Algorithmic Game Theory and Applications

Nash Equilibrium and Zero-Sum Games

Solution Concept #3: Pure Nash Equilibrium

Pure Nash Equilibrium (PNE): A pure strategy profile $(s_1, ..., s_n)$ such that for any player $i \in N$, fixing the pure strategies s_{-i} of the other players, player *i* cannot get higher utility from choosing a different pure strategy.

<u>Mathematically</u>: $u_i(s_i, s_{-i}) \ge u_i(s'_i, s_{-i})$ for all $s'_i \in S_i$.

Equivalently: $s_i \in \arg \max_{\hat{s}_i \in S_i} u_i(\hat{s}_i, s_{-i})$

In words: s_i is a pure strategy that maximises the utility of the player, given the fixed strategies s_{-i} of the other players.

<u>Terminology</u>: s_i is a *pure best response* to s_{-i} .

<u>Terminology</u>: Player *i* does not have a profitable *unilateral deviation*.

Solution Concept #3*: (Mixed) Nash Equilibrium

Pure Nash Equilibrium (MNE): A mixed strategy profile $(x_1, ..., x_n)$ such that for any player $i \in N$, fixing the mixed strategies x_{-i} of the other players, player *i* cannot get higher utility from choosing a different mixed strategy.

<u>Mathematically</u>: $u_i(x_i, x_{-i}) \ge u_i(x'_i, x_{-i})$ for all $x'_i \in \Delta(S_i)$.

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In words: x_i is a mixed strategy that maximises the utility of the player, given the fixed strategies x_{-i} of the other players.

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Solution Concept #3*: (Mixed) Nash Equilibrium

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Equivalently: $x_i \in \arg \max_{\hat{x}_i \in \Delta(S_i)} u_i(\hat{x}_i, x_{-i})$ Recall: $u_i(\hat{x}_i, x_{-i}) = \mathbb{E}_{(s_i, s_{-i}) \sim (x_i, x_{-i})}[u_i(s_i, s_{-i})]$

In words: x_i is a mixed strategy that maximises the utility of the player, given the fixed strategies x_{-i} of the other players.

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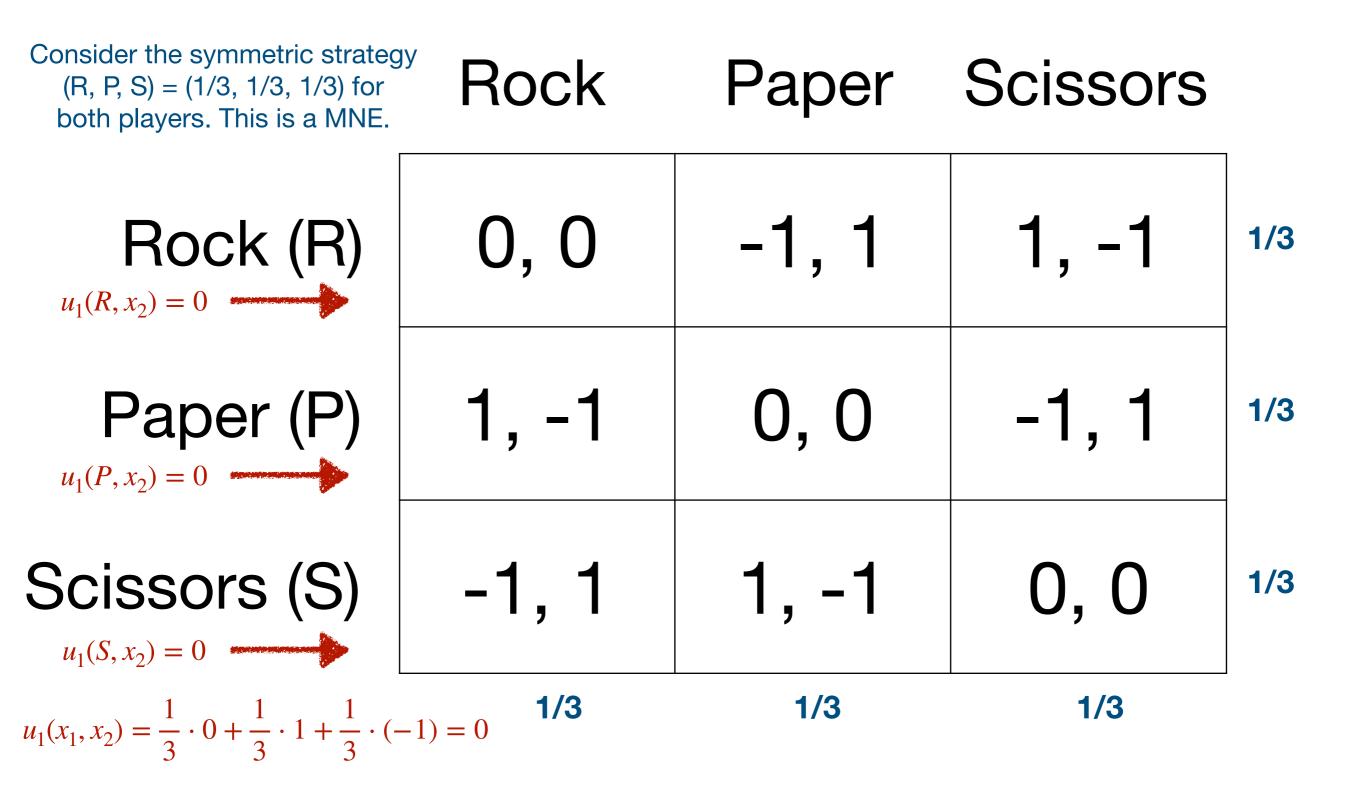
Terminology: Player *i* does not have a profitable *unilateral deviation*.

Fundamental Proposition

Proposition 1: A mixed strategy profile $x = (x_i, x_{-i})$ is a mixed Nash Equilibrium (MNE) if and only if, for every player $i \in N$ and every pure strategy $s'_i \in S_i$, we have

 $u_i(x_i, x_{-i}) \ge u_i(s'_i, x_{-i})$

Rock-Paper-Scissors



$O(\log n)$	O(n)	$O(n\log n)$	$O(n^2)$	$O(n^{lpha})$	$O(c^n)$
logarithmic	linear		quadratic	polynomial	exponential
The algorithm does not even read the whole input.	The algorithm accesses the input only a constant number of times.	The algorithm splits the inputs into two pieces of similar size, solves each part and merges the solutions.	The algorithm considers pairs of elements.	The algorithm performs many nested loops.	The algorithm considers many subsets of the input elements.
constant	O(1)	superlinear	$\omega(n)$		
superconstant	$\omega(1)$	superpolynomial	$\omega(n^{lpha})$		
sublinear	o(n)	subexponential	$o(c^n)$		

Polynomial time

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Before we talk about efficient algorithms, we need to be sure about what our input is.

Informally:

Input: A game in normal form, a mixed strategy profile $x = (x_1, ..., x_n)$.

Output: Yes if x is a MNE and No if it is not.

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Formally:

Input: The number *n* of players, the pure strategy sets S_i , given explicitly, by listing all of their elements, the utility functions u_i given explicitly as a list of *rational* numbers, one for each pure strategy profile, e.g., $u_i(s_1, ..., s_n)$, the mixed strategies x_i , given as vectors $(x_{i1}, ..., x_{im})$ of *rational* numbers, where $m = |S_i|$.

Output: Yes if x is a MNE and No if it is not.

