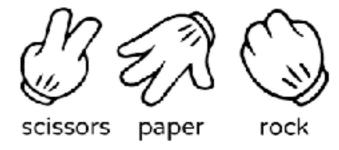
## **Equilibrium Computation**

**Zhengyang Liu, BIT** 

## Games

A set of Players/Agents
A set of Actions/Strategies
A set of Payoffs/Utilities



|   | S    | Р    | R    |
|---|------|------|------|
| S | 0,0  | 1,-1 | -1,1 |
| Р | -1,1 | 0,0  | 1,-1 |
| R | 1,-1 | -1,1 | 0,0  |

## **Two-Player Games**

- A pair of payoff matrices (R, C) of size  $m \times n$ , where Row player has m actions and Column player has n actions. (action  $\iff$  pure strategy)
- $R_{i,j}$  and  $C_{i,j}$  are the payoffs when the row player uses the i-th action and the column player uses the j-th one, respectively.
- Mixed strategy: a distribution over pure strategies. Denoted by  $\Delta_n$  the set of all mixed strategies over n actions. That is,

$$\Delta_n := \{ \mathbf{x} = (x_1, ..., x_n) \in \mathbb{R}^n \mid \sum_{i \in [n]} x_i = 1, x_i \ge 0 \}.$$

• Expected payoff: given  $\mathbf{x} \in \Delta_m$ ,  $\mathbf{y} \in \Delta_n$ , they are  $\mathbf{x}^T R \mathbf{y}$  and  $\mathbf{x}^T C \mathbf{y}$ .

## Nash Equilibrium

#### **Two-player version**

• A pair of strategies (x, y) is NE iff neither can increase her payoff by deviating from her strategy unilaterally. That is

$$\mathbf{x}^T R \mathbf{y} \ge \mathbf{x}^{T} R \mathbf{y}, \ \forall \mathbf{x}' \in \Delta_m;$$
  
 $\mathbf{x}^T C \mathbf{y} \ge \mathbf{x}^T C \mathbf{y}', \ \forall \mathbf{y}' \in \Delta_n.$ 

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

$$i \in \text{supp}(\mathbf{x}) \Rightarrow \mathbf{e}_i^T R \mathbf{y} \ge \mathbf{e}_k^T R \mathbf{y}, \forall k \in [m]$$
  
 $j \in \text{supp}(\mathbf{y}) \Rightarrow \mathbf{x}^T C \mathbf{e}_i \ge \mathbf{x}^T C \mathbf{e}_k, \forall k \in [n]$ 

## **Normal Form Games**

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

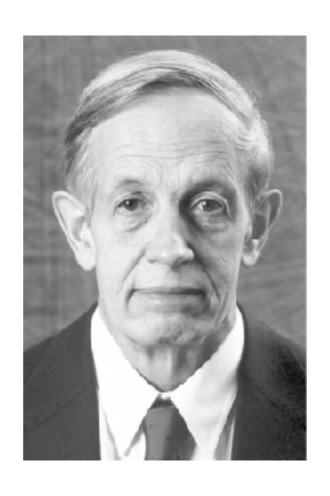
## More natation...

- The set  $\Delta^{S_p}$  of mixed strategies to player p over  $S_p$
- The set  $S := \times_{p \in [n]} S_p$  of all the pure strategy profile.  $\mathbf{s} = (s_1, ..., s_n) \sim S$
- The set  $\Delta:=\mathbf{x}_{p\in[n]}\,\Delta^{S_p}$  of all the mixed strategy profile.  $\mathbf{x}=(\mathbf{x_1},...,\mathbf{x_n})\sim\Delta$
- Given  $\mathbf{x} \in \Delta$ , we define the expected payoff of player p is

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

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

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



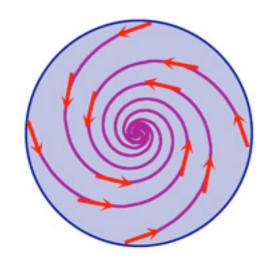
## Nash's Theorem: "Every (finite) game has a Nash equilibrium."

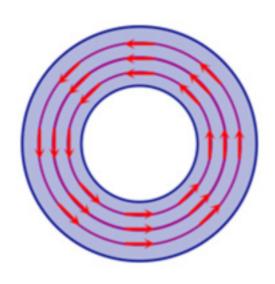
John Forbes Nash Jr.

