

Algorithms for Computing Approximate Nash Equilibria

Vangelis Markakis

Athens University of Economics and Business

Outline

- Introduction to Games
 - The concepts of Nash and ε -Nash equilibrium

- Computing approximate Nash equilibria
 - A subexponential algorithm for any constant $\varepsilon > 0$
 - Polynomial time approximation algorithms

- Conclusions

What is Game Theory?

- Game Theory aims to help us understand situations in which *decision makers* interact
- Goals:
 - Mathematical models for capturing the properties of such interactions
 - Prediction (given a model how should/would a *rational agent* act?)

Rational agent: when given a choice, the agent always chooses the option that yields the highest utility

Models of Games

- Cooperative or noncooperative
- Simultaneous moves or sequential
- Finite or infinite
- Complete information or incomplete information

In this talk:

- Cooperative or noncooperative
- Simultaneous moves or sequential
- Finite or infinite
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Noncooperative Games in Normal Form





The Hawk-Dove game

Column Player



Row
player



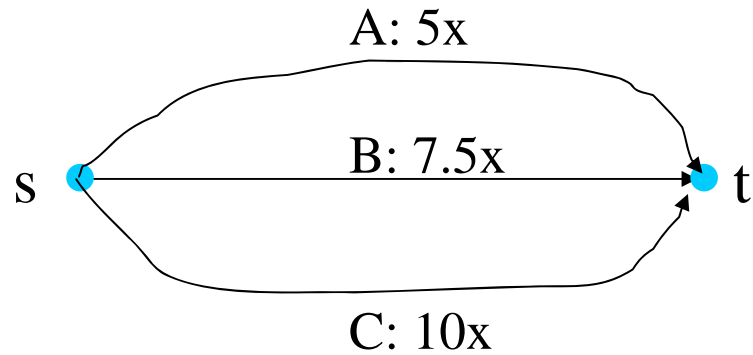
		
	2, 2	0, 4
	4, 0	-1, -1

Example 2: The Bach or Stravinsky game (BoS)



$2, 1$	$0, 0$
$0, 0$	$1, 2$

Example 3: A Routing Game



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	A	B	C
A	10, 10	5, 7.5	5, 10
B	7.5, 5	15, 15	7.5, 10
C	10, 5	10, 7.5	20, 20

Definitions

- 2-player game (R, C) :
 - n available *pure strategies* for each player
 - $n \times n$ payoff matrices R, C
 - i, j played \Rightarrow payoffs : R_{ij}, C_{ij}
- **Mixed strategy**: Probability distribution over $[n]$

$$x = (x_1, \dots, x_n), \quad \sum x_i = 1, \quad x_i \geq 0$$

- **Expected payoffs** : (x, Ry) and (x, Cy)

$$(x, Ry) = \sum_{i,j} x_i y_j R_{ij}$$

Solution Concept



x^* , y^* is a **Nash equilibrium** if no player has a unilateral incentive to deviate:

$$(x, Ry^*) \leq (x^*, Ry^*) \quad \forall x$$

$$(x^*, Cy) \leq (x^*, Cy^*) \quad \forall y$$

[Nash, 1951]: Every finite game has a mixed strategy equilibrium.

(think of it as a steady state)

Proof: Based on **Brouwer's fixed point theorem**.

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Proof: Based on **Brouwer's fixed point theorem**.

Solution Concept



It suffices to consider only deviations to *pure strategies*

Let $x^i = (0, 0, \dots, 1, 0, \dots, 0)$ be the i th pure strategy

x^* , y^* is a **Nash equilibrium** if no player has a unilateral incentive to deviate to a pure strategy:

$$(x^i, Ry^*) \leq (x^*, Ry^*) \quad \forall x^i$$

$$(x^*, Cy^j) \leq (x^*, Cy^*) \quad \forall y^j$$

Example: The Hawk-Dove Game

Column Player



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	2, 2	0, 4
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Example 2: The Bach or Stravinsky game (BoS)



	2, 1	0, 0
	0, 0	1, 2

3 equilibrium points:

