

Computation of Nash Equilibria in Bimatrix Games

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Skeleton of the Talk

- 1 Bimatrix Games Preliminaries
 - Complexity of 2NASH
 - Formulations for 2NASH
 - The algorithm of Lemke & Howson
- 2 Polynomial-time Tractable Subclasses
- 3 Approximability of 2NASH
 - Theoretical Analysis
 - Experimental Study
- 4 Conclusions

Bimatrix Games: Representation

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- Representation: By the $m \times n$ **bimatrix** of **normalized** payoffs:

$$\Gamma = \langle R \in [0, 1]^{m \times n}, C \in [0, 1]^{m \times n} \rangle$$

	1	...	j	...	n
1	** ,	** ,	** ,	** ,	** ,
...	** ,	** ,	** ,	** ,	** ,
k	** ,	** ,	$R_{k,j}, C_{k,j}$	** ,	** ,
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Payoff to ROW player when row plays k and col plays j...

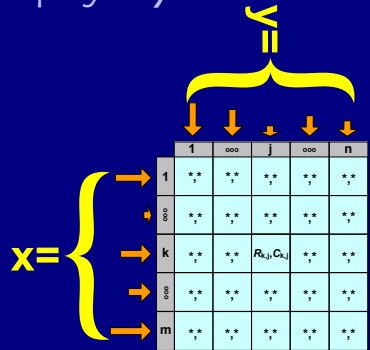
Payoff to COL player when row plays k and col plays j...

- Size of representation: $O(m \times n)$ **rational numbers**.

Uncorrelated Strategies (for the players)

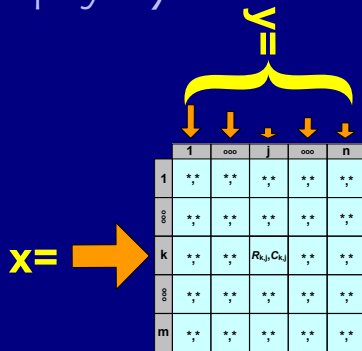
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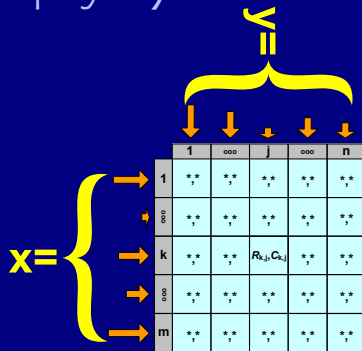
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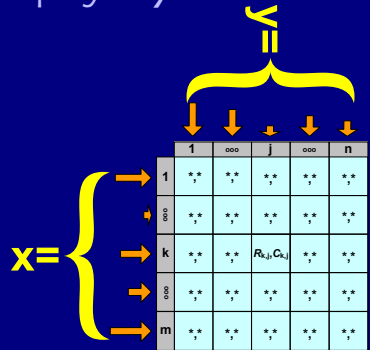
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- Each player is interested in optimizing the **expected value** of her own payoff, as a function of the announced **strategies profile** for both players (\mathbf{x}, \mathbf{y}):
 - ▶ ROW player: $\mathbf{x}^T \mathbf{R} \mathbf{y} = \sum_{i \in [m]} \sum_{j \in [n]} x_i \cdot R_{ij} \cdot y_j$.
 - ▶ column player: $\mathbf{x}^T \mathbf{C} \mathbf{y} = \sum_{i \in [m]} \sum_{j \in [n]} x_i \cdot C_{ij} \cdot y_j$.



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...	**	**	**	**	**
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- The mediator *recommends* via private channels the corresponding action per player in the chosen profile, without revealing it to the opponent. Each player *freely chooses* an action, *already knowing* mediator's recommendation to her.
- The **expected value** of the payoff to each player, for a correlated strategy \mathbf{W} of the mediator, is:

$$\text{ROW player: } \sum_{k \in [m]} \sum_{j \in [n]} W_{k,j} R_{k,j} \quad \text{column player: } \sum_{k \in [m]} \sum_{j \in [n]} W_{k,j} C_{k,j}$$

Uncorrelated vs Correlated Strategies

- Any *uncorrelated strategies-profile* $(\mathbf{x}, \mathbf{y}) \in \Delta([m]) \times \Delta([n])$ for the players, induces an **equivalent correlated strategy** (wrt to expected payoffs) for the mediator $\mathbf{W} = \mathbf{x} \cdot \mathbf{y}^T \in \Delta([m] \times [n])$.

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- Some correlated strategies **cannot be decomposed** into equivalent uncorrelated strategies profiles for the players. Eg, in the following (chicken) game, the correlated strategy $[(C,c) : 1/3, (C,d) : 1/3, (D,c) : 1/3, (D,d) : 0]$ is not decomposable into a pair of independent strategies for the players:

		col	
		dare	chicken
ROW	DARE	0, 0	7, 2
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Popular Solution Concepts (I)

DEFINITION: Approximations of Nash Equilibrium

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- **ε -approximate Nash equilibrium** (ε -NE) iff no player can improve her expected payoff more than an additive term of $\varepsilon \geq 0$, by changing *unilaterally* her strategy, against the given strategy of the opponent: $\forall \mathbf{x} \in \Delta([m]), \forall \mathbf{y} \in \Delta([n]),$

$$\bar{\mathbf{x}}^T R \bar{\mathbf{y}} \geq \mathbf{x}^T R \bar{\mathbf{y}} - \varepsilon \quad \wedge \quad \bar{\mathbf{x}}^T C \bar{\mathbf{y}} \geq \bar{\mathbf{x}}^T C \mathbf{y} - \varepsilon$$

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- **ε -well-supported approximate Nash equilibrium** (ε -WSNE) iff no player assigns *positive probability mass* to any of her actions whose expected payoff against the given strategy of the opponent is less than an additive term $\varepsilon \geq 0$ from the maximum expected payoff: $\forall i \in [m], \forall j \in [n]$,

$$[\bar{x}_i > 0 \rightarrow \mathbf{e}_i^T R \bar{\mathbf{y}} \geq \max(R \bar{\mathbf{y}}) - \varepsilon] \quad \wedge \quad [\bar{y}_j > 0 \rightarrow \bar{\mathbf{x}}^T C \mathbf{e}_j \geq \max(\bar{\mathbf{x}}^T C) - \varepsilon]$$

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- 4 Approximate Nash equilibria are **invariant under shifts** but are affected by scalings of the payoff matrices. Exact Nash equilibria are also **invariant under positive scalings**.

Popular Solution Concepts (II)

DEFINITION: Correlated Equilibrium

A *correlated strategy* $\bar{\mathbf{W}} \in \Delta([m] \times [n])$ (for the mediator) is a **correlated equilibrium** iff no player can improve her expected payoff by *unilaterally* ignoring the recommendation of the mediator, given that the opponent will adopt her own recommendation by the mediator: $\forall i, k \in [m], \forall j, \ell \in [n]$,

$$\sum_{j \in [n]} (R_{ij} - R_{k,j}) \bar{W}_{ij} \geq 0 \quad \text{and} \quad \sum_{i \in [m]} (C_{ij} - C_{i,\ell}) \bar{W}_{ij} \geq 0$$

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Remarks:

- 1 The space of correlated equilibria is a **polytope!!!**
- 2 The existence of a mediator, although helpful in having the players' actions coordinated, raises serious **concerns wrt implementation**, such as trust, manipulability, objectivity, etc.

Popular Solution Concepts (III)

DEFINITION: MAXMIN Strategies

A profile of (uncorrelated) strategies $(\bar{\mathbf{x}}, \bar{\mathbf{y}})$ is **MAXMIN profile** iff:

$$\bar{\mathbf{x}} \in \arg \max_{\mathbf{x} \in \Delta([m])} \min_{\mathbf{y} \in \Delta([n])} \mathbf{x}^T R \mathbf{y} = \arg \max_{\mathbf{x} \in \Delta([m])} \min_{j \in [n]} \mathbf{x}^T R \mathbf{e}_j$$

$$\bar{\mathbf{y}} \in \arg \max_{\mathbf{y} \in \Delta([n])} \min_{\mathbf{x} \in \Delta([m])} \mathbf{x}^T C \mathbf{y} = \arg \max_{\mathbf{y} \in \Delta([n])} \min_{i \in [m]} \mathbf{e}_i^T C \mathbf{y}$$

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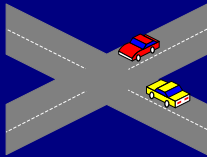
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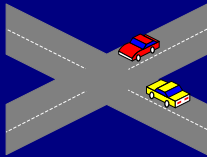
- 1 Efficiently computable via **Linear Programming**.
- 2 Extremely *pessimistic predictions*: It is possible that a MAXMIN profile is "too far" from any notion of approximate equilibrium (not only as points, but also wrt the approximation guarantee).

AN EXAMPLE: Chicken Game



		col	
		dare	chicken
ROW	DARE	0, 0	7, 2
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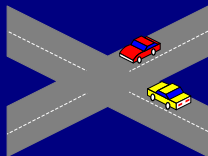
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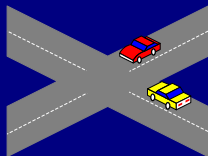
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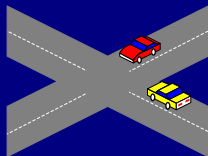
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- One more (extreme) (which are the others?) *correlated equilibrium*, **external** to the set $\text{conv}(\text{NE}(R, C))$:

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Expected payoff per player: $2 \cdot \frac{1}{3} + 7 \cdot \frac{1}{3} + 6 \cdot \frac{1}{3} = 5$.

