

## Lecture 5 – Approximation of Nash Equilibria

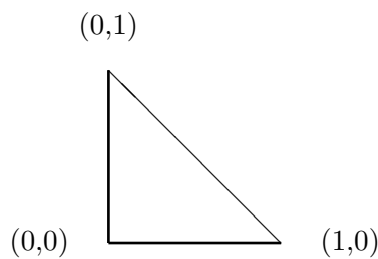
Instructor: *Xi Chen*Scribes: *Yundi Zhang*

## 1 Brouwer's fixed point theorem

We are going to show Brouwer's fixed point theorem for triangles:

**Theorem 1.** *Let  $\Delta$  be a triangle in  $\mathbb{R}^2$ . Then every continuous function  $f$  from  $\Delta$  to itself has a fixed point  $\mathbf{x} \in \Delta$  such that  $f(\mathbf{x}) = \mathbf{x}$ .*

*Proof.* For convenience, we will prove the theorem for the following particular triangle  $\Delta$ :



Without loss of generality, we assume the three vertices of  $\Delta$ ,  $(0,0)$ ,  $(1,0)$  and  $(0,1)$ , are not fixed point; otherwise we are already done.

The plan of the proof is as follows. For every  $i > 1$ , we let  $S_i$  denote the standard  $i$ -th triangulation of  $\Delta$ . Given  $f$ , we will define carefully a 3-coloring  $C_i$  over the vertices of  $S_i$  for every  $i > 1$ . We will then show that  $C_i$  is a proper coloring for all  $i$  and thus, by Sperner's lemma, has at least one trichromatic triangle, denoted by  $\Delta_i$ . As  $i$  goes up, this sequence of trichromatic triangles  $\{\Delta_i\}$  becomes smaller and smaller. We use  $\mathbf{u}_i, \mathbf{v}_i, \mathbf{w}_i \in \mathbb{R}^2$  to denote the red, blue, green vertex of  $\Delta_i$ , respectively. Because  $\{\mathbf{u}_i\}$  is an infinite sequence of points in  $\Delta$ , it must have a converging subsequence  $\{\mathbf{u}_{i_j}\}_{j \geq 1}$ . We finish the proof by showing that the limit of  $\{\mathbf{u}_{i_j}\}_{j \geq 1}$  must be a fixed point of  $f$ .

### Definition of $C_i$ over $S_i$ :

Let  $\mathbf{v} = (v_1, v_2)$  be any vertex of  $S_i$ , where  $v_1$  is the  $x$ -coordinate of  $\mathbf{v}$  and  $v_2$  is the  $y$ -coordinate of  $\mathbf{v}$ . We use  $f(\mathbf{v}) = (f_1(\mathbf{v}), f_2(\mathbf{v}))$  to color  $\mathbf{v}$  as follows:

1. If  $f_2(\mathbf{v}) < v_2$ , set  $C_i(\mathbf{v})$  to be red;
2. If  $f_2(\mathbf{v}) \geq v_2$  and  $f_1(\mathbf{v}) < v_1$ , set  $C_i(\mathbf{v})$  to be blue;
3. Otherwise (when  $f_2(\mathbf{v}) \geq v_2$  and  $f_1(\mathbf{v}) \geq v_1$ ), set  $C_i(\mathbf{v})$  to be green.

By following these rules (and using the assumption that the three vertices of  $\Delta$  are not fixed point of  $f$ ), it is easy to check that the color of  $(0,1)$  must be red; the color of  $(1,0)$  must be blue; the color of  $(0,0)$  must be green; and moreover,  $C_i$  is a proper 3-coloring over  $S_i$ .

Then by Sperner's lemma, we know that  $C_i$  has at least one trichromatic triangle  $\Delta_i$ , and we denote its red, blue and green vertex by  $\mathbf{u}_i, \mathbf{v}_i$  and  $\mathbf{w}_i \in \Delta$ , respectively. In this way, we get an infinite sequence of points  $\{\mathbf{u}_i\}$  in  $\Delta$ . Because  $\Delta$  is clearly bounded and closed,  $\{\mathbf{u}_i\}$  must have a converging subsequence  $\{\mathbf{u}_{i_j}\}_{j \geq 1}$ , with indices  $i_1 < i_2 < \dots$ . We use  $\mathbf{x} \in \Delta$  to denote its limit.

