

Game Theory
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Lecture - 20
Non-Zero-Sum Games:
Existence of Nash Equilibrium - II

Welcome back to NPTEL course on game theory. In the previous session, we have proved the existence of Nash equilibrium using Brouwer fixed point theorem and of course the proof is for a general class of games, that means the strategy spaces can be any convex and compact subsets of Euclidean space. As I mentioned, the convex compact subsets in Euclidean space that can be relaxed and you can go to any infinite dimensional spaces, you can take the convex and compact subsets of any infinite dimensional space.

The only issue that requires to be changed is instead of using the Brouwer fixed point theorem, we have to use for example Schauder fixed point theorem, that is mainly the place what we need to change. Now, we will consider a situation where the game is given by bi-matrices, 2 matrices, and we will again derive the proof but unlike in zero-sum games, in zero-sum games we have we could avoid using Brouwer fixed point theorem by using the convexity arguments, but in a non-zero-sum games, we cannot do that, but we will give another proof which is originally due to John Nash.

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$$\pi_1(x, y) = x^T A y$$

$$\pi_2(x, y) = x^T B y$$

mixed Payoff functions.

These are bilinear functions.

\therefore The existence theorem proved in prev. session can be applied. to guarantee the existence of mixed Nash equilibrium.

So we will consider the a bimatrix game where A is the payoff matrix corresponding to player 1, B corresponds to player 2 and of course we are looking that these $m \times n$ matrices okay. So, let me recall the pure strategies here. Pure strategies are basically for player 1, the pure strategies are exactly the rows, so the player 1 is going to choose one of the row, that is his pure strategies and similarly choosing a column is a pure strategy for player 2. Now, what are mixed strategies

It is exactly like in zero-sum games, there is no difference, you are choosing the rows with probabilities certain probabilities. So, it is like x_1, x_2, \dots, x_m Δ_1 is the corresponding simplex, these are all x_i are greater than or equal to 0 and this sum to 1, so this is basically the Δ_1 is all points like this, that is Δ_1 . Similarly, this is for player 1, for player 2, y_1, y_2, \dots, y_n in Δ_2 where y_j are nonnegative and they sum to 1. These are the mixed strategies for player 2 and this defines Δ_2 okay.

So, once we have this pure and mixed strategies, the payoff extension is given by $\pi_1(x, y)$ which is nothing but $x^T A y$ $\pi_2(x, y)$ is nothing but $x^T B y$, these are the mixed payoff functions. The most important thing is that these are bilinear functions. These are bilinear functions, therefore π_1 is concave in x variable certainly and similarly π_2 is concave in y variable, therefore, the min-max the existence theorem proved in previous session can be applied to guarantee the existence of mixed Nash equilibrium.

So of course before applying it, we need to realize that Δ_1 and Δ_2 both are convex, this is obvious, we have seen it previously also, Δ_1 and Δ_2 are convex and compact and π_1, π_2 satisfies the necessary assumption, so therefore, this theorem can be applied. So therefore, there is always a mixed Nash equilibrium.

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Another Proof:

claim (x^*, y^*) is Nash equilibrium

iff $x^{*T} A y^* \geq \underline{e_i} A y^* \quad \forall i=1,2,\dots,m$

$x^* B y^* \geq x^* B \underline{e_j} \quad \forall j=1,2,\dots,n.$

Define

$$f: \Delta_1 \times \Delta_2 \rightarrow \Delta_1 \times \Delta_2$$

as follows.

This is the theorem, but we will try to give you another proof, another proof for this result. So, first thing what I would like to say here is that when we want to make the following claim x^*, y^* is Nash equilibrium if and only if $x^{*T} A y^*$ is greater than or equals to $e_i A y^*$ this should be true for all i equal to 1 to m and similarly $x^* B y^*$, this should be greater than or equals to $x^* B e_j$ for all j is equals to 1 to n , remember e_i and e_j that we have this notation that we have been using throughout this course, e_i are the pure strategies for player 1, e_j are the pure strategies for player 2 okay.

This is, why is this true? Basically, this comes from the bilinearity of π_1 and π_2 , so which the ideas we have been using again and again, so therefore, this does not require any further clarification, so this is a kind of an obvious statement once you recall all the arguments that we have been using okay. Now, we will define a function f . So, we will define a function f from the $\Delta_1 \times \Delta_2$ to $\Delta_1 \times \Delta_2$, which like the previously also we have done the same thing, we have used the best response structure there, but here we are using something different, so how we define.