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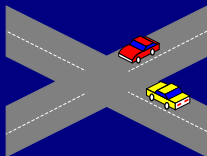
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- *MAXMIN* profile? (C, c) with payoff 6 per player.

Complexity of Equilibria

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- Nash equilibria: Harder case, *PPAD*–hard problem, even for bimatrix games, or arbitrarily good approximations!!!

Solving Bimatrix Games

Determination of One / All Nash Equilibria

We are interested in the computation, if possible in time polynomial in the representation of the game and / or the produced output, of the following problems:

- 2NASH:

- ▶ **INPUT:** A bimatrix game with *non-negative rational* payoff matrices: $R, C \in \mathbb{Q}_{\geq 0}^{m \times n}$.
- ▶ **OUTPUT:** Any (exact) Nash equilibrium, ie, any point of $NE(R, C)$.

- ALL2NASH:

- ▶ **INPUT:** A bimatrix game with *non-negative rational* payoff matrices: $R, C \in \mathbb{Q}_{\geq 0}^{m \times n}$.
- ▶ **OUTPUT:** All the **extreme** Nash equilibria, that determine $NE(R, C)$.

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 - ▶ **OUTPUT:** Any (exact) Nash equilibrium, ie, any point of $NE(R, C)$.

Complexity of 2NASH

- [Nash (1950)] : *Existence* of NE points, for *finite* games.
- [Kuhn (1961), Mangasarian (1964), Lemke-Howson (1964), Rosenmüller (1971), Wilson (1971), Scarf (1967), Eaves (1972), Laan-Talman (1979), van den Elzen-Talman (1991), ...] : Algorithms for 2NASH. None of them is *provably* of polynomial complexity.
- [Savani-von Stengel (2004)] : LH may take an **exponential number of pivots**, to converge to a NE point, for *any* initial choice of the label to be rejected.
- [Goldberg-Papadimitriou-Savani (2011)] : Any algorithm for 2NASH based on the **homotopy method**, has no hope of being polynomial-time, (unless $\mathcal{P} = \mathcal{PSPACE}$).
- [CD / DGP (2006)] : \mathcal{PPAD} -completeness of k NASH, $\forall k \geq 2$.
- [Gilboa-Zemel (1989), Conitzer-Sandholm (2003)] : \mathcal{NP} -complete to determine *special* NE points (eg, \exists more than one NE points? \exists NE with a lower bound on the payoff of one player? ...)

Formulations of 2NASH

Formulations for Nash Equilibrium Sets (I)

As a Linear Complementarity Problem (LCP)

- The set $NE(R, C)$ of Nash equilibria of the bimatrix game $\langle R, C \rangle$ can be expressed as the space of **non-zero feasible solutions** to a **Linear Complementarity Problem**, after proper *scaling* so that its points become probability-distribution pairs:

$$NE(R, C) \approx LCP(M, \mathbf{q}) - \{\mathbf{0}\}$$

where: $R, C \in \mathbb{R}_{>0}^{m \times n}$, $M = \begin{bmatrix} \mathbf{0} & -R \\ -C^T & \mathbf{0} \end{bmatrix}$, $\mathbf{q} = \begin{bmatrix} \mathbf{1}_m \\ \mathbf{1}_n \end{bmatrix}$, and

$$LCP(M, \mathbf{q}) = \{ (\mathbf{w}, \mathbf{z}) : \mathbf{q} + M\mathbf{z} = \mathbf{w} \geq \mathbf{0}; \mathbf{z} \geq \mathbf{0}; \mathbf{w}^T \mathbf{z} = 0 \}$$

Remark: The positivity of the payoff matrices is not a substantial constraint, due to invariance under shifting of $NE(R, C)$.

Formulations for Nash Equilibrium Sets (II)

As a Quadratic Programming Problem (QP)

- The space of Nash equilibria can be expressed as the space of **optimal solutions** in a **Quadratic Programming Problem**. Eg:

[Mangasarian-Stone (1964)]

(MS)

$$\begin{array}{ll} \text{minimize} & (r - \mathbf{x}^T R \mathbf{y}) + (c - \mathbf{x}^T C \mathbf{y}) \\ \text{s.t.} & r \cdot \mathbf{1} - R \mathbf{y} \geq \mathbf{0} \\ & c \cdot \mathbf{1} - C^T \mathbf{x} \geq \mathbf{0} \\ & \mathbf{x} \in \Delta_m \quad \mathbf{y} \in \Delta_n \end{array}$$

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- Remark: The objective function is the sum of two *upper bounds* on two players' **regrets** against the given strategy of the opponent:

$$\begin{array}{l} \text{ROW player: } \text{reg}_I(\mathbf{x}, \mathbf{y}) = \max(R \mathbf{y}) - \mathbf{x}^T R \mathbf{y} \\ \text{column player: } \text{reg}_{II}(\mathbf{x}, \mathbf{y}) = \max(C^T \mathbf{x}) - \mathbf{x}^T C \mathbf{y} \end{array}$$

Formulations of Nash Equilibrium Sets (III)

An alternative, *parameterized* QP formulation for $NE(R,C)$:

- **Marginal distributions** of a correlated strategy \mathbf{W} : $\forall k \in [m], \forall j \in [n]$,

$$x_k(\mathbf{W}) = \sum_{\ell \in [n]} W_{k,\ell}$$

$$y_j(\mathbf{W}) = \sum_{k \in [m]} W_{k,j}$$

	y_1	...	y_j	...	y_n
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THEOREM: [Kontogiannis-Spirakis (2010)]

$NE(R, C)$ is the set of marginal distributions for all the **optimal solutions** in the following *parameterized* quadratic program, for *any* choice of the parameter $\lambda \in (0, 1)$ and $Z(\lambda) = \lambda R + (1 - \lambda)C$:

$$\begin{array}{ll}
 \text{(KS}(\lambda)\text{)} & \text{minimize} \quad \sum_i \sum_j W_{ij} Z(\lambda)_{ij} - \mathbf{x}(\mathbf{W})^T Z(\lambda) \mathbf{y}(\mathbf{W}) \\
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Lemke & Howson Algorithm

A Combinatorial Algorithm for 2NASH (I)

LH Algorithm [Lemke-Howson (1964)]

- Based on **pivoting** (like Simplex for LPs).

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- Based on **pivoting** (like Simplex for LPs).
- Exploits the **best response polyhedra** of the game, that are also used in the LCP formulation of $NE(R, C)$, if we ignore the complementarity conditions:

$$\bar{P} = \left\{ (\mathbf{y}, u) : \mathbf{1}u - R\mathbf{y} \geq \mathbf{0}; \mathbf{1}^T \mathbf{y} = 1; \mathbf{y} \geq \mathbf{0} \right\}$$

$$\bar{Q} = \left\{ (\mathbf{x}, v) : \mathbf{1}v - C^T \mathbf{x} \geq \mathbf{0}; \mathbf{1}^T \mathbf{x} = 1; \mathbf{x} \geq \mathbf{0} \right\}$$

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$$Q = \{\chi : \mathbf{1} - C^T\chi \geq \mathbf{0}; \chi \geq \mathbf{0}\}$$

ASSUMPTION (wlog): The payoff matrices are positive.

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ASSUMPTION (*wlog*): The payoff matrices are positive.

- **Labels:** $\forall (\chi, \psi) \in Q \times P,$

$$L(\chi, \psi) = \begin{array}{l} \{i \in [m] : \chi_i = 0\} \cup (m + \{j \in [n] : (C^T\chi)_j = 1\}) \\ \cup \\ \{i \in [m] : (R\psi)_i = 1\} \cup (m + \{j \in [n] : \psi_j = 0\}) \end{array}$$

A Combinatorial Algorithm for 2NASH (II)

LH Algorithm [Lemke-Howson (1964)]

- Crucial Observation: A profile of strategies (\bar{x}, \bar{y}) is Nash equilibrium iff the corresponding (non-zero) point $(\bar{\chi}, \bar{\psi}) \in Q \times P$ is **completely labeled**: all actions appear as labels in $L(\chi, \psi)$.
- For non-degenerate games: Only **pair of vertices** in $Q \times P$ may be completely labeled.

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Pseudocode of LH (for non-degenerate games)

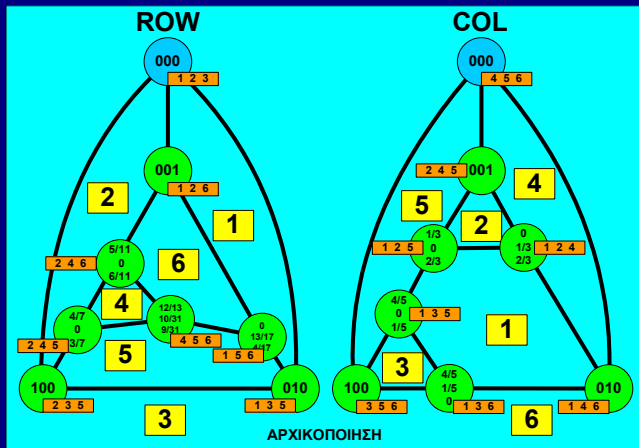
1. Initialization: Starting from the completely labeled point $(\mathbf{0}, \mathbf{0})$ (artificial equilibrium), **pivot-in** (ie, label-out) an *arbitrary label* from $(\mathbf{0}, \mathbf{0})$.
2. **Pivot-in** (ie, label-out) the *unique double-label*, at the "other" polyhedron.
3. **if** the uniquely missing label is **pivoted-out** (labeled-in)
4. **then** return the new, *completely labeled* point (χ, ψ) .
5. **else** goto step 2.

