

# **Algorithmic Game Theory**

## **Algorithms for normal-form games and approximate Nash equilibria**

Vangelis Markakis  
[markakis@gmail.com](mailto:markakis@gmail.com)

# Outline

- Algorithms for finding equilibria in general normal form games
  - The support theorem
  - Analysis of  $2 \times 2$  and  $2 \times n$  games
  - Complexity of general  $n \times m$  games
- Approximate Nash equilibria
  - A subexponential algorithm for any constant  $\epsilon > 0$
  - Polynomial time algorithms

# Nash equilibria: Existence and computation

- In 0-sum games
  - von Neumann's theorem establishes both existence and an algorithm for finding an equilibrium
  - Boils down to solving one linear program
- In general games?
  - Nash's theorem guarantees only existence
  - Big research question over the last 25 years

# The support of a strategy

- To come up with efficient algorithms, we need to understand better the properties of Nash equilibria
- Definition: For a mixed strategy  $\mathbf{p} = (p_1, p_2, \dots, p_n)$ , the *support* of  $\mathbf{p}$  is the set of pure strategies that have a positive probability of being selected, when we play  $\mathbf{p}$

$$\text{Supp}(\mathbf{p}) = \{i: p_i > 0\}$$

- E.g. if  $\mathbf{p} = (2/7, 0, 0, 3/7, 0, 2/7)$ , then  $\text{Supp}(\mathbf{p}) = \{1, 4, 6\}$ 
  - For pl. 1,  $\text{Supp}(\mathbf{p})$  shows us which rows have a chance to be selected according to  $\mathbf{p}$
  - Respectively, for a strategy of pl. 2, it shows the columns

# Utility functions revisited

- Let  $(\mathbf{p}, \mathbf{q})$  be a strategy profile in a  $n \times m$  game
  - $\mathbf{p} = (p_1, p_2, \dots, p_n)$ ,  $\mathbf{q} = (q_1, q_2, \dots, q_m)$
- Analyzing the utility function of pl. 1:

$$u_1(\mathbf{p}, \mathbf{q}) = \sum_{i=1}^n \sum_{j=1}^m p_i \cdot q_j \cdot u_1(s_i, t_j) = \sum_{i=1}^n p_i \sum_{j=1}^m q_j \cdot u_1(s_i, t_j) = \sum_{i=1}^n p_i \cdot u_1(e^i, \mathbf{q})$$

- The last term can also be written in terms of the support of  $\mathbf{p}$ , hence:

$$u_1(\mathbf{p}, \mathbf{q}) = \sum_{i \in \text{Supp}(\mathbf{p})} p_i \cdot u_1(e^i, \mathbf{q})$$

# Support properties at Nash equilibria

- Let  $(\mathbf{p}, \mathbf{q})$  be a Nash equilibrium and let  $i, j \in \text{Supp}(\mathbf{p})$ 
  - $p_i > 0, p_j > 0$
- How are the quantities  $u_1(e^i, \mathbf{q})$  and  $u_1(e^j, \mathbf{q})$  related?
- If  $u_1(e^i, \mathbf{q}) > u_1(e^j, \mathbf{q})$ , then pl. 1 has an incentive to reduce the probability  $p_j$  and increase the probability  $p_i$ 
  - But then  $(\mathbf{p}, \mathbf{q})$  would not be a Nash equilibrium
  - Similarly, if  $u_1(e^i, \mathbf{q}) < u_1(e^j, \mathbf{q})$
  - The only choice at an equilibrium is to have  $u_1(e^i, \mathbf{q}) = u_1(e^j, \mathbf{q})$
- If  $i \in \text{Supp}(\mathbf{p})$  and  $j \notin \text{Supp}(\mathbf{p})$ ?
  - Then it must hold that  $u_1(e^i, \mathbf{q}) \geq u_1(e^j, \mathbf{q})$ , otherwise  $(\mathbf{p}, \mathbf{q})$  is not an equilibrium

# Support properties at Nash equilibria

Support theorem: A profile  $(\mathbf{p}, \mathbf{q})$  is a Nash equilibrium if and only if

- i.  $\forall i, j \in \text{Supp}(\mathbf{p}), u_1(e^i, \mathbf{q}) = u_1(e^j, \mathbf{q})$
- ii.  $\forall i, j \in \text{Supp}(\mathbf{q}), u_2(\mathbf{p}, e^i) = u_2(\mathbf{p}, e^j)$
- iii.  $\forall i \in \text{Supp}(\mathbf{p}) \text{ and } \forall j \notin \text{Supp}(\mathbf{p}), u_1(e^i, \mathbf{q}) \geq u_1(e^j, \mathbf{q})$
- iv.  $\forall i \in \text{Supp}(\mathbf{q}) \text{ and } \forall j \notin \text{Supp}(\mathbf{q}), u_2(\mathbf{p}, e^i) \geq u_2(\mathbf{p}, e^j)$

# Support properties at Nash equilibria

## In other words:

- If a pure strategy is used with positive probability at a Nash equilibrium, then this strategy should be at least as good as any other pure strategy, **given** the other player's strategy
- 2 pure strategies that have positive probability at a Nash equilibrium must have the same utility, given the other player's strategy
- The theorem yields a way to check if a profile is a Nash equilibrium
- And helps us understand why some profiles cannot form an equilibrium



# Example

Use the support theorem to check if the profile  $(\mathbf{p}, \mathbf{q})$  with  $\mathbf{p} = (3/4, 0, 1/4)$ ,  $\mathbf{q} = (0, 1/3, 2/3)$  is an equilibrium in the following game

	$t_1$	$t_2$	$t_3$
$s_1$	1, 2	3, 3	1, 1
$s_2$	3, 2	0, 1	2, 5
$s_3$	2, 4	5, 1	0, 7

# Finding Nash equilibria

**Corollary:** If we knew the support of the strategies in one equilibrium profile, then we could compute a Nash equilibrium in polynomial time

In other words: if we only knew which rows and columns are needed in an equilibrium, we could then compute the probabilities of the mixed strategies

**Proof:**

- Suppose that someone guesses the support for both players
- All the conditions of the support theorem are linear functions of  $p_1, p_2, \dots, p_n, q_1, q_2, \dots, q_m$
- We would also need to add that  $\sum_i p_i = 1, \sum_i q_i = 1$
- By solving a single linear program (or a system of linear inequalities) we can compute the probabilities of the mixed strategies

# Finding Nash equilibria

- At the end, finding a Nash equilibrium is a combinatorial problem
- It suffices to find the right supports
- Brute-force algorithm:
  - Enumerate all possible pairs of supports for the two players
  - For each pair of supports, check if the corresponding linear program has a solution
- Complexity of brute-force in nxm games: prohibitive!
  - $2^n$  choices for pl. 1
  - $2^m$  choices for pl. 2
  - We need to run  $O(2^{n+m})$  linear programs

# Finding Nash equilibria

- Can we reduce it to solving only a few linear programs?
- Or a single LP?
- Probably no...
- **Note:** If the problem is solvable in polynomial time, then it can be reduced to a 0-sum game, by what we said in previous lecture
- It turns out that finding Nash equilibria is a special case of a “linear complementarity problem” [Cottle, Dantzig, 1960s]