For every player $i \in N$ do

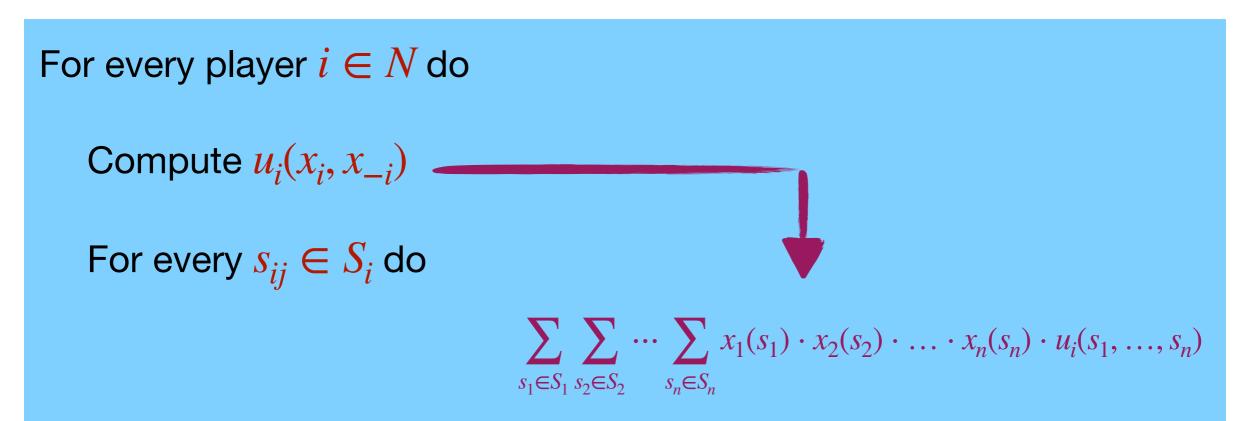
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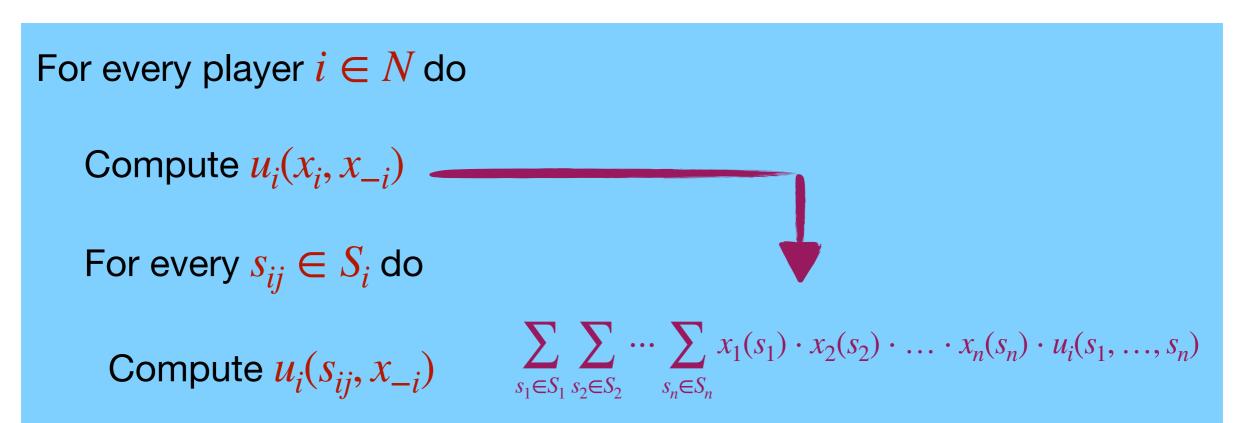
Compute $u_i(x_i, x_{-i})$

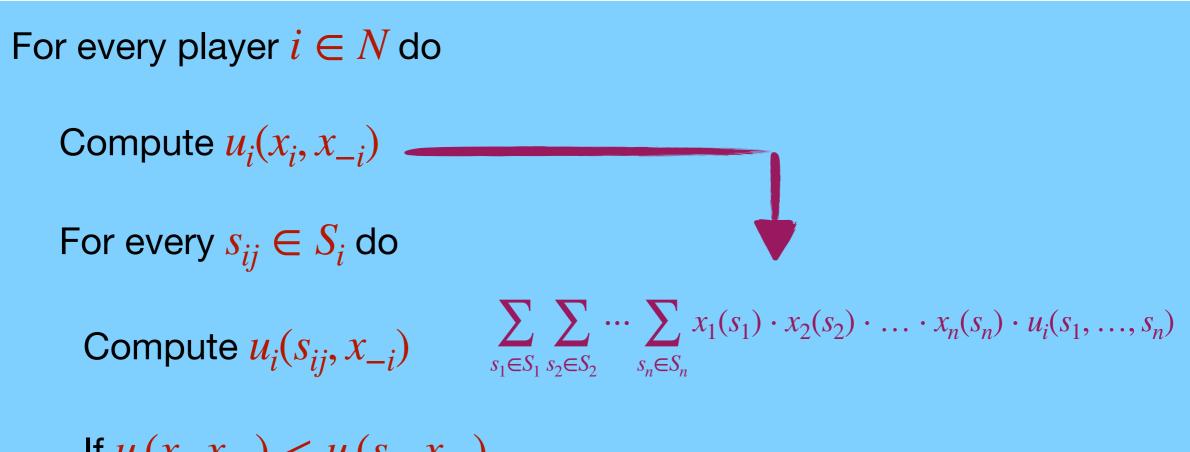
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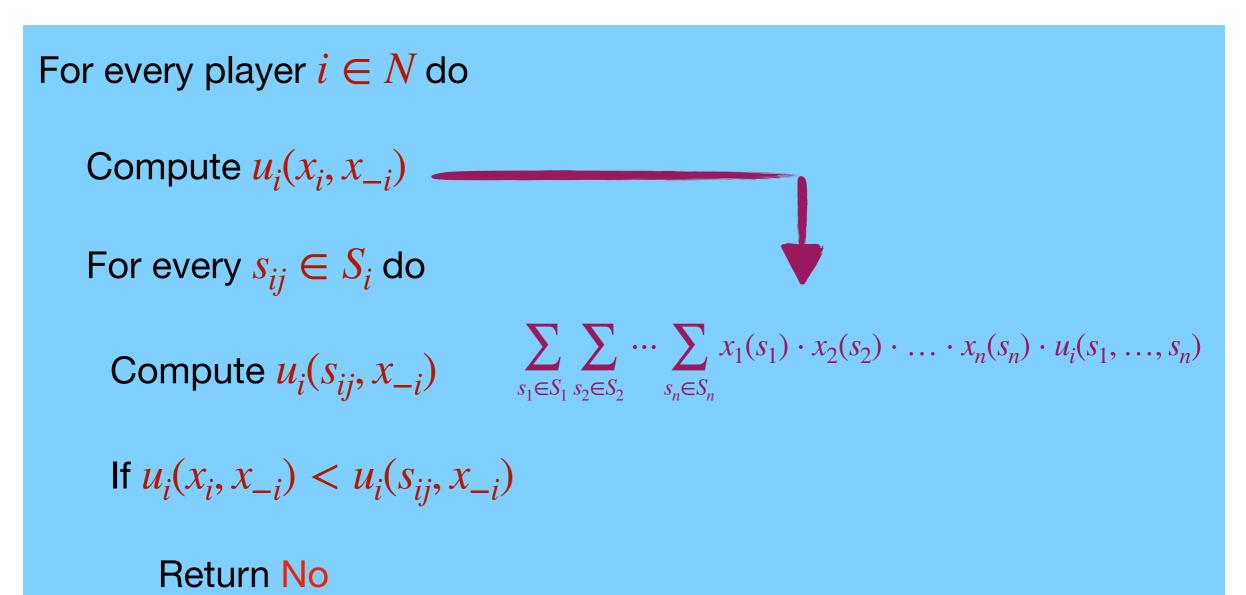
 $\sum_{s_1 \in S_1} \sum_{s_2 \in S_2} \cdots \sum_{s_n \in S_n} x_1(s_1) \cdot x_2(s_2) \cdot \ldots \cdot x_n(s_n) \cdot u_i(s_1, \ldots, s_n)$