EXAMPLE: Execution of LH

	4	5	6
1	4, 6	4, 12	4, 0
2	0, 0	0, 4	6, 0
3	5, 8	0, 0	0, 13

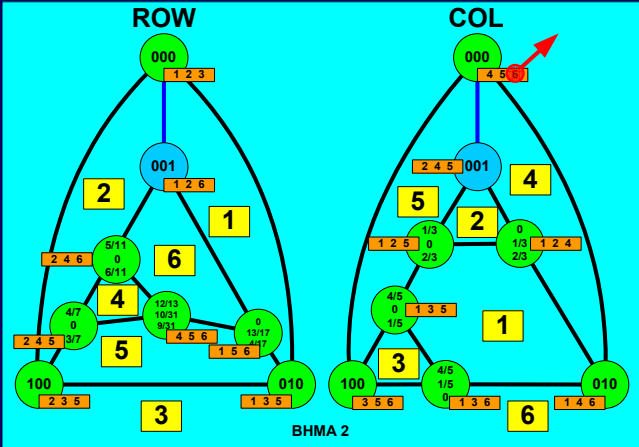
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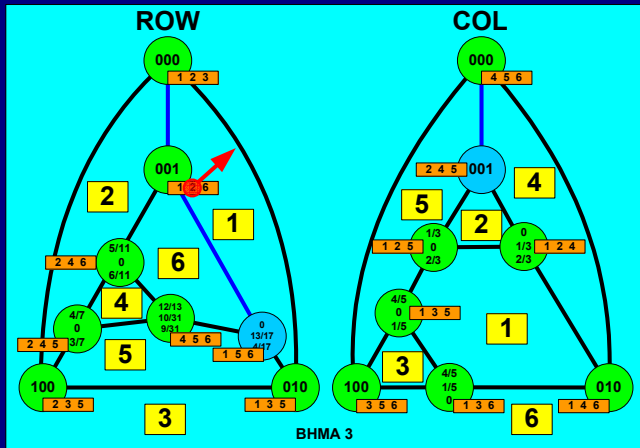
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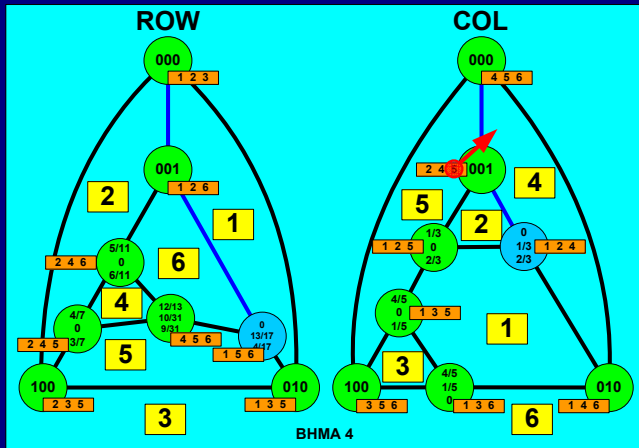
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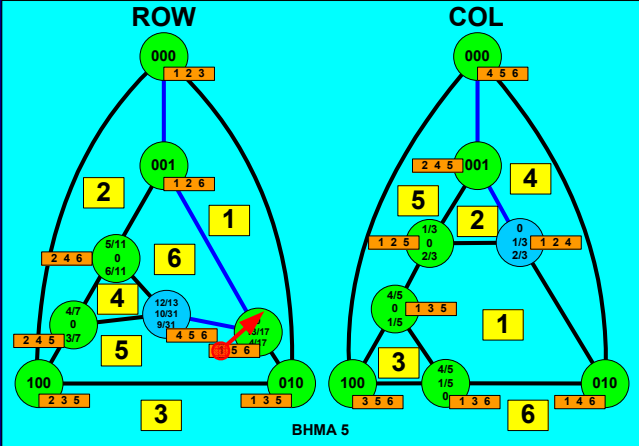
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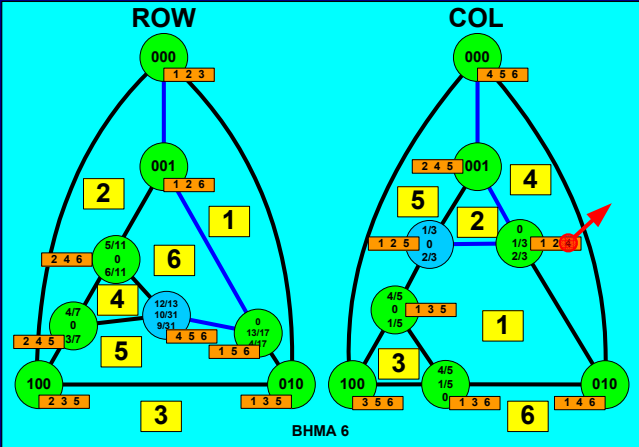
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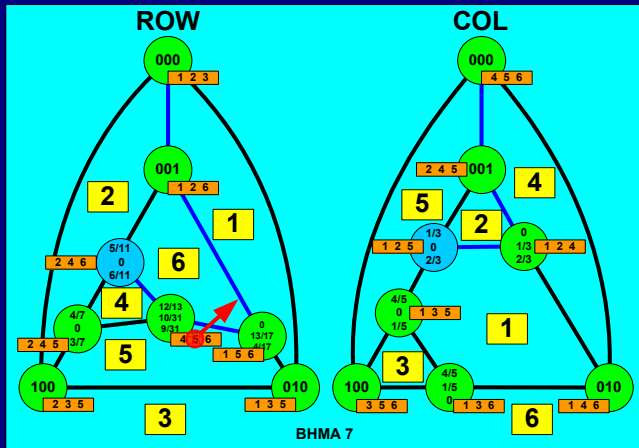
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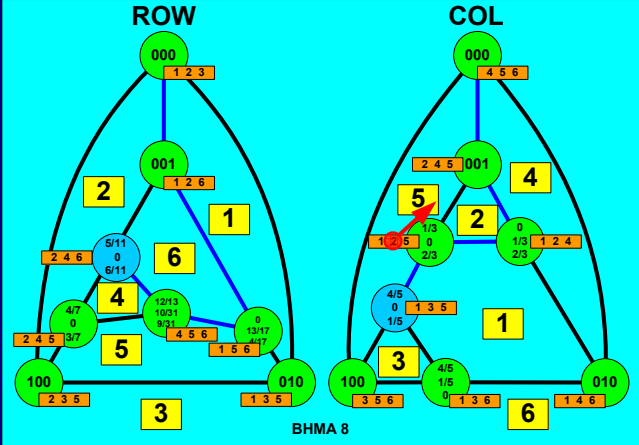
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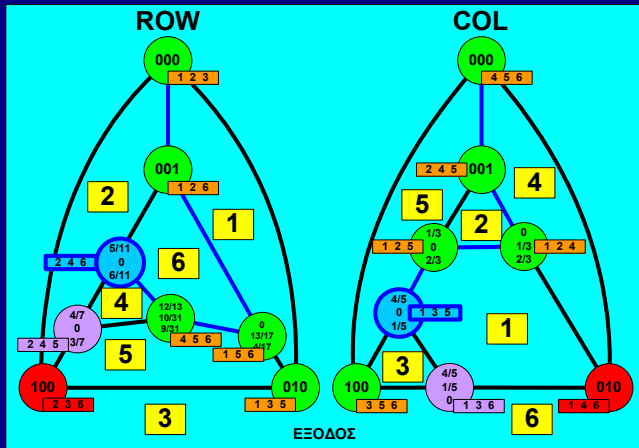
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Why LH Works (for non-degenerate games)

- The artificial equilibrium $(\mathbf{0}, \mathbf{0})$ is *completely labeled*.
- The current pair of points, during the execution of LH, has *exactly one missing label* and *two adjacent edges* (one per polyhedron), for labeling-out each of the only two copies of the unique double-label.
- The “other ends” of these two edges lead to pairs of vertices with at most one double-label. The only missing label (if any) is always the one initially labeled-out.
- Each edge is traversed *towards new vertices*, so that no cycles may appear.
- **Termination:** Starting from one end of a *finite path*, we move towards the other end of this unique path, that is necessarily a completely-labeled pair of vertices.