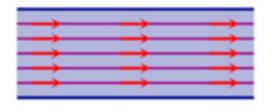
### **Proof of Nash's Theorem**

#### 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 welldefined domain.
- [Brouwer's Fixed Point Thm] Let D be a good (convex, compact) subset of  $\mathbb{R}^n$ . If a function  $f:D\to D$  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  $f: \Delta \to \Delta$ .
- 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  $\Delta$  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 **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 (Not mentioned)

## **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  $S_R = \operatorname{supp}(\mathbf{x})$  and  $S_C = \operatorname{supp}(\mathbf{y})$ .
- How many possible pairs of  $S_R$  and  $S_C$ ? So the running time is not good...

$$\max 0$$
s.t.  $\mathbf{e}_{i}^{T}R\mathbf{y} \geq \mathbf{e}_{j}^{T}R\mathbf{y}, \forall i \in S_{R}, j \in [m]$ 

$$\mathbf{x}^{T}C\mathbf{e}_{i} \geq \mathbf{x}^{T}C\mathbf{e}_{j}, \forall i \in S_{C}, j \in [n]$$

$$\mathbf{x}^{T}\mathbf{1} = 1, \mathbf{y}^{T}\mathbf{1} = 1$$

$$x_{i} = 0, \forall i \notin S_{R}, y_{j} = 0, \forall j \notin S_{C}$$

## Relax the goal!

#### **Approximate NE**

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

$$\mathbf{x}^T R \mathbf{y} \ge \mathbf{x}^T R \mathbf{y} - \epsilon, \ \forall \mathbf{x}' \in \Delta_n;$$
  
 $\mathbf{x}^T C \mathbf{y} \ge \mathbf{x}^T C \mathbf{y}' - \epsilon, \ \forall \mathbf{y}' \in \Delta_n.$ 

• " $\epsilon$ -Well-Supported" NE: given any  $\epsilon > 0$ ,

$$x_i > 0 \Rightarrow \mathbf{e}_i^T R \mathbf{y} \ge \mathbf{e}_k^T R \mathbf{y} - \epsilon, \forall k \in [n]$$
$$y_i > 0 \Rightarrow \mathbf{x}^T C \mathbf{e}_i \ge \mathbf{x}^T C \mathbf{e}_k - \epsilon, \forall k \in [n]$$

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

## The LMM Algorithm

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

#### Theorem (Liption et al.)

For any  $\epsilon \in (0,1)$ , there exists an  $\epsilon$ -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 (x, y) with large enough samples from x, y. What is the sample complexity?

#### **Theorem (Chernoff Bound)**

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

## **Proof**

- Let  $(\mathbf{x}, \mathbf{y})$  be any NE of our instance.
- Take k i.i.d. samples (actions)  $(r_1, ..., r_k)$  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:  $|\mathbf{e}_i^T R \mathbf{y} \mathbf{e}_i^T R \tilde{\mathbf{y}}| \le \epsilon/2$  and  $|\mathbf{x}^T C \mathbf{e}_j \tilde{\mathbf{x}}^T C \mathbf{e}_j| \le \epsilon/2$  where  $i, j \in [n]$ .
- If so, we have

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

#### **Theorem 3 (The Union Bound)**

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

- 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  $X_j = \mathbf{e}_i^T R \mathbf{e}_{r_j}$ )  $\Pr[|\mathbf{e}_i^T R \mathbf{y} \mathbf{e}_i^T R \tilde{\mathbf{y}}| > \epsilon/2] \le 2 \exp(-k\epsilon^2/2).$
- By the union bound, we have 2n bad cases, so the probability that any of the bad cases happens is at most  $4n \exp(-ke^2/2)$ .
- 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 
$$\binom{n}{k}^2 = n^{O\left(\frac{\log n}{\epsilon^2}\right)}$$
.

• With reasonable assumption (ETH for PPAD), [Rub'16] proved that LMM is optimal, that is, finding an  $\epsilon$ -ANE needs at least  $n^{\log^{1-o(1)}n}$ .

# Thanks!

zhengyang@bit.edu.cn