1. (B, B)
2. (S, S)
3. $((2/3, 1/3), (1/3, 2/3))$

Complexity issues

- $m = 2$ players, known algorithms: worst case exponential time
[Kuhn '61, Lemke, Howson '64, Mangasarian '64, Lemke '65]
- If **NP**-hard \Rightarrow **NP** = co-**NP** [Megiddo, Papadimitriou '89]
- **NP**-hard if we add more constraints (e.g. maximize sum of payoffs)
[Gilboa, Zemel '89, Conitzer, Sandholm '03]
- Representation problems
 $m = 3$, there exist games with rational data BUT irrational equilibria
[Nash '51]
- **PPAD**-complete even for $m = 2$
[Daskalakis, Goldberg, Papadimitriou '06, Chen, Deng, Teng '06]
Poly-time equivalent to:
 - finding approximate fixed points of continuous maps on convex and compact domains

Approximate Nash Equilibria

- Recall definition of Nash eq. :

$$(x, Ry^*) \leq (x^*, Ry^*) \quad \forall x$$

$$(x^*, Cy) \leq (x^*, Cy^*) \quad \forall y$$

- ε -Nash equilibria** (incentive to deviate $\leq \varepsilon$) :

$$(x, Ry^*) \leq (x^*, Ry^*) + \varepsilon \quad \forall x$$

$$(x^*, Cy) \leq (x^*, Cy^*) + \varepsilon \quad \forall y$$

Normalization: entries of R, C in $[0,1]$

Searching for Approximate Equilibria

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

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

[Lipton, M., Mehta '03]: For any ε in $(0,1)$, and for every $k \geq 9 \log n / \varepsilon^2$, there exists a pair of k -uniform strategies x, y that form an ε -Nash equilibrium.

A Subexponential Algorithm (Quasi-PTAS)

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

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

[Lipton, M., Mehta '03]: For any ε in $(0,1)$, and for every $k \geq 9 \log n / \varepsilon^2$, there exists a pair of k -uniform strategies x, y that form an ε -Nash equilibrium.

Corollary : We can compute an ε -Nash equilibrium in time $n^{O(\log n / \varepsilon^2)}$

Proof: There are $n^{O(k)}$ pairs of strategies to look at.
Verify ε -equilibrium condition.

Proof of Existence

Based on the probabilistic method (sampling)

Let x^* , y^* be a Nash equilibrium.

- **Sample k times** from the set of pure strategies of the row player, independently, at random, according to x^* \Rightarrow k -uniform strategy x
- Same for column player \Rightarrow k -uniform strategy y

Suffices to show $\Pr[x, y \text{ form an } \varepsilon\text{-Nash eq.}] > 0$

Proof (cont'd)

Enough to consider deviations to **pure strategies**

$$(x^i, Ry) \leq (x, Ry) + \varepsilon \quad \forall i$$

(x^i, Ry) : sum of k random variables with mean (x^i, Ry^*)

Chernoff-Hoeffding bounds $\Rightarrow (x^i, Ry) \approx (x^i, Ry^*)$ with high probability

$$(x^i, Ry) \approx (x^i, Ry^*) \leq (x^*, Ry^*) \approx (x, Ry)$$

Finally when $k = \Omega(\log n / \varepsilon^2)$:

$$\Pr[\exists \text{ deviation with gain more than } \varepsilon] = O(n)e^{-k\varepsilon^2/8} < 1$$

Multi-player Games

For m players, same technique:

support size: $k = O(m^2 \log(m^2 n)/\varepsilon^2)$

running time: $\exp(\log n, m, 1/\varepsilon)$

Previously [**Scarf '67**]: $\exp(n, m, \log(1/\varepsilon))$
(fixed point approximation)

[**Lipton, M. '04**]: $\exp(n, m)$ but $\text{poly}(\log(1/\varepsilon))$
(using algorithms for polynomial equations)

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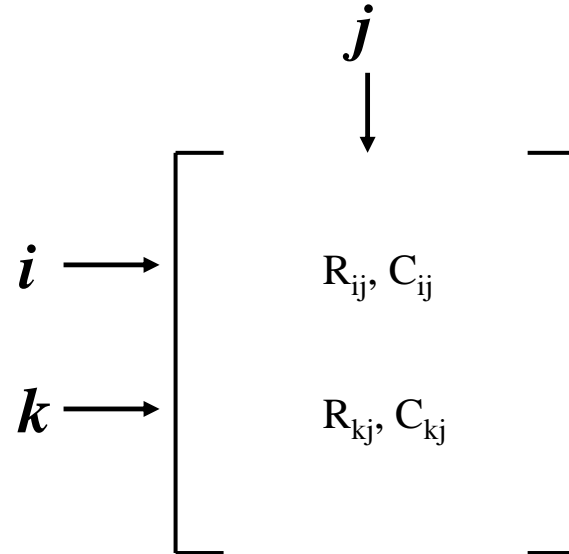
- Computing approximate Nash equilibria
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Polynomial Time Approximation Algorithms