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$$f(x, y) = (x', y') \text{ where } x', y' \text{ are defined as follows:}$$

$$c_i(x, y) = \max\{0, e_i^T A y - x^T A y\} \rightarrow \text{Cont}$$

$$d_j(x, y) = \max\{0, x^T B e^j - x^T B y\} \leftarrow \text{Cont}$$

and

$$x'_i = \frac{x_i + c_i(x, y)}{1 + \sum_{i=1}^m c_i(x, y)}, \quad y'_j = \frac{y_j + d_j(x, y)}{1 + \sum_{j=1}^n d_j(x, y)}$$

I will define $f(x, y)$ to be (x', y') where x' , y' are defined as follows. So, I define first $c_i(x, y)$, this is nothing but $\max\{0, e_i^T A y - x^T A y\}$ and $d_j(x, y)$ is $\max\{0, x^T B e^j - x^T B y\}$ and x'_i the i th coordinate of x' is given by $x_i + c_i(x, y)$ by $1 + \sum_{i=1}^m c_i(x, y)$ where i goes from 1 to m . Similarly y'_j is given by $y_j + d_j(x, y)$ by $1 + \sum_{j=1}^n d_j(x, y)$ and $d_j(x, y)$ okay. So, let us try to understand what these particular terms are giving.

So what is this term, $e_i^T A y - x^T A y$. Suppose if the player has played x and player 2 has played y and player 1 has played x , so he is going to get $x^T A y$. Instead of x , if the player 1 uses the pure strategy e_i , how much is he going to get, that is how much extra he is going to get? Suppose if he is getting more, then I would like to increase the probability of the e_i , then in x let us say I am playing with probability x_i , and then if by playing the pure strategy e_i , if I am going to get more than 0, then I would like to move towards e_i .

So, that is exactly captured here in this term, c_i , originally x_i is there and now I am moving towards the x' , I increased this probability because c_i is bigger than 0, therefore x'_i . Now if $e_i^T A y$ is not, is less than $x^T A y$ for example, then the means it is going to be negative value, so therefore this is 0, then I will not change x_i . So this is the direction in which I am moving the x the probability with which I play i th pure strategy.

Now, of course, when I move like that, I do not know whether that is going to be a probability vector or not, so therefore, I am normalizing. So sum over all these things and

sum over x_i is nothing but 1 and sum over the c_i is that is exactly this and similarly for the player 2 d_j , x, y is giving the excess pay the player 2 will get by deviating to pure strategy e_j , if he instead of playing y , if he deviates to e_j , the j th pure strategy, the excess payoff that he is going to get that is given by d_j , x, y .

Now if it is greater than 0, then the player 2 would like to move increase y_j in the direction of the d_j , however, that probability is this y_j plus d_j , x, y and that normalizing and this is the normalizing thing. Now, this is. So now, f , x, y is going to x' and y' . How is this x' defined, as x_i plus c_i , x, y , c_i , x, y is nothing but this x 's payoff function, this is clearly continuous function and this is also a continuous function.

So therefore, x_i plus c_i , x, y is the continuous function, y_j plus d_j , x, y this is also a continuous function and the term that is there in the denominator is a non-zero term because c_i are always non-negative and 1 plus sum non-negative terms, so therefore this is always greater than or equals to 1. So therefore, these are all well-defined things and continuous function and bivaried because we have normalized by these factors

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$$\sum x_i' = 1, \quad \sum y_j' = 1$$

$$\therefore f: \Delta_1 \times \Delta_2 \rightarrow \Delta_1 \times \Delta_2$$

we have a cont. map

$$\text{Brouwer} \rightarrow \exists (x^*, y^*) \text{ s.t.}$$

$$f(x^*, y^*) = (x^*, y^*)$$

The sum x_i' is going to be 1, similarly sum y_j' is also going to be 1, therefore the function f that we have defined actually takes the values of Δ_1 cross Δ_2 into Δ_1 cross Δ_2 . Therefore, we have a continuous map now and Brouwer fixed point theorem immediately implies there exist x^* , y^* such that $f(x^*, y^*)$ is same as x^* , y^* . Brouwer fixed point theorem now gives a fixed point x^* and y^* such that $f(x^*, y^*)$ is same as x^* , y^* .