# Finding Nash equilibria

## Linear Complementarity Problems (LCP)

- They arise in various contexts in Operations Research
- A class of non-linear programs
- Non-linear constraints for Nash equilibria:
  - By the support theorem, we need to express the fact that if  $p_i > 0$  at an equilibrium, then the  $i$ -th pure strategy gives maximum payoff among all pure strategies
- We cannot express such “if” statements with a linear program
- Instead: let  $w$  be the expected payoff of pl. 1 at an equilibrium  $(\mathbf{p}, \mathbf{q})$
- Support theorem  $\Rightarrow$  if  $p_i > 0$ , then  $u_1(e^i, \mathbf{q}) = w$
- Equivalently:  $p_i \cdot (u_1(e^i, \mathbf{q}) - w) = 0$  [complementarity condition]



# Nash equilibria as a LCP

- Variables:
  - $p_1, p_2, \dots, p_n, q_1, q_2, \dots, q_m$ : for the probabilities of the mixed strategies
  - $w, w'$ : for the expected utilities of the 2 players
- Constraints:
  - $\sum_i p_i = 1, \sum_i q_i = 1$
  - $p_1 \geq 0, p_2 \geq 0, \dots, q_1 \geq 0, \dots, q_m \geq 0$
  - $w \geq u_1(e^i, \mathbf{q})$  for  $i=1, \dots, n$
  - $w' \geq u_2(\mathbf{p}, e^j)$  for  $j=1, \dots, m$
  - $p_i \cdot (u_1(e^i, \mathbf{q}) - w) = 0$ , for  $i=1, \dots, n$
  - $q_j \cdot (u_2(\mathbf{p}, e^j) - w') = 0$ , for  $j=1, \dots, m$
- Algorithm for solving LCPs: [Lemke, Howson '64]
  - Exponential time in worst case, but relatively ok on average
  - Based on ideas similar to simplex but for non-linear problems
    - see GAMBIT <http://www.gambit-project.org/>

# Finding Nash equilibria

- So far, we have only seen exponential time algorithms...
- In what cases can the support theorem help us in having better algorithms?
- 2x2 games:
  - If there is a mixed strategy equilibrium then the support for pl. 1 must contain both rows
  - The support of pl. 2 must contain both columns
  - Applying the support theorem, it must hold that
$$u_1(e^1, \mathbf{q}) = u_1(e^2, \mathbf{q}), \text{ and } u_2(\mathbf{p}, e^1) = u_2(\mathbf{p}, e^2)$$

# Applying the support theorem to Bach-or-Stravinsky (BoS)

		 B                      S	
 B                      S	B	2, 1	0, 0
	S	0, 0	1, 2

If there exists a Nash equilibrium with mixed strategies, in the form  $((p_1, 1-p_1), (q_1, 1-q_1))$ , with  $p_1, q_1 \in (0, 1)$ , it should hold that

- $2q_1 = 1 - q_1 \Rightarrow q_1 = 1/3$
- $p_1 = 2(1 - p_1) \Rightarrow p_1 = 2/3$
- The conditions for pl. 1 give us the mixed strategy of pl. 2
- Similarly the conditions for pl. 2 give the strategy of pl. 1
- Hence we have the mixed equilibrium  $((2/3, 1/3), (1/3, 2/3))$



# From 2x2 to 2xn games

	$t_1$	$t_2$	$t_3$	$t_4$
$s_1$	3, -2	1, 2	4, 6	2, 8
$s_2$	1, 12	5, 10	2, 4	3, -4

- What are the Nash equilibria in this game?
- There is no Nash equilibrium with pure strategies, hence, there must be one with mixed strategies
- We will start with pl. 1
  - i.e., with the player who has 2 pure strategies
- We are looking for a strategy  $\mathbf{p} = (p_1, p_2) = (p_1, 1 - p_1)$  of pl. 1

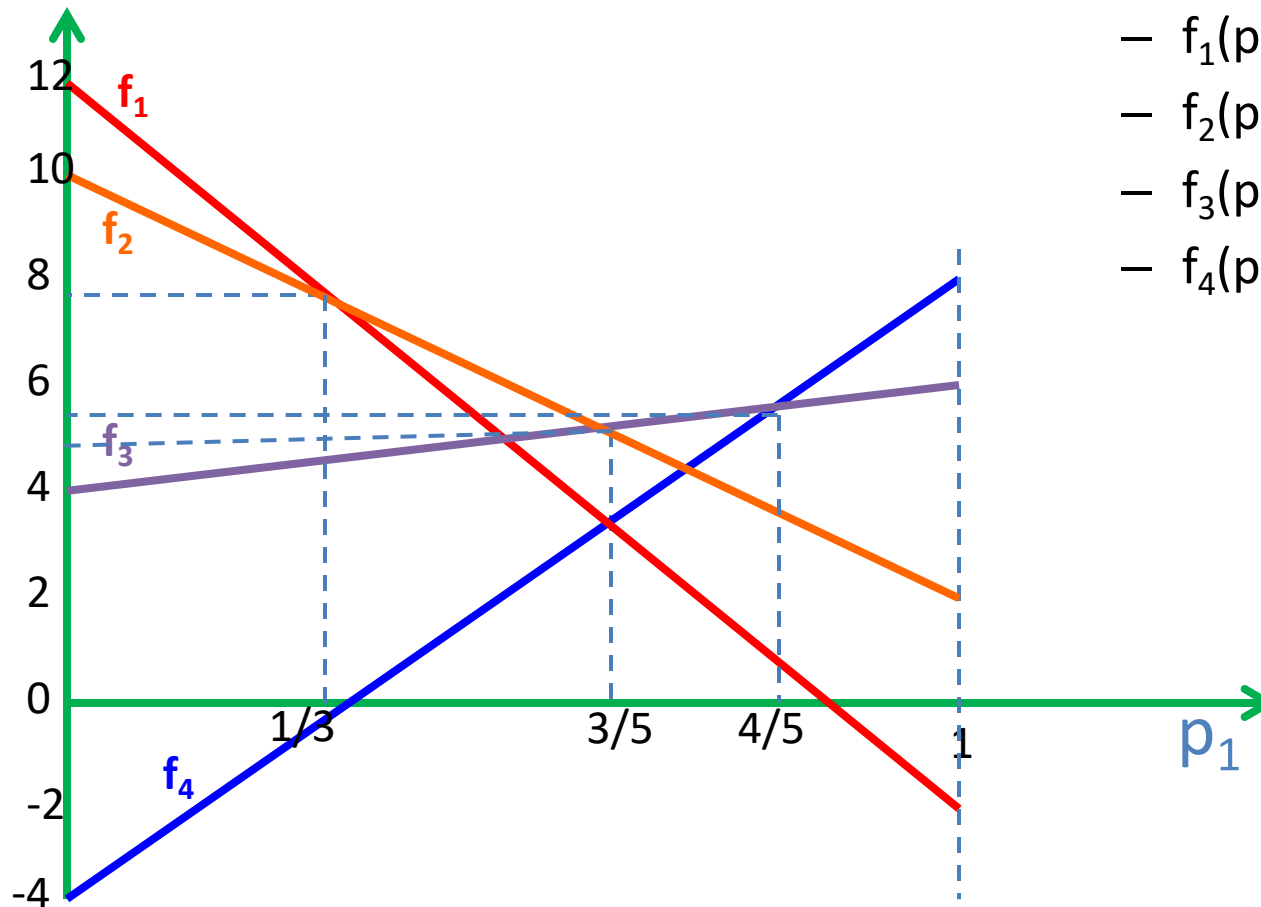
# Analysis of 2xn games

	$t_1$	$t_2$	$t_3$	$t_4$
$s_1$	3, -2	1, 2	4, 6	2, 8
$s_2$	1, 12	5, 10	2, 4	3, -4

- Step 1: We look at pl. 2 and compute the terms
  - $u_2(\mathbf{p}, e^1) = f_1(p_1) = -14p_1 + 12,$
  - $u_2(\mathbf{p}, e^2) = f_2(p_1) = -8p_1 + 10,$
  - $u_2(\mathbf{p}, e^3) = f_3(p_1) = 2p_1 + 4$
  - $u_2(\mathbf{p}, e^4) = f_4(p_1) = 12p_1 - 4$