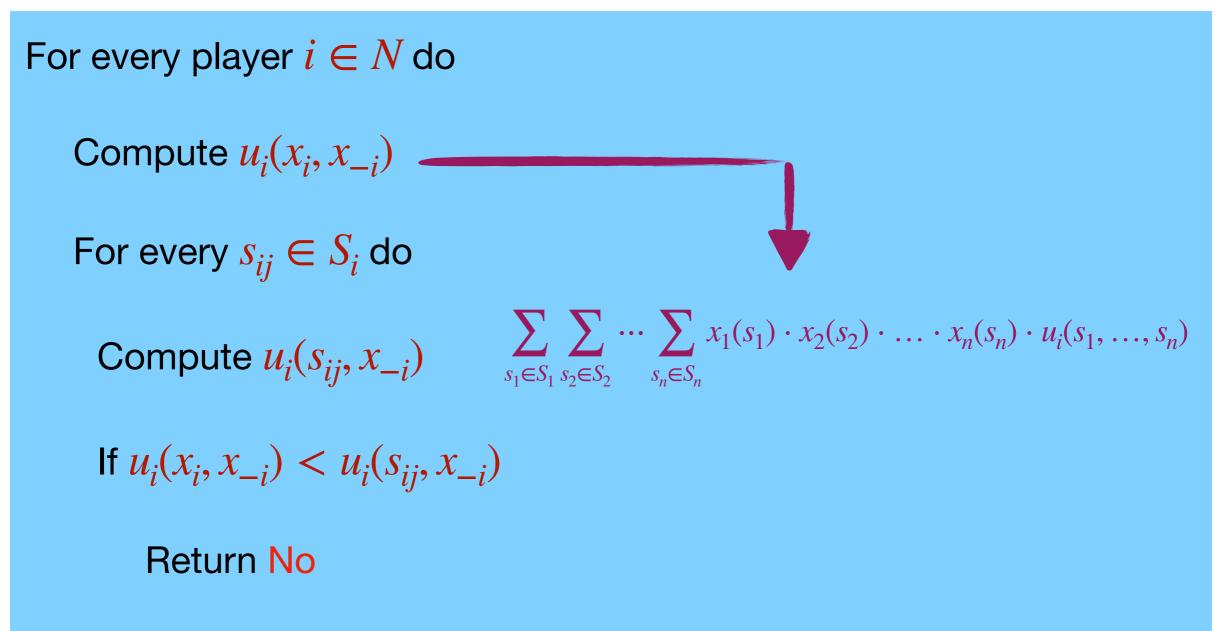






If $u_i(x_i, x_{-i}) < u_i(s_{ij}, x_{-i})$





Return Yes

Fundamental Proposition

Proposition 1: A mixed strategy profile $x = (x_i, x_{-i})$ is a mixed Nash Equilibrium (MNE) if and only if, for every player $i \in N$ and every pure strategy $s'_i \in S_i$, we have

 $u_i(x_i, x_{-i}) \ge u_i(s'_i, x_{-i})$

Another Fundamental Proposition

Proposition 2: A mixed strategy profile $x = (x_i, x_{-i})$ is a mixed Nash Equilibrium (MNE) if and only if, for every player $i \in N$, and for every pure strategy $s_i \in S_i$ in the support of x_i (i.e., $x_i(s_i) > 0$), we have $u_i(x_i, x_{-i}) = u_i(s_i, x_{-i})$.

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Let $x = (x_i, x_{-i})$ be a MNE. This immediately implies $u_i(s_i, x_{-i}) \le u_i(x_i, x_{-i})$ for all $s_i \in S_i$.

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Consider the alternative mixed strategy x'_i such that $x'_i(s_i) = x_i(s_i)$ for all pure strategies $s_i \neq s'_i, s^*_i$ and $x_i(s'_i) = 0$ $x'_i(s^*_i) = x_i(s^*_i) + x_i(s'_i)$

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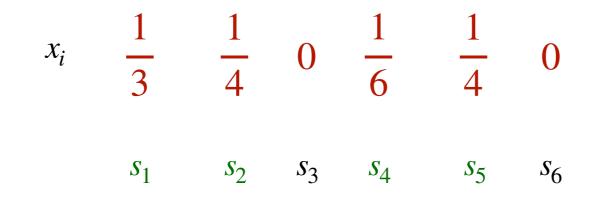
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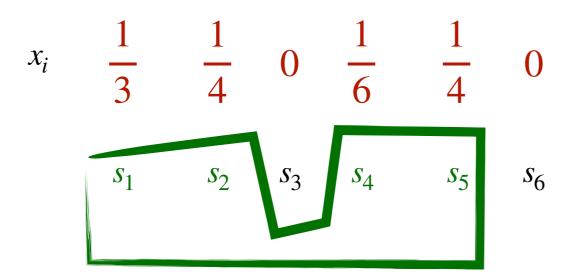
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 x'_i results in higher utility, a contradiction!

Via example:

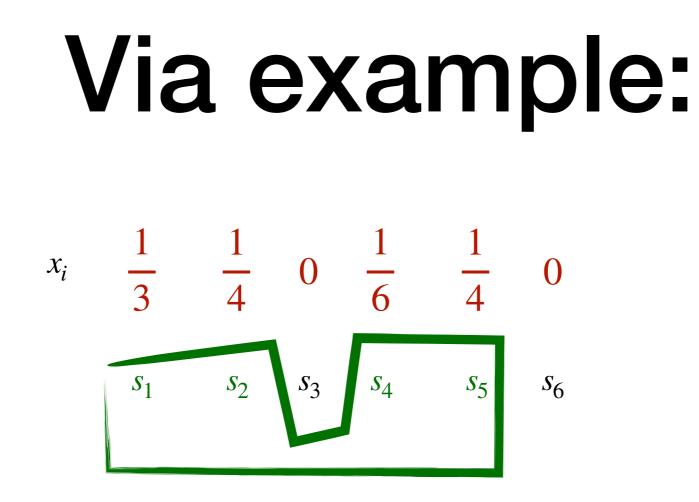


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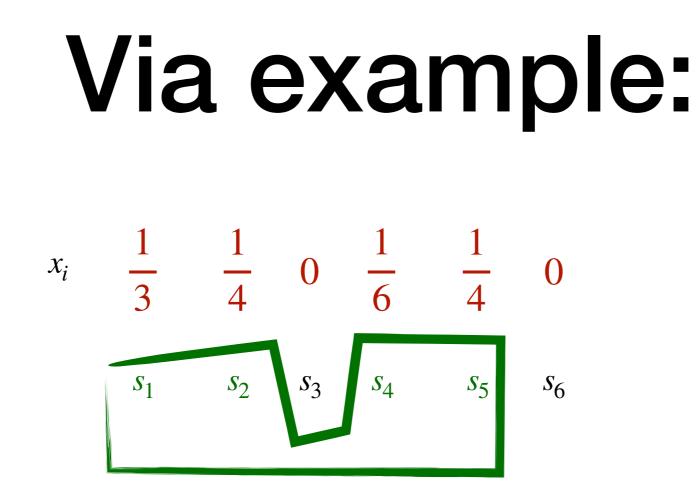


Via example: x_i $\frac{1}{3}$ $\frac{1}{4}$ 0 $\frac{1}{6}$ $\frac{1}{4}$ 0 s_1 s_2 s_3 s_4 s_5 s_6