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$$\begin{aligned} \therefore x_i^* &= \frac{x_i^* + c_i(x^*, y^*)}{1 + \sum_{i'} c_{i'}(x^*, y^*)} \\ \Rightarrow x_i^* \sum_{i'} c_{i'}(x^*, y^*) &= c_i(x^*, y^*) \\ \text{Need to show} \\ \underline{c_i(x^*, y^*)} &= 0 \text{ whenever } x_i^* > 0 \end{aligned}$$

Therefore, what we have is that x_i^* is same as x_i^* plus $c_i(x^*, y^*)$ by 1 plus summation $c_{i'}(x^*, y^*)$. So, let us look at this very carefully. From here, we would like to get some contradictions or to say that x^* and y^* are Nash equilibrium, how do we prove it? This immediately implies as by cross multiplication, we have $x_i^* \sum_{i'} c_{i'}(x^*, y^*) = c_i(x^*, y^*)$.

So, now the interesting thing here in this summation, for example i' where $c_{i'}(x^*, y^*) = 0$ that need not be considered if for some because the whole idea here for us is to show that this $c_{i'}(x^*, y^*)$ has to be 0. So whenever we need to show $c_i(x^*, y^*) = 0$ whenever $x_i^* > 0$. So, why do we want to do this one. If $x_i^* > 0$, that means the player 1 is playing the pure strategy e_i with the positive probability.

Now, look at the definition of c_i , if the player has played e_i with a positive probability, that means $e_i^T A y^*$ should be same as $x_i^T A y^*$, so that should happen. Therefore, this $c_i(x^*, y^*)$ should be 0, so this has to happen whenever $x_i^* > 0$. So, this is essentially the idea now. So, let us look at we need to show this fact okay.

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$$I = \{i \mid x_i^* > 0\}$$

$$J = \{i \mid c_i(x^*, y^*) > 0\}$$

claim $\sum c_{i'}(x^*, y^*) = 0$

Suppose not $\sum c_{i'}(x^*, y^*) > 0$

$$\sum_{i' \in J} c_{i'}(x^*, y^*) > 0$$

So let us take I to be set of all i such that x_i^* is greater than 0 okay. So, now therefore, let me also take J to be all i such that $c_i(x^*, y^*)$ is greater than 0 okay. So, let me take. Therefore, clearly from here, whenever x_i^* is greater than 0, look at those i's and here I am looking at i's where $c_i(x^*, y^*)$ is greater than 0. So now look at this. If x_i^* is greater than 0, okay, because we are interested in proving this one if x_i^* is greater than 0, I need to show that $c_i(x^*, y^*)$ should be 0.

Suppose if that does not happen, we are going via a contradiction, so in fact, our claim is going to be summation $c_{i'}(x^*, y^*)$ this is going to be 0 okay. So, suppose this does not happen, that means summation $c_{i'}(x^*, y^*)$ this is greater than 0. So, therefore, the summation in some sense I can take it to be i' in J, $c_{i'}(x^*, y^*)$, this is greater than 0, of course, these two are same okay.

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$$\begin{aligned}
i \in I &\Rightarrow \lambda_i^* > 0 \\
&\Rightarrow c_i(x^*, y^*) > 0 \\
&\Rightarrow e_i^T A y^* > \lambda^* A y^* \\
\lambda^{*T} A y^* &= \sum_{i=1}^m \lambda_i^* (e_i^T A y^*) \\
u_1 &\geq \sum_{i \in I} \lambda_i^* (e_i^T A y^*) > \sum \lambda_i^* u_1 \\
&= u_1
\end{aligned}$$

So, now look at for all. Let us take i belongs to I . This implies λ_i^* is greater than 0. This implies $c_i(x^*, y^*)$ is greater than 0 because this is by our contradiction, $c_i(x^*, y^*)$ is greater than 0, this is coming from this contradiction because we have assumed this. Therefore, this $c_i(x^*, y^*)$ is strictly greater than 0. What this implies by the definition of c_i , c_i is basically the excess pay that he is getting, what it says is that $e_i^T A y^*$ is bigger than $\lambda^* A y^*$, of course λ^* transposes okay, this happens okay.

Now, what is a $\lambda^{*T} A y^*$, this is same as summation λ_i^* of $e_i^T A y^*$ where i is equals to 1 to m , this is certainly greater than or equals to summation i prime i belongs to I of $\lambda_i^* e_i^T A y^*$ because if i is not in I then λ_i^* is 0, therefore this happens, and then from this previous thing, we have this j is there here, so this is going to be greater than summation λ_i^* into let me call this as a u_1 and this is going to be u_1 okay. So, what we have got is the u_1 is strictly bigger than u_1 , so this is a contradiction, this contradiction happened because we have assumed this.