# Analysis of 2xn games

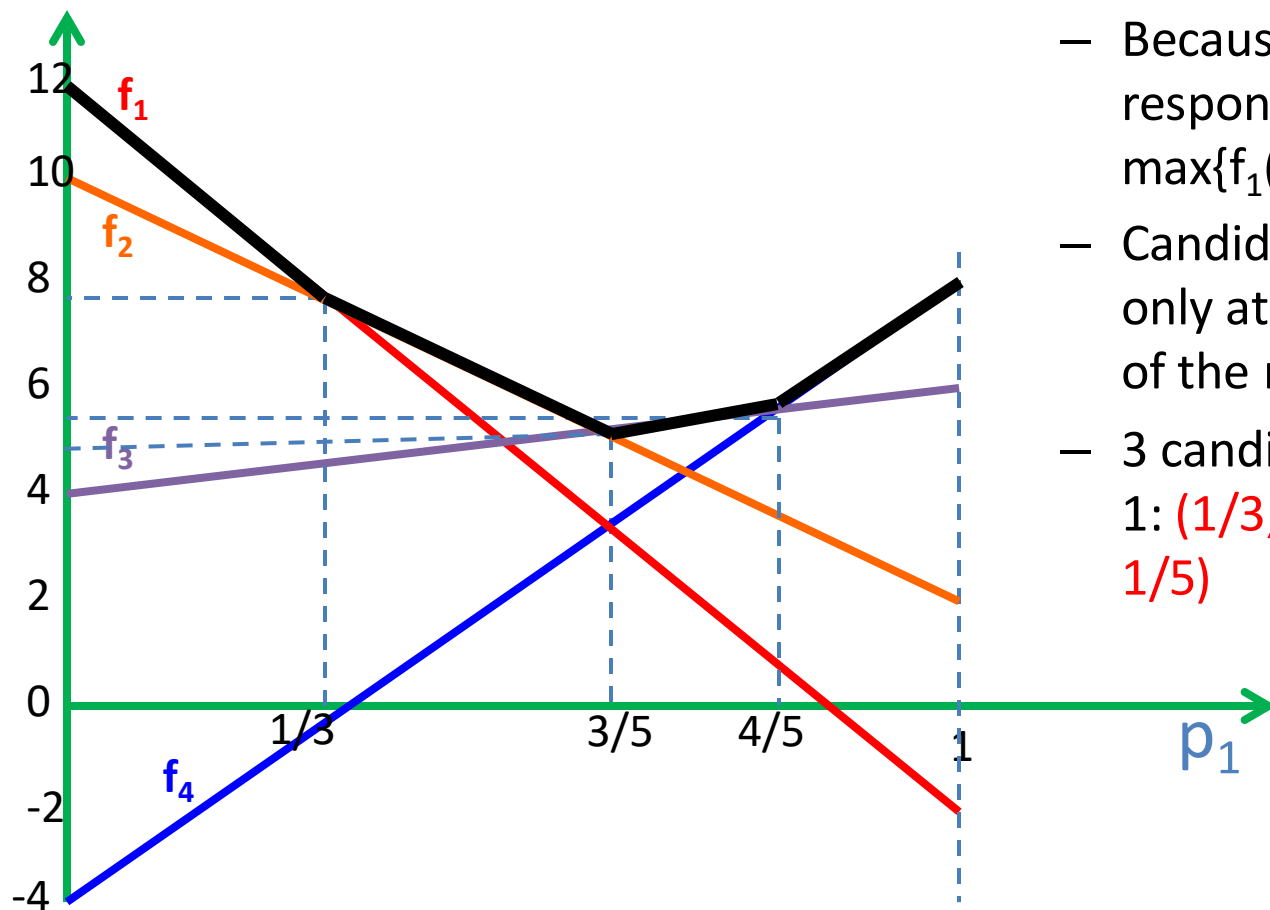
## Step 2: Graphical representation



- $f_1(p_1) = -14p_1 + 12$ ,
- $f_2(p_1) = -8p_1 + 10$ ,
- $f_3(p_1) = 2p_1 + 4$
- $f_4(p_1) = 12p_1 - 4$

# Analysis of 2xn games

## Step 3: Candidate strategies for pl. 1



- Because pl. 2 will play a best response, we look at  $\max\{f_1(p_1), f_2(p_1), f_3(p_1), f_4(p_1)\}$
- Candidate strategies for pl. 1 only at the intersection points of the max function
- 3 candidate strategies for pl. 1:  $(1/3, 2/3)$ ,  $(3/5, 2/5)$ ,  $(4/5, 1/5)$

# Analysis of 2xn games

	$t_1$	$t_2$	$t_3$	$t_4$
$s_1$	3, -2	1, 2	4, 6	2, 8
$s_2$	1, 12	5, 10	2, 4	3, -4

- Step 4: We check all the candidate strategies to see if they can yield an equilibrium

1<sup>st</sup> candidate strategy of pl. 1:  $(1/3, 2/3)$

- We will search for a strategy of pl. 2 in the form:  $\mathbf{q} = (q_1, 1 - q_1, 0, 0)$
- Since from the diagram, the 1<sup>st</sup> and 2<sup>nd</sup> columns are the best responses of pl. 2 to the strategy of pl. 1
- From the support theorem, it must hold that  $u_1(e^1, \mathbf{q}) = u_1(e^2, \mathbf{q})$
- $3q_1 + 1 - q_1 = q_1 + 5(1 - q_1) \Rightarrow q_1 = 2/3$
- Since we found a valid probability, we have found a Nash equilibrium

# Analysis of 2xn games

	$t_1$	$t_2$	$t_3$	$t_4$
$s_1$	3, -2	1, 2	4, 6	2, 8
$s_2$	1, 12	5, 10	2, 4	3, -4

- Step 4: We check all the candidate strategies to see if they can yield an equilibrium

2<sup>nd</sup> candidate strategy of pl. 1:  $(3/5, 2/5)$

- We will search for a strategy of pl. 2 in the form:  $\mathbf{q} = (0, q_2, 1 - q_2, 0)$
- Since from the diagram, the 2<sup>nd</sup> and 3<sup>rd</sup> columns are the best responses against the strategy of pl. 1
- From the support theorem, it should hold that  $u_1(e^2, \mathbf{q}) = u_1(e^3, \mathbf{q})$
- By solving this, we get  $q_2 = 1/3$
- Since we found a valid probability, we have found one more equilibrium

# Analysis of 2xn games

	$t_1$	$t_2$	$t_3$	$t_4$
$s_1$	3, -2	1, 2	4, 6	2, 8
$s_2$	1, 12	5, 10	2, 4	3, -4

- Step 4: We check all the candidate strategies to see if they can yield an equilibrium

3<sup>rd</sup> candidate strategy of pl. 1:  $(4/5, 1/5)$

- We will search for a strategy of pl. 2 of the form:  $\mathbf{q} = (0, 0, q_3, 1 - q_3)$
- In a similar way, we get  $q_3 = 1/3$
- Hence we have a 3<sup>rd</sup> Nash equilibrium