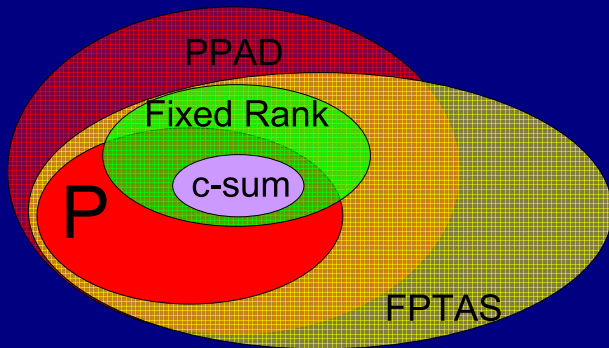
Skeleton of the Talk

- 1 Bimatrix Games Preliminaries
 - Complexity of 2NASH
 - Formulations for 2NASH
 - The algorithm of Lemke & Howson
- 2 Polynomial-time Tractable Subclasses
- 3 Approximability of 2NASH
 - Theoretical Analysis
 - Experimental Study
- 4 Conclusions

Polynomial-time Tractable Classes wrt 2NASH

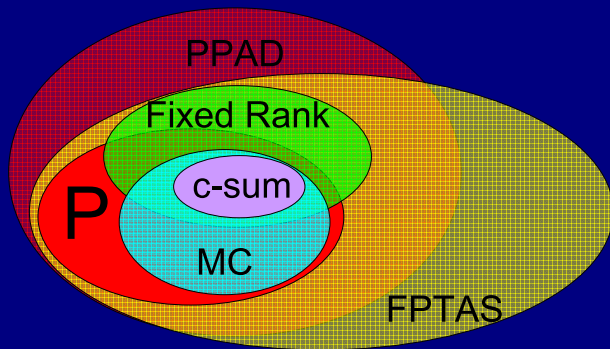
- **Zero-sum Games:** Any profile of strategies is Nash equilibrium iff it is a MAXMIN profile
 - ▶ [J. von Neumann (1928)] : Existence proof for NE in zero-sum bimatrix games, based on a *Fixed Point* argument.
 - ▶ [Dantzig (1947)] : MAXMIN profiles for bimatrix games are equivalent to a pair of primal-dual linear programs.
 - ▶ [Khachiyan (1979), Karmakar (1984)] : Polynomial-tractability of LP.
- **Constant-rank Games:** $\text{rank}(R + C) = k$
[Kannan-Theobald (2007)] : Existence of FPTAS for constructing ε -NE points.
- **Rank-1 Games:** $\text{rank}(R + C) = 1$
[Adsul-Garg-Mehta-Sohoni (2011)] : Polynomial-time algorithm for determining *exact* Nash equilibria.
- **(Very) Sparse Games & Games with Pure Equilibria:** Relatively easy cases.

Other Tractable Classes?



- ☑ Constant-sum games are poly-time solvable. Constant-rank games admit a FPTAS.

Other Tractable Classes?



☺ Constant-sum games are poly-time solvable. Constant-rank games admit a FPTAS.

☺ Another subclass of poly-time solvable games:
Mutually-concave games.

The Class of Mutually Concave Games

DEFINITION: Mutually Concave (MC) Games

A bimatrix game $\langle R, C \rangle$ is **mutually concave**, iff $\exists \lambda \in (0, 1)$ s.t. for $Z(\lambda) = \lambda R + (1 - \lambda)C$, the function $H_\lambda(\mathbf{x}, \mathbf{y}) \equiv \mathbf{x}^T Z(\lambda) \mathbf{y}$ is *concave*.

Poly-time Solvability of 2NASH for MC Games

THEOREM: [Kontogiannis-Spirakis (2010)]

For arbitrary *normalized* bimatrix MC game $\langle R, C \rangle$, with *rational* payoff matrices, there exists a (*unique, except for some trivial cases*) rational number $\lambda^* \in (0, 1)$ s.t. for $Z(\lambda) = \lambda^*R + (1 - \lambda^*)C$ the following *quadratic program* is convex, and therefore polynomial-time solvable:

$$\begin{array}{ll} \text{minimize} & \sum_i \sum_j W_{ij} Z(\lambda^*)_{ij} - \mathbf{x}(\mathbf{W})^T Z(\lambda^*) \mathbf{y}(\mathbf{W}) \\ \text{s.t.} & \mathbf{W} \in CE(R, C) \end{array}$$

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- Are we done?

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THEOREM: [Kontogiannis-Spirakis (2010)]

For arbitrary *normalized* bimatrix MC game $\langle R, C \rangle$, with *rational* payoff matrices, there exists a (*unique, except for some trivial cases*) rational number $\lambda^* \in (0, 1)$ s.t. for $Z(\lambda) = \lambda^*R + (1 - \lambda^*)C$ the following **quadratic program** is convex, and therefore polynomial-time solvable:

$$\begin{array}{ll} \text{minimize} & \lambda^* \cdot (r - \mathbf{x}^T R \mathbf{y}) + (1 - \lambda^*) \cdot (c - \mathbf{x}^T C \mathbf{y}) \\ \text{s.t.} & r \cdot \mathbf{1} - R \mathbf{y} \geq 0 \\ & c \cdot \mathbf{1} - C^T \mathbf{x} \geq 0 \\ & \mathbf{x} \in \Delta_m \quad \quad \quad \mathbf{y} \in \Delta_n \end{array}$$

- Are we done?

☹ **NOT YET!!!**

It is crucial to be able to **recognize in polynomial time** whether a bimatrix game belongs to the MC class.

Recognition of Poly-time Solvable Bimatrix Classes

- Trivial issue for a game $\langle R, C \rangle$ that...
 - ▶ ...has *constant-sum payoffs*.
 - ▶ ...has *constant rank*.
 - ▶ ...possesses a *pure Nash* equilibrium.
 - ▶ ...is a *very sparse win-lose* game.

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- Is there a way to detect *mutual concavity* also in **polynomial time**?



YES!!!

Characterizations of Mutual Concavity

PROPOSITION: [Kontogiannis-Spirakis (2010)]

A bimatrix game $\langle R, C \rangle$ is mutually concave iff any of the following properties holds:

- 1 $\exists \lambda \in (0, 1) : \xi^T Z(\lambda) \psi = 0$, for any pair of *directions of change in strategies* ξ, ψ for the two players (ie, such that $\mathbf{1}^T \xi = \mathbf{1}^T \psi = 0$).
- 2 $\exists \lambda \in (0, 1) : Z(\lambda) \cdot \psi = \mathbf{1} \cdot c$, for an arbitrary constant c and any direction of change, $\psi \in \mathbb{R}^n : \mathbf{1}^T \psi = 0$, for the strategy of the column player.

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COROLLARY: Constant-Sum Games & MC Class

Every constant-sum game $\langle A, -A + c \cdot \mathbf{1} \cdot \mathbf{1}^T \rangle$ is mutually concave.

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COROLLARY: Constant-Sum Games & MC Class

Every constant-sum game $\langle A, -A + c \cdot \mathbf{1} \cdot \mathbf{1}^T \rangle$ is mutually concave.

- Question: How do we detect the existence (or not) of the proper λ^* -value?

Mutual Concavity for 2×2 Games

PROPOSITION: [Kontogiannis-Spirakis (2010)]

For any 2×2 game $\langle A, B \rangle$, let $\alpha = A_{1,1} + A_{2,2} - A_{1,2} - A_{2,1}$ and $b = B_{1,1} + B_{2,2} - B_{1,2} - B_{2,1}$. Then, $\langle A, B \rangle$ is mutually concave iff:

$$\alpha = b = 0 \vee \min \{ \alpha, b \} < 0 < \max \{ \alpha, b \}$$

If $\alpha, b \neq 0$, then the *unique value* $\lambda^* = \frac{-b}{\alpha - b}$ proves (if it holds) the mutual concavity of the game.

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If $\alpha, b \neq 0$, then the *unique value* $\lambda^* = \frac{-b}{\alpha-b}$ proves (if it holds) the mutual concavity of the game.

COROLLARY: A Necessary Condition for MC

If an $m \times n$ bimatrix game $\langle A, B \rangle$ is mutually concave, then the following must hold: $\exists \lambda^* \in (0, 1) : \forall 1 \leq i < k \leq m, \forall 1 \leq j < \ell \leq n$,

$$[\alpha_{ik,j\ell} = b_{ik,j\ell} = 0]$$

\vee

$$\left[\max \{ \alpha_{ik,j\ell}, b_{ik,j\ell} \} > 0 > \min \{ \alpha_{ik,j\ell}, b_{ik,j\ell} \} \quad \wedge \quad \lambda^* = \frac{-b_{ik,j\ell}}{\alpha_{ik,j\ell} - b_{ik,j\ell}} \right]$$

Examples of MC / non-MC Games

MC-
games

		col	
		left	right
ROW	TOP	2, 1	1, 1+ γ
	BOTTOM	1, 1	3, 0

(a) MC-game, $\forall \gamma > -1$.

		prisoner 2	
		betray	silent
PRISONER 1	BETRAY	4, 4	10, 0
	SILENT	0, 10	6, 6

(b) MC version of PD game

		col	
		left	right
ROW	TOP	2, 1	1, 1+ γ
	MIDDLE	1, 1	3, 0
	BOTTOM	δ_1, δ_2	ϵ_1, ϵ_2

(c) MC-game $\forall \gamma > -1$, arbitrary $\delta_1, \delta_2, \epsilon_1$ and ϵ_2 be their function.

Non-MC-
games

		he	
		theater? ok	basket !!!
SHE	BASKET? OK THEATER !!!	5, 1	0, 0
	BASKET? OK	0, 0	1, 5

(d) Battle of Sexes.

		prisoner 2	
		betray	silent
PRISONER 1	BETRAY	-5, -5	0, -10
	SILENT	-10, 0	-1, -1

(e) Non-MC version of PD game.

		col	
		dare	chicken
ROW	DARE	0, 0	7, 2
	CHICKEN	2, 7	6, 6

(f) Chicken Game.

Checking Mutual Concavity in Poly-time

ALGORITHM: Detecting MC for non-trivial games

INPUT: $(R, C) \in \mathbb{R}^{m \times n}$.

- (1) Check all 2×2 subgames of (R, C) , for the induced λ -values.
- (2) **if** all 2×2 subgames have zero α - and b -values
- (3) **then return** ("there is **PNE**")
- (4) **if** there is a *unique* induced λ^* -value by all 2×2 subgames with nonzero α - and b -values
- (5) **then if** $\begin{pmatrix} \bigcirc & Z(\lambda^*) \\ Z(\lambda^*)^T & \bigcirc \end{pmatrix}$ is negative semidefinite
- (6) **then return** ("MC-game")
- (7) **return** ("non-MC-game")

MC-games vs. Fixed-Rank Games

- Even rank-1 games may not be MC-games.

		prisoner 2	
		betray	silent
PRISONER 1	BETRAY	-5, -5	0, -10
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MC-games vs. Fixed-Rank Games

- Even **rank-1** games may not be MC-games.