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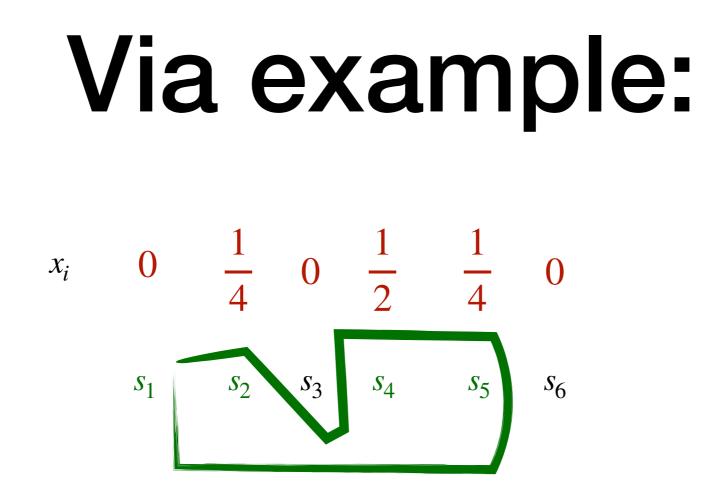
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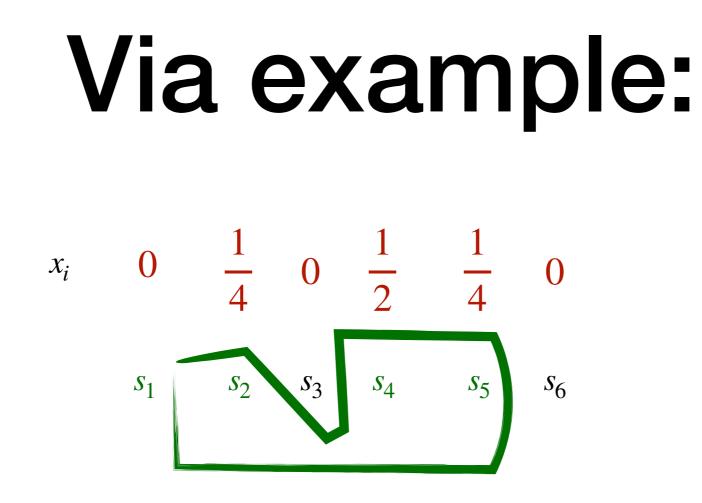
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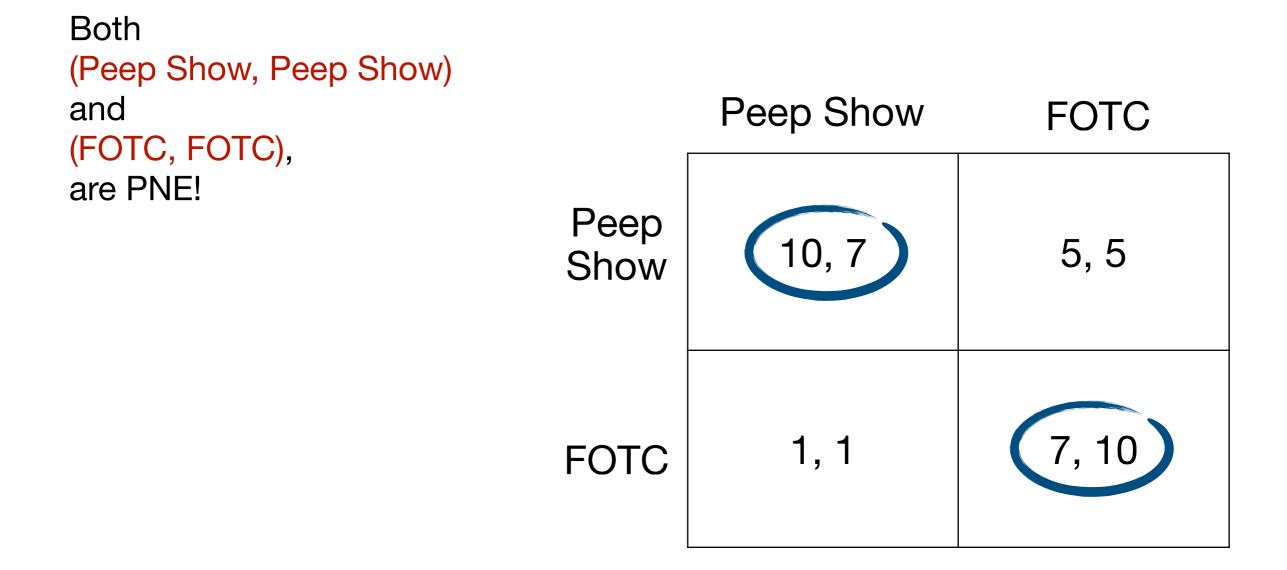
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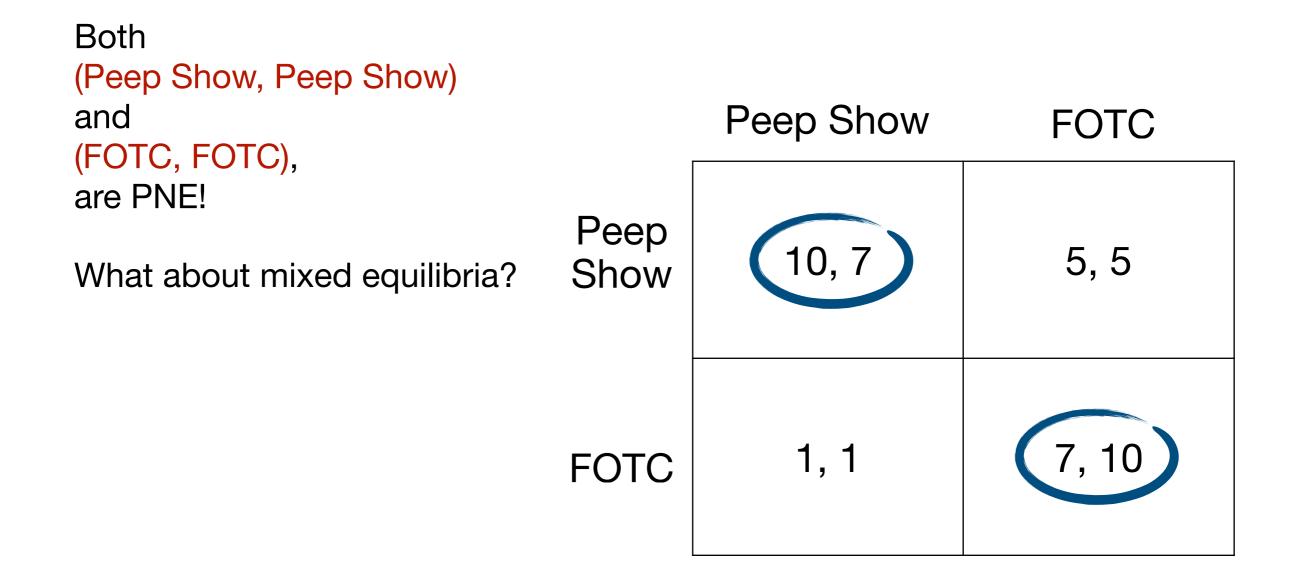


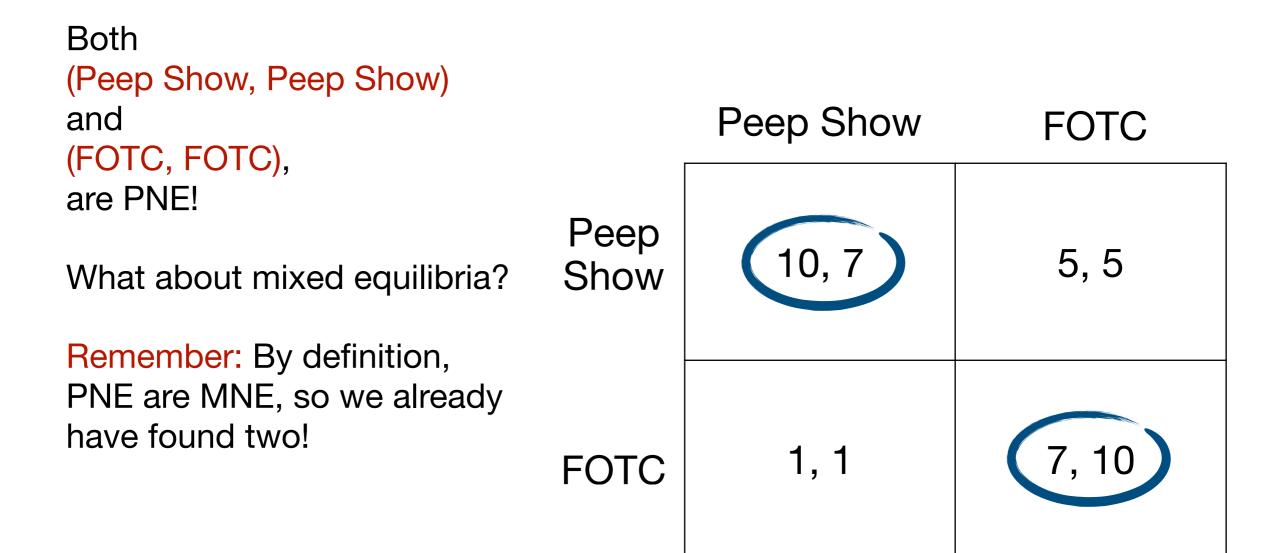
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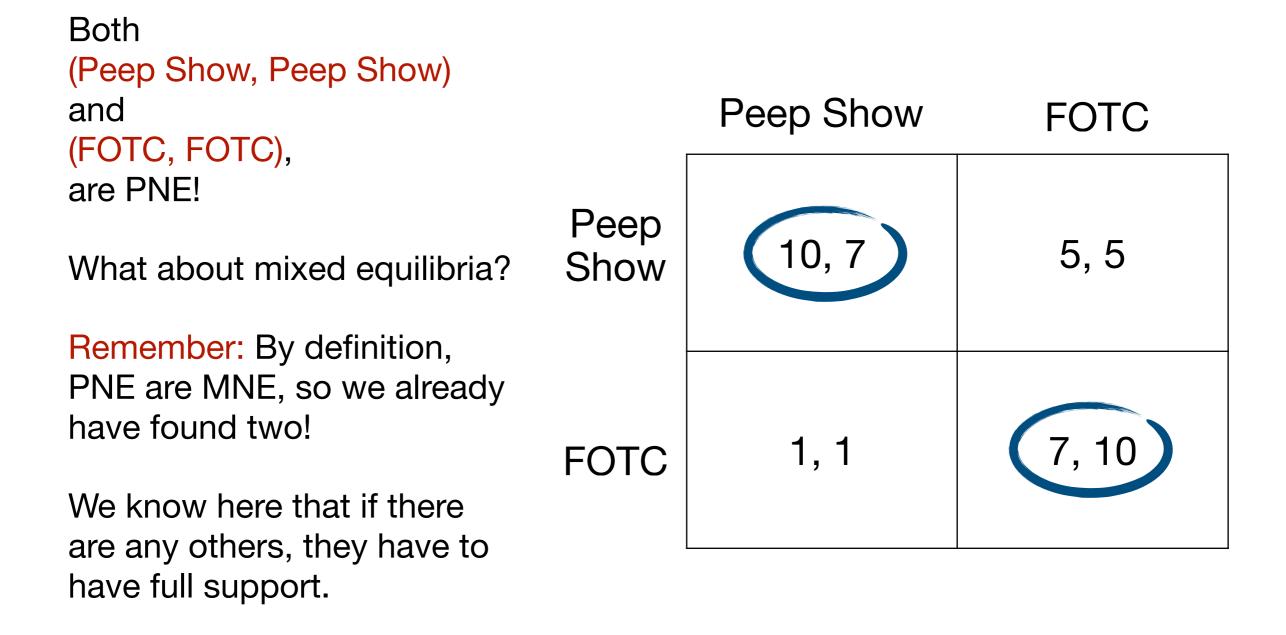
Then there are two pure strategies s_i , s_j such that s_i gives less utility than s_j . Take the probability from s_i and move it to s_j .