# Analysis of 2xn games

	$t_1$	$t_2$	$t_3$	$t_4$
$s_1$	3, -2	1, 2	4, 6	2, 8
$s_2$	1, 12	5, 10	2, 4	3, -4

- In total: 3 Nash equilibria
  - $((1/3, 2/3), (2/3, 1/3, 0, 0))$
  - $((3/5, 2/5), (0, 1/3, 2/3, 0))$
  - $((4/5, 1/5), (0, 0, 1/3, 2/3,))$



# A modified example

	$t_1$	$t_2$	$t_3$	$t_4$
$s_1$	3, -2	5, 2	4, 6	2, 8
$s_2$	1, 12	1, 10	2, 4	3, -4

- Suppose we change some of the payoffs of pl. 1 (here we changed the 2<sup>nd</sup> column)
- Which parts of the analysis change?
  - **Observation:** The candidate mixed strategies of pl. 1 were determined by the payoff matrix of pl. 2!
  - Hence, steps 1-3 remain exactly the same
  - Again, 3 candidate strategies for pl. 1

# A modified example

	$t_1$	$t_2$	$t_3$	$t_4$
$s_1$	3, -2	5, 2	4, 6	2, 8
$s_2$	1, 12	1, 10	2, 4	3, -4

- Step 4: We check all the candidate strategies to see if they can yield an equilibrium

1<sup>st</sup> candidate strategy of pl. 1:  $(1/3, 2/3)$

- We will search for a strategy of pl. 2 in the form:  $\mathbf{q} = (q_1, 1 - q_1, 0, 0)$
- From the support theorem, it must hold that  $u_1(e^1, \mathbf{q}) = u_1(e^2, \mathbf{q})$
- $3q_1 + 5(1 - q_1) = q_1 + 1 - q_1 \Rightarrow q_1 = 2$
- Not a valid probability!
- Hence, this candidate strategy does not yield an equilibrium

# A modified example

	$t_1$	$t_2$	$t_3$	$t_4$
$s_1$	3, -2	5, 2	4, 6	2, 8
$s_2$	1, 12	1, 10	2, 4	3, -4

- Step 4: We check all the candidate strategies to see if they can yield an equilibrium

2<sup>nd</sup> candidate strategy of pl. 1: (3/5, 2/5)

- We will search for a strategy of pl. 2 in the form :  $\mathbf{q} = (0, q_2, 1 - q_2, 0)$
- From the support theorem, it should hold that  $u_1(e^2, \mathbf{q}) = u_1(e^3, \mathbf{q})$
- $5q_2 + 4(1 - q_2) = q_2 + 2(1 - q_2) \Rightarrow q_2 = -1$
- Not a valid probability
- Hence, no equilibrium

# A modified example

	$t_1$	$t_2$	$t_3$	$t_4$
$s_1$	3, -2	5, 2	4, 6	2, 8
$s_2$	1, 12	1, 10	2, 4	3, -4

- Step 4: We check all the candidate strategies to see if they can yield an equilibrium

3<sup>rd</sup> candidate strategy of pl. 1: (4/5, 1/5)

- Since we have not found any other equilibrium, Nash's theorem guarantees that now we will find one
- We will search for a strategy of pl. 2 of the form:  $\mathbf{q} = (0, 0, q_3, 1 - q_3)$
- In the modified example, columns 3 and 4 have not changed
- Hence, we will arrive at the same result:  $q_3 = 1/3$
- Unique Nash equilibrium: ((4/5, 1/5), (0, 0, 1/3, 2/3,))

# Back to nxm games

- Summarizing known algorithms:
  - Brute-force, based on the support theorem, worst case: need to solve  $O(2^{n+m})$  linear programs
  - [Lemke, Howson '64], worst case: still exponential
  - Other approaches: [Kuhn '61, Mangasarian '64, Lemke '65], also exponential worst case running time
- Polynomial time algorithms only for special cases
  - 0-sum games
  - $2 \times n$  games
  - Games with constant rank payoff matrices
- We are not aware of any polynomial time algorithm for general  $n \times m$  normal form games!

# Algorithms for normal form games

- Could it be that the problem is **NP**-complete?
- Probably not
  - [Megiddo, Papadimitriou '89]: strong evidence that it cannot be **NP**-complete
  - If it were  $\Rightarrow$  **NP** = co-**NP** (highly unlikely to be true)
- It is **NP**-complete if we add more requirements
  - E.g. Find a Nash equilibrium that maximizes the sum of the utilities  
[Gilboa, Zemel '89, Conitzer, Sandholm '03]
  - A different problem than just finding a Nash equilibrium
- Further issues
  - There exist games, with integer payoff matrices, and with  $\geq 3$  players, where the probabilities in their Nash equilibria are irrational numbers  
[Nash '51]
  - Hence, we cannot even represent the mixed strategies by a finite number of bits

# Back to the proof of Nash's theorem

- Theorem [Nash 1951]: Every finite game possesses at least one equilibrium when we allow mixed strategies
- Nash's proof reduces to using Brouwer's fixed point theorem
- Brouwer's theorem reduces to using Sperner's lemma

# Brouwer's theorem

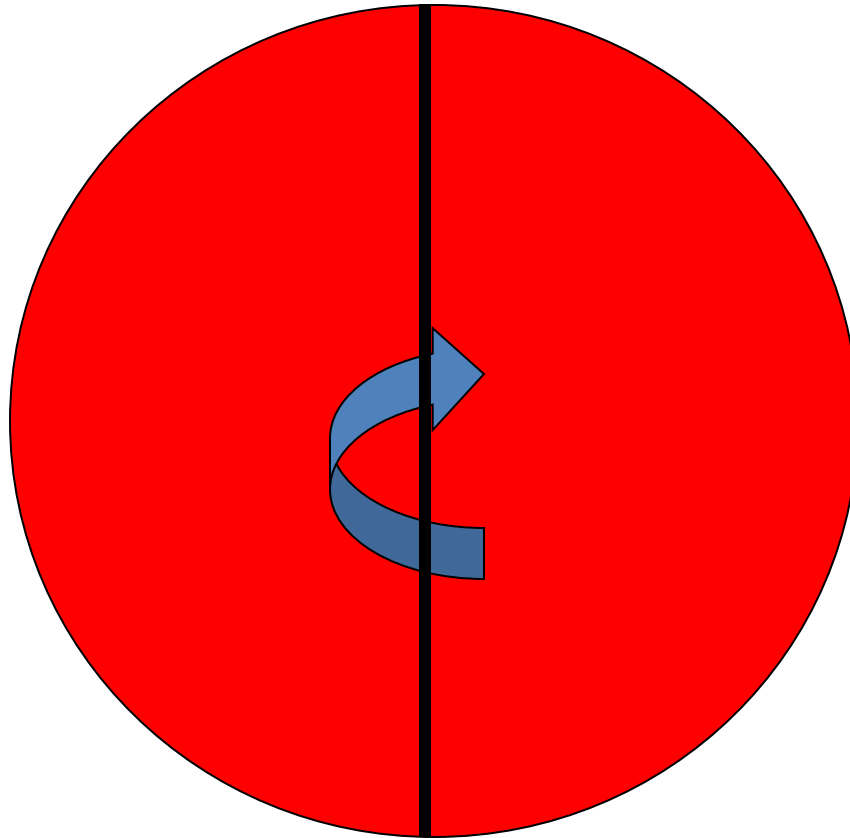
- **Brouwer's theorem:** Let  $f:D \rightarrow D$ , be a continuous function, and suppose  $D$  is convex and compact. Then there exists  $x$  such that  $f(x) = x$