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		betray	silent
PRISONER 1	BETRAY	-5, -5	0, -10
	SILENT	-10, 0	-1, -1

- There exist MC games that have **full rank**. Eg, for:

$$Z = \begin{bmatrix} 1 & 2 & 4 & 8 & 16 & 32 & 64 \\ 0 & 1 & 3 & 7 & 15 & 31 & 63 \\ 2 & 3 & 5 & 9 & 17 & 33 & 65 \\ -1 & 0 & 2 & 6 & 14 & 30 & 62 \\ 3 & 4 & 6 & 10 & 18 & 34 & 66 \\ -2 & -1 & 1 & 5 & 13 & 29 & 61 \\ 4 & 5 & 7 & 11 & 19 & 35 & 67 \end{bmatrix}$$

with $\text{rank}(Z) = 2$, the game $\langle R, C \rangle$ with $R = I_7$ and $C = \frac{4}{3}Z - \frac{1}{3}R$ is indeed (cf. next slide's characterization) an MC-game, but it has $\text{rank}(R + C) = 7$.

MC Games vs. Strategically Zero-Sum Games

PROPOSITION: [Kontogiannis-Spirakis (2010)]

For any $m, n \geq 2$ and payoff matrices $R, C \in \mathbb{R}^{m \times n}$, the game $\langle R, C \rangle$ is an MC-game iff: $\exists \lambda \in (0, 1), \exists \mathbf{a} \in \mathbb{R}^m, \exists \mathbf{d} = [0, d_2, \dots, d_n]^T \in \mathbb{R}^n :$

$$\forall j \in [n], Z(\lambda)[*, j] = -d_j \cdot \mathbf{1} + \mathbf{a}$$

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$$\forall j \in [n], Z(\lambda)[*, j] = -d_j \cdot \mathbf{1} + \mathbf{a}$$

Some Remarks:

- 1 The MC-class *matches* the class of *strategically-zero-sum (SZS) games* of [Moulin-Vial (1978)] .
- 2 Characterizing the SZS-property implies the solution of a large *linear program*, in time $O(n^6)$.
- 3 Characterizing the MC-property implies the solution of a much smaller *quadratic program*, in time $O(n^4)$.

Skeleton of the Talk

- 1 Bimatrix Games Preliminaries
 - Complexity of 2NASH
 - Formulations for 2NASH
 - The algorithm of Lemke & Howson
- 2 Polynomial-time Tractable Subclasses
- 3 Approximability of 2NASH
 - Theoretical Analysis
 - Experimental Study
- 4 Conclusions

Reminder...

DEFINITION: Approximate Nash Equilibria

For a *normalized* bimatrix game $\langle R, C \rangle$, a profile of (*uncorrelated*) strategies $(\bar{\mathbf{x}}, \bar{\mathbf{y}})$ is:

- ε -**approximate Nash equilibrium** (ε -NE) iff no player can improve her expected payoff more than an additive term of $\varepsilon \geq 0$ by *unilaterally changing* her strategy, against the given strategy of the opponent: $\forall \mathbf{x} \in \Delta_m, \forall \mathbf{y} \in \Delta_n$,
$$\bar{\mathbf{x}}^T R \bar{\mathbf{y}} \geq \mathbf{x}^T R \bar{\mathbf{y}} - \varepsilon \quad \wedge \quad \bar{\mathbf{x}}^T C \bar{\mathbf{y}} \geq \bar{\mathbf{x}}^T C \mathbf{y} - \varepsilon$$

- ε -**well supported approximate Nash equilibrium** (ε -WSNE) iff no player assigns positive probability mass to actions that are less than an additive term $\varepsilon \geq 0$ than the maximum payoff she may get against the given strategy of the opponent:
 $\forall i \in [m], \forall j \in [n],$

$$[\bar{x}_i > 0 \rightarrow \mathbf{e}_i^T R \bar{\mathbf{y}} \geq \max(R \bar{\mathbf{y}}) - \varepsilon] \quad \wedge \quad [\bar{y}_j > 0 \rightarrow \bar{\mathbf{x}}^T C \mathbf{e}_j \geq \max(\bar{\mathbf{x}}^T C) - \varepsilon]$$

Approximability of 2NASH

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- [Althöfer (1994) / Lipton-Markakis-Mehta (2003)] : Subexponential-time approximation scheme for ε -WSNE, in time $n^{\mathcal{O}(\varepsilon^{-2} \cdot \log n)}$.

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- ε -NE:
- ▶ [Kontogiannis-Panagopoulou-Spirakis (2006)] : 0.75
 - ▶ [Daskalakis-Papadimitriou-Mehta (2006)] : 0.5
 - ▶ [Daskalakis-Papadimitriou-Mehta (2007)] : ~ 0.38
 - ▶ [Bosse-Byrka-Markakis (2007)] : ~ 0.36
 - ▶ [Spirakis-Tsaknakis (2007)] : ~ 0.3393
 - ▶ [Kontogiannis-Spirakis (2011)] : $\sim 1/3 + \delta$, for any *constant* $\delta > 0$ and *symmetric games*.

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ε -WSNE:

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- ▶ [Fearnley-Goldberg-Savani-Sørensen (2012)] : < 0.667

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ε -WSNE:

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- Question: Can we break any of the bounds, $1/3$ for ε -NE and $2/3$ for ε -WSNE? Is there a PTAS for either case?

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Theoretical Analysis of SYMMETRIC-2NASH Approximations

About Symmetric Bimatrix Games...

- $n \times n$ games $\langle R, C \rangle$, where the players may **exchange roles** (ie, the payoff matrices are: $R = S, C = S^T$).
- [Nash (1950)] : Every *finite symmetric* game has a **symmetric Nash equilibrium** (in which all players adopt the same strategy).
- For *symmetric strategy profiles* in symmetric bimatrix games, the players have **common expected payoffs** and also **common expected payoff vectors**, against the opponent's strategy.
- A *formalism* for SYMMETRIC-2NASH: For

$$\mathbf{x} = \begin{pmatrix} \mathbf{z} \\ \mathbf{s} \end{pmatrix}, \quad Q = \begin{pmatrix} \mathbf{0} & S^T \\ S & \mathbf{0} \end{pmatrix},$$

(SMS)

$$\begin{array}{ll} \text{minimize} & f(\mathbf{s}, \mathbf{z}) = \mathbf{s} - \mathbf{z}^T S \mathbf{z} = \mathbf{s} - \frac{1}{2} \mathbf{x}^T Q \mathbf{x} \\ \text{s.t.} & -\mathbf{1} \mathbf{s} + S \mathbf{z} \leq \mathbf{0} \\ & -\mathbf{1}^T \mathbf{z} + \mathbf{1} = 0 \\ & \mathbf{s} \in \mathbb{R}, \quad \mathbf{z} \in \mathbb{R}_{\geq 0}^n \end{array}$$

Necessary Optimality (KKT) Conditions for (SMS)

(KKT SMS)

$$\nabla f(\bar{s}, \bar{z}) = \begin{pmatrix} \mathbf{1} \\ -S\bar{z} - S^T\bar{z} \end{pmatrix} = \begin{pmatrix} \mathbf{1}^T \bar{\mathbf{w}} \\ -S^T \bar{\mathbf{w}} + \bar{\mathbf{u}} + \mathbf{1} \bar{\zeta} \end{pmatrix}$$

$$0 \leq \begin{pmatrix} \bar{\mathbf{w}} \\ \bar{\mathbf{u}} \end{pmatrix}^T \cdot \begin{pmatrix} \mathbf{1} \bar{s} - S\bar{z} \\ \bar{z} \end{pmatrix} \leq \delta$$

$$\bar{s} \in \mathbb{R}, \quad S\bar{z} \leq \mathbf{1}\bar{s}, \quad \mathbf{1}^T \bar{z} = 1, \quad \bar{z} \geq \mathbf{0}$$

$$\bar{\mathbf{w}} \geq \mathbf{0}, \quad \bar{\zeta} \in \mathbb{R}, \quad \bar{\mathbf{u}} \geq \mathbf{0}$$

- **δ -KKT Points** of (SMS): Feasible solutions $(\bar{s}, \bar{z}, \bar{\mathbf{w}}, \bar{\zeta}, \bar{\mathbf{u}})$ for (KKT SMS).
- Some Remarks:
 - ① The Lagrange multiplier $\bar{\mathbf{w}}$ is an alternative strategy for the players, ie, a point from $\Delta([n])$.
 - ② $\bar{\mathbf{w}}$ is also a δ -*approximate best response* of the ROW player against the given strategy \bar{z} of the opponent: $\bar{s} \leq \bar{\mathbf{w}}^T S\bar{z} + \delta$.

Computing (approximate) KKT Points of QPs

- Exact computation of a KKT point of Quadratic Programs: \mathcal{NP} -hard problem.

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THEOREM: Approximate KKT Points in QP [Ye (1998)]

There is a FPTAS for computing δ -KKT points of a n -variable Quadratic Program, in time:

$$O\left(\left[\frac{n^6}{\delta} \log\left(\frac{1}{\delta}\right) + n^4 \log(n)\right] \cdot \left[\log\log\left(\frac{1}{\delta}\right) + \log(n)\right]\right)$$

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- Question: What is the *quality as a Nash approximation* of a δ -KKT point?