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$$\therefore \sum c_i(x^*, y^*) = 0$$

$$\Rightarrow c_i(x^*, y^*) = 0 \quad \forall i$$

$$\Rightarrow e_i^T A y^* \leq x^{*T} A y^* \quad \forall i \in \{1, \dots, m\}$$

$\Rightarrow x^*$ is optimal for player 1.

Why y^* is optimal for pl. 2.



$\therefore (x^*, y^*)$ is NE.

Therefore, summation c_i prime x star, y star is going to be 0, therefore c_i x star, y star is 0 for each i , this implies e_i transpose A y star, this is certainly less than or equals to x star transpose A y , this is true for all i running from 1 to m . This implies okay, it is not y , y star, x star is optimal for player 1. In a similar fashion, y star is optimal for player 2. Therefore, x star, y star is Nash equilibrium okay

So this proof is again a simple proof which requires you to construct this specific function by this way, and then we show that this is a continuous function and this gives you a fixed point and we have to finally show that this fixed point is indeed a Nash equilibrium. So, this proves the existence of a Nash equilibrium.

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How do we compute NE?

optimization Problem:

$$\begin{aligned} \max_{x, y, \alpha, \beta} \quad & x^T(A+B)y - \alpha - \beta \\ \text{s.t.} \quad & Ay - \alpha \mathbb{1} \leq 0 \\ & B^T x - \beta \mathbb{1} \leq 0 \\ & x \in \Delta_1, \quad y \in \Delta_2. \end{aligned}$$

Our next task now is to get some optimization problem. So, basically how do we compute Nash equilibrium? Are there ways to do, ways to compute the Nash equilibrium? So, we will now discuss one optimization problem now, and of course, the solving algorithms we will postpone to next session, but now we will please look at a optimization problem which gives you the reformulation of a Nash equilibrium. So the problem is the following thing, optimization problem. Let me write it first.

This is nothing but maximize x, y, α, β so that $x^T A + B y$ minus α minus β subject to $A y$ minus $\alpha \mathbf{1}$, I will put the bold one means it is a vector of ones less than or equal to 0. Similarly summation okay $B^T x$ minus β again a vector of ones, this is less than or equals to 0 and of course x belongs to Δ_1 , y belongs to Δ_2 okay. So this is a quadratic programming. So what we have is that in this there are 4 decision variables x, y , and α, β and we need to choose the x, y, α, β which maximizes this.

Whatever maximizes this one, the x^* , y^* , and then α^* and β^* they correspond to the Nash equilibrium, x^* is going to be the optimal strategy for player 1, y^* is for player 2, and α^* is the value of player 1 and β^* is going to be the value of player 2. So, we will try to prove this fact.

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$$\begin{aligned} & \text{Let } (x^*, y^*) \text{ be NE.} \\ & \alpha^* = x^{*T} A y^*, \quad \beta^* = x^{*T} B y^* \\ & e_i A y^* \leq \alpha^* \quad \forall i \\ & \Rightarrow \| A y^* - \alpha^* \mathbf{1} \| \leq 0 \\ & \quad B^T x^* - \beta^* \mathbf{1} \leq 0 \\ & * x \in \Delta_1, \quad x^T A y^* \leq \alpha^* \\ & \quad y \in \Delta_2, \quad x^{*T} A y^* \leq \beta^* \end{aligned}$$

So, first let us see let x^*, y^* be Nash equilibrium. Let α^* to be $x^* A y^*$, y^* and similarly β^* let me put it as $x^* B y^*$, let us take this. Now, we know that in the previous itself we have seen that is that $e_i A y^*$ is really less than or

equals to alpha star, this is true for all i , that means $e_i^T A y^*$ is let us suppose to alpha star for every i , that means every entry of $A y^*$ is going to be less than or equals to alpha star. This implies $A y^* - \alpha^* \mathbf{1}$, the vector of ones, this is less than or equals to 0, this is obvious. In a similar fashion from here, from beta star, the definition of beta star we can easily see that $B^T x^* - \beta^* \mathbf{1} \leq 0$. This is an obvious thing from here and of course, x^*, y^* are all there and then the next thing is that for any x in Δ_1 , $x^T A y^*$ is less than or equals to alpha star. Similarly, for any y in Δ_2 , $x^{*T} A y$ is less than or equals to beta star.

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we can easily verify that
 $(x^*, y^*, \alpha^*, \beta^*)$ is optimal solution
for the optimization problem.
Next let $(x^*, y^*, \alpha^*, \beta^*)$ be optimal solution
of the optimization problem

Putting all these things together and combining with these facts, we can easily verify that $x^*, y^*, \alpha^*, \beta^*$ is optimal solution for the optimization problem. So $x^*, y^*, \alpha^*, \beta^*$ will satisfy. So, this here, when you are trying to prove from here, we have to use these facts as well okay. This is not a very hard thing, it is straightforward, but it requires just little effort, so one should try proving it. Here, we also have to understand the following fact.