For $\varepsilon = 1/2$:

- Pick arbitrary row i
- Let $j = \text{best response to } i$
- Find $k = \text{best response to } j$,
play i or k with prob. $1/2$



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

Polynomial Time Approximation Algorithms

Daskalakis, Mehta, Papadimitriou (EC '07):

in \mathbf{P} 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

Bosse, Byrka, M. (WINE '07): a different LP-based method

1. Algorithm 1: $1 - 1/\varphi$
2. Algorithm 2: 0.364

Running time: need to solve one linear program

Approach

0-sum games: games of the form $(R, -R)$

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



- Start with an equilibrium of the 0-sum game $(R-C, C-R)$

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

Similar idea used in [Kontogiannis, Spirakis '07] for a different notion of approximation

Algorithm 1

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

1. Find an equilibrium x^*, y^* of the 0-sum game $(R - C, C - R)$
2. Let g_1, g_2 be the incentives to deviate for row and column player respectively. 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: Algorithm 1 with $\alpha = 1 - 1/\varphi$ and $\delta_2 = (1 - g_1) / (2 - g_1)$ achieves a $(1 - 1/\varphi)$ -approximation

Analysis of Algorithm 1

Why start with an equilibrium of $(R - C, C - R)$?

Intuition: If row player profits from a deviation from x^* then column player also gains at least as much

Case 1: $g_1 \leq \alpha \Rightarrow \alpha$ -approximation

Case 2: $g_1 > \alpha$

Incentive to deviate:

