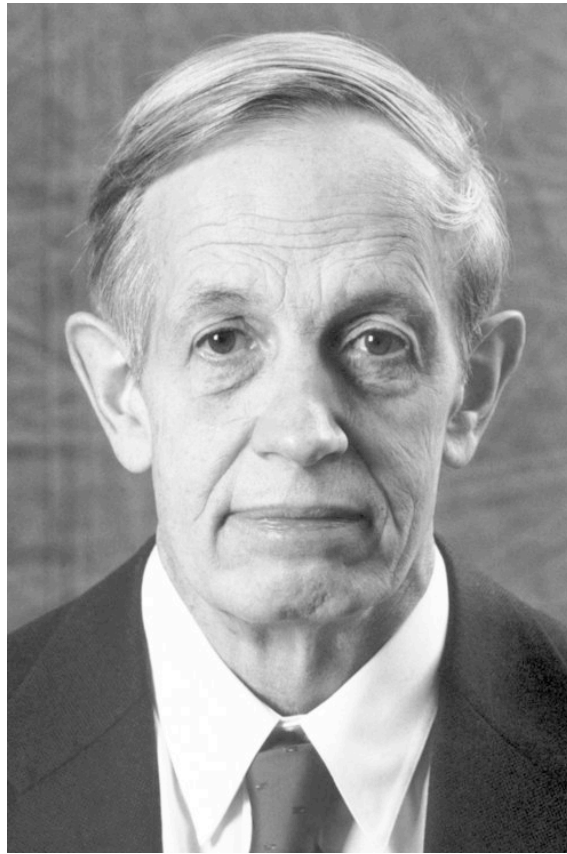
More math...

- The set Δ^{S_p} of mixed strategies to player p over S_p
- The set $S := \times_{p \in [n]} S_p$ of all the pure strategy profile.
 $\mathbf{s} = (s_1, \dots, s_n) \sim S$
- The set $\Delta := \times_{p \in [n]} \Delta^{S_p}$ of all the mixed strategy profile.
 $\mathbf{x} = (\mathbf{x}_1, \dots, \mathbf{x}_n) \sim \Delta$
- Given $\mathbf{x} \in \Delta$, we define the expected payoff of player p is

$$u_p(\mathbf{x}) = \sum_{\mathbf{s} \in S} u_p(\mathbf{s}) \prod_{q \in [n]} \mathbf{x}_q(s_q) = \mathbb{E}_{\mathbf{s} \sim \mathbf{x}} [u_p(\mathbf{s})].$$

- NE $\mathbf{x} \in \Delta$ in multi-player games iff given any $\mathbf{x}'_p \in \Delta^{S_p}$

$$u_p(\mathbf{x}) \geq u_p(\mathbf{x}'_p; \mathbf{x}_{-p})$$



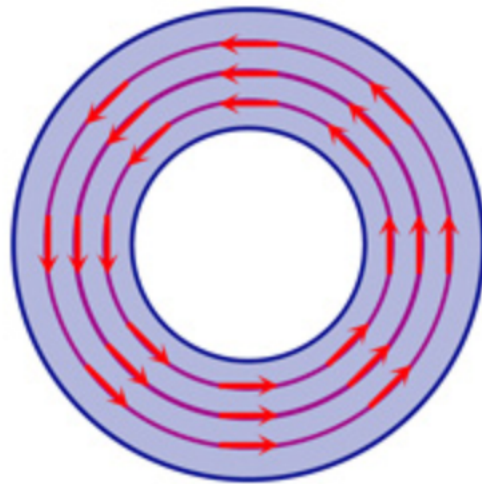
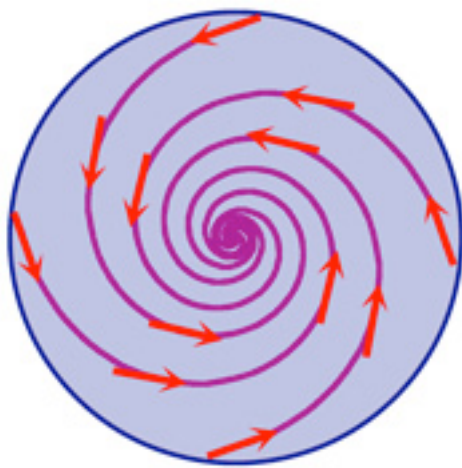
Nash's Theorem: "Every (finite) game has a Nash equilibrium."

John Forbes Nash Jr.

Proof of Nash's Theorem

An reduction to fixed point.

