

# Computing Nash Equilibria in Bimatrix Games

## GPU-based Parallel Support Enumeration



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### Problem Statement

#### Computing Nash equilibria using GPUs

- **Application Constraints:** Real world strategic interactions usually require the modeling of large number of agents having a large number of choices or actions.
- **Processing Constraints:** Computing all Nash equilibria for large bimatrix games using single-processor computers is computationally expensive.

### Nash Equilibria in Bimatrix Games

#### Bimatrix Game $\Gamma(A, B)$

- A set of two players: {Player 1, Player 2}
- A finite set of actions for each player
  - Player 1's actions:  $M = (s_1, s_2, \dots, s_m)$
  - Player 2's actions:  $N = (t_1, t_2, \dots, t_n)$
- Player payoff matrices  $A, B \in \mathbb{R}^{m \times n}$

#### Strategies $\{(x, y)\}$

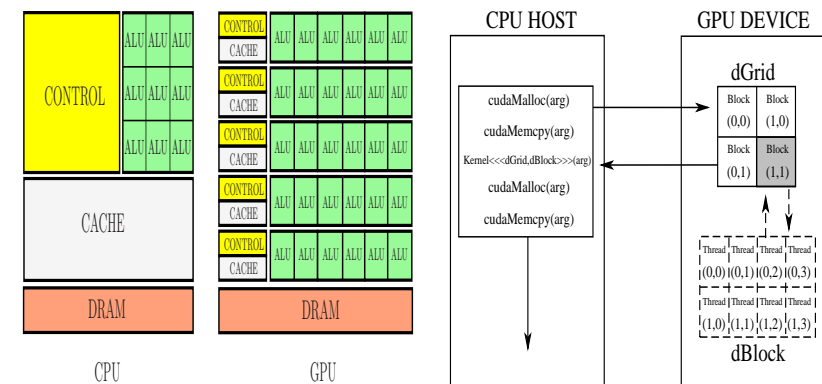
- Strategies are probabilities representing player's choice of actions.
- $x = \{(x_1, \dots, x_m) \mid \Pr\{(\text{Player 1}) \leftarrow s_i\} = x_i\}$
- $y = \{(y_1, \dots, y_n) \mid \Pr\{(\text{Player 2}) \leftarrow t_j\} = y_j\}$

#### Support Enumeration Method

1. Enumerate all pairs of supports  $(M_x, N_y)$ 
  - $M_x = \{s_i \mid x_i > 0\}$  where  $M_x \subset M$
  - $N_y = \{t_j \mid y_j > 0\}$  where  $N_y \subset N$
2. Compute Nash equilibria  $(x, y)$  in  $\Gamma(A, B)$ 
  - $x \mid \forall s_i \in M_x, (Ay)_i = u = \max_{q \in M} (Ay)_q$
  - $y \mid \forall t_j \in N_y, (x^T B)_j = v = \max_{r \in N} (x^T B)_r$

### CPU-GPU

Graphics Processing Units (GPUs) are specialized hardware dedicated to building graphic images as well as supporting parallel processing.



### GPU Parallel Support Enumeration

**Input:** Player 1 payoff, Player 2 payoff  $(A, B)$

**Output:** Set of equilibria  $\Phi$

- 1:  $\Phi = \emptyset$
- 2:  $q = \min(m, n)$
- 3:  $\Theta = \text{Generate}(1, q)$
- 4:  $\Phi = \text{Pure}(A, B, q, \Theta)$
- 5: **for**  $k = 2, \dots, q$
- 6:  $\Theta = \text{Generate}(k, q)$
- 7:  $\Phi = \Phi \cup \text{Mixed}(A, B, k, q, \Theta)$
- 8: **output**  $\Phi$

### Computing Nash Equilibria

$\text{Pure}(A, B, q, \Theta)$ :

Computes pure Nash Equilibria in  $\Gamma(A, B)$ .

A *pure* strategy  $x$  is Nash equilibrium strategy where players choose a single action with probability 1.

$\text{Mixed}(A, B, k, q, \Theta)$ :

Computes mixed Nash Equilibria in  $\Gamma(A, B)$ .

A *mixed* strategy  $x$  is Nash equilibrium where players choose actions according to a probability distribution over their pure actions.

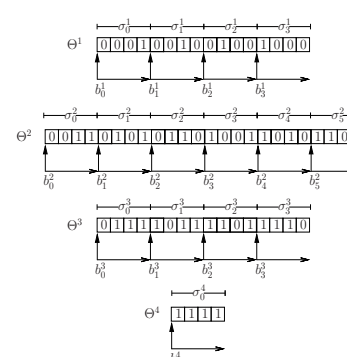
### Support Keys

- Support key  $\sigma_j^i$
- Indicates available actions
- Support size  $i$
- Order of permutation  $j$
- 69 strategy pair combinations

		Player 2				
		$\sigma_0^3$				
		0	1	1	1	
Player 1	1	A	7.2	9.4	5.8	6.3
	1	B	4.9	1.1	6.4	9.1
	1	C	8.5	4.6	1.1	3.4
	0	D	3.6	1.9	4.3	2.7