We have created a better (i.e., with higher expected utility) mixed strategy x'_i .



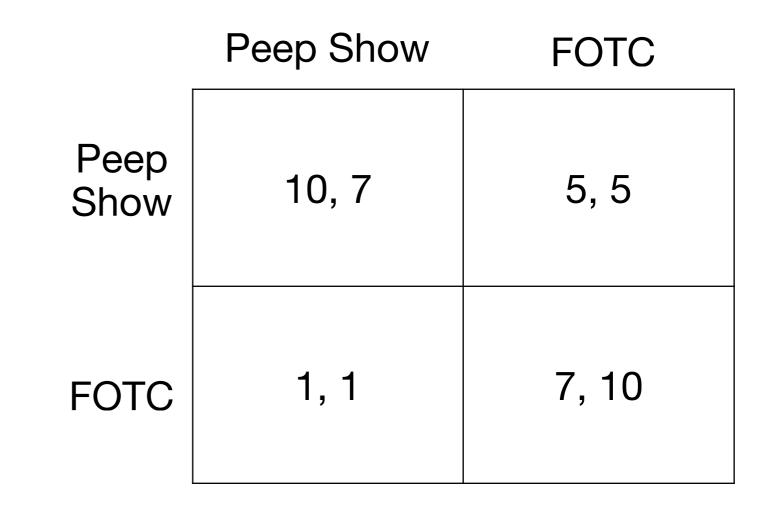




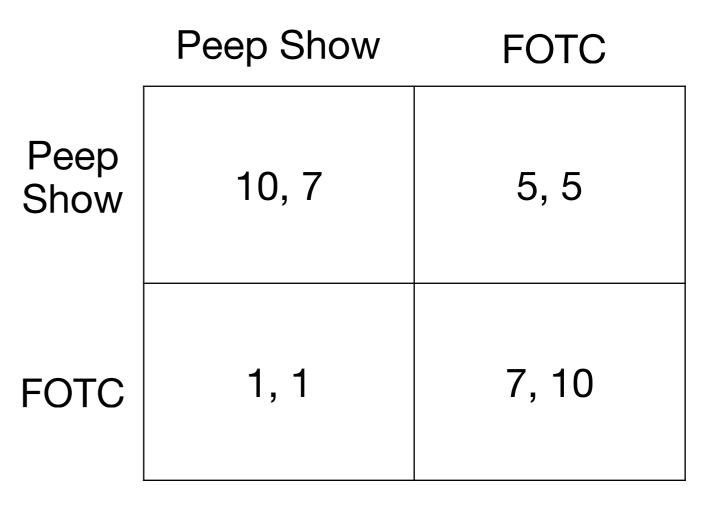


Both (Peep Show, Peep Show) and Peep Show FOTC (FOTC, FOTC), are PNE! Peep 10, 7 5, 5 Show What about mixed equilibria? **Remember:** By definition, PNE are MNE, so we already have found two! 1, 1 7, 10 FOTC We know here that if there are any others, they have to have full support.

We call those *fully mixed*.



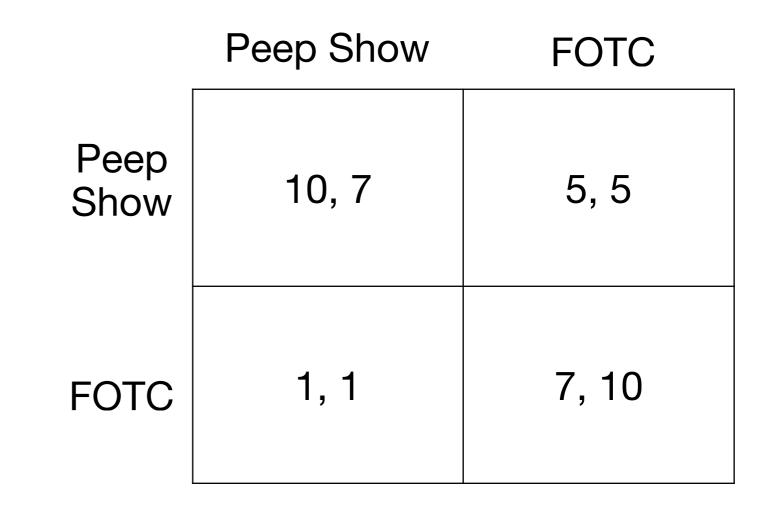
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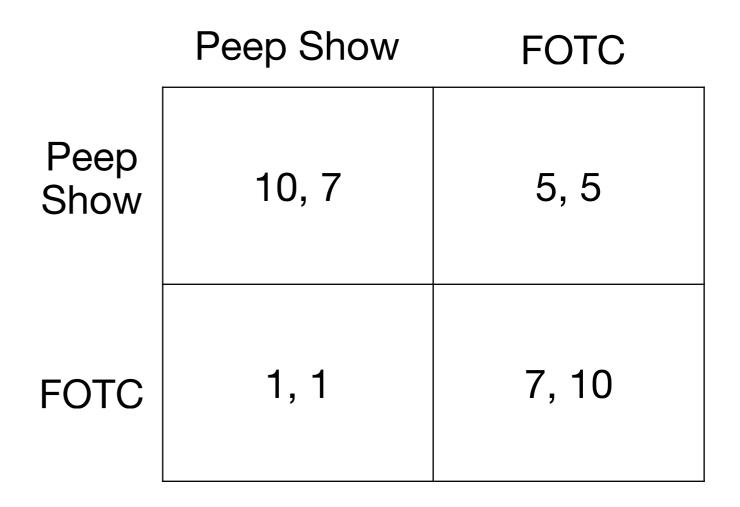
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		Peep Show	FOTC
Note: We use x and y here instead of x_1 and x_2 because we only have two players. We will therefore	Peep Show	10, 7	5, 5
use x_i , y_i to denote probabilities.	FOTC	1, 1	7, 10

Assume that we have a mixed equilibrium (x, y)Peep Show FOTC Note: We use *x* and *y* here Peep instead of x_1 and x_2 10, 7 5, 5 Show because we only have two players. We will therefore use x_i, y_i to denote probabilities. 1, 1 7, 10 FOTC Let (x_1, x_2) be the mixed strategy of Player 1 and (y_1, y_2) be the mixed

strategy of Player 2.