**$\mathbf{x}$  is a fixed point of  $f$ :**

First of all, since the size of  $\Delta_i$  decreases strictly as  $i$  goes up. It is easy to show that both sequences  $\{\mathbf{v}_{i_j}\}_{j \geq 1}$  and  $\{\mathbf{w}_{i_j}\}_{j \geq 1}$  converge to  $\mathbf{x}$ .

Because every point  $\mathbf{u}$  in the sequence  $\{\mathbf{u}_{i_j}\}$  is red, by the coloring rule, we have

$$f_2(\mathbf{u}) < u_2, \quad \text{for all } \mathbf{u} \text{ in the sequence.}$$

Since  $\mathbf{x}$  is the limit of the sequence  $\{\mathbf{u}_{i_j}\}$  and  $f$  is continuous, we have  $f_2(\mathbf{x}) \leq x_2$ .

Similarly, because every point  $\mathbf{v}$  in the sequence  $\{\mathbf{v}_{i_j}\}$  is blue, by the coloring rule, we have

$$f_1(\mathbf{v}) < v_1, \quad \text{for all } \mathbf{v} \text{ in the sequence.}$$

Since  $\mathbf{x}$  is the limit of the sequence  $\{\mathbf{v}_{i_j}\}$  and  $f$  is continuous, we have  $f_1(\mathbf{x}) \leq x_1$ .

Finally, because every point  $\mathbf{w}$  in the sequence  $\{\mathbf{w}_{i_j}\}$  is green, by the coloring rule, we have

$$f_1(\mathbf{w}) \geq w_1 \quad \text{and} \quad f_2(\mathbf{w}) \geq w_2, \quad \text{for all } \mathbf{w} \text{ in the sequence.}$$

Since  $\mathbf{x}$  is the limit of the sequence  $\{\mathbf{w}_{i_j}\}$  and  $f$  is continuous, we have  $f_1(\mathbf{x}) \geq x_1$  and  $f_2(\mathbf{x}) \geq x_2$ .

Combining all four inequalities, we conclude that  $\mathbf{x}$  is a fixed point of  $f$ . □

## 2 Existence of Rational Nash Equilibria in Two-Player Games

Given a two-player game  $G = (\mathbf{A}, \mathbf{B})$ , where every entry of  $\mathbf{A}$  and  $\mathbf{B}$  is rational, does it always have a rational Nash equilibrium  $(\mathbf{x}, \mathbf{y})$  in which all the entries are rational numbers? In Nash's paper, he gave a very simple three-player rational game with no rational Nash equilibrium. However, we will prove the following theorem:

**Theorem 2.** *Every rational two-player game  $G = (\mathbf{A}, \mathbf{B})$  has a rational Nash Equilibrium  $(\mathbf{x}, \mathbf{y})$ . Moreover, the number of bits needed to describe  $(\mathbf{x}, \mathbf{y})$  is polynomial in the input size of  $G$ .*

*Proof.* We will use the following property: If a rational linear program has a solution, then it always has a rational solution. Furthermore, the number of bits needed to describe it is polynomial in the input size of the linear program.

We use the idea of **Support Enumeration**. Given vectors  $\mathbf{x} \in \Delta_m$  and  $\mathbf{y} \in \Delta_n$ , we let

$$\text{Supp}(\mathbf{x}) = \{i | x_i > 0\} \subseteq [m] \quad \text{and} \quad \text{Supp}(\mathbf{y}) = \{j | y_j > 0\} \subseteq [n].$$