- The **idea** is to construct a reduction from the problem of finding an NE in a NFG to the problem of finding a fixed point in a well-defined domain.
- [Brouwer's Fixed Point Thm] Let D be a good (**convex**, **compact**) subset of \mathbf{R}^n . If a function $f : D \rightarrow D$ is continuous, then there exists an $x \in D$ such that $f(x) = x$.



- Let's make a mapping between these two problems.
- So the question is how to construct the continuous function f .
 - It's a good choice to set $f : \Delta \rightarrow \Delta$.
- We define a **gain function** $G_{p,s_p}(\mathbf{x}) := \max\{u_p(s_p; \mathbf{x}_{-p}) - u_p(\mathbf{x}), 0\}$.
 - Can you increase your utility when only using s_p instead of \mathbf{x}_p ?
- We define $\mathbf{y} = f(\mathbf{x})$, where $y_{p,s_p} := \frac{x_{p,s_p} + G_{p,s_p}(\mathbf{x})}{1 + \sum_{s'_p \in S_p} G_{p,s'_p}(\mathbf{x})}$.
- f is well-defined, continuous and Δ is good enough \Rightarrow Bingo!
- Next we will show that any fixed point of f is an NE of the game.

$$y_{p,s_p} := \frac{x_{p,s_p} + G_{p,s_p}(\mathbf{x})}{1 + \sum_{s'_p \in S_p} G_{p,s'_p}(\mathbf{x})}$$

- Given $\mathbf{x} = f(\mathbf{x})$, sufficient to show that $G_{p,s_p}(\mathbf{x}) = 0$, $\forall p, s_p$
- Proof by contradiction!
 - Assume that there exists p, s_p such that $G_{p,s_p}(\mathbf{x}) > 0$
 - $x_{p,s_p} > 0$, otherwise $x_{p,s_p} = 0$ but $y_{p,s_p} > 0$
 - There exists some other pure strategy s'_p such that $x_{p,s'_p} > 0$ and $u_p(s'_p; \mathbf{x}_{-p}) - u_p(\mathbf{x}) < 0$
 - By $u_p(\mathbf{x}) = \sum_{s \in S_p} x_{p,s} \cdot u_p(s; \mathbf{x}_{-p})$
 - We have $y_{p,s'_p} < x_{p,s'_p}$, so \mathbf{x} is not a fixed point!

Algorithms for 2-player NE

We will never discuss the multi-player case in the future...

Overview

- Support Enumeration Algorithm
- The Lipton-Markakis-Mehta (LMM) **Approximation** Algorithm
- The Lemke-Howson (LH) Algorithm (Next lecture)

Support Enumeration Algorithm

What if we know the supports of an NE?

- Let (R, C) be a two-player game, where $R, C \in \mathbb{R}^{m \times n}$.
- Someone tells us the supports S_R and S_C of their NE (\mathbf{x}, \mathbf{y}) , that is $S_R = \text{supp}(\mathbf{x})$ and $S_C = \text{supp}(\mathbf{y})$.
- How many possible pairs of S_R and S_C ? So the running time is not good...

$$\begin{aligned} & \max 0 \\ \text{s.t. } & \mathbf{e}_i^T R \mathbf{y} \geq \mathbf{e}_j^T R \mathbf{y}, \forall i \in S_R, j \in [m] \\ & \mathbf{x}^T C \mathbf{e}_i \geq \mathbf{x}^T C \mathbf{e}_j, \forall i \in S_C, j \in [n] \\ & \mathbf{x}^T \mathbf{1} = 1, \mathbf{y}^T \mathbf{1} = 1 \\ & x_i = 0, \forall i \notin S_R, y_j = 0, \forall j \notin S_C \end{aligned}$$

Relax the goal!

Approximate NE

- In the literature, we have two different definition of approximate NE. (We assume that $R, C \in [0,1]^{n \times n}$)

- “ ϵ -Approximate” NE: given any $\epsilon > 0$,

$$\begin{aligned} \mathbf{x}^T R \mathbf{y} &\geq \mathbf{x}'^T R \mathbf{y} - \epsilon, \quad \forall \mathbf{x}' \in \Delta_n; \\ \mathbf{x}^T C \mathbf{y} &\geq \mathbf{x}^T C \mathbf{y}' - \epsilon, \quad \forall \mathbf{y}' \in \Delta_n. \end{aligned}$$