A Fundamental Property of (KKT SMS) – (I)

LEMMA: [Kontogiannis-Spirakis (SEA 2011)]

For any $m, n \geq 2$, $S \in [0, 1]^{m \times n}$, and any point $(\max(S\bar{z}), \bar{z}, \bar{w}, \bar{u}, \bar{\zeta}) \in (KKT SMS)$ the following properties hold:

- 1 $\bar{\zeta} = f(\bar{z}) - \bar{z}^T S \bar{z}$.
- 2 $2f(\bar{z}) = \bar{w}^T S \bar{w} - \bar{z}^T S \bar{w} - \bar{w}^T \bar{u}$.
- 3 $2f(\bar{z}) + f(\bar{w}) = R_I(\bar{z}, \bar{w}) - \bar{w}^T \bar{u}$.

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- 3 $2f(\bar{z}) + f(\bar{w}) = R_I(\bar{z}, \bar{w}) - \bar{w}^T \bar{u}$.

Some Remarks:

- $f(\bar{z}) = \max(S\bar{z}) - \bar{z}^T S \bar{z}$ is either player's regret, for the *symmetric* profile (\bar{z}, \bar{z}) .
- $R_I(\bar{z}, \bar{w}) = \max(S\bar{w}) - \bar{z}^T S \bar{w} \leq 1$ is (only) the row player's regret, for the *asymmetric profile* (\bar{w}, \bar{z}) .
- The third property assures that any (exact) KKT point (is not necessarily itself, but) indicates a 1/3-NE of $\langle S, S^T \rangle$, in *normalized* games.

A Fundamental Property of (KKT SMS) – (II)

Proof of the Lemma

$$-S\bar{\mathbf{z}} - S^T\bar{\mathbf{z}} = -S^T\bar{\mathbf{w}} + \bar{\mathbf{u}} + \mathbf{1}\bar{\zeta}$$

$$\Rightarrow \begin{cases} -\bar{\mathbf{z}}^T S\bar{\mathbf{z}} - \bar{\mathbf{z}}^T S^T\bar{\mathbf{z}} = -\bar{\mathbf{z}}^T S^T\bar{\mathbf{w}} + \underbrace{\bar{\mathbf{z}}^T\bar{\mathbf{u}}}_{=0} + \underbrace{\bar{\mathbf{z}}^T\mathbf{1}\bar{\zeta}}_{=1} \\ -\bar{\mathbf{w}}^T S\bar{\mathbf{z}} - \bar{\mathbf{w}}^T S^T\bar{\mathbf{z}} = -\bar{\mathbf{w}}^T S^T\bar{\mathbf{w}} + \bar{\mathbf{w}}^T\bar{\mathbf{u}} + \underbrace{\bar{\mathbf{w}}^T\mathbf{1}\bar{\zeta}}_{=1} \end{cases}$$

$$\Rightarrow \begin{cases} \bar{\zeta} = -2\bar{\mathbf{z}}^T S\bar{\mathbf{z}} + \bar{\mathbf{z}}^T S^T\bar{\mathbf{w}} = f(\bar{\mathbf{z}}) - \bar{\mathbf{z}}^T S\bar{\mathbf{z}} \\ \bar{\zeta} = -\bar{\mathbf{w}}^T S\bar{\mathbf{z}} - \bar{\mathbf{z}}^T S\bar{\mathbf{w}} + \bar{\mathbf{w}}^T S\bar{\mathbf{w}} - \bar{\mathbf{w}}^T\bar{\mathbf{u}} \end{cases}$$

$$\Rightarrow \begin{cases} \bar{\zeta} = f(\bar{\mathbf{z}}) - \bar{\mathbf{z}}^T S\bar{\mathbf{z}} \\ 2f(\bar{\mathbf{z}}) = -2\bar{\mathbf{z}}^T S\bar{\mathbf{z}} + 2\bar{\mathbf{w}}^T S\bar{\mathbf{z}} = -\bar{\mathbf{z}}^T S\bar{\mathbf{w}} + \bar{\mathbf{w}}^T S\bar{\mathbf{w}} - \bar{\mathbf{w}}^T\bar{\mathbf{u}} \end{cases}$$

A Fundamental Property of (KKT SMS) – (II)

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$$-S\bar{z} - S^T\bar{z} = -S^T\bar{w} + \bar{u} + \mathbf{1}\bar{\zeta}$$

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$$\Rightarrow \begin{cases} \bar{\zeta} = -2\bar{z}^T S\bar{z} + \bar{z}^T S^T\bar{w} = f(\bar{z}) - \bar{z}^T S\bar{z} \\ \bar{\zeta} = -\bar{w}^T S\bar{z} - \bar{z}^T S\bar{w} + \bar{w}^T S\bar{w} - \bar{w}^T\bar{u} \end{cases}$$

$$\Rightarrow \begin{cases} \bar{\zeta} = f(\bar{z}) - \bar{z}^T S\bar{z} \\ 2f(\bar{z}) = -2\bar{z}^T S\bar{z} + 2\bar{w}^T S\bar{z} = -\bar{z}^T S\bar{w} + \bar{w}^T S\bar{w} - \bar{w}^T\bar{u} \end{cases}$$

- We add $f(\bar{w}) = \max(S\bar{w}) - \bar{w}^T S\bar{w}$ to both sides of the equation:

$$2f(\bar{z}) + f(\bar{w}) = \max(S\bar{w}) - \bar{w}^T S\bar{w} - \bar{z}^T S\bar{w} + \bar{w}^T S\bar{w} - \bar{w}^T\bar{u}$$

$$\Rightarrow \boxed{3 \cdot \min\{f(\bar{z}), f(\bar{w})\} \leq 2f(\bar{z}) + f(\bar{w}) = R_I(\bar{z}, \bar{w}) - \bar{w}^T\bar{u} \leq 1}$$

$(\leq 1/3)$ -NE from a Given Exact KKT Point – (I)

THEOREM: [Kontogiannis-Spirakis (2011)]

Starting from any (exact) KKT point of (KKT SMS) for a normalized symmetric bimatrix game $\langle S, S^T \rangle$, computing a $(\leq \frac{1}{3})$ -NE can be done in polynomial time.

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Proof Sketch:

- $(\max(S\bar{z}), \bar{z}, \bar{w}, \bar{u}, \bar{\zeta})$: The given KKT point, along with the proper Lagrange multipliers.
 - **if** $f(\bar{z}) \neq f(\bar{w})$ **then** $3 \cdot \min\{f(\bar{z}), f(\bar{w})\} < R_I(\bar{z}, \bar{w}) - \bar{w}^T \bar{u} \leq 1$.
- \therefore ASSUMPTION 1: $f(\bar{z}) = f(\bar{w}) = \frac{1}{3}$.

$(< 1/3)$ -NE from a Given Exact KKT Point – (I)

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- \therefore ASSUMPTION 1: $f(\bar{z}) = f(\bar{w}) = \frac{1}{3}$.
- **if** $(\max(S\bar{w}), \bar{w}) \notin (\text{KKT SMS})$
then starting from $(\max(S\bar{w}), \bar{w})$, the next step towards a KKT point will give a $(< 1/3)$ -NE.
- \therefore ASSUMPTION 2: $(\max(S\bar{w}), \bar{w}) \in (\text{KKT SMS})$.

(< 1/3)–NE from a Given Exact KKT Point – (II)

- $(\bar{\mathbf{w}}', \bar{\mathbf{u}}', \bar{\boldsymbol{\zeta}}')$: The appropriate Lagrange multipliers for $(\max(S\bar{\mathbf{w}}), \bar{\mathbf{w}}) \in (\text{KKT SMS})$.
- From the **Basic Lemma**, applied now to $(\max(S\bar{\mathbf{w}}), \bar{\mathbf{w}})$:

$$2f(\bar{\mathbf{w}}) + f(\bar{\mathbf{w}}') = R_I(\bar{\mathbf{w}}, \bar{\mathbf{w}}') - (\bar{\mathbf{w}}')^T \bar{\mathbf{u}}'$$

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- Observation 1:

$$\begin{aligned} 1 &= 3f(\bar{\mathbf{z}}) = R_I(\bar{\mathbf{z}}, \bar{\mathbf{w}}) - \bar{\mathbf{w}}^T \bar{\mathbf{u}} \\ \Rightarrow \max(S\bar{\mathbf{w}}) = 1 &\wedge \bar{\mathbf{z}}^T S\bar{\mathbf{w}} = 0 \wedge \bar{\mathbf{w}}^T \bar{\mathbf{u}} = 0 \end{aligned}$$

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($< 1/3$)–NE from a Given Exact KKT Point – (II)

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- Observation 2: $\frac{1}{3} = f(\bar{\mathbf{w}}) = \max(S\bar{\mathbf{w}}) - \bar{\mathbf{w}}^T S\bar{\mathbf{w}} \Rightarrow \bar{\mathbf{w}}^T S\bar{\mathbf{w}} = \frac{2}{3}$

$(< 1/3)$ -NE from a Given Exact KKT Point – (III)

• **if** $f(\bar{\mathbf{w}}) \neq f(\bar{\mathbf{w}}')$ **then** $3 \min\{f(\bar{\mathbf{w}}), f(\bar{\mathbf{w}}')\} < 1$.

\therefore ASSUMPTION 3: $f(\bar{\mathbf{z}}) = f(\bar{\mathbf{w}}) = f(\bar{\mathbf{w}}') = \frac{1}{3}$.