Now for any pair of nonempty subsets  $S \subseteq [m]$  and  $T \subseteq [n]$ , we let  $\text{LP}(S, T)$  denote the following linear

program with variables  $x_1, \dots, x_m, y_1, \dots, y_n$ :

$$\begin{aligned}
& \text{LP}(S, T) : \\
& \sum_{i \in [m]} x_i = 1 \\
& x_i > 0 \quad \text{for all } i \in S \\
& x_i = 0 \quad \text{for all } i \notin S \\
& \sum_{j \in [n]} y_j = 1 \\
& y_j > 0 \quad \text{for all } j \in T \\
& y_j = 0 \quad \text{for all } j \notin T \\
& \mathbf{A}_{i,*} \mathbf{y} \geq \mathbf{A}_{j,*} \mathbf{y} \quad \text{for all } i \in S \text{ and } j \in [m] \\
& \mathbf{x}^T \mathbf{B}_{*,i} \geq \mathbf{x}^T \mathbf{B}_{*,j} \quad \text{for all } i \in T \text{ and } j \in [n]
\end{aligned}$$

By the definition of Nash equilibria, it is easy to prove the following property:

**Property 3.** *The linear program  $\text{LP}(S, T)$  has a solution  $(\mathbf{x}, \mathbf{y})$  if and only if  $(\mathbf{x}, \mathbf{y})$  is a Nash equilibrium of  $G = (\mathbf{A}, \mathbf{B})$  such that*

$$\text{Supp}(\mathbf{x}) = S \quad \text{and} \quad \text{Supp}(\mathbf{y}) = T.$$

Now by Nash's theorem, we know  $G = (\mathbf{A}, \mathbf{B})$  has a Nash equilibrium  $(\mathbf{x}^*, \mathbf{y}^*)$  (even though it may not be rational). Let  $S = \text{Supp}(\mathbf{x}^*)$  and  $T = \text{Supp}(\mathbf{y}^*)$ , then by the property above,  $(\mathbf{x}^*, \mathbf{y}^*)$  is a solution to the linear program  $\text{LP}(S, T)$ . As a result, we know that  $\text{LP}(S, T)$  has a rational solution which we denote by  $(\mathbf{x}, \mathbf{y})$ , and the number of bits needed to describe  $(\mathbf{x}, \mathbf{y})$  is polynomial in the input size of  $G$ . Using the property above again,  $(\mathbf{x}, \mathbf{y})$  must also be an equilibrium of  $G$ , and the theorem follows.  $\square$

### 3 Approximation of Nash Equilibrium

We combine support enumeration with the probabilistic method to give an approximation algorithm for Nash equilibria. In this section, we always assume that the entries of  $\mathbf{A}$  and  $\mathbf{B}$  are between 0 and 1. For simplicity, we also assume that both matrices are  $n$ -by- $n$ .

**Definition 4.** *Given  $G = (\mathbf{A}, \mathbf{B})$  with  $A_{i,j}, B_{i,j} \in [0, 1]$  for all  $i, j \in [n]$ , we say  $(\mathbf{x}, \mathbf{y})$  is an  $\epsilon$ -approximate Nash equilibrium for some  $\epsilon > 0$  if*

$$\begin{aligned}
\mathbf{x}^T \mathbf{A} \mathbf{y} &\geq (\mathbf{x}')^T \mathbf{A} \mathbf{y} - \epsilon, & \text{for all } \mathbf{x}' \in \Delta_n; \\
\mathbf{x}^T \mathbf{B} \mathbf{y} &\geq \mathbf{x}^T \mathbf{B} \mathbf{y}' - \epsilon, & \text{for all } \mathbf{y}' \in \Delta_n.
\end{aligned}$$

We say a probability distribution  $\mathbf{x}$  is  $k$ -uniform, for some  $k \geq 1$ , if every entry  $x_i$  of  $\mathbf{x}$  is a multiple of  $1/k$ . One way to interpret  $k$ -uniform distributions is to imagine that there are  $k$  balls numbered from 1 to  $k$ ; and there are  $n$  bins numbered from 1 to  $n$ . The balls are then tossed arbitrarily into the bins.