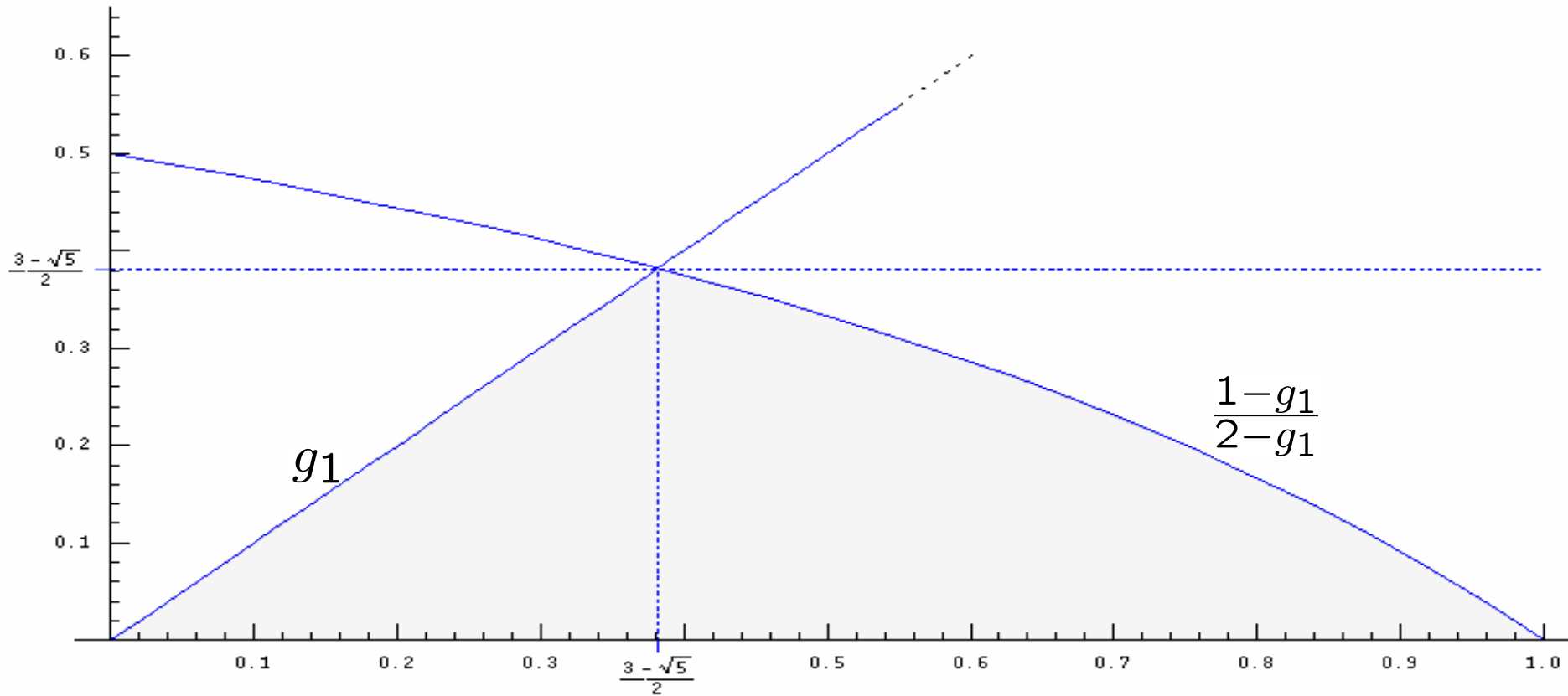
for row player $\leq \delta_2$

for column player $\leq (1 - \delta_2)(1 - (b_1, Cy^*))$

$$\leq (1 - \delta_2)(1 - g_1) = (1 - g_1) / (2 - g_1)$$

$\Rightarrow \max\{\alpha, (1 - \alpha)/(2 - \alpha)\}$ -approximation

Analysis of Algorithm 1



Towards a better algorithm

1. Find an equilibrium x^*, y^* of the 0-sum game $(R - C, C - R)$
2. Let g_1, g_2 be the incentives to deviate for row and column player respectively. 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:

$$x = b_1$$

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

Algorithm 2

1. Find an equilibrium x^*, y^* of the 0-sum game $(R - C, C - R)$
2. Let g_1, g_2 be the incentives to deviate for row and column player respectively. Suppose $g_1 \geq g_2$
3. If $g_1 \in [0, 1/3]$, output x^*, y^*
4. If $g_1 \in (1/3, \beta]$,
 - let $r_1 = \text{best response to } y^*$, $x = (1 - \delta_1) x^* + \delta_1 r_1$
 - let $b_2 = \text{best response to } x$, $y = (1 - \delta_2) y^* + \delta_2 b_2$
5. If $g_1 \in (\beta, 1]$ output:

$$x = r_1$$

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

Analysis of Algorithm 2

(Reducing to an optimization question)

- We set δ_2 so as to equalize the incentives of the players to deviate
- Let $h = (x^*, Cb_2) - (x^*, Cy^*)$

Theorem: The approximation guarantee of Algorithm 2 is 0.364 and is given by:

$$\max_{g_1 \in [1/3, 1/2]} \min_{\delta_1 \in [0, 1]} \max_{h \in [0, g_1]} F(g_1, \delta_1, h)$$