# Illustrations of Brouwer's theorem

Suppose  $D$  is a disc

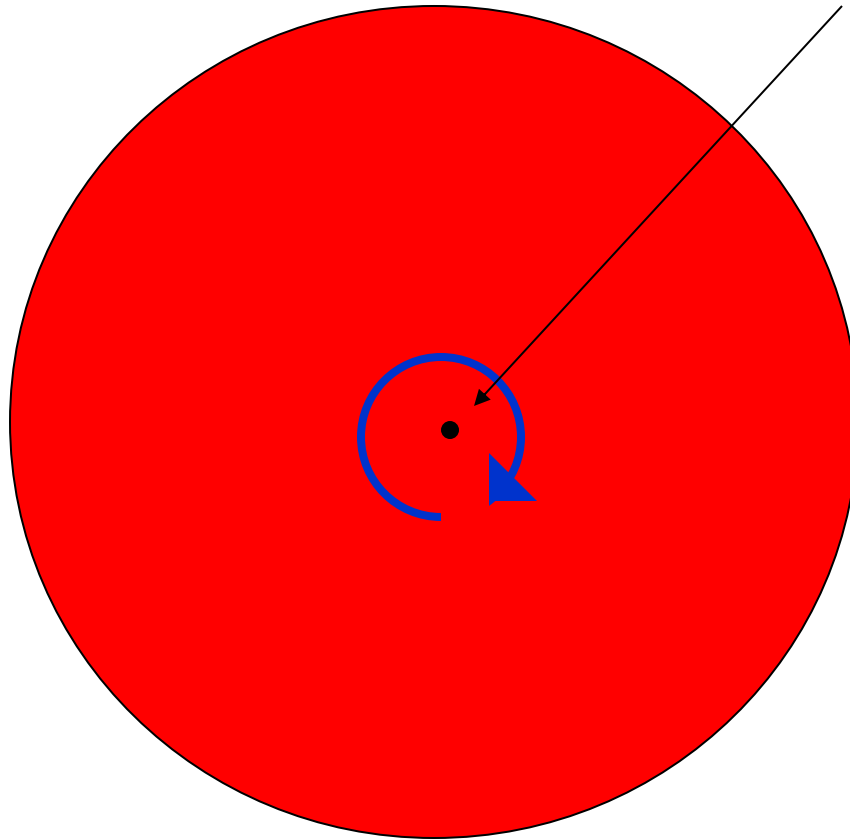
Flip?



# Illustrations of Brouwer's theorem

Suppose  $D$  is a disc

Rotate?



# Sperner's lemma

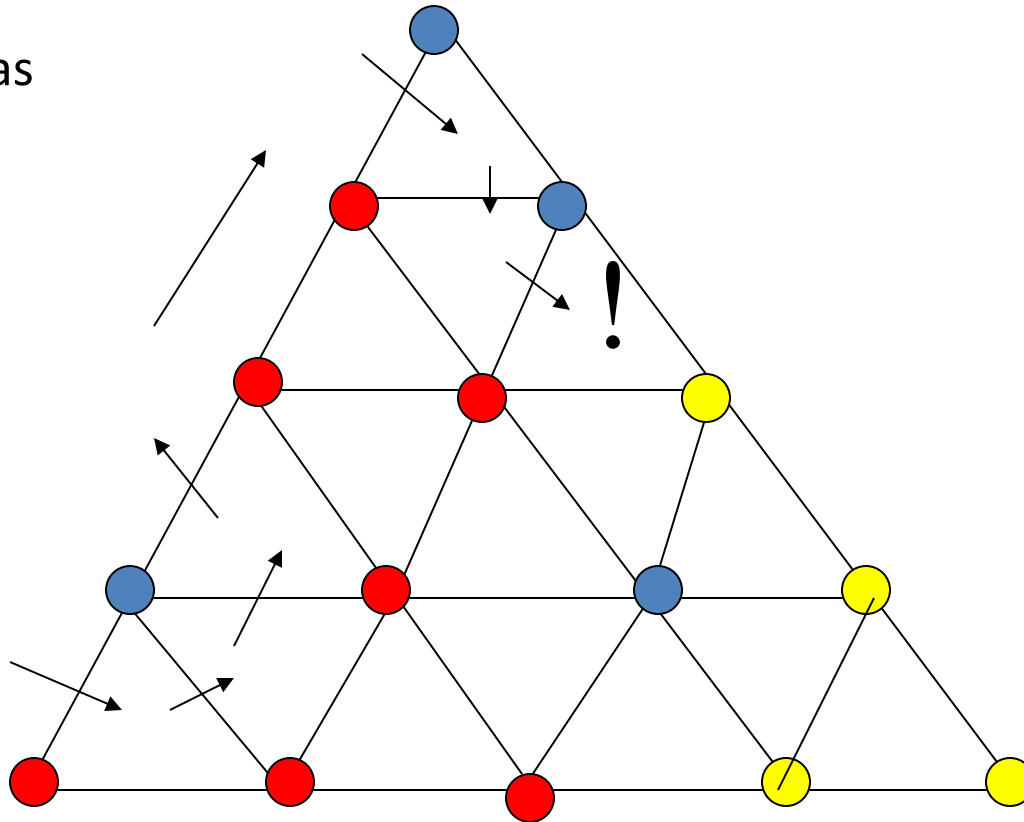
## In 2 dimensions

- Let  $D$  be the 2-dimensional simplex
  - $D = \{(x_1, x_2, x_3) : x_1 + x_2 + x_3 = 1, x_i \geq 0, \text{ for } i=1, 2, 3\}$
  - $D$  is a triangle
- Consider a triangulation of  $D$
- Color all the vertices of the small triangles, using 3 colors such that:
  - The 3 vertices of  $D$  have a different color
  - Along each edge of  $D$ , we use only the colors of the 2 vertices of the edge (1 color forbidden)
  - No restriction for the interior of  $D$

# Sperner's lemma

## Sperner's

**Lemma:** Any such coloring has at least one trichromatic triangle



# Algorithms for normal form games

Let us look at the computational problems:

- **SPERNER:** Given a coloring satisfying the conditions of Sperner's lemma, find a trichromatic triangle
- **BROUWER:** Given a function satisfying the conditions of Brouwer's theorem, find a fixed point
- **NASH:** Given a finite normal form game, find a Nash equilibrium

What is common with all 3?

- They are search problems, where we know a solution always exists

# Complexity classes for search problems

Informal descriptions

- **FP (Function P)**: The version of P for search problems
- **FNP (Function NP)**: The version of NP for search problems
- **TFNP (Total FNP)**: The class of search problems that always have a solution

**Fact:**  $FP \subseteq TFNP \subseteq FNP$

# Complexity classes for search problems

- TFNP has several interesting subclasses
- Depending on how the proof of existence is established
- PLS (Polynomial time Local Search)
- PPA (Polynomial time Parity Argument)
- PPAD (Polynomial time Parity Argument, Directed)
- PPP (Polynomial time Pigeonhole Principle)
- And more...