Every possible result gives a  $k$ -uniform distribution:

$$x_i = \frac{\# \text{ of balls in bin } i}{k}, \quad \text{for all } i \in [n].$$

We will use the probability method to prove the following theorem:

**Theorem 5.** *Given any two-player game  $G = (\mathbf{A}, \mathbf{B})$  with  $A_{i,j}, B_{i,j} \in [0, 1]$  for all  $i, j \in [n]$ , it has an  $\epsilon$ -approximate Nash Equilibrium  $(\mathbf{x}, \mathbf{y})$  in which both  $\mathbf{x}$  and  $\mathbf{y}$  are  $k$ -uniform distributions with*

$$k = \frac{100 \cdot \ln n}{\epsilon^2}.$$

This theorem gives us the following algorithm to compute an  $\epsilon$ -approximate Nash equilibrium:

1. Enumerate all pairs of  $k$ -uniform probability distributions  $(\mathbf{x}, \mathbf{y})$ ;
2. Output  $(\mathbf{x}, \mathbf{y})$  if it is an  $\epsilon$ -approximate Nash equilibrium.

The correctness of this (support enumeration) algorithm (that it always outputs an  $\epsilon$ -approximate Nash equilibrium of  $G$ ) follows from the theorem above. It is also easy to see that its time complexity is

$$n^{O(k)} = n^{O(\ln n / \epsilon^2)}.$$

*Proof Sketch of Theorem 5.* First of all, by Nash's theorem,  $G$  has an equilibrium  $(\mathbf{x}, \mathbf{y})$  with  $\mathbf{x}, \mathbf{y} \in \Delta_n$ .

We use the probabilistic method. To this end, we randomly pick a  $k$ -uniform probability distribution  $\hat{\mathbf{x}}$  as follows:

1. For each  $i \in [k]$ , independently put ball  $i$  into bin  $j$ ,  $j \in [n]$ , with probability  $x_j$ ;
2. Then set  $\hat{x}_j = \# \text{ of balls in bin } j / k$  for all  $j \in [n]$ .

We also randomly and independently pick a  $k$ -uniform distribution  $\hat{\mathbf{y}} \in \Delta_n$  using  $\mathbf{y}$  in the same way.

To prove there exists an  $\epsilon$ -approximate Nash equilibrium in which both distributions are  $k$ -uniform, it suffices to show that

$$\Pr \left[ (\hat{\mathbf{x}}, \hat{\mathbf{y}}) \text{ is an } \epsilon\text{-approximate Nash equilibrium of } G = (\mathbf{A}, \mathbf{B}) \right] > 0.$$

By the definition of  $\epsilon$ -approximate equilibria, it suffices to show that

$$\Pr \left( \begin{array}{l} \forall i, \mathbf{A}_{i,*} \hat{\mathbf{y}} \leq \hat{\mathbf{x}}^T \mathbf{A} \hat{\mathbf{y}} + \epsilon \\ \forall j, \hat{\mathbf{x}}^T \mathbf{B}_{*,j} \leq \hat{\mathbf{x}}^T \mathbf{B} \hat{\mathbf{y}} + \epsilon \end{array} \right) > 0.$$

This will follow directly if we can prove that: For every  $i \in [n]$ ,

$$\Pr \left[ \mathbf{A}_{i,*} \hat{\mathbf{y}} - \hat{\mathbf{x}}^T \mathbf{A} \hat{\mathbf{y}} > \epsilon \right] < \frac{1}{n^{20}} \tag{1}$$

and for every  $j \in [n]$ ,

$$\Pr \left[ \hat{\mathbf{x}}^T \mathbf{B}_{*,j} - \hat{\mathbf{x}}^T \mathbf{B} \hat{\mathbf{y}} > \epsilon \right] < \frac{1}{n^{20}}. \tag{2}$$

To prove (1), we rewrite it as

$$\Pr \left[ (\mathbf{A}_{i,*}\widehat{\mathbf{y}} - \mathbf{A}_{i,*}\mathbf{y}) + (\mathbf{A}_{i,*}\mathbf{y} - \mathbf{x}^T \mathbf{A}\mathbf{y}) + (\mathbf{x}^T \mathbf{A}\mathbf{y} - \widehat{\mathbf{x}}^T \mathbf{A}\mathbf{y}) + (\widehat{\mathbf{x}}^T \mathbf{A}\mathbf{y} - \widehat{\mathbf{x}}^T \mathbf{A}\widehat{\mathbf{y}}) > \epsilon \right]. \quad (3)$$