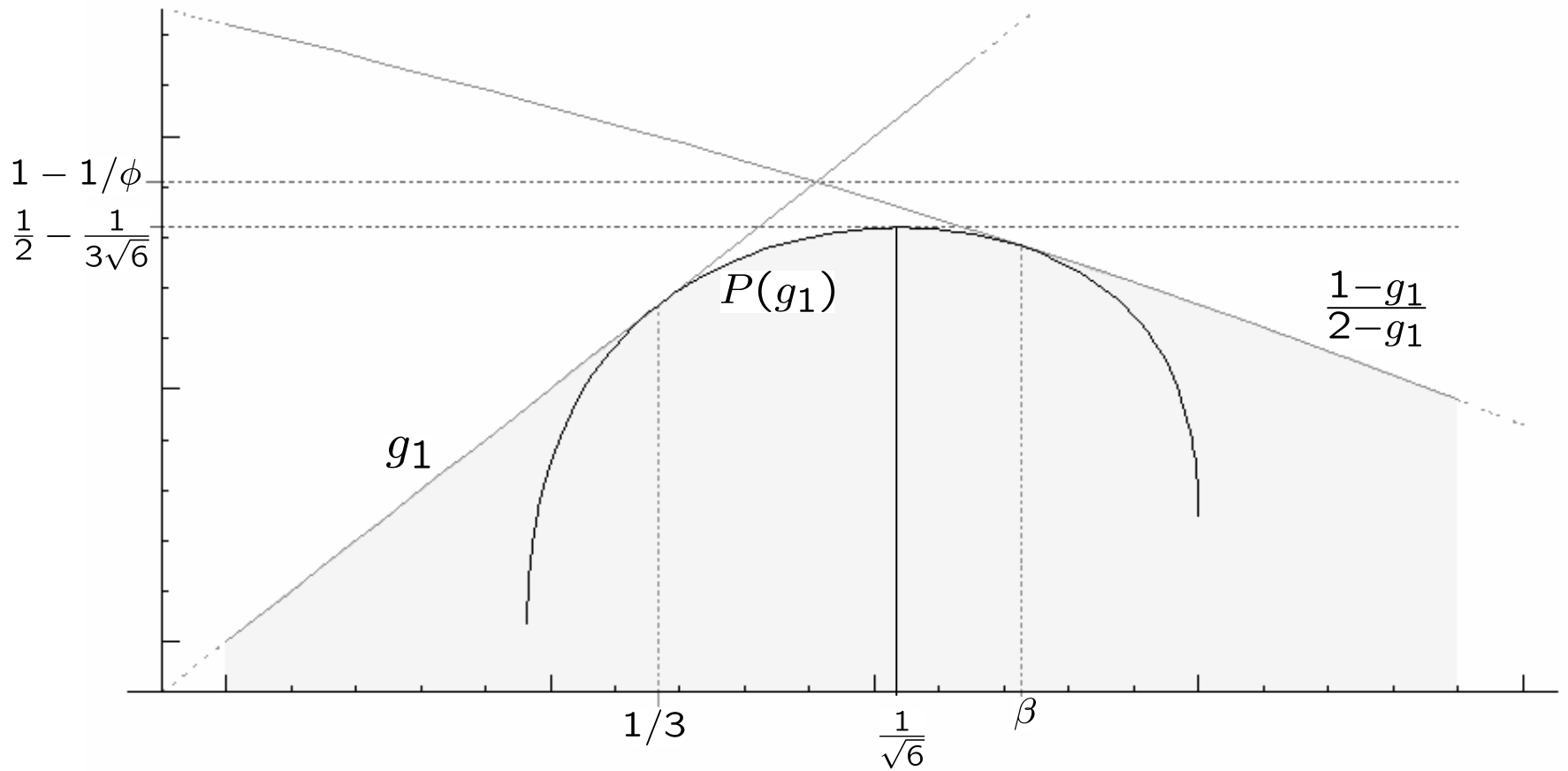
Analysis of Algorithm 2 (solution)

Optimization yields:

$$\delta_1(g_1) = (1 - g_1) \left(\sqrt{1 + \frac{1}{1-2g_1}} - \frac{1}{g_1} - 1 \right)$$

$$\delta_2(g_1, \delta_1, h) = \frac{\delta_1 - g_1 + (1 - \delta_1)h}{1 + \delta_1 - g_1}$$

Graphically:



Analysis – tight example

(R, C) =

0, 0	α, α	α, α
α, α	0, 1	1, 1/2
α, α	1, 1/2	0, 1

$$\alpha = 1/\sqrt{6}$$

Remarks and Open Problems

- **Spirakis, Tsaknakis (WINE '07)**: currently best approximation of **0.339**
 - yet another LP-based method
- Polynomial Time Approximation Scheme (PTAS)?
Yes if:
 - $\text{rank}(R) = O(1)$ & $\text{rank}(C) = O(1)$ [**Lipton, M. Mehta '03**]
 - $\text{rank}(R+C) = O(1)$ [**Kannan, Theobald '06**]
- **PPAD**-complete for $\varepsilon = 1/n$ [**Chen, Deng, Teng '06**]

Other Notions of Approximation

- **ϵ -well-supported equilibria:** every strategy in the support is an approximate best response
 - [Kontogiannis, Spirakis '07]: 0.658-approximation, based also on solving 0-sum games
- **Strong approximation:** output is geometrically close to an exact Nash equilibrium
 - [Etessami, Yannakakis '07]: mostly negative results

Thank You!