In fact, our problems belong to one of these subclasses

# The class PPAD

[Papadimitriou '94]

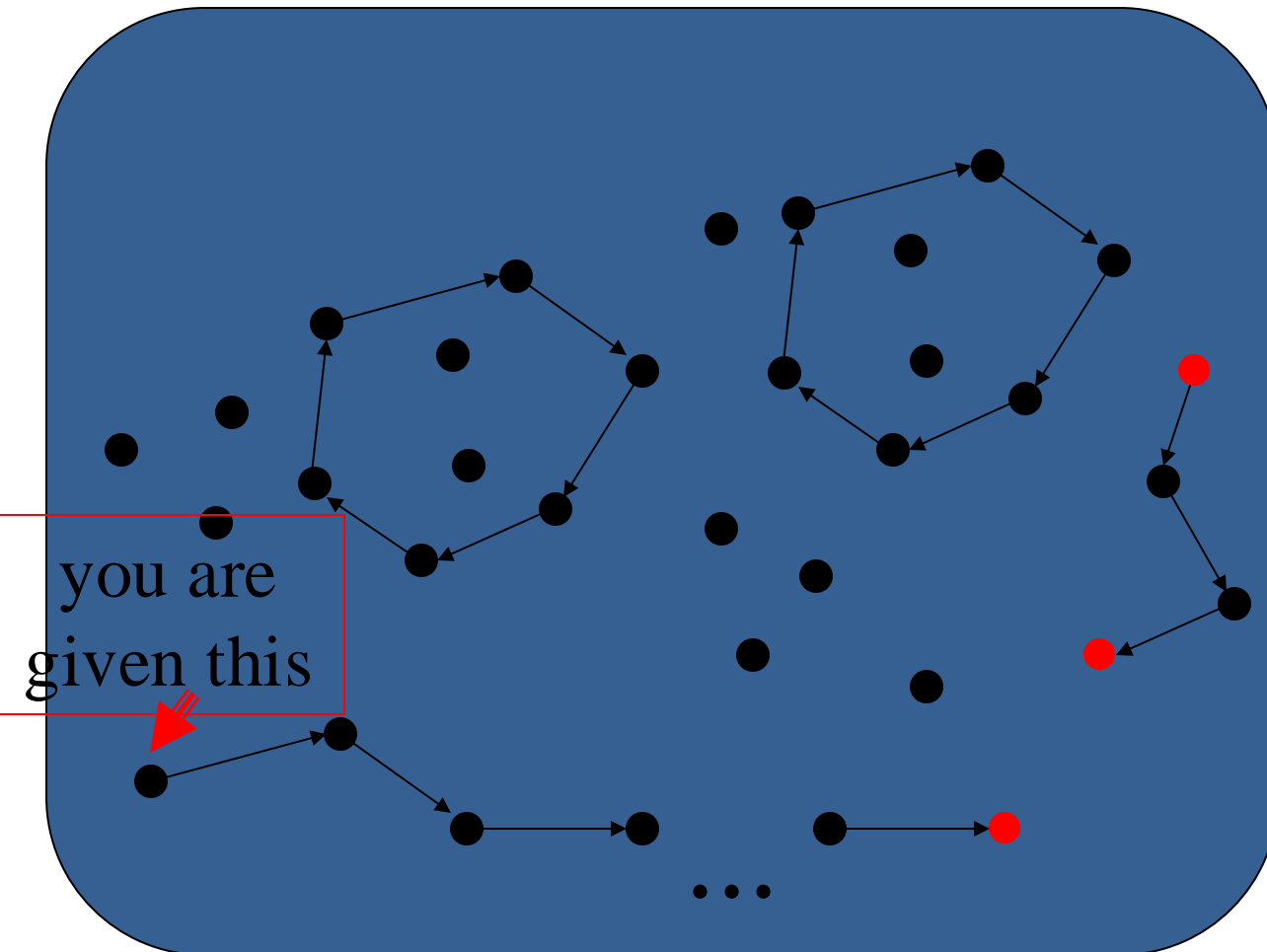
- Consists of problems where the existence of a solution can be established by a particular kind of parity argument
- Namely, PPAD contains all problems that can be reduced to:

END OF THE LINE:

- We are given a directed graph with  $\text{in-degree}(u) \leq 1$ ,  $\text{out-degree}(u) \leq 1$  for every vertex  $u$
- The graph is given implicitly by two circuits  $P, C$ 
  - $(u,v)$  is an edge iff  $u = P(v)$  and  $v = C(u)$
  - i.e., we are **only** allowed to ask **queries** for the successor or the predecessor of a node (at most polynomially many queries)
- We are also given a source node ( $\text{in-degree}=0$ ,  $\text{out-degree}=1$ )
- *Goal: Find the sink, or another source*
  - existence of such a node is guaranteed, by a parity argument: **the total number of sources and sinks is even**



# The class PPAD



Q: Is there an efficient algorithm for finding another unbalanced node **without actually following the path?**

# Complexity of finding a Nash equilibrium

- Open problem for many years
- Eventually:
  - The problem belongs to **PPAD**
    - Membership in PPAD is established via the Lemke-Howson algorithm
  - [Daskalakis, Goldberg, Papadimitriou, September 2005]: **PPAD**-complete for 4-player games, conjectured that for 2 players there is an efficient algorithm
  - [Chen, Deng, November 2005]: **PPAD**-complete even for 2-player games!
  - [Chen, Deng, Teng, February 2006]: **PPAD**-complete even for some approximate versions of equilibria
  - Current belief is that problems in **PPAD** are not poly-time solvable
  - Finding an exact Nash equilibrium is most probably intractable

# Other PPAD-complete problems

How can we define **BROUWER** as a computational problem?

- Consider a function  $f$  that satisfies the conditions of Brouwer's theorem
  - It may not be easy to succinctly describe  $f$  as input to the algorithm
  - Also, the fixed point may contain irrational numbers
- Thus, the function is given implicitly via a circuit (only allowed to ask queries for the value of the function at any point of the domain)
- **Goal:** Find an approximate fixed point: a point  $x$  such that  $|f(x) - x| < \epsilon$

**Theorem:** BROUWER is PPAD-complete

Finding a Nash equilibrium is **equivalent** to finding approximate fixed points of continuous functions

- Note that the proof of Nash's theorem only showed that finding an equilibrium is at most as difficult as finding fixed points

# Approximate Nash equilibria

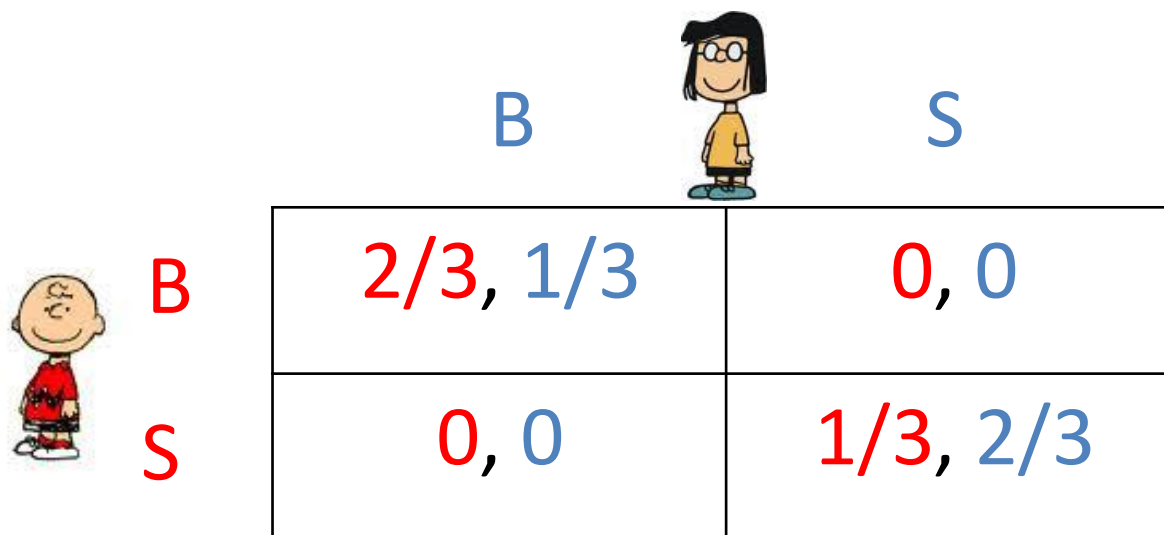
# Approximate Nash equilibria

- Since the problem of computing equilibria is hard, we can consider possible relaxations of the initial definition
- Recall the definition of Nash equilibria: A profile of mixed strategies  $(\mathbf{p}, \mathbf{q})$  is a Nash equilibrium if
  - $u_1(\mathbf{p}, \mathbf{q}) \geq u_1(\mathbf{e}^i, \mathbf{q})$  for every pure strategy  $\mathbf{e}^i$  of pl. 1
  - $u_2(\mathbf{p}, \mathbf{q}) \geq u_2(\mathbf{p}, \mathbf{e}^j)$  for every pure strategy  $\mathbf{e}^j$  of pl. 2

