Correlated-Q Learning

Greenwald & Hall, 2003

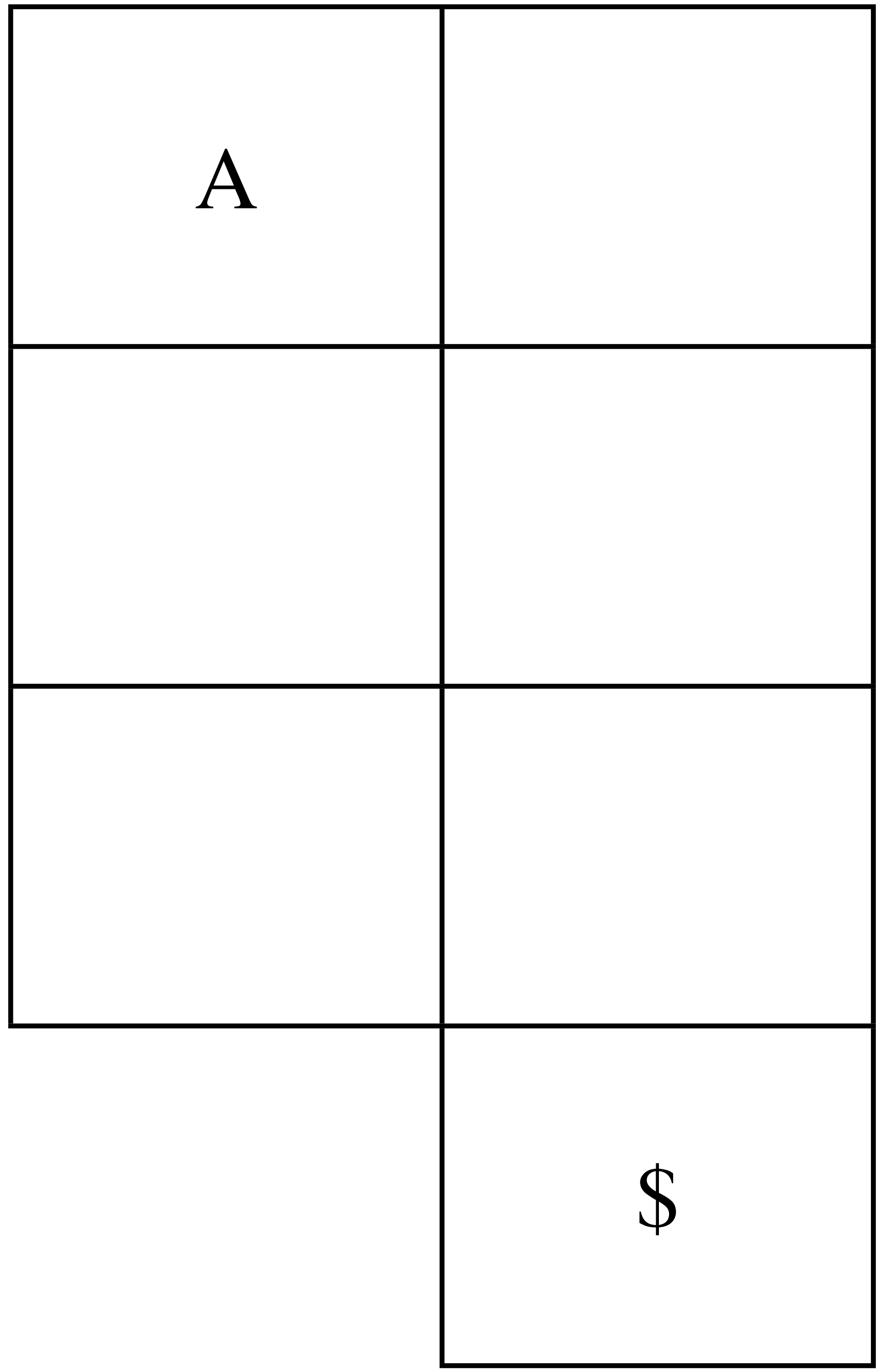
and

Cooperation In Strategic Games, Revisited

Kalai & Kalai

Adam Abeshouse, Betsy Hilliard and Eric Sodomka

December 12, 2012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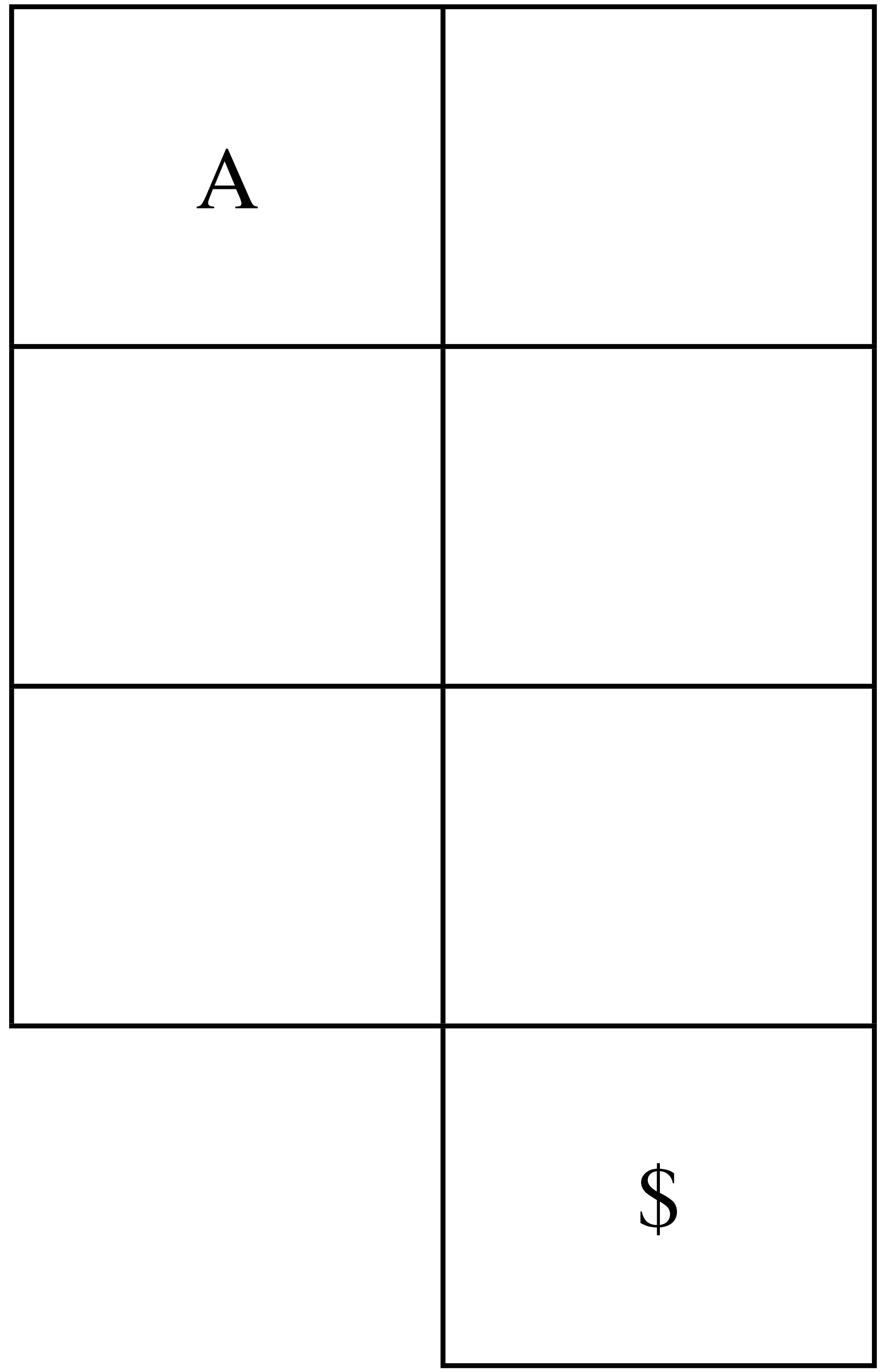
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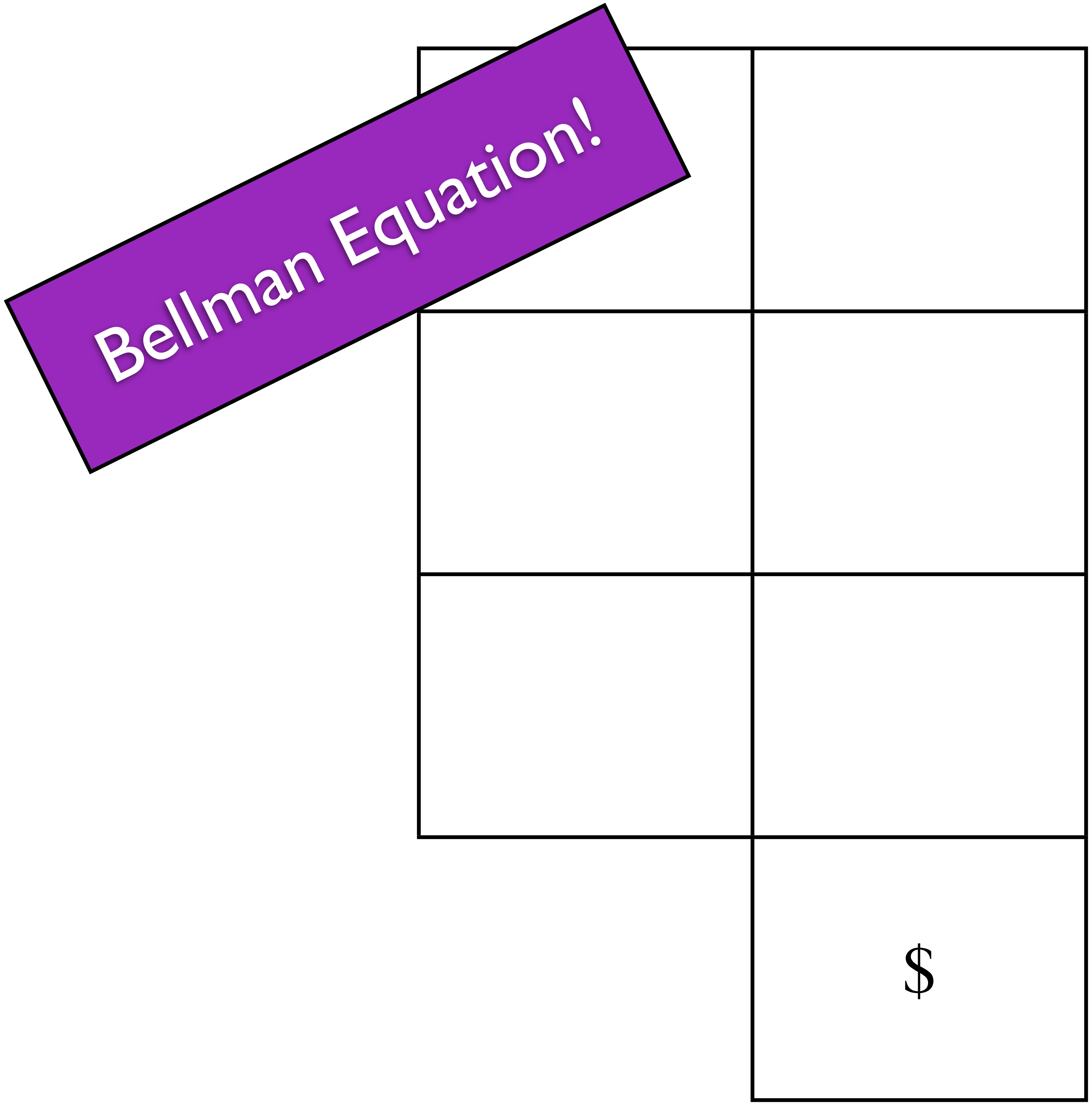
Bellman Equation!