(< 1/3)–NE from a Given Exact KKT Point – (III)

- **if** $f(\bar{\mathbf{w}}) \neq f(\bar{\mathbf{w}}')$ **then** $3 \min\{f(\bar{\mathbf{w}}), f(\bar{\mathbf{w}}')\} < 1$.

∴ ASSUMPTION 3: $f(\bar{\mathbf{z}}) = f(\bar{\mathbf{w}}) = f(\bar{\mathbf{w}}') = \frac{1}{3}$.

- $(\max(S\bar{\mathbf{z}}, \bar{\mathbf{z}}) \in (\text{KKT SMS})$:

$$\left. \begin{aligned} -S\bar{\mathbf{z}} - S^T\bar{\mathbf{z}} + S^T\bar{\mathbf{w}} &= \bar{\mathbf{u}} + \mathbf{1}\bar{\zeta} \\ \bar{\zeta} &= f(\bar{\mathbf{z}}) - \bar{\mathbf{z}}^T S\bar{\mathbf{z}} \end{aligned} \right\} \Rightarrow$$

$$-(\bar{\mathbf{w}}')^T S\bar{\mathbf{z}} - \bar{\mathbf{z}}^T S\bar{\mathbf{w}}' + \underbrace{\bar{\mathbf{w}}^T S\bar{\mathbf{w}}'}_{=0} = \bar{\mathbf{w}}'^T \bar{\mathbf{u}} + f(\bar{\mathbf{z}}) - \bar{\mathbf{z}}^T S\bar{\mathbf{z}} \Rightarrow$$

$$0 \leq (\bar{\mathbf{w}}')^T \bar{\mathbf{u}} = -(\bar{\mathbf{w}}')^T S\bar{\mathbf{z}} - \bar{\mathbf{z}}^T S\bar{\mathbf{w}}' - f(\bar{\mathbf{z}}) + \bar{\mathbf{z}}^T S\bar{\mathbf{z}} \Rightarrow$$

$$\boxed{(\bar{\mathbf{w}}')^T S\bar{\mathbf{z}} - \bar{\mathbf{z}}^T S\bar{\mathbf{z}} \leq -\frac{1}{3} - \bar{\mathbf{z}}^T S\bar{\mathbf{w}}' \leq -\frac{1}{3} < 0}$$

(< 1/3)–NE from a Given Exact KKT Point – (IV)

- $(\max(S\bar{\mathbf{w}}), \bar{\mathbf{w}}) \in (\text{KKT SMS})$:

$$\left. \begin{aligned}
 -S\bar{\mathbf{w}} - S^T \bar{\mathbf{w}} + S^T \bar{\mathbf{w}}' &= \bar{\mathbf{w}}' + \mathbf{1} \bar{\zeta}' \\
 \bar{\zeta}' &= f(\bar{\mathbf{w}}) - \bar{\mathbf{w}}^T S \bar{\mathbf{w}} = -\frac{1}{3}
 \end{aligned} \right\} \Rightarrow$$

$$-\underbrace{\bar{\mathbf{z}}^T S \bar{\mathbf{w}}}_{=0} - \underbrace{\bar{\mathbf{z}}^T S^T \bar{\mathbf{w}}}_{=\max(S\bar{\mathbf{z}})} + \bar{\mathbf{z}}^T S^T \bar{\mathbf{w}}' = \bar{\mathbf{z}}^T \bar{\mathbf{u}}' - \frac{1}{3} \Rightarrow$$

$$0 \leq \bar{\mathbf{z}}^T \bar{\mathbf{u}}' = \frac{1}{3} - \max(S\bar{\mathbf{z}}) + (\bar{\mathbf{w}}')^T S \bar{\mathbf{z}} \Rightarrow$$

$$\underbrace{\max(S\bar{\mathbf{z}}) - \bar{\mathbf{z}}^T S \bar{\mathbf{z}}}_{=f(\bar{\mathbf{z}})=\frac{1}{3}} \leq \frac{1}{3} + (\bar{\mathbf{w}}')^T S \bar{\mathbf{z}} - \bar{\mathbf{z}}^T S \bar{\mathbf{z}} \Rightarrow$$

$$(\bar{\mathbf{w}}')^T S \bar{\mathbf{z}} - \bar{\mathbf{z}}^T S \bar{\mathbf{z}} \geq 0$$

(< 1/3)–NE from a Given Exact KKT Point – (IV)

- $(\max(S\bar{\mathbf{w}}), \bar{\mathbf{w}}) \in (\text{KKT SMS})$:

$$\left. \begin{aligned} -S\bar{\mathbf{w}} - S^T \bar{\mathbf{w}} + S^T \bar{\mathbf{w}}' &= \bar{\mathbf{w}}' + \mathbf{1} \bar{\zeta}' \\ \bar{\zeta}' &= f(\bar{\mathbf{w}}) - \bar{\mathbf{w}}^T S \bar{\mathbf{w}} = -\frac{1}{3} \end{aligned} \right\} \Rightarrow$$

$$-\underbrace{\bar{\mathbf{z}}^T S \bar{\mathbf{w}}}_{=0} - \underbrace{\bar{\mathbf{z}}^T S^T \bar{\mathbf{w}}}_{=\max(S\bar{\mathbf{z}})} + \bar{\mathbf{z}}^T S^T \bar{\mathbf{w}}' = \bar{\mathbf{z}}^T \bar{\mathbf{u}}' - \frac{1}{3} \Rightarrow$$

$$0 \leq \bar{\mathbf{z}}^T \bar{\mathbf{u}}' = \frac{1}{3} - \max(S\bar{\mathbf{z}}) + (\bar{\mathbf{w}}')^T S \bar{\mathbf{z}} \Rightarrow$$

$$\underbrace{\max(S\bar{\mathbf{z}}) - \bar{\mathbf{z}}^T S \bar{\mathbf{z}}}_{=f(\bar{\mathbf{z}})=\frac{1}{3}} \leq \frac{1}{3} + (\bar{\mathbf{w}}')^T S \bar{\mathbf{z}} - \bar{\mathbf{z}}^T S \bar{\mathbf{z}} \Rightarrow$$

$$(\bar{\mathbf{w}}')^T S \bar{\mathbf{z}} - \bar{\mathbf{z}}^T S \bar{\mathbf{z}} \geq 0$$

\therefore if $f(\bar{\mathbf{z}}) = f(\bar{\mathbf{w}}) = f(\bar{\mathbf{w}}') = \frac{1}{3} \wedge (\max(S\bar{\mathbf{z}}), \bar{\mathbf{z}}), (\max(S\bar{\mathbf{w}}), \bar{\mathbf{w}}) \in (\text{KKT SMS})$

then

$$0 \leq (\bar{\mathbf{w}}')^T S \bar{\mathbf{z}} - \bar{\mathbf{z}}^T S \bar{\mathbf{z}} \leq -\frac{1}{3}$$

/* CONTRADICTION */

Efficient Computation of $\left(\frac{1}{3} + \delta\right)$ -NE

THEOREM: [Kontogiannis-Spirakis (2011)]

For any normalized symmetric bimatrix game $\langle S, S^T \rangle$ with *rational* payoff values, $S \in [0, 1]^{n \times n}$, and any *constant* $\delta > 0$, it is possible to construct a *symmetric* $(1/3 + \delta)$ -NE point, in time polynomial in the description of the game and quasi-linear in the value of δ .

Efficient Computation of $\left(\frac{1}{3} + \delta\right)$ -NE

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For any normalized symmetric bimatrix game $\langle S, S^T \rangle$ with *rational* payoff values, $S \in [0, 1]^{n \times n}$, and any *constant* $\delta > 0$, it is possible to construct a *symmetric* $(1/3 + \delta)$ -NE point, in time polynomial in the description of the game and quasi-linear in the value of δ .

- Similar proof with that for the NE approximability of exact KKT points, only working now with δ -approximate (rather than exact) KKT points of (SMS).

Experimental Study of SYMMETRIC-2NASH Approximations

Experimental Evaluation of 2NASH Approximations

- Goal: Try various **heuristics** for providing approximate NE points in symmetric bimatrix games.
- Random Game Generator: Win-Lose symmetric games $\langle R, R^T \rangle$, provided by rounding a normalized-random game $\langle S, S^T \rangle$ whose entries are normal r.v.s with mean 0 and deviation 1. A **fine-tuning parameter** allows for favoring either sparse or dense win-lose games.
- OPTION: Clear the random win-lose game by avoiding...
 - ▶ “all-ones” rows in R , (weakly dominates all actions of row player).
 - ▶ “all-zeros” rows in R , (weakly dominated row which cannot disturb an approximate NE point).
 - ▶ $(1, 1)$ –elements in the bimatrix $\langle R, R^T \rangle$ (trivial pure NE points).

1st Basic Approach

KKT Points of (SMS) as ε -NE Points

- Method: Use any polynomial-time construction algorithm to converge to a KKT point of SMS.
- Our approach: KKT SMS Use the **quadprog** (active-set) method of MatLab to locate a KKT point of (SMS).