In this optimization problem using these facts, we need to show that this is always less than or equal to 0, because $A y^* - \alpha^* \mathbf{1} \leq 0$, therefore $x^{*T} (A y^* - \alpha^* \mathbf{1}) \leq 0$ that has to be used here. Therefore, this maximum value is always non-positive and at Nash equilibrium, this is equal to 0, therefore $x^*, y^*, \alpha^*, \beta^*$ is going to be the optimal solution. So the details have to be furnished here, but they are a simple exercise.

Next, let x^* , y^* , α^* , β^* be optimal solution of the optimization problem. So, once we take this one, we need to show that this x^* , y^* corresponds to saddle Nash equilibrium. So let us see how we prove.

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$$\begin{aligned}
 & Ay^* - \alpha \mathbf{1} \leq 0 \\
 \Rightarrow & x^{*T} A y^* \leq \alpha. \\
 \text{||} & \text{||} \Rightarrow x^{*T} B y^* \leq \beta. \\
 \text{Take any } & x \in \Delta, \\
 \Rightarrow & x(A+B)y^* - \alpha^* - \beta^* \\
 & \leq x^*(A+B)y^* - \alpha^* - \beta^*
 \end{aligned}$$

First thing is because it is a solution of this optimization problem, we have the following thing conditions $Ay^* - \alpha \mathbf{1} \leq 0$, this immediately tells me that $x^* A y^* \leq \alpha$ that is there and similarly $x^* B y^* \leq \beta$ that is also there, so these are there. Now if this is always true, so that is the first fact that we need to show here. Then we will try to show that x^* , y^* satisfies the equilibrium condition, how do we prove that?

So, take any x in Δ . This implies $x(A+B)y^* - \alpha^* - \beta^* \leq x^*(A+B)y^* - \alpha^* - \beta^*$. As I said, we have to verify that x^* , y^* , α^* , β^* is an optimal, is corresponds to the Nash equilibrium, how do we do this? Let us look at it.

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$$\lambda^*(A+B)y^* - \alpha^* - \beta^* = \max_{x,y,\alpha,\beta} \left(\lambda(A+B)y - \alpha - \beta \right) \leq 0$$

$$\therefore \lambda^*(A+B)y^* - \alpha^* - \beta^* = 0$$

$$\left(\lambda^*Ay^* - \alpha^* \right) + \left(\lambda^*By^* - \beta^* \right) = 0$$

$$\Rightarrow \lambda^*Ay^* = \alpha^*, \quad \lambda^*By^* = 0$$

First thing is that we know that $x^* \text{ into } xA + By^* \text{ minus } \alpha^* \text{ minus } \beta^*$, this is nothing but the maximum over x, y, α, β of $xA + By^* \text{ minus } \alpha^* \text{ minus } \beta^*$, this is true. Now, what we really need to understand here is that this is always less than or equals to 0. Therefore, this is less than or equal to 0. Now, here is another important thing that we need to show here is that there is we already proved the existence of Nash equilibrium, so therefore there exist a Nash equilibrium.

So let me call that as x^* and y^* . For the Nash equilibrium, x^* and y^* , this value is going to be 0 because x^* , y^* corresponding values satisfy the constraints of this optimization problem, therefore this value is going to be 0, therefore this is going to be 0, that is the first important thing. Once this is there, now we use the constraints. So by using the constraints, we can easily see that because we can write it as $x^*Ay^* \text{ minus } \alpha^*$ this is one term plus another term is $x^*By^* \text{ minus } \beta^*$.

The sum of these 2 terms is equal to 0, but by the constraints, this is $x^*Ay^* \text{ minus } \alpha^*$ should be less than or equals to 0, this is also less than or equal to 0, both of them are non-negative numbers, therefore what we get is that they must be 0.

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$$\Rightarrow (x^*, y^*) \text{ is NE}$$

Once these are 0s, then now using the constraint this thing immediately we can prove that $x^* y^*$ is Nash equilibrium. So this proves the equivalence between these 2 problems. So if you have an existence of a Nash equilibrium, that immediately says that the Nash equilibrium is the solution corresponding to this optimization problem. Similarly, a solution of this optimization problem is a Nash equilibrium. So in the second part, we have used the fact that the equilibrium existence happens. Okay, with this, we conclude this session. We will meet again in the next session.