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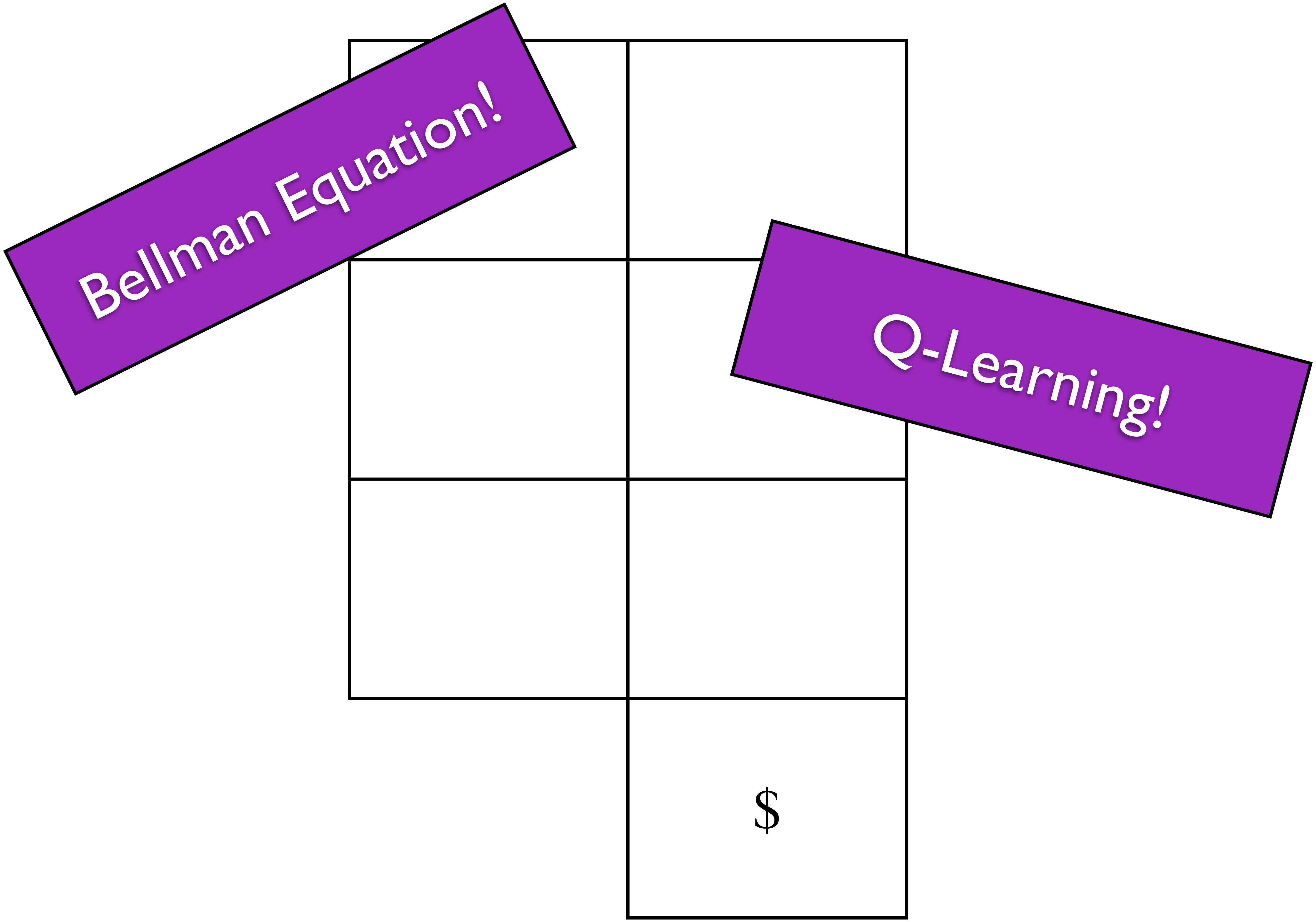
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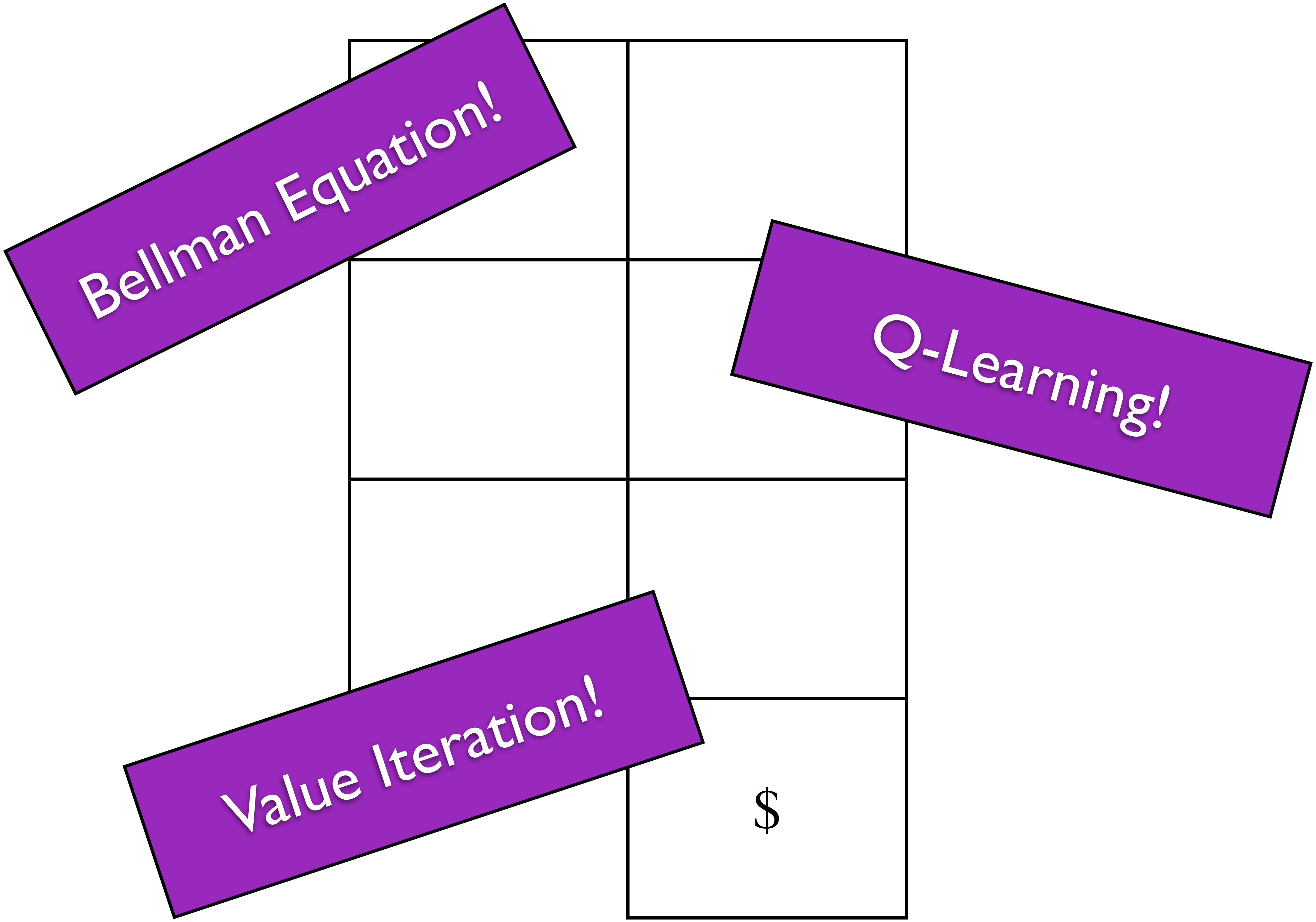
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Q-Learning!