Because  $(\mathbf{x}, \mathbf{y})$  is a Nash equilibrium, it follows from the definition that  $(\mathbf{A}_{i,*}\mathbf{y} - \mathbf{x}^T \mathbf{A}\mathbf{y}) \leq 0$ . As a result, the probability in (3) is upper bounded by

$$\begin{aligned} & \Pr \left[ \mathbf{A}_{i,*}\widehat{\mathbf{y}} - \mathbf{A}_{i,*}\mathbf{y} > \epsilon/3 \text{ or } \mathbf{x}^T \mathbf{A}\mathbf{y} - \widehat{\mathbf{x}}^T \mathbf{A}\mathbf{y} > \epsilon/3 \text{ or } \widehat{\mathbf{x}}^T \mathbf{A}\mathbf{y} - \widehat{\mathbf{x}}^T \mathbf{A}\widehat{\mathbf{y}} > \epsilon/3 \right] \\ & \leq \Pr \left[ \mathbf{A}_{i,*}\widehat{\mathbf{y}} - \mathbf{A}_{i,*}\mathbf{y} > \epsilon/3 \right] + \Pr \left[ \mathbf{x}^T \mathbf{A}\mathbf{y} - \widehat{\mathbf{x}}^T \mathbf{A}\mathbf{y} > \epsilon/3 \right] + \Pr \left[ \widehat{\mathbf{x}}^T \mathbf{A}\mathbf{y} - \widehat{\mathbf{x}}^T \mathbf{A}\widehat{\mathbf{y}} > \epsilon/3 \right]. \end{aligned}$$

We bound the first term using the Hoeffding inequality. For each  $\ell \in [k]$ , let  $z_\ell$  denote the following random variable:  $z_\ell = A_{i,j}$ , if ball  $\ell$  is tossed into bin  $j$  (when generating  $\widehat{\mathbf{y}}$  randomly from  $\mathbf{y}$ ), which happens with probability  $y_j$ . As a result,

$$E(z_\ell) = \sum_{j \in [n]} A_{i,j} \cdot y_j = \mathbf{A}_{i,*}\mathbf{y} \quad \text{and} \quad E(z_1 + \cdots + z_k) = k \cdot \mathbf{A}_{i,*}\mathbf{y}.$$

We also have

$$z_1 + \cdots + z_k = \sum_{j \in [n]} A_{i,j} \cdot \# \text{ of balls in bin } j = k \cdot \mathbf{A}_{i,*}\widehat{\mathbf{y}}.$$

By using the Hoeffding inequality, we have

$$\Pr \left[ \mathbf{A}_{i,*}\widehat{\mathbf{y}} - \mathbf{A}_{i,*}\mathbf{y} > \epsilon/3 \right] = \Pr \left[ (z_1 + \cdots + z_k) - E(z_1 + \cdots + z_k) > k \cdot \epsilon/3 \right] \leq e^{-\frac{2k\epsilon^2}{9}} = e^{-\frac{200 \ln n}{9}} \ll \frac{1}{n^{20}}.$$

We can see that the probability of event  $[\mathbf{A}_{i,*}\widehat{\mathbf{y}} - \mathbf{A}_{i,*}\mathbf{y} > \epsilon/3]$  is pretty small. Similarly, one can use Hoeffding inequality to prove that both

$$\Pr \left[ \mathbf{x}^T \mathbf{A}\mathbf{y} - \widehat{\mathbf{x}}^T \mathbf{A}\mathbf{y} > \epsilon/3 \right] \quad \text{and} \quad \Pr \left[ \widehat{\mathbf{x}}^T \mathbf{A}\mathbf{y} - \widehat{\mathbf{x}}^T \mathbf{A}\widehat{\mathbf{y}} > \epsilon/3 \right]$$

are small. This proves (1). The same argument can be used to prove (2), and the theorem follows.  $\square$