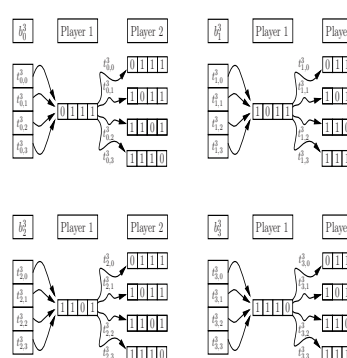
### Support Key Set & Block Distribution

- Set of Support keys  $\Theta^i$
- Support size  $i$
- Co-lexicographical order.
- Blocks  $b_j^i$  select strategies for Player 1
- Support size  $i$
- Order of permutation  $j$

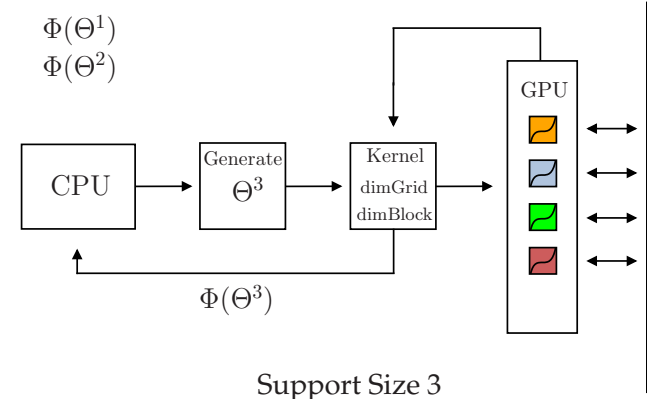


### Thread Distribution

- Threads  $t_{j,k}^i$  selects strategies for Player 2
- Processes strategy pairs
- Computes  $(x, y)$  probabilities
- Support size  $i$
- Thread index  $k$  in block  $j$



### GPU Processing



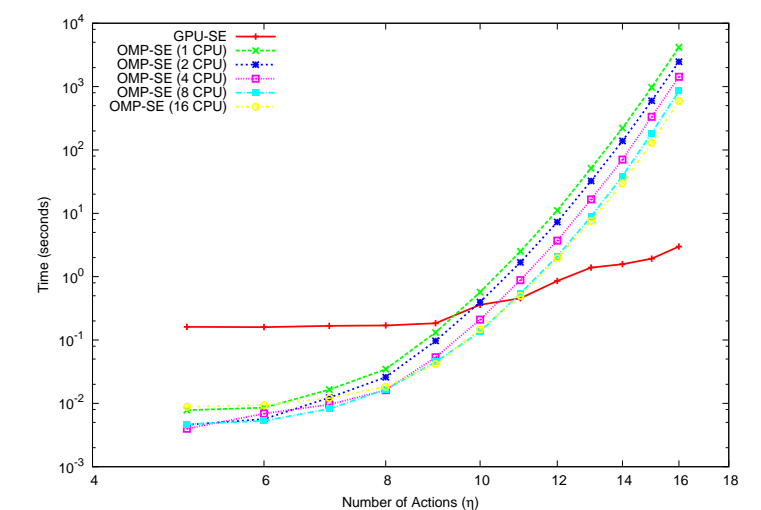
### Experimental Setup GPU

- Nvidia™ GT 440
- 96 CUDA Cores
- 1.6 (GHz) Processor Speed
- 13 (billion/sec.) Texture Fill Rate

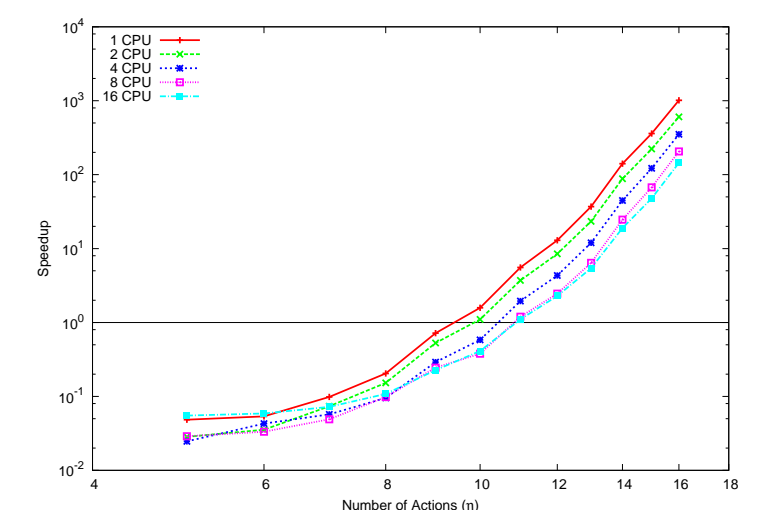
### OpenMP

- Wayne State University Grid
- 40 Node 16-Core Quad AMD Processors
- 2.6 (GHz) Processor Speed
- 128 GB RAM

### Average Execution vs. Number of Actions



### Average Speedup vs. Number of Actions



### Conclusion

- GPU processing outperforms OpenMP implementations for computing equilibria in larger games.
- GPU speedups range from 144.07 to 1013.53 against OpenMP configurations from 1 to 16 CPUs.

### Acknowledgment

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