Value Iteration!
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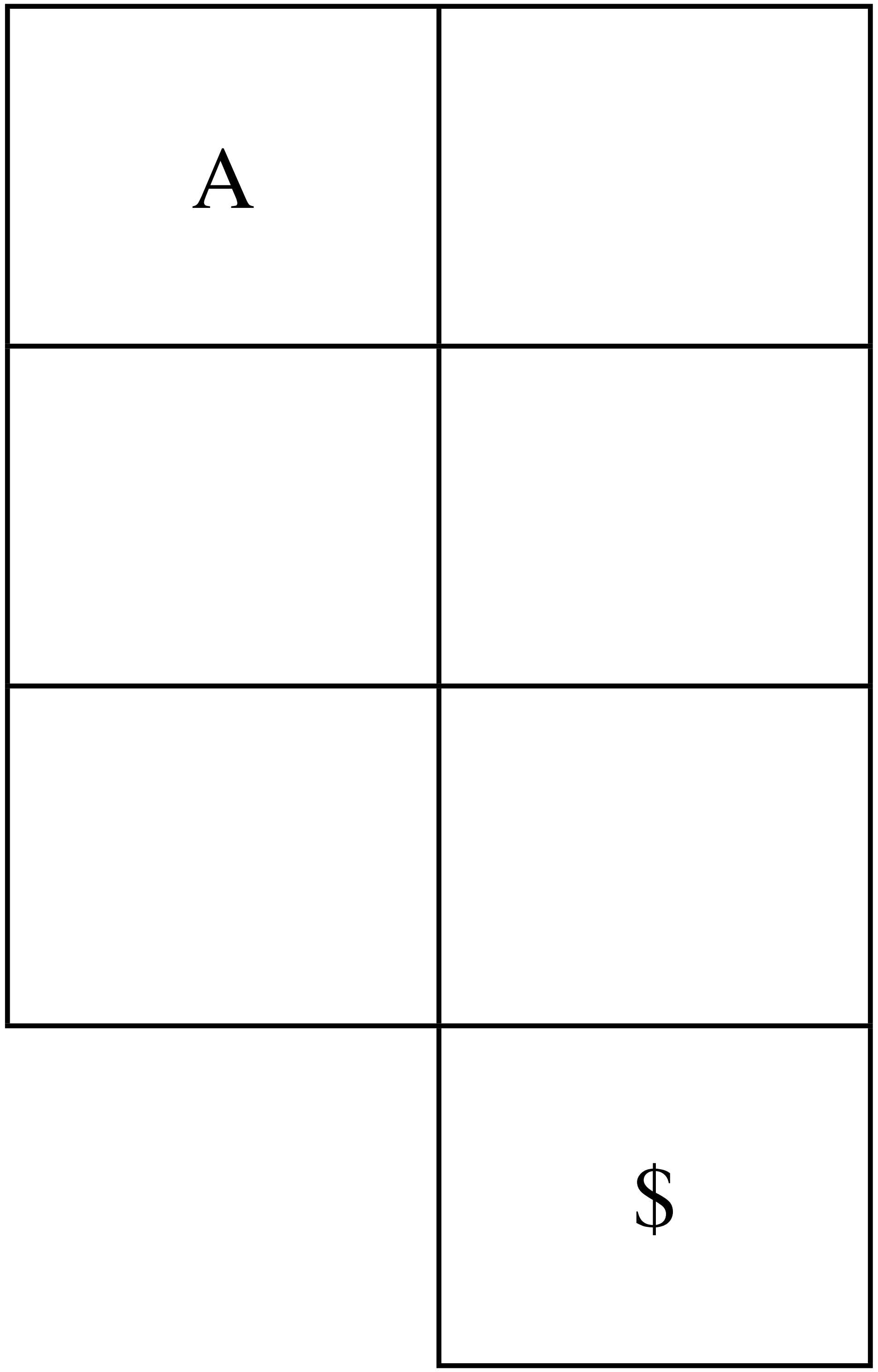
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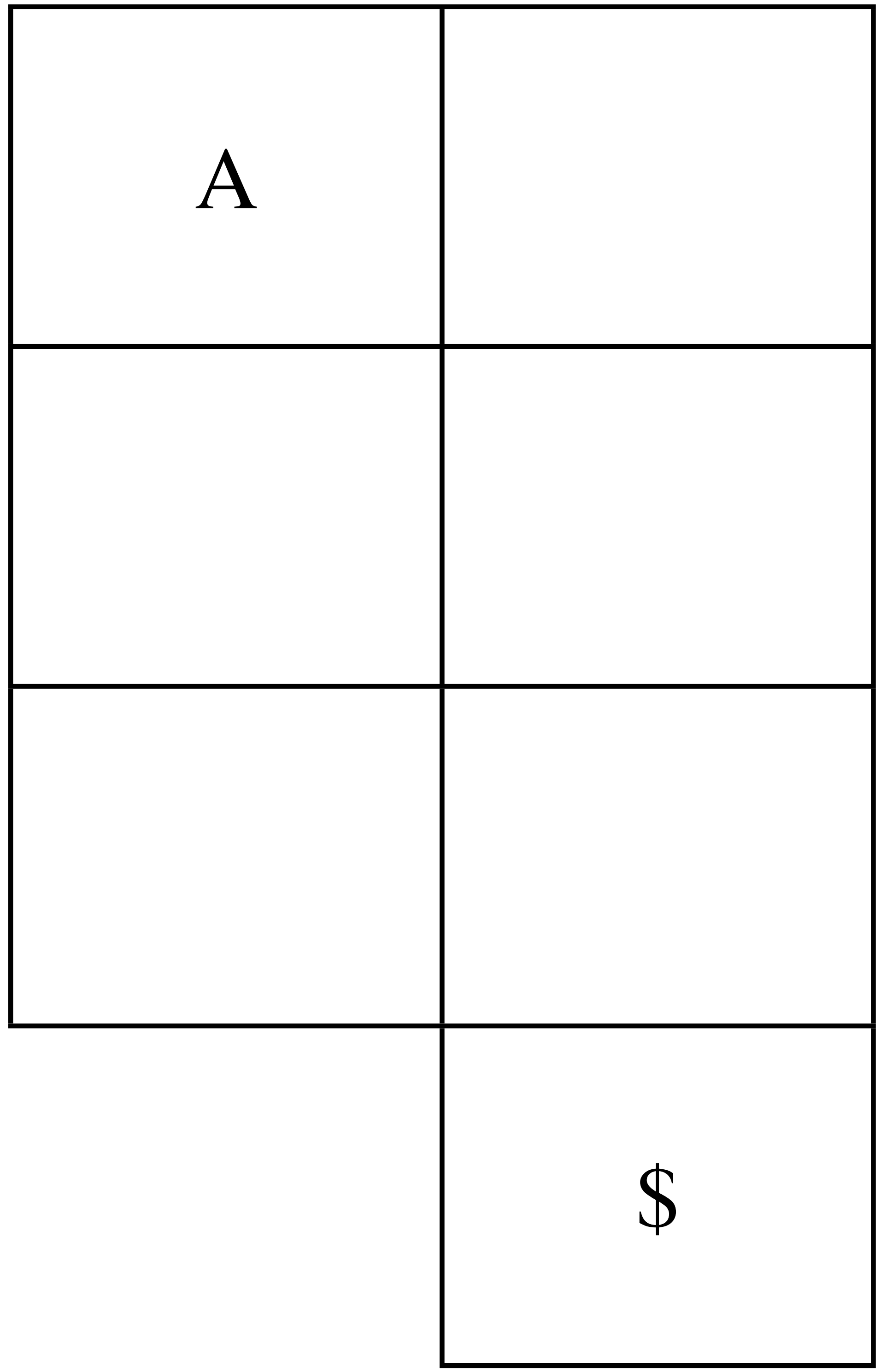
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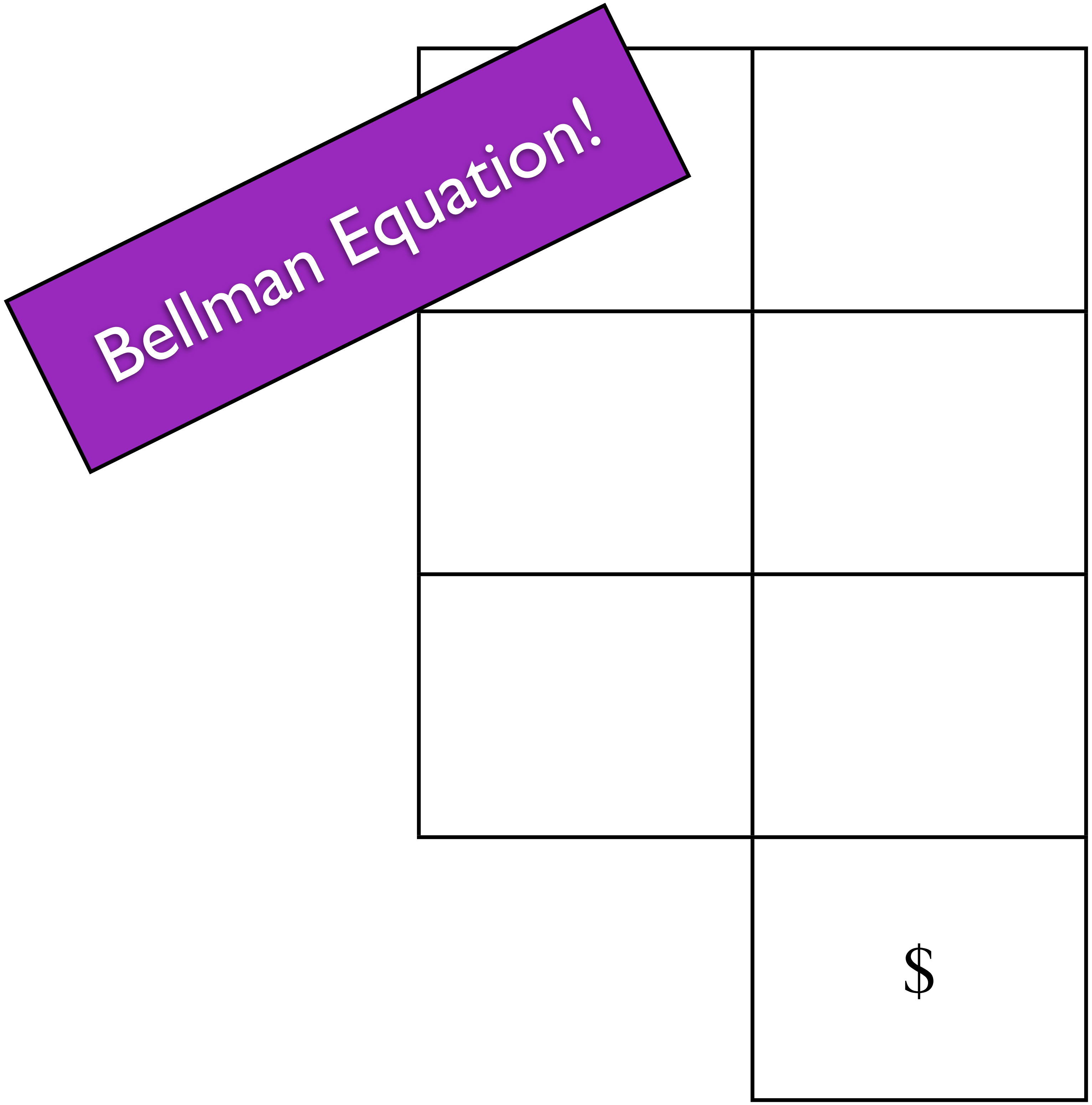
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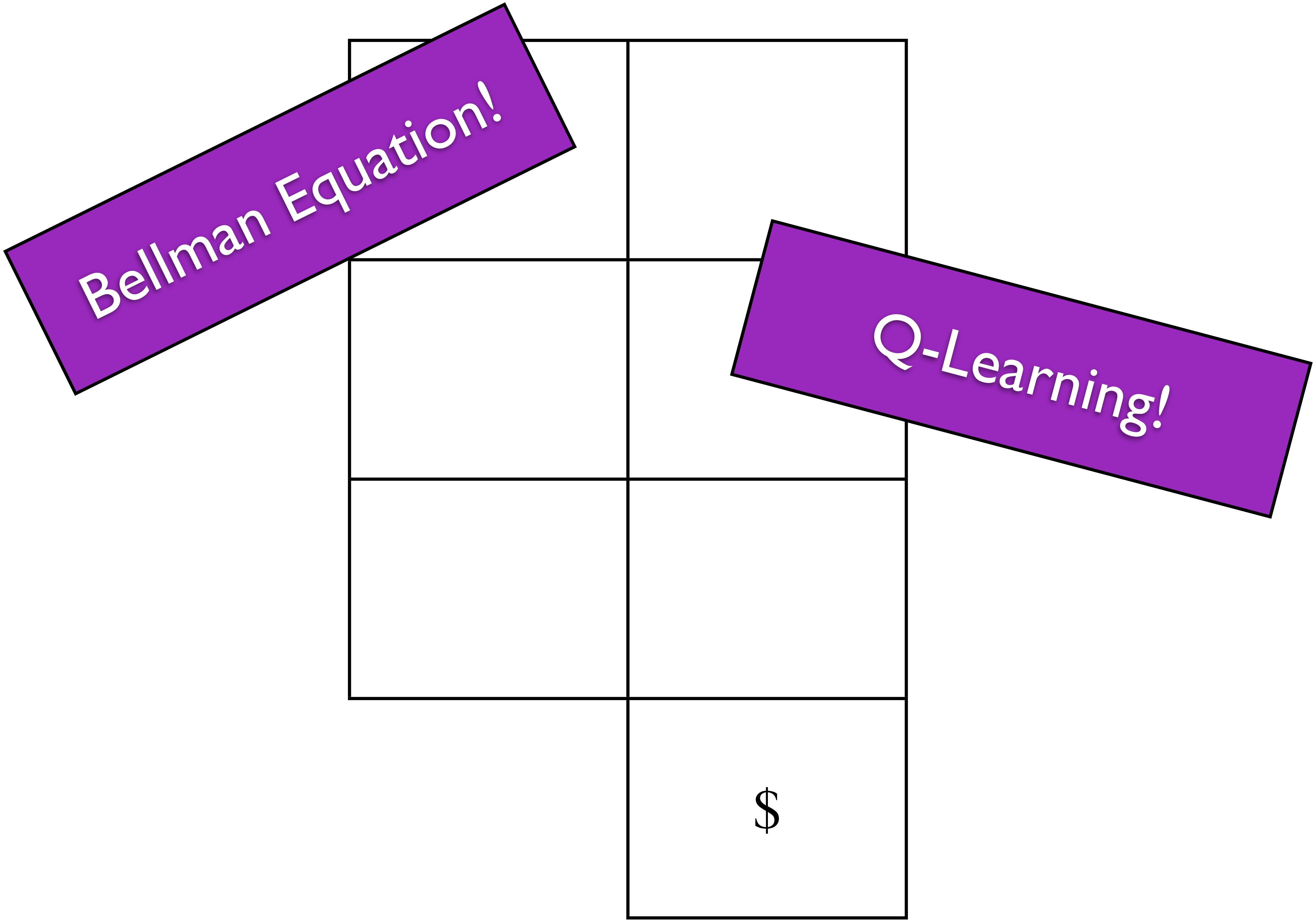
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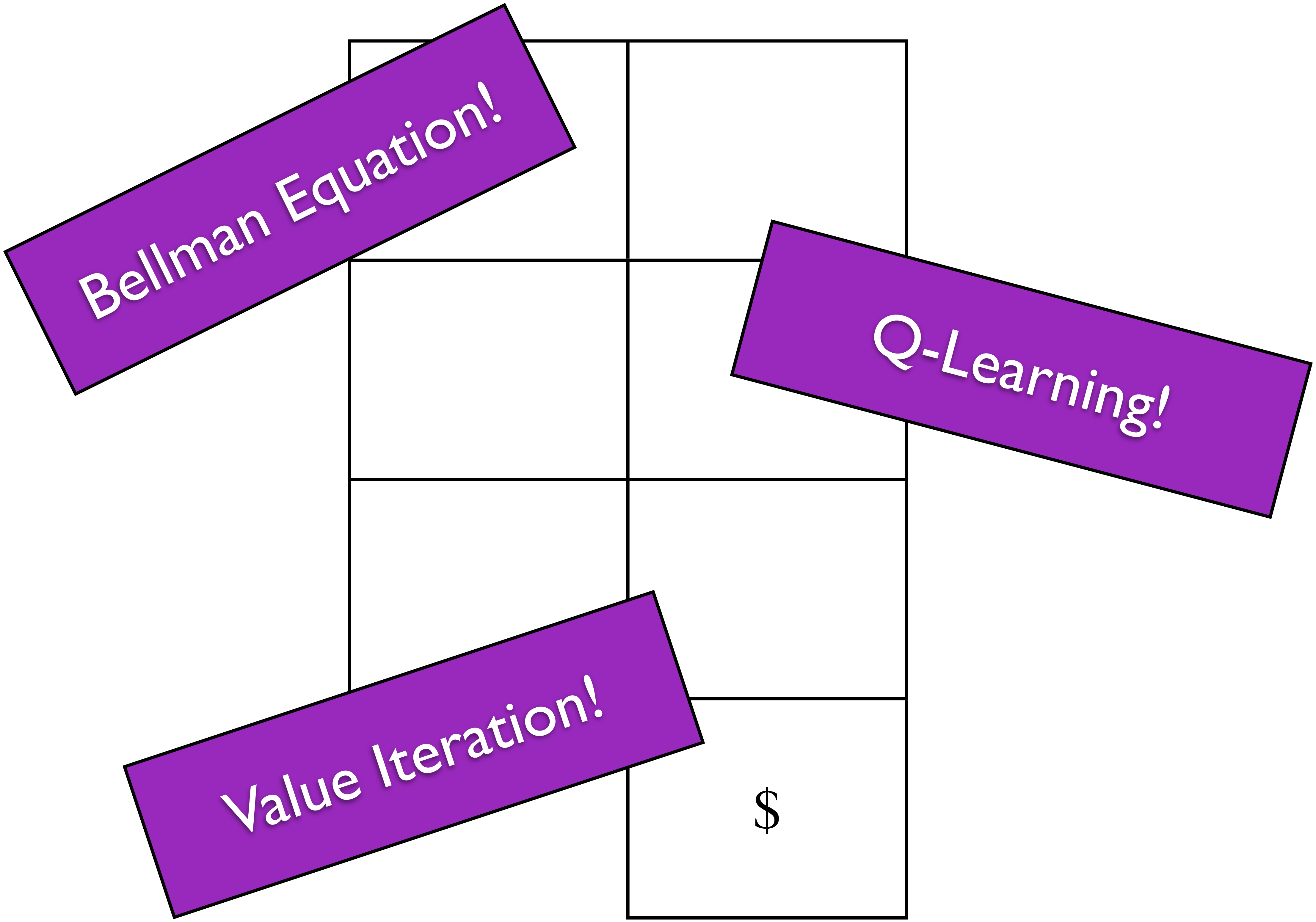
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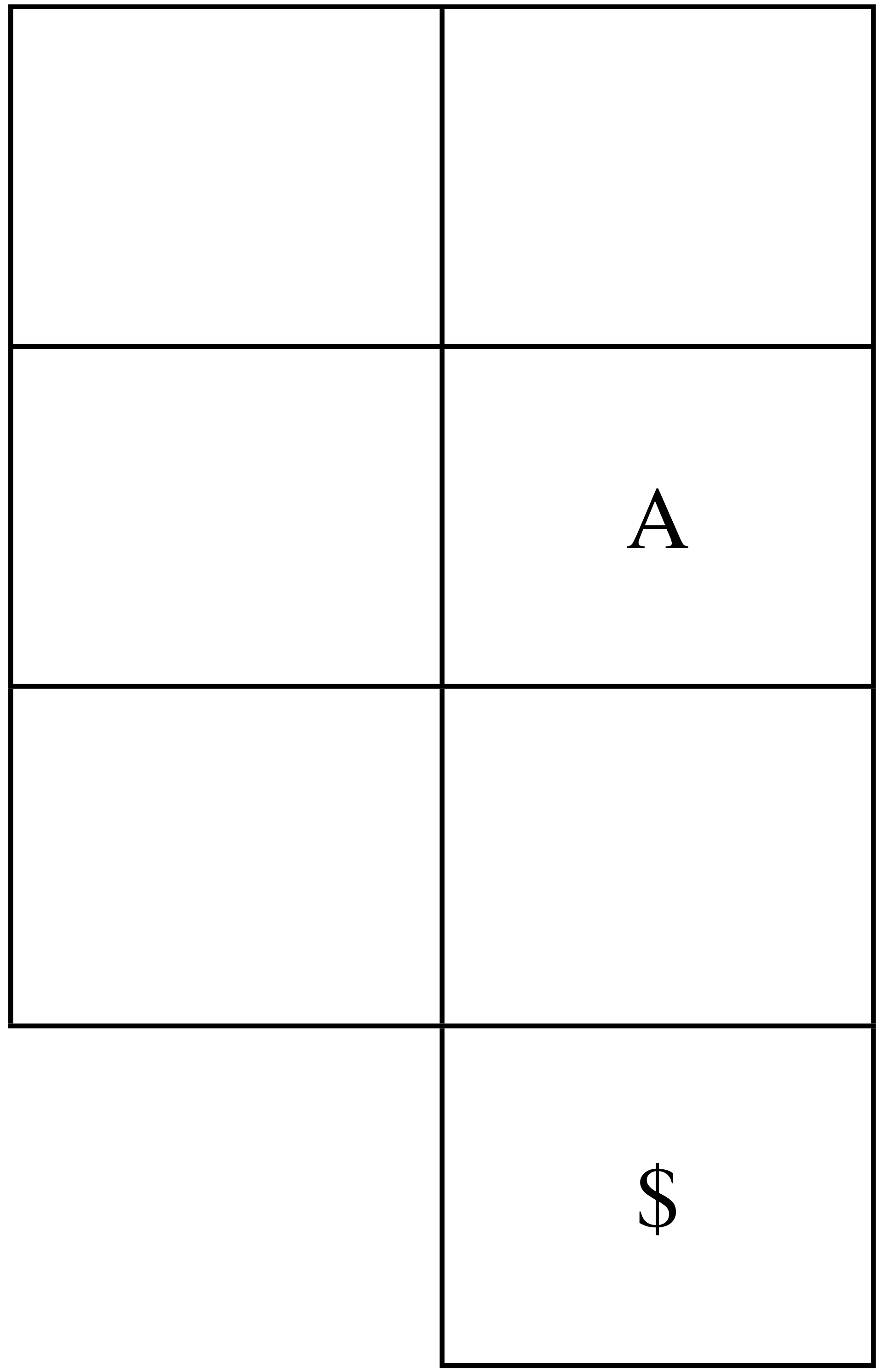
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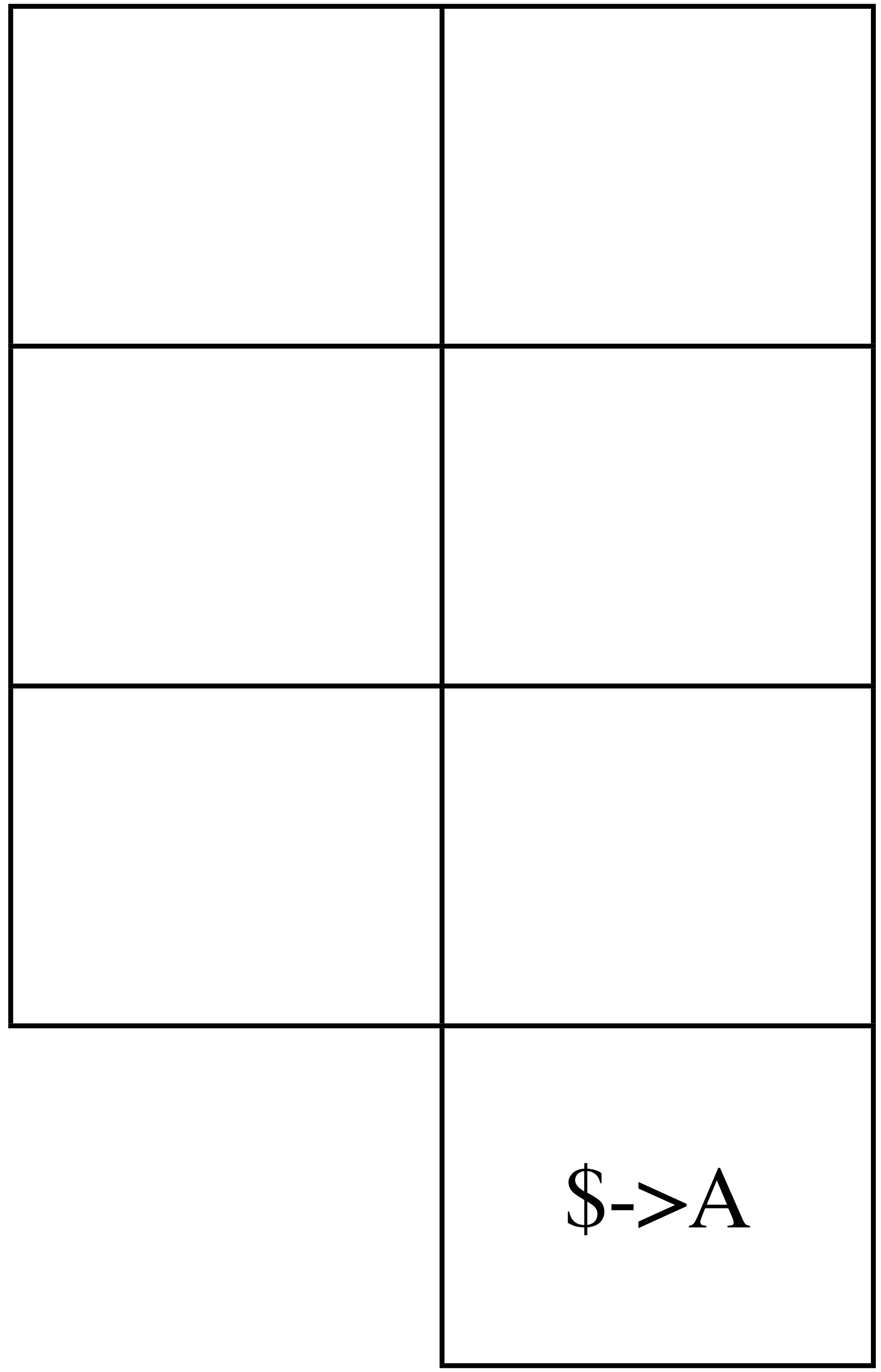
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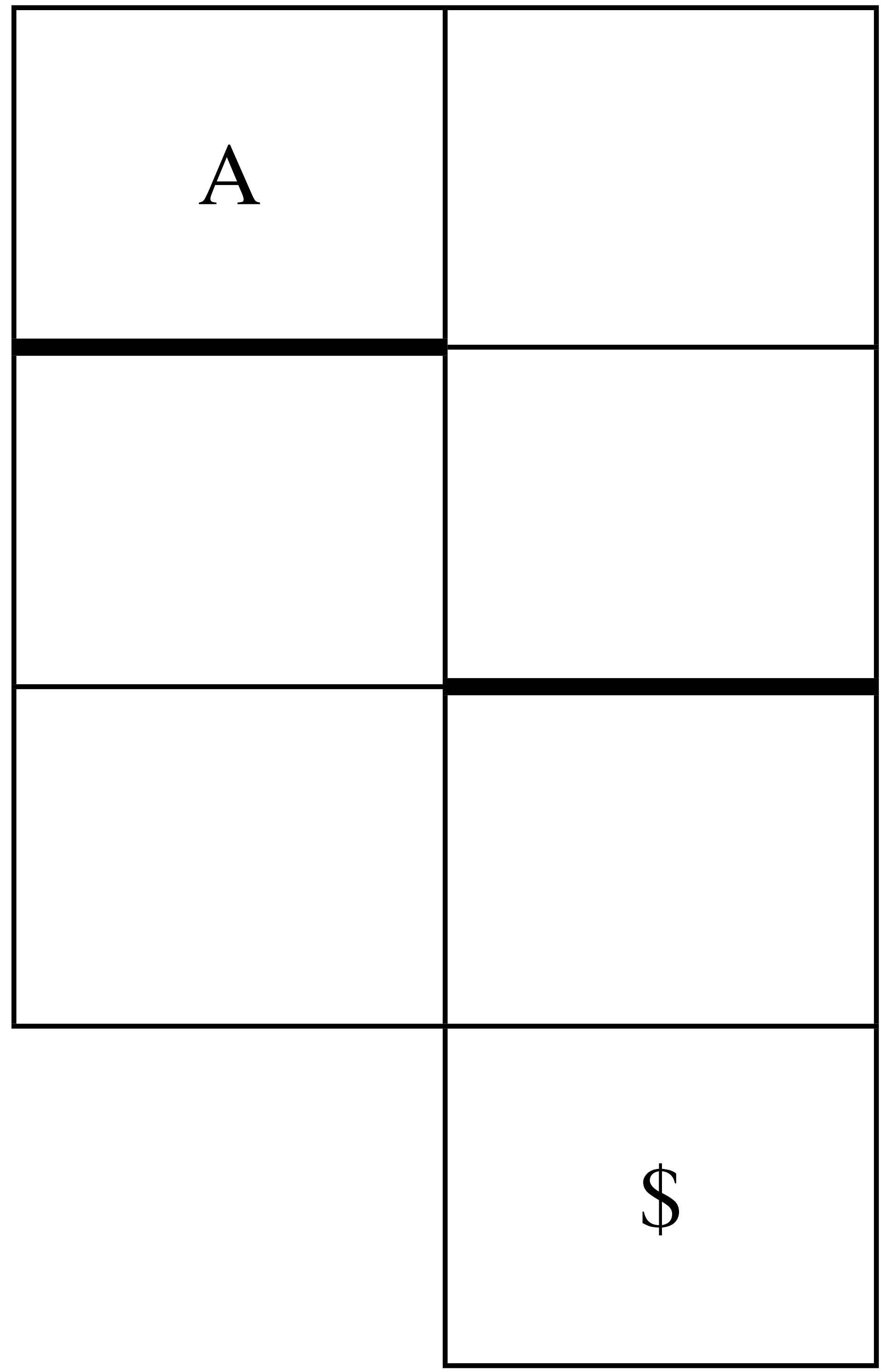
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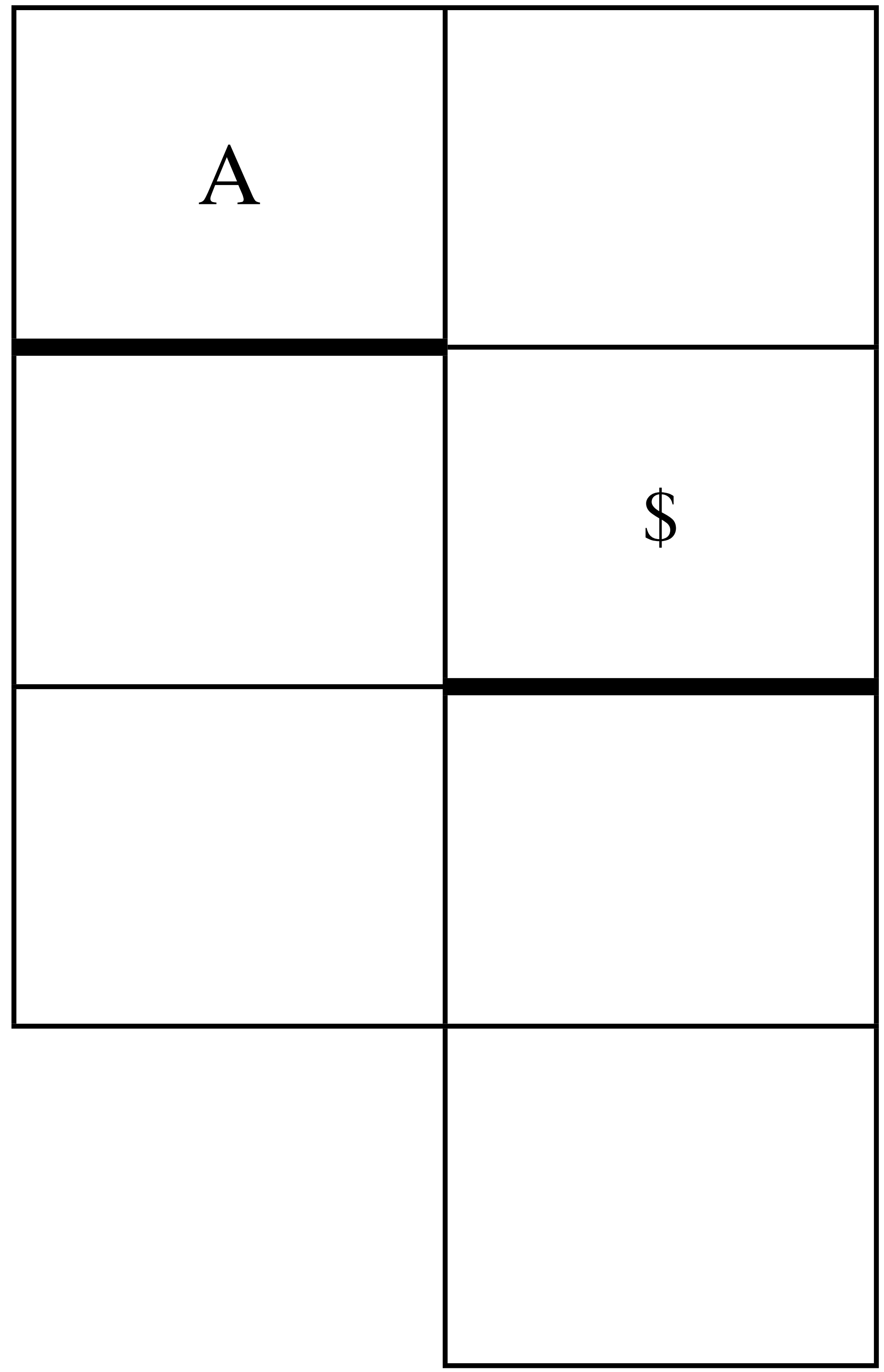
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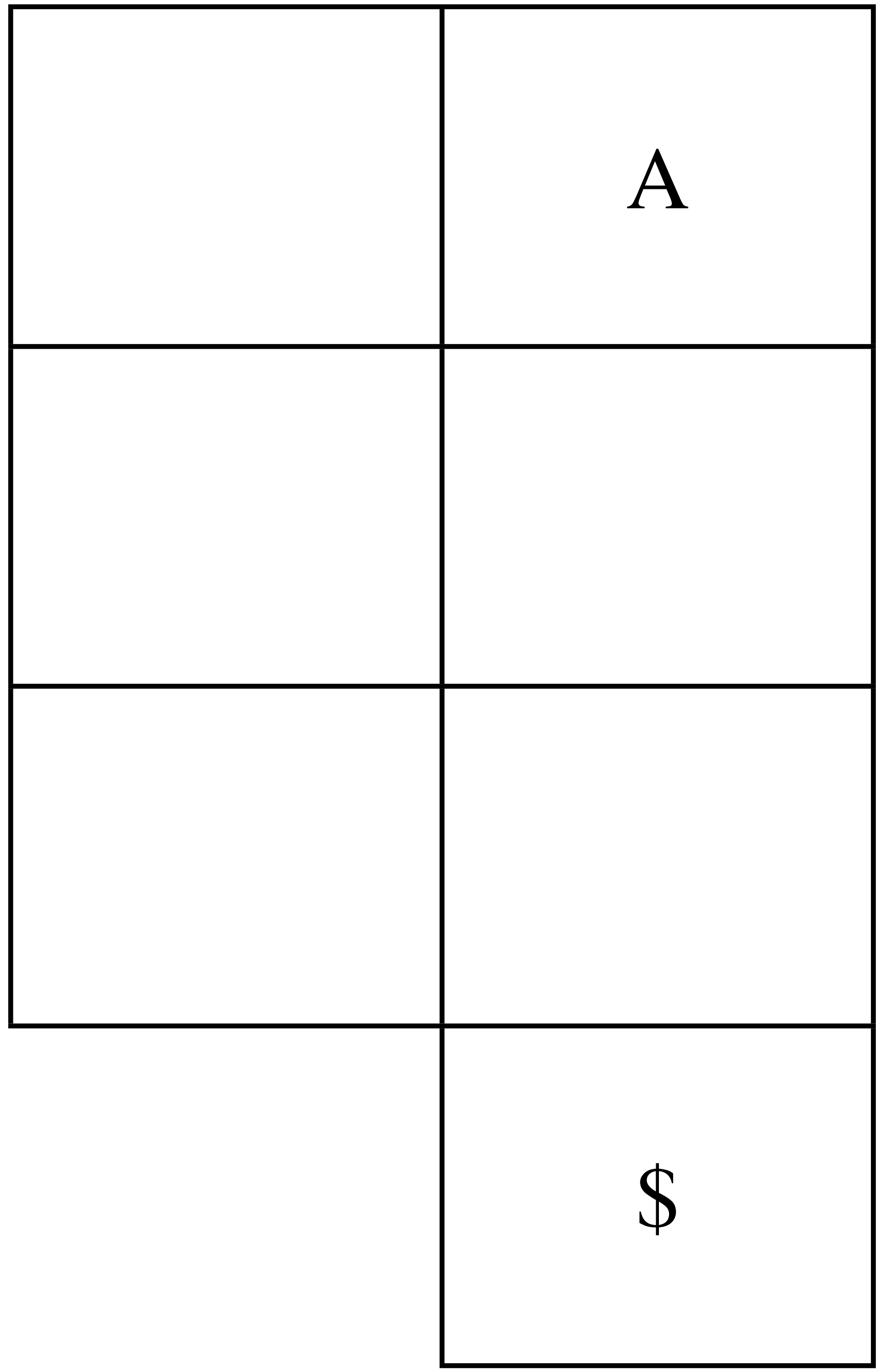
A	B $a
	$a
	$b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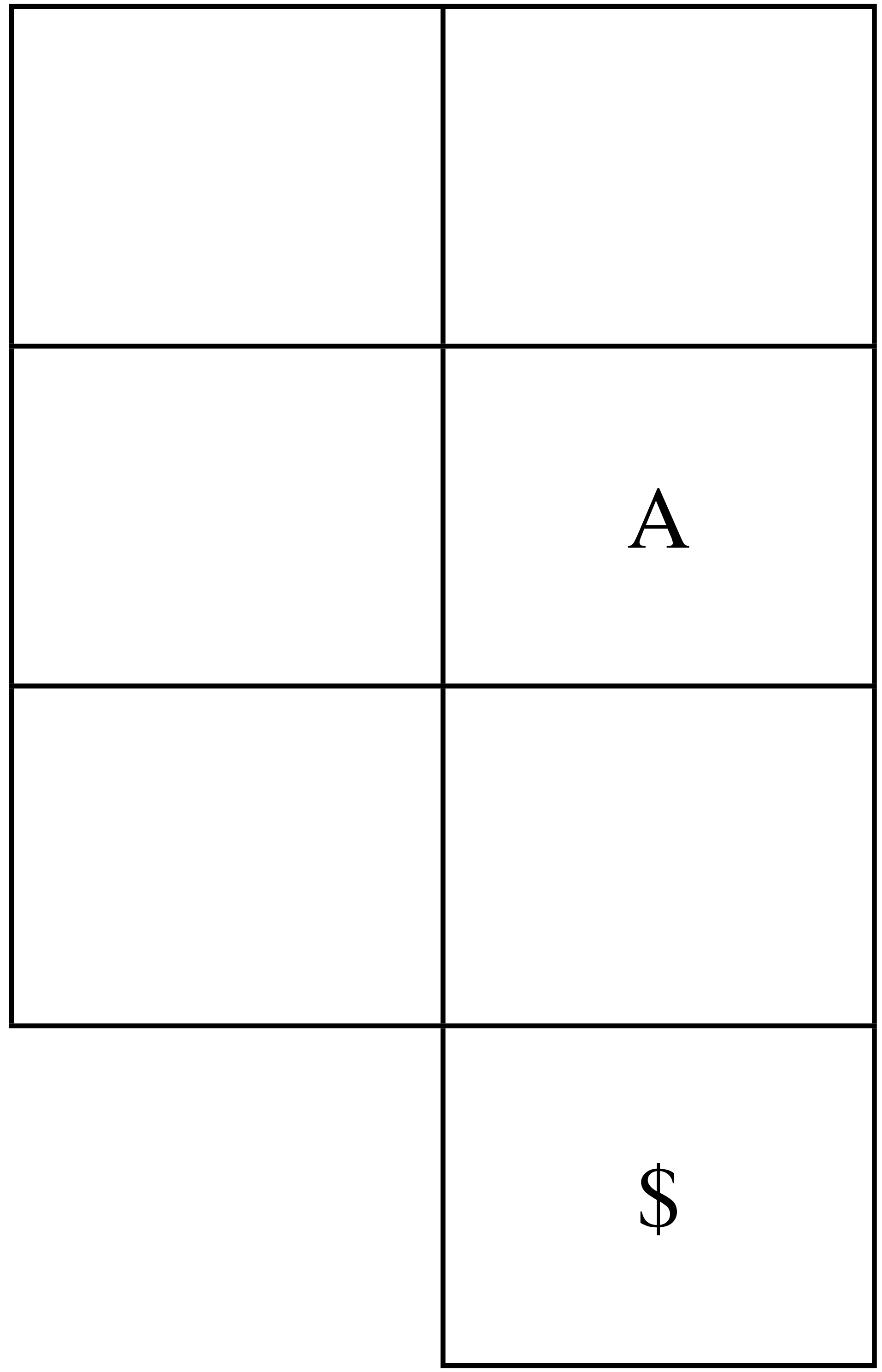
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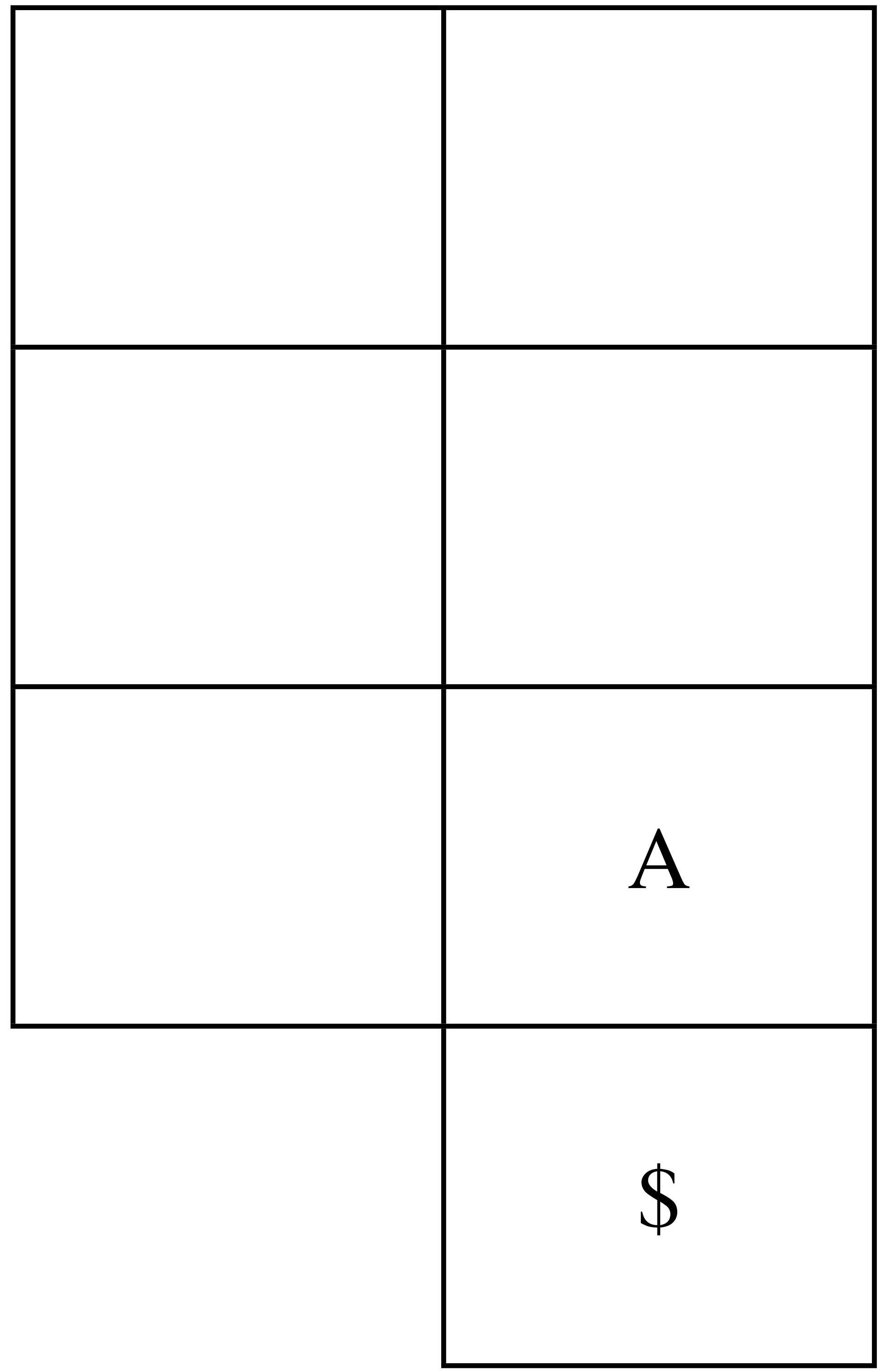
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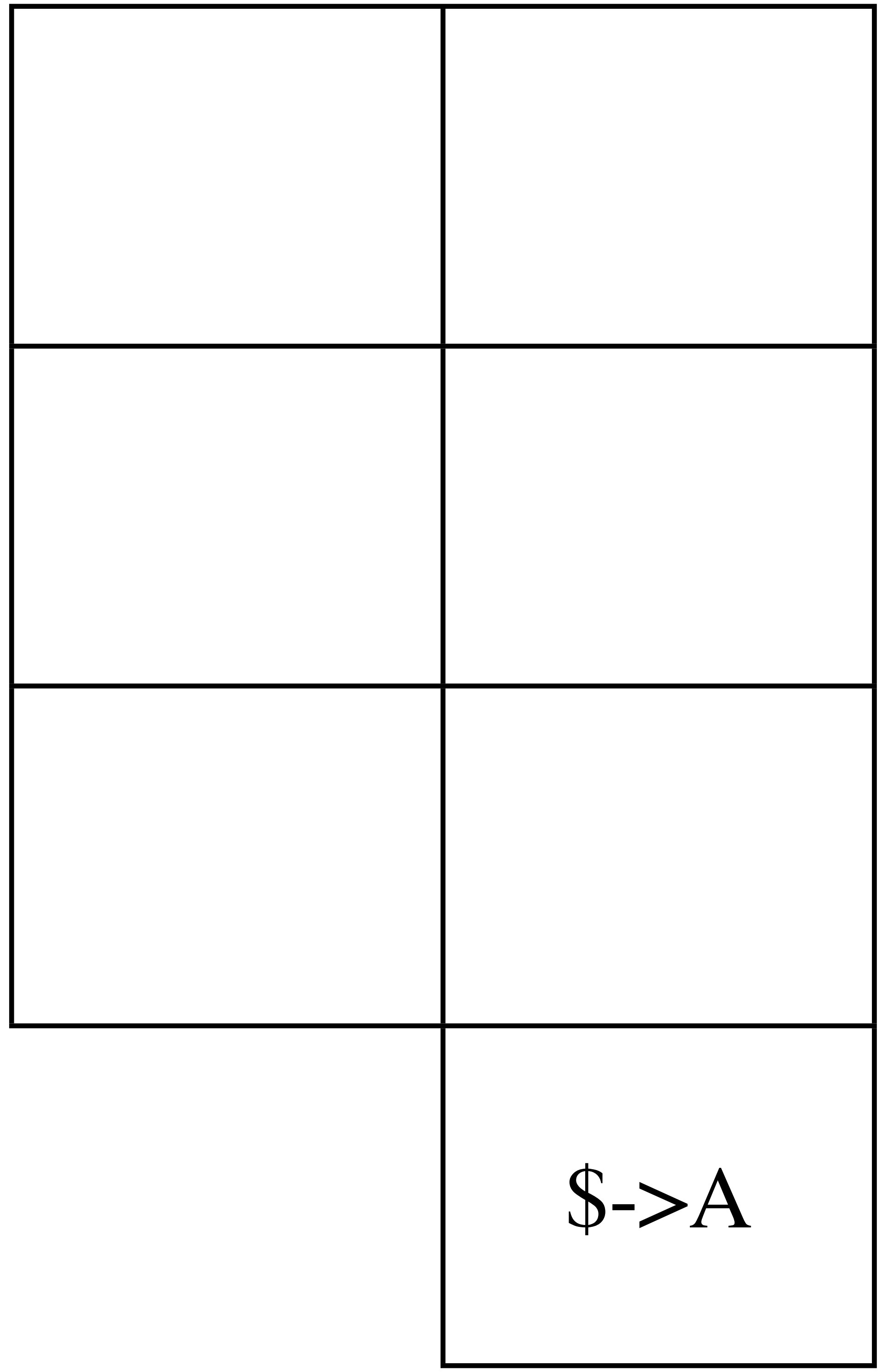
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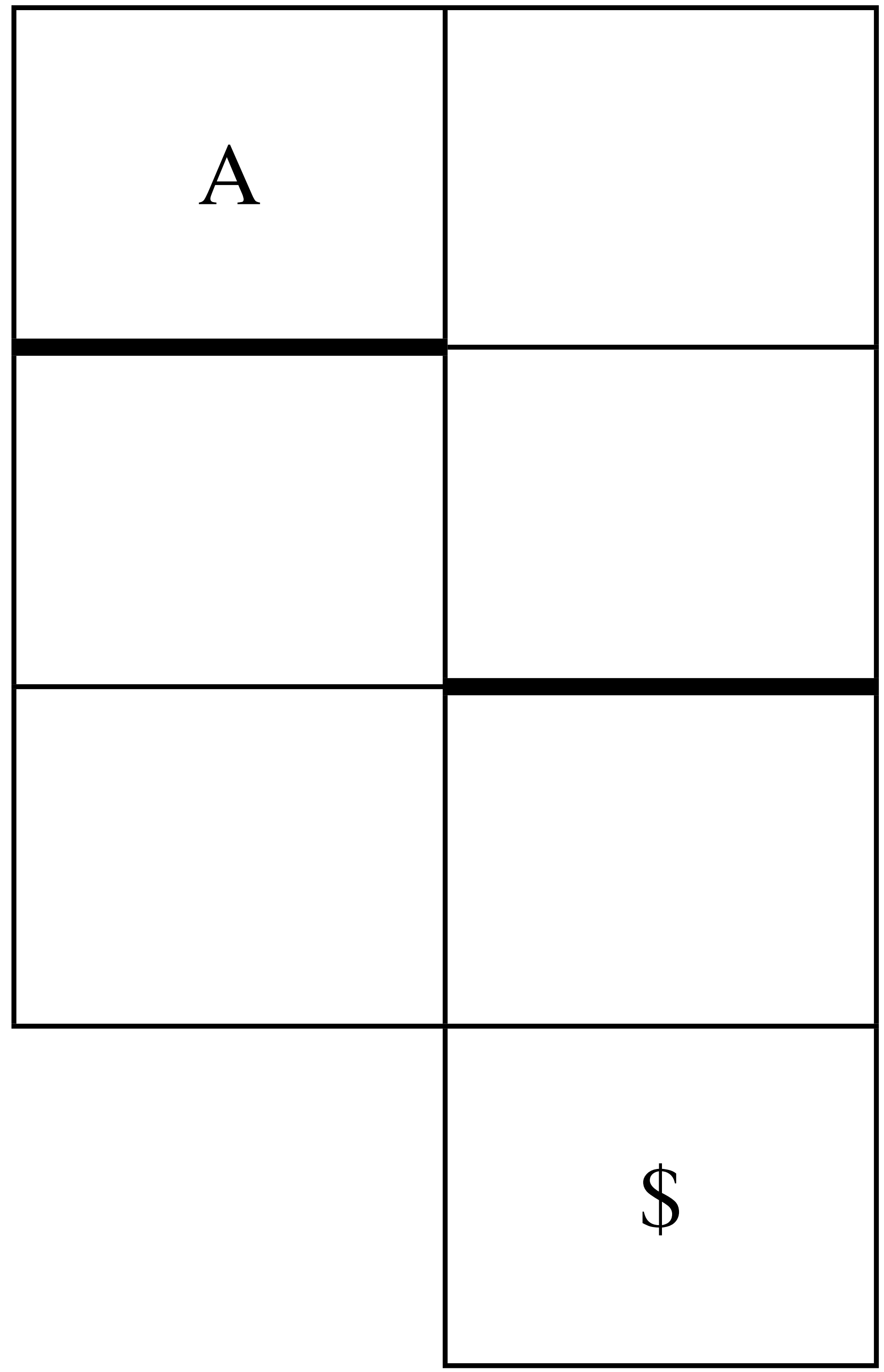
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A	B $a
	$a
	$b

Correlated-Q Learning

Greenwald and Hall, 2