# Approximate Nash equilibria

- Definition: A profile of mixed strategies  $(\mathbf{p}, \mathbf{q})$  is an  $\varepsilon$ -Nash equilibrium if
  - $u_1(\mathbf{p}, \mathbf{q}) \geq u_1(\mathbf{e}^i, \mathbf{q}) - \varepsilon$ , for every pure strategy  $\mathbf{e}^i$  of pl. 1
  - $u_2(\mathbf{p}, \mathbf{q}) \geq u_2(\mathbf{p}, \mathbf{e}^j) - \varepsilon$ , for every pure strategy  $\mathbf{e}^j$  of pl. 2
- In words: a profile of strategies is an  $\varepsilon$ -Nash equilibrium if no player can gain more than  $\varepsilon$  by deviating
- When we study  $\varepsilon$ -Nash equilibria, we usually normalize the utilities to be in  $[0, 1]$ 
  - Thus also  $\varepsilon \in [0, 1]$

# Example of approximate Nash equilibria



		B	S
	B	2/3, 1/3	0, 0
	S	0, 0	1/3, 2/3

Consider the profile  $(\mathbf{p}, \mathbf{q}) = ((0.6, 0.4), (0.4, 0.6))$

- $u_1(\mathbf{p}, \mathbf{q}) = 0.6 \times 0.4 \times 2/3 + 0.4 \times 0.6 \times 1/3 = 0.24$
- $u_1(\mathbf{e}^1, \mathbf{q}) = 0.4 \times 2/3 = 0.267 = u_1(\mathbf{p}, \mathbf{q}) + 0.027$
- $u_1(\mathbf{e}^2, \mathbf{q}) = 0.6 \times 1/3 = 0.2 < 0.24$
- Similar analysis for pl. 2
- Hence, this profile is a 0.027-Nash equilibrium

None of the players can gain more than 0.027 by deviating to another strategy

# Searching for Approximate Equilibria

- We will focus on the simpler version of  $\epsilon$ -Nash equilibria
- At the same time, we also want to focus on strategy profiles that are simple, and easy to describe

**Definition:** A  $k$ -uniform strategy is a strategy where all probabilities are integer multiples of  $1/k$

e.g.  $(3/k, 0, 0, 1/k, 5/k, 0, \dots, 6/k)$

**Important observation:** Support size of a  $k$ -uniform strategy  $\leq k$

Can we have approximate equilibria with  $k$ -uniform strategies for small values of  $k$ ?



# A Subexponential Algorithm (Quasi-PTAS)

**Theorem [Lipton, Markakis, Mehta '03]:** Consider a  $n \times n$  game. For any  $\varepsilon$  in  $(0,1)$ , and for every  $k \geq 9 \log n / \varepsilon^2$ , there exists a pair of  $k$ -uniform strategies  $(\mathbf{p}, \mathbf{q})$  that forms an  $\varepsilon$ -Nash equilibrium

**Lesson learnt:** there is no need to use a big support!

- For 0-sum games already proved in [Althofer '94, Lipton, Young '94]

**Proof idea:**

- Use of the "Probabilistic Method"
- Sample a mixed strategy for each player according to the distribution of a Nash equilibrium
  - Feasible because of Nash's theorem
- Then prove that with positive probability the desired property holds

# A Subexponential Algorithm (Quasi-PTAS)

**Theorem [Lipton, Markakis, Mehta '03]:** Consider a  $n \times n$  game. For any  $\varepsilon$  in  $(0,1)$ , and for every  $k \geq 9 \log n / \varepsilon^2$ , there exists a pair of  $k$ -uniform strategies  $(\mathbf{p}, \mathbf{q})$  that forms an  $\varepsilon$ -Nash equilibrium

**Corollary :** We can compute an  $\varepsilon$ -Nash equilibrium in time

$$n^{O(\log n / \varepsilon^2)}$$

**Proof of Corollary:** There are  $n^{O(k)}$  pairs of supports to look at. Verify the  $\varepsilon$ -equilibrium condition.

# An application

[McCarthy, Laan, Wang, Vayanos, Sinha, Tambe '18]

- **Threat Screening Games:** Games for modeling decision problems related to screening at airports, borders, and other areas
- Motivated by a collaboration of USC with the US Transportation Security Administration
- Use of mixed strategies for selecting how to screen quite popular during last years
- **Main practical result:** Simulations for screening in a large airport (comparable to the Los Angeles International Airport) show that approximate equilibria with  $k$ -uniform small support strategies behave very well in terms of the airport security objectives

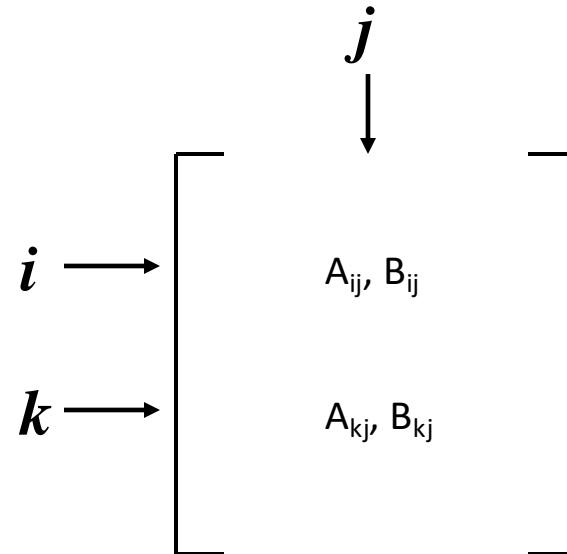
# Moving on...

- How good is an algorithm with running time  $n^{O(\log n / \epsilon^2)}$  ?
- For sure better than exponential
  - Better than  $n^n$  or  $2^n$
- But still not polynomial running time
  - Usually referred to as quasi-polynomial
- For what values of  $\epsilon$  can we have polynomial time algorithms?