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In other words,	Doop		
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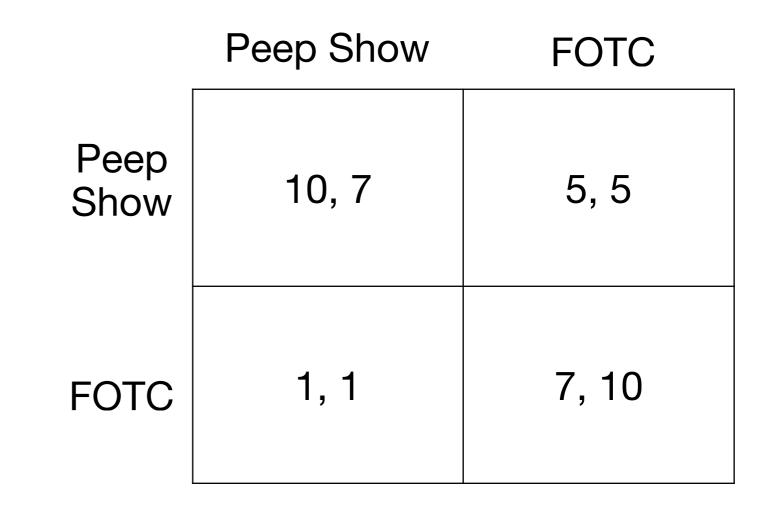
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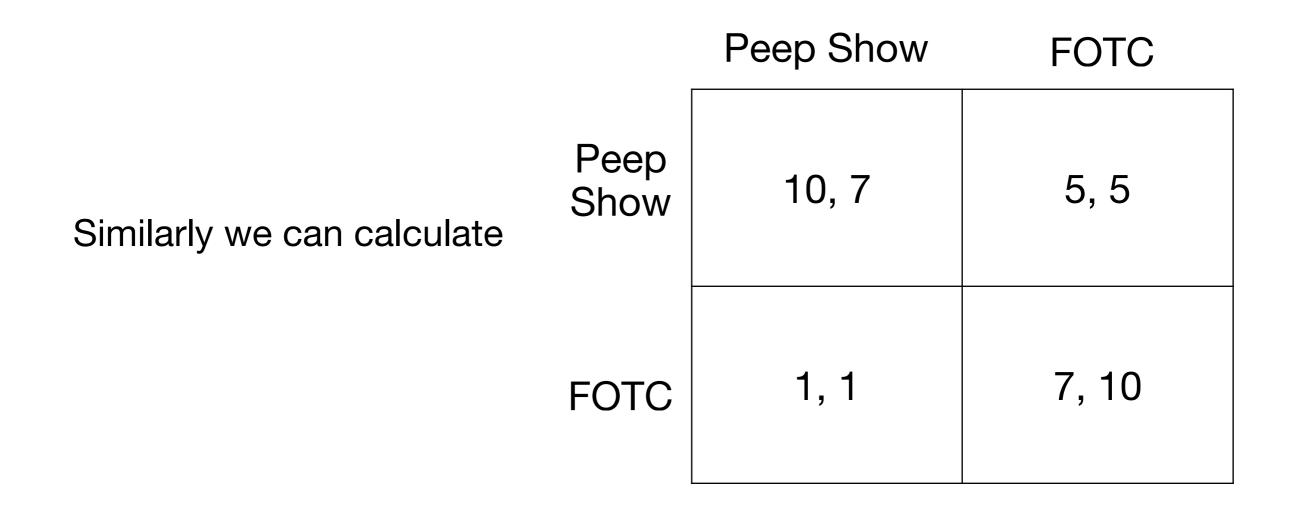
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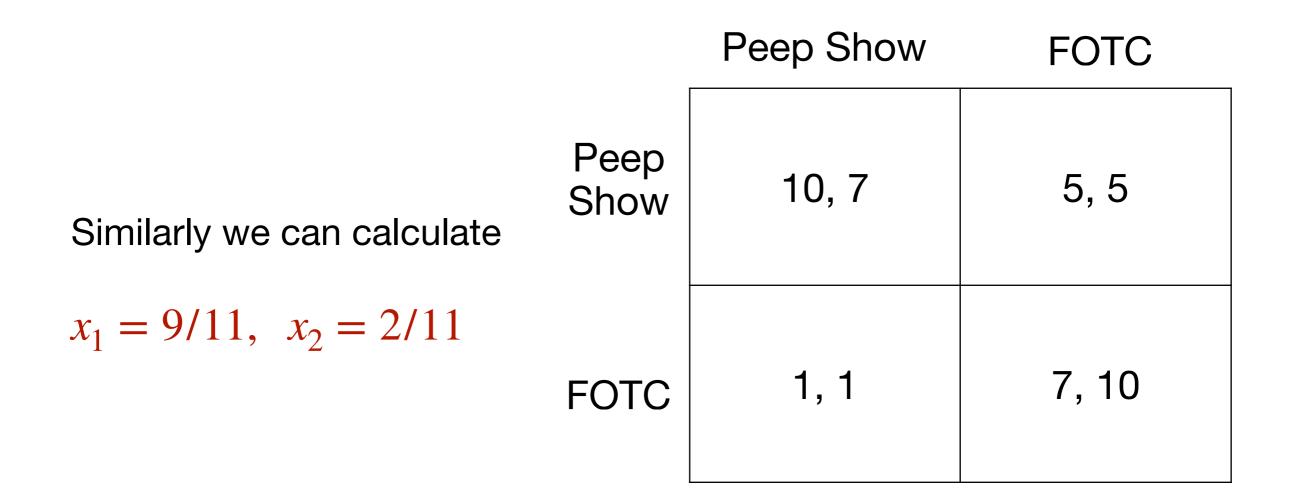
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 $y_1 = 2/11, y_2 = 9/11$







Another Fundamental Proposition

Proposition 2: A mixed strategy profile $x = (x_i, x_{-i})$ is a mixed Nash Equilibrium (MNE) if and only if, for every player $i \in N$, and for every pure strategy $s_i \in S_i$ in the support of x_i (i.e., $x_i(s_i) > 0$), we have $u_i(x_i, x_{-i}) = u_i(s_i, x_{-i})$.

Question: Can you translate the idea we just used into an algorithm, which takes advantage of the proposition above?

Assume that we have *magical access* to the supports for all mixed strategies in the MNE.

In algorithms, we often call this *oracle access*.

We can then write a set of inequalities:

$$\sum_{\substack{y_j \in \text{ supp}(y) \\ y_j \in \text{ supp}(y)}} y(t_j) \cdot u_i(s_i', t_j) = \sum_{\substack{y_j \in \text{ supp}(y) \\ y_j \in \text{ supp}(y)}} y(t_j) \cdot u_i(s_i', t_j) \text{ for all } s_i, s_i \in \text{ supp}(x)$$

 $y(t_j) = \Pr[y \text{ chooses } t_j]$

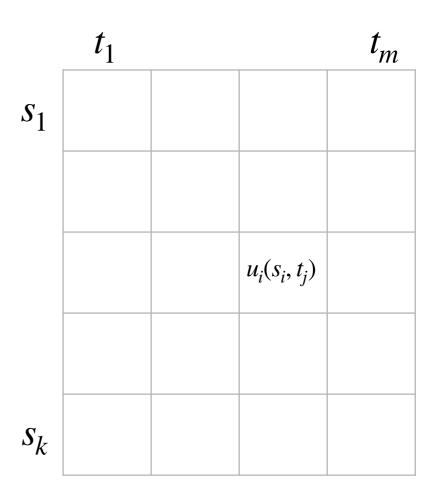
 $\sum_{y_j \in \text{supp}(y)} y(t_j) = 1$

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 $\sum_{\substack{y_j \in \text{supp}(y) \\ y_j \in \text{supp}(y)}} y(t_j) \cdot u_i(s_i', t_j) = \sum_{\substack{y_j \in \text{supp}(y) \\ y_j \in \text{supp}(y)}} y(t_j) \cdot u_i(s_i', t_j) \text{ for all } s_i, s_i \in \text{supp}(x)$



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This computes the equilibrium strategy of Player 2, based on Player 1

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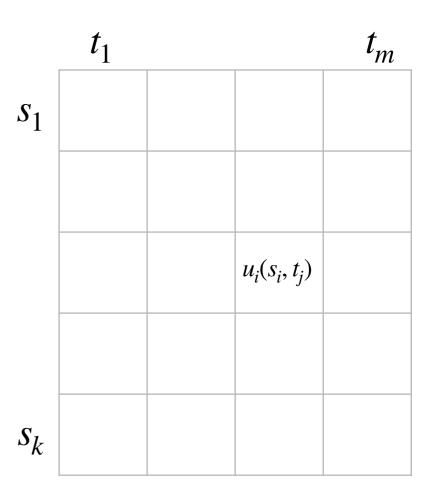
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A bit more precisely

By using the notation of utilities, we want a solution to the following system of inequalities:

1. $\forall i \in N, \forall s_j \in \text{supp}(x_i), u_i(s_j, x_{-i}) = w_i$ (Proposition 2)

2. $\forall i \in N, \forall s_j \notin \text{supp}(x_i), u_i(s_j, x_{-i}) \leq w_i \text{ (MNE condition)}$

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$$\forall i \in N$$
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This actually holds for any number of players, but the inequalities are linear only for two players. Why?