2nd Basic Approach

Reformulation-Linearization Relaxation of (SMS)

- Method: Create a (1st-level) LP relaxation of SMS, based on the RLT method of [Sherali-Adams (1998)] .
- Our approach: RLTSMS Solve the following relaxation:

$$\begin{aligned} & \text{minimize} && \alpha - \sum_{i \in [n]} \sum_{j \in [n]} R_{ij} W_{ij} \\ \text{s.t.} & && \beta - \sum_j (R_{ij} + R_{kj}) \gamma_j + \sum_j \sum_\ell R_{ij} R_{k,\ell} W_{j,\ell} \geq 0, \quad i, k \in [n] \\ & && \alpha - \sum_j R_{ij} x_j - \gamma_k + \sum_j R_{ij} W_{j,k} \geq 0, \quad i, k \in [n] \\ & && -x_i - x_j + W_{ij} \geq -1, \quad i, j \in [n] \\ & && \gamma_k - \sum_j R_{ij} \gamma_j \geq 0, \quad i, k \in [n] \\ & && x_i - \sum_j W_{ij} = 0, \quad i \in [n] \\ & && \sum_j x_j = 1, \\ & && -x_i - \alpha + \gamma_i \geq -1, \quad i \in [n] \\ & && x_i - \gamma_i \geq 0, \quad i \in [n] \\ & && \beta - \sum_j R_{ij} \gamma_j \geq 0, \quad i \in [n] \\ & && \sum_i \gamma_i - \alpha = 0, \\ & && \alpha - \beta \geq 0, \\ & && \beta \geq 0; \quad \gamma_i \geq 0, \quad i \in [n]; \quad W_{ij} \geq 0, \quad i, j \in [n] \end{aligned}$$

3rd Basic Approach

Doubly Positive SDP Relaxation of (SMS)

- Method: Create an SDP-relaxation of (SMS), considering also the non-negativity of the produced matrix.
- Our approach: DPSDP Solve the following relaxation:

$$\begin{array}{ll} \text{minimize} & \alpha - \sum_i \sum_j R_{ij} W_{ij} \\ \text{s.t} & \alpha - \sum_j R_{ij} x_j \geq 0, \quad i \in [n] \\ & \sum_j x_j = 1, \\ & W_{ij} - W_{j,i} = 0, \quad i, j \in [n] \\ & Z \equiv \begin{bmatrix} W & \mathbf{x} \\ \mathbf{x}^T & 1 \end{bmatrix} \succcurlyeq 0, \\ & Z \leq \mathbf{1} \cdot \mathbf{1}^T, \\ & Z \geq \mathbf{0} \cdot \mathbf{0}^T \end{array}$$

4th Basic Approach

Marginals of Extreme CE points of (SMS)

- Method: Return the marginals of extreme points in the CE-polytope of $\langle R, R^T \rangle$.
- Our approach: BMXCEV4 Solve the following relaxation and return the profile with the marginals of the optimum correlated strategy $\mathbf{W} \in \Delta([n]) \times \Delta([n])$:

$$\begin{array}{ll} \text{min.} & \sum_i \sum_j [R_{ij} \cdot R_{j,i}] W_{ij} \\ \text{s.t.} & \forall i, k \in [m], \sum_{j \in [n]} (R_{ij} - R_{kj}) W_{ij} \geq 0 \\ & \sum_{i \in [m]} \sum_{j \in [n]} W_{ij} = 1 \\ & \forall (i, j) \in [m] \times [n], W_{ij} \geq 0 \end{array}$$

Hybrid Approaches

- Method: Consider only best-of results for various (couples, or triples of) methods.

Experimental Results for Pure Methods (I)

	RLTSMS	KKTSMS	DPSDP	BMXCEV4
Worst-case ε	0.512432	0.22222	0.6	0.49836
#unsolved games	112999	110070	0	405
Worst-case round	10950	15484	16690	12139

- Experimental results for worst-case approximation among **500K** random **10x10** symmetric win-lose games.

Experimental Results for Pure Methods (II)

	RLTSMS	KKTSMS	DPSDP	BMXCEV4
Worst-case ε	0.41835	0.08333	0.51313	0.21203
#unsolved games	11183	32195	0	1553
Worst-case round	45062	42043	55555	17923

- Experimental results for worst-case approximation among **500K** random **10x10** symmetric win-lose games, which *avoid* $(1, 1)$ -elements, $(1, *)$ - and $(0, *)$ -rows.

Experimental Results for Hybrid Methods (I)

	KKTSMS + BMXCEV4	KKTSMS + RLT + BMXCEV4	KKTSMS + RLT + DPSDP
Worst-case ε	0.45881	0.47881	0.54999
#unsolved games	0	0	0
Worst-case round	652	1776	737

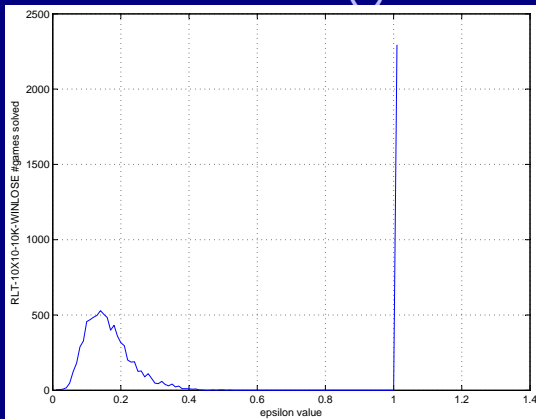
- Experimental results for worst-case approximation among **500K** random **10x10** symmetric win-lose games.

Experimental Results for Hybrid Methods (II)

	KKTSMS + BMXCEV4	KKTSMS + RLT + BMXCEV4	KKTSMS + RLT + DPSDP
Worst-case ε	0.08576	0.08576	0.28847
#unsolved games	0	0	0
Worst-case round	157185	397418	186519

- Experimental results for worst-case approximation among **500K** random **10x10** symmetric win-lose games, which *avoid* $(1, 1)$ -elements, $(1, *)$ - and $(0, *)$ -rows.

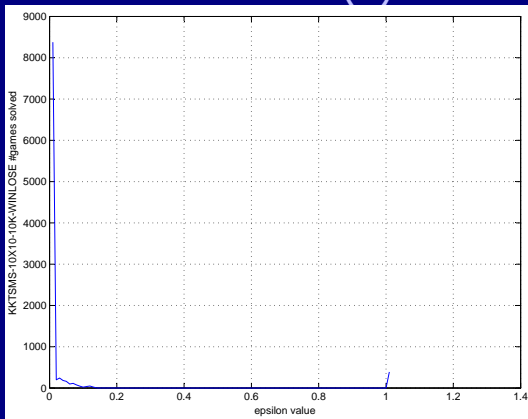
Distribution of Solved Games (I)



(a) RLTSMS

- Distribution of games solved for particular values of approximation, in runs of **10K** random **10x10** symmetric win-lose games. The games that remain unsolved in each case accumulate at the epsilon value 1.

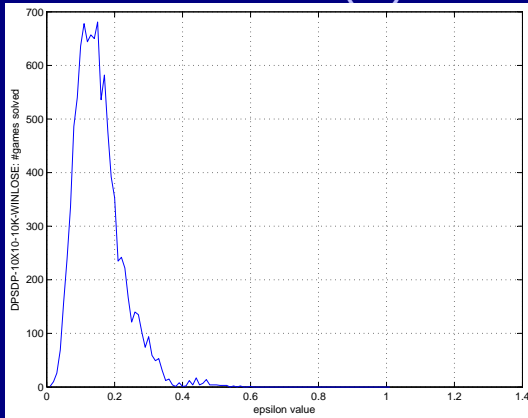
Distribution of Solved Games (II)



(b) KKTSMs

- Distribution of games solved for particular values of approximation, in runs of **10K** random **10x10** symmetric win-lose games. The games that remain unsolved in each case accumulate at the epsilon value 1.

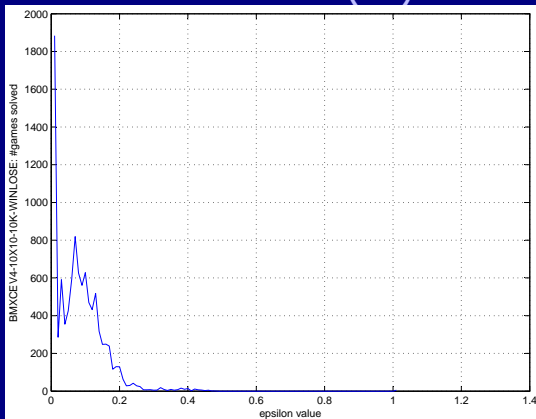
Distribution of Solved Games (III)



(c) DPSPD

- Distribution of games solved for particular values of approximation, in runs of **10K** random **10x10** symmetric win-lose games. The games that remain unsolved in each case accumulate at the epsilon value 1.

Distribution of Solved Games (IV)



(d) BMXCEV4

- Distribution of games solved for particular values of approximation, in runs of **10K** random **10x10** symmetric win-lose games. The games that remain unsolved in each case accumulate at the epsilon value 1.

Skeleton of the Talk

- 1 Bimatrix Games Preliminaries
 - Complexity of 2NASH
 - Formulations for 2NASH
 - The algorithm of Lemke & Howson
- 2 Polynomial-time Tractable Subclasses
- 3 Approximability of 2NASH
 - Theoretical Analysis
 - Experimental Study
- 4 Conclusions

Recap & Open Problems

- [Papadimitriou (2001)] k NASH is, together with FACTORING, probably the most important problems at the intersection of \mathcal{P} and \mathcal{NP} .
- Even 2NASH seems already too hard to solve.
- Is there a PTAS, or a *lower bound* that, unless something extremely unlikely holds (eg, $\mathcal{P} = \mathcal{NP}$), excludes the existence of a better approximation ratio for ε -NE points?
 - ▶ Extensive experimentation on randomly constructed win-lose games shows that probably $1/3$ is not the end of the story...
- How about ε -WSNE points?
- Are there any other, more general subclasses of bimatrix game for which 2NASH is polynomial-time tractable, or at least a PTAS exists?

Thanks for your attention!

Questions / Remarks ?