- “ ϵ -Well-Supported” NE: given any $\epsilon > 0$,

$$\begin{aligned} x_i > 0 &\Rightarrow \mathbf{e}_i^T R \mathbf{y} \geq \mathbf{e}_k^T R \mathbf{y} - \epsilon, \quad \forall k \in [n] \\ y_j > 0 &\Rightarrow \mathbf{x}^T C \mathbf{e}_j \geq \mathbf{x}^T C \mathbf{e}_k - \epsilon, \quad \forall k \in [n] \end{aligned}$$

- ϵ -WSNE \Rightarrow ϵ -ANE; one can prove that $\epsilon^2/8$ -ANE \Rightarrow ϵ -WSNE

The LMM Algorithm

Lipton, R. J., Markakis, E., and Mehta, A. (2003). Playing large games using simple strategies. (EC'03)

Theorem 1 (Lipton et al.)

For any $\epsilon \in (0,1)$, there exists an ϵ -ANE where each player plays only $k = O(\log n/\epsilon^2)$ actions with positive probability.

- We use probabilistic method, that is, $\Pr[A] > 0 \Rightarrow A$ exists.
- Idea: approximating the original NE (\mathbf{x}, \mathbf{y}) with large enough samples from \mathbf{x}, \mathbf{y} . What is the **sample complexity**?

Theorem 2 (Chernoff Bound)

Let X_1, \dots, X_m be m random variables over $[0,1]$. For any $\epsilon > 0$ and X be the mean of $\{X_i\}_{i \in [m]}$, we have $\Pr \left[|X - \mathbb{E}[X]| \geq \epsilon \right] \leq 2 \exp(-2m\epsilon^2)$.

Proof of Theorem 1

- Let (\mathbf{x}, \mathbf{y}) be any NE of our instance.
- Take k i.i.d. samples (actions) (r_1, \dots, r_k) from the distribution \mathbf{x} .
- Let $\tilde{\mathbf{x}}$ be the “empirical” strategy which plays r_i uniformly at random. Similarly with $\tilde{\mathbf{y}}$.
- We will show, when k is large enough, below could happen:
 $|\mathbf{e}_i^T R \mathbf{y} - \mathbf{e}_i^T R \tilde{\mathbf{y}}| \leq \epsilon/2$ and $|\mathbf{x}^T C \mathbf{e}_j - \tilde{\mathbf{x}}^T C \mathbf{e}_j| \leq \epsilon/2$ where $i, j \in [n]$.
- If so, we have

$$\mathbf{e}_i^T R \tilde{\mathbf{y}} \leq \mathbf{e}_i^T R \mathbf{y} + \epsilon/2 \leq \frac{1}{k} \sum_{j=1}^k \mathbf{e}_{r_j}^T R \mathbf{y} + \epsilon/2 \leq \frac{1}{k} \sum_j \mathbf{e}_{r_j}^T R \tilde{\mathbf{y}} + \epsilon = \tilde{\mathbf{x}}^T R \tilde{\mathbf{y}} + \epsilon$$



Proving that $|\mathbf{e}_i^T R \mathbf{y} - \mathbf{e}_i^T R \tilde{\mathbf{y}}| \leq \epsilon/2$

Theorem 3 (The Union Bound)

$$\Pr[A_1 \cup A_2] \leq \Pr[A_1] + \Pr[A_2]$$

- We focus on a **bad case** that $|\mathbf{e}_i^T R \mathbf{y} - \mathbf{e}_i^T R \tilde{\mathbf{y}}| > \epsilon/2$ for fixed i
- By Chernoff bound, we have (by setting $X_j = \mathbf{e}_i^T R \mathbf{e}_{r_j}$)
 $\Pr[|\mathbf{e}_i^T R \mathbf{y} - \mathbf{e}_i^T R \tilde{\mathbf{y}}| > \epsilon/2] \leq 2 \exp(-k\epsilon^2/2).$
- By the union bound, we have $2n$ bad cases, so the probability that any of the bad cases happens is at most $4n \exp(-k\epsilon^2/2).$
- For $k > 2 \log(4n)/\epsilon^2$, the probability above is less than 1!

Remark for LMM algo

- One can approximate any NE w.r.t. ANE
- The running time is $\binom{n}{k}^2 = n^{O(\frac{\log n}{\epsilon^2})}$.
- With reasonable assumption ([ETH for PPAD](#)), Rubinstein (FOCS'16) proved that LMM is optimal, that is, finding an ϵ -ANE needs at least $n^{\log^{1-o(1)} n}$.

Comments

- 师者，所以传道受业解惑也
- 大学与中学的区别
- 《实践论》和《矛盾论》

Q&A?

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