# Polynomial Time Approximation Algorithms

For  $\varepsilon = 1/2$ :

- Pick arbitrary row  $i$
- Let  $j = \text{BR}(i)$  = best response to  $i$
- Find  $k = \text{BR}(j)$ , pl. 1 plays  $i$  or  $k$  with prob.  $1/2$  each
- Pl. 2 just plays  $j$



**Proposition:** This is a  $1/2$ -approximate equilibrium with support size  $\leq 2$  for both players!

**[Feder, Nazerzadeh, Saberi '07]:** For  $\varepsilon < 1/2$ , we need in worst case, support at least  $\Omega(\log n)$

# Improved Approximation Algorithms for Approximate Nash equilibria (ΕΚΤΟΣ ΥΛΗΣ)

# Polynomial Time Approximation Algorithms

Better than  $\frac{1}{2}$ -approximations in polynomial time

[Daskalakis, Mehta, Papadimitriou '07]: polynomial time algorithm for  $\varepsilon = 1 - 1/\varphi = (3 - \sqrt{5})/2 \approx 0.382$  ( $\varphi$  = golden ratio)

- Based on sampling + Linear Programming
- Need to solve polynomial number of linear programs
- Not a very fast algorithm
- Polynomial time algorithm but still a large number of linear programs to be solved

# Polynomial Time Approximation Algorithms

[Bosse, Byrka, Markakis '07]: a different LP-based method with the same approximation of 0.382

- Needs to solve only 1 linear program
- Similar idea in [Kontogiannis, Spirakis '07] for well-supported approximation
- A small tweak can also yield a better approximation of 0.36

**Recall:** 0-sum games can be solved in polynomial time (equivalent to linear programming)



- Given a game defined by the arrays  $(A, B)$ , start with an equilibrium of the 0-sum game  $(A-B, B-A)$

- If incentives to deviate are “high”, players adjust their strategies via best response moves



# A 0.382-approximation algorithm

Parameters of the algorithm:  $\alpha, \delta_2 \in [0,1]$

1. Find an equilibrium  $x^*, y^*$  of the 0-sum game  $(A - B, B - A)$
2. Let  $g_1, g_2$  be the maximum gain by deviating to a pure strategy for row and column player. Suppose  $g_1 \geq g_2$
3. If  $g_1 \leq \alpha$ , output  $x^*, y^*$
4. Else: let  $b_1 = \text{best response to } y^*$ ,  $b_2 = \text{best response to } b_1$
5. Output:

$$x = b_1$$

$$y = (1 - \delta_2) y^* + \delta_2 b_2$$

**Theorem:** The algorithm with  $\alpha = 1 - 1/\varphi$  and  $\delta_2 = (1 - g_1) / (2 - g_1)$  achieves a  $(1 - 1/\varphi)$ -approximation

# Yet another approach

- [Spirakis, Tsaknakis '07]: algorithm with an approximation of  $\varepsilon = 0.339$ 
  - Best known approximation for many years, till recently
  - A different optimization approach, but yet another LP-based method
  - It starts with a descent-based method to identify a stationary point
  - Needs to solve a polynomial number of linear programs (one per each iteration)
- [Deligkas, Fasoulakis, Markakis '22]: Currently best approximation of  $\varepsilon = 1/3$ 
  - Based on a tweak of the Spirakis-Tsaknakis algorithm
  - Improving the bottleneck case of their algorithm
- **Big open problem:**
  - Can we find algorithms for lower values of  $\varepsilon$ , closer to 0?
  - Is it possible to have a poly-time algorithm for **any** constant  $\varepsilon > 0$ ?
    - **Probably not...** [Rubinstein '16]
- So far, there have been further improvements for several special classes of games
  - Low-rank matrices, sparse matrices, symmetric games, win-lose games, ...

# Progress on other notions of approximation

- $\epsilon$ -well-supported equilibria:
  - a profile of strategies  $(\mathbf{p}, \mathbf{q})$  is an  $\epsilon$ -well-supported Nash equilibrium if any strategy from  $\text{Supp}(\mathbf{p})$  is an approximate best response to  $\mathbf{q}$  and vice versa
  - [Kontogiannis, Spirakis '10]: Polynomial time only for  $\epsilon = 2/3$ , based also on solving 0-sum games
  - More recently improved to 0.6528 [Czumaj et al. '18]
  - And even more recently improved to  $1/2$  [Deligkas, Fasoulakis, Markakis '23]
- Even stronger notion of approximation: require that the profile found is geometrically close to an exact Nash equilibrium
  - [Etessami, Yannakakis '07]: mostly negative results
- Open problem to provide more positive results, even for special cases, for these concepts as well

# The story so far for $\epsilon$ -NE

**$\epsilon$ -NE:**

PPAD-complete  
for  $\epsilon < n^{-6}$

0

$\epsilon^*$

1/3

0.364

0.339

0.382

0.5

0.75

1

[Rubinstein '16]

Under ETH for PPAD,  $\exists$  very  
small constant  $\epsilon^*$  s.t. no  
poly-time algorithm for  $\epsilon < \epsilon^*$

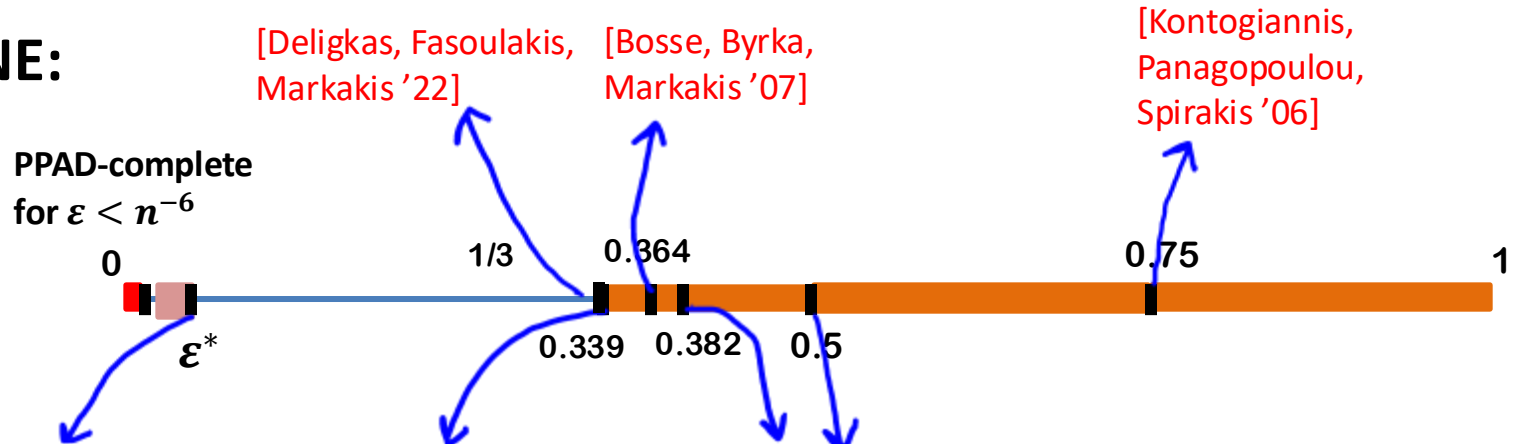
[Tsaknakis, Spirakis '07]

[Deligkas, Fasoulakis,  
Markakis '22]

[Bosse, Byrka,  
Markakis '07]

[Daskalakis, Mehta,  
Papadimitriou '06, '07]

[Kontogiannis,  
Panagopoulou,  
Spirakis '06]



# Post-Mortem

- Difficult to find exact Nash equilibria for an arbitrary 2-player game
- A bit less difficult to find approximate Nash equilibria
  - But still challenging and not yet well understood
- Is it a catastrophe if we do not have efficient algorithms for every game?
  - Players in practice may also be able to adjust their strategies and gradually converge to an equilibrium by observing each other's actions
  - Still, “if your laptop cannot find an equilibrium, then neither can the market”, quote from Kamal Jain (2003)
- Despite the high complexity, the notion of a Nash equilibrium remains among the most important notions in game theory

# Post-Mortem

- **Take-home story:** Nash equilibria form a good starting point from a conceptual point of view
- But when intractable, we should think towards alternative and tractable variations of equilibrium concepts
- Ongoing research:
  - Learning algorithms with convergence guarantees
  - Also connected to training neural networks
  - Many positive results for 0-sum games (starting with fictitious play [Robinson '51])
  - Not as easy for general games
  - No-regret algorithms provide convergence “on average”
  - Several variations of gradient descent under consideration during last 5 years...