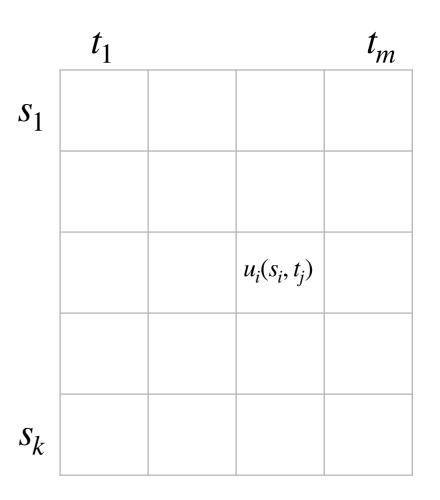
An algorithm for computing Nash equilibria in 2-player games

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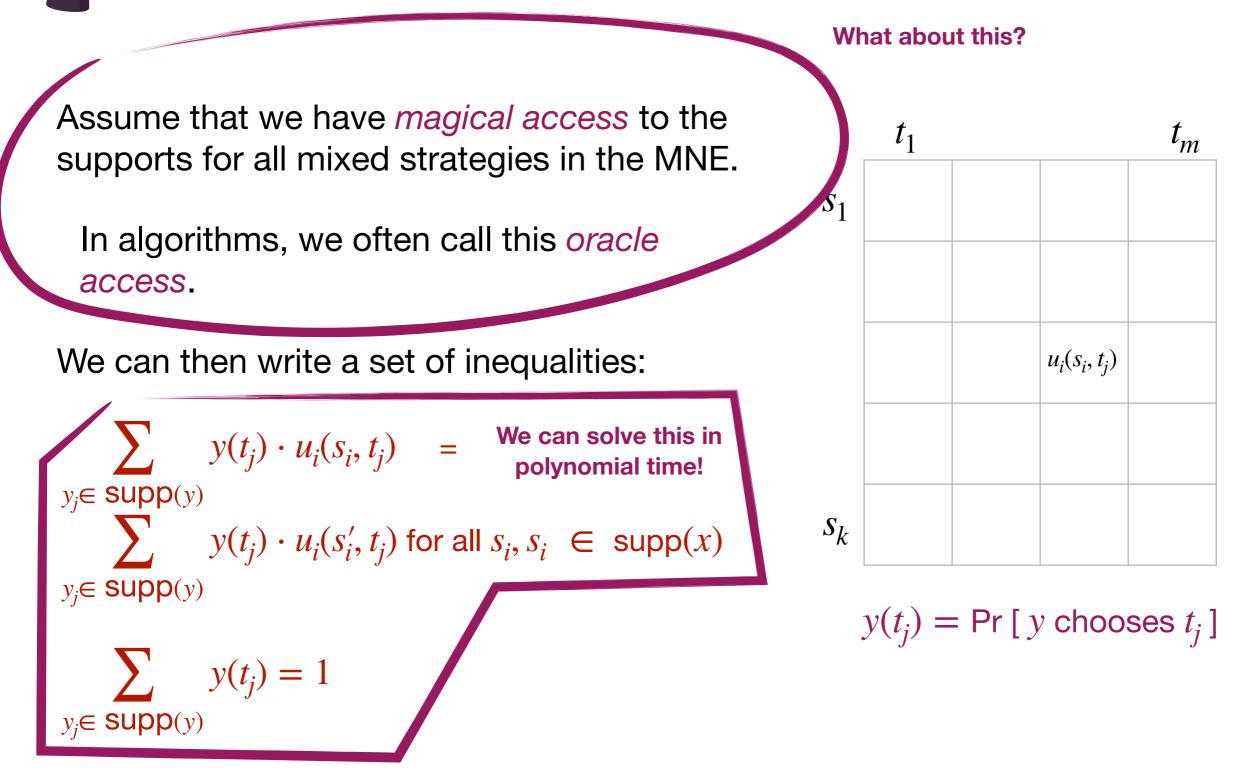
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Question 1: How do we know that one of the supports will indeed give us a MNE?

Question 2: How fast is this algorithm? How many possible supports are there?

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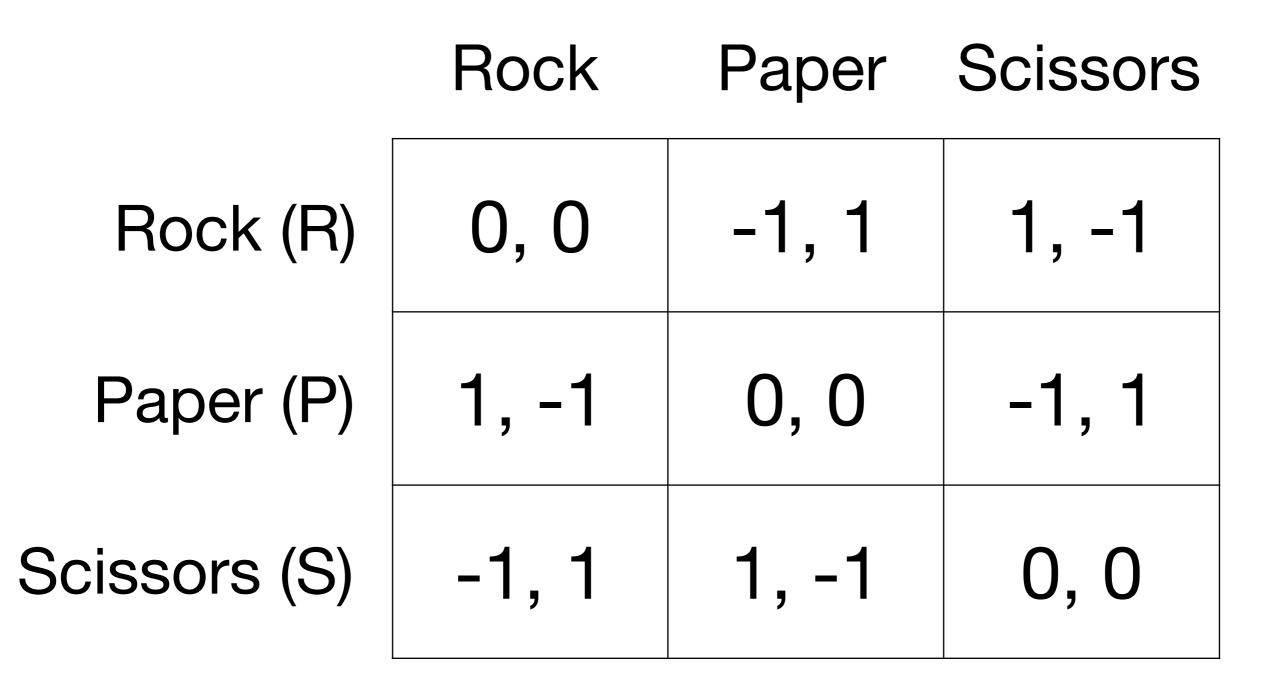
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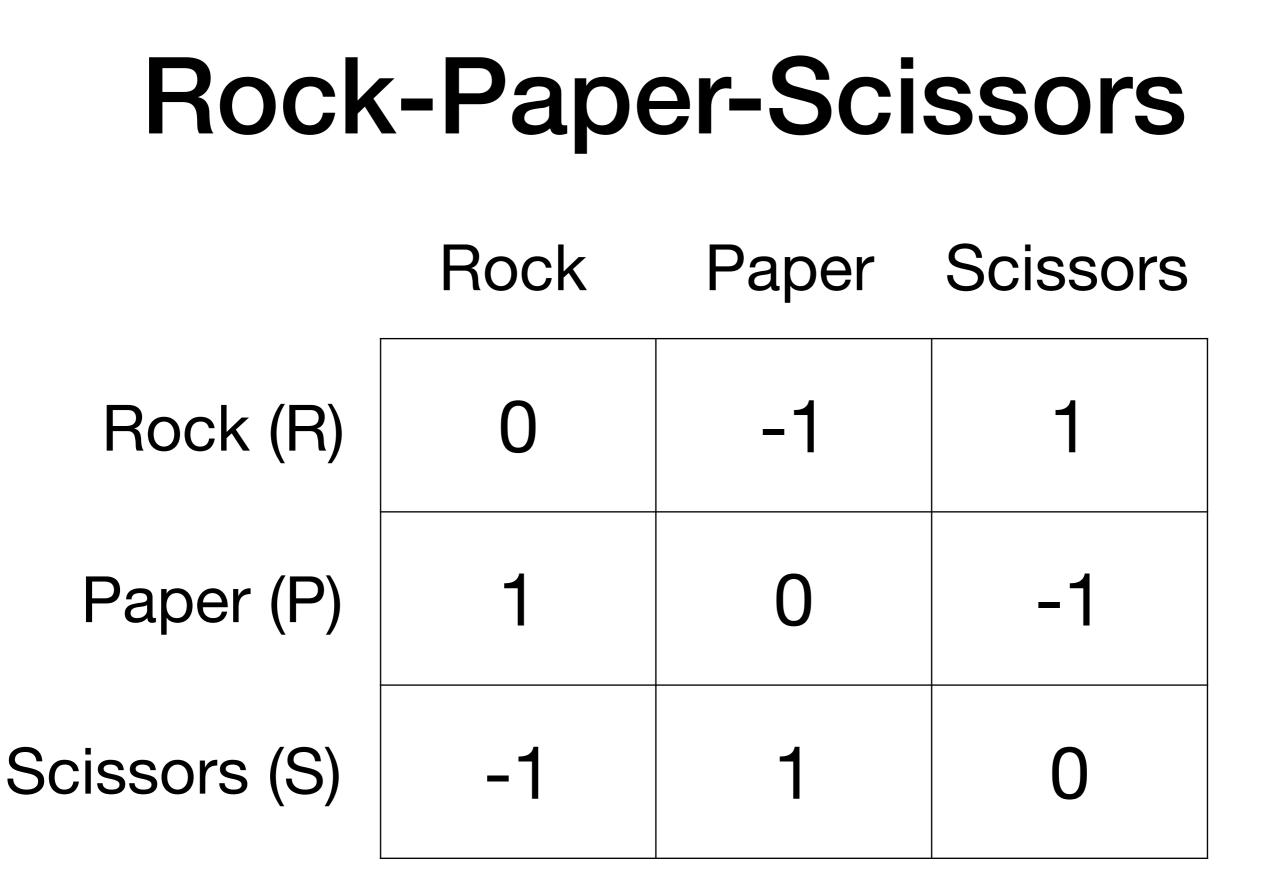
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Player 1 is trying to maximise the utility (maximiser) and Player 2 is trying to minimise it (minimiser).

Rock-Paper-Scissors





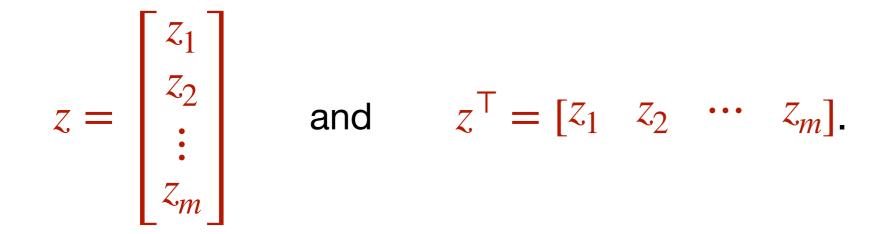
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Solution Concept #4: Minimax (Optimal) Strategies

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Why is this the rational thing to do in Zero-Sum games?

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von Neumann's Minimax Theorem (1928, 1944): $v_x = v_y$

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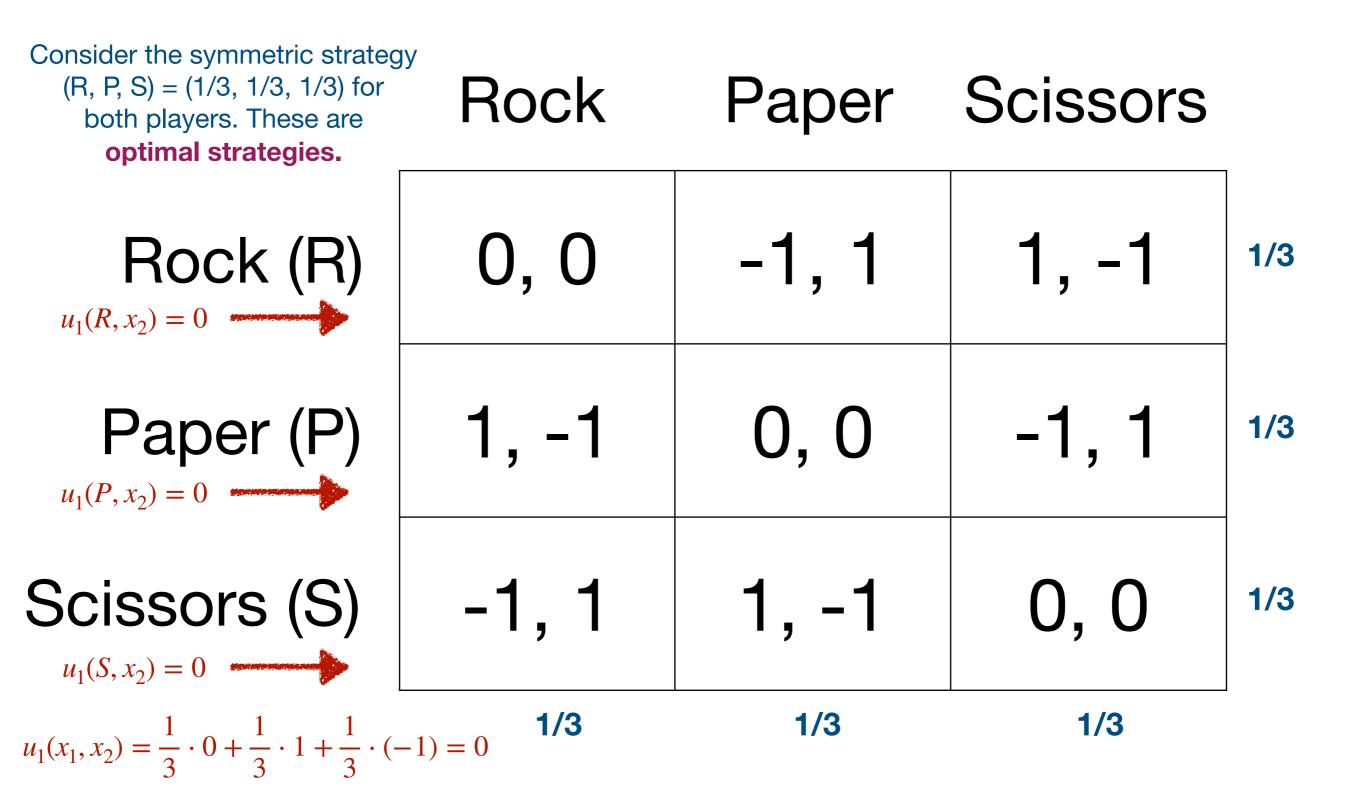
- So these strategies are the only reasonable/rational outcomes of the game.

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Rock-Paper-Scissors



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<u>Theorem</u>: Let (x^*, y^*) be a pair of mixed strategies of a 2-player Zero-Sum game. Then x^* and y^* are both optimal strategies if and only if (x^*, y^*) is a MNE.

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Consider a deviation of the maximiser to x'. From the above, it has to hold that $(x')^{\mathsf{T}}Ay^* \leq (x^*)^{\mathsf{T}}Ay^*$, i.e., the utility of the maximiser cannot increase.

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By the minimax theorem, we know that

$$\max_{x \in \Delta(X)} x^{\mathsf{T}} A y^* = \min_{y \in \Delta(Y)} (x^*)^{\mathsf{T}} A y = (x^*)^{\mathsf{T}} A y^*$$

Consider a deviation of the maximiser to x'. From the above, it has to hold that $(x')^{\mathsf{T}}Ay^* \leq (x^*)^{\mathsf{T}}Ay^*$, i.e., the utility of the maximiser cannot increase.

The argument for the minimiser is similar.

Assume that (x^*, y^*) is a MNE.

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By the minimax theorem, we know that the RHS of both (1) and (2) are equal. This is only possible if the two inequalities are satisfied with equality \Rightarrow both strategies are optimal.

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<u>Theorem</u>: Let (x^*, y^*) be a pair of mixed strategies of a 2-player Zero-Sum game. Then x^* and y^* are both optimal strategies if and only if (x^*, y^*) is a MNE.

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This provides a proof of the minimax theorem. How?

How do we solve those systems of linear equations to run the support enumeration algorithms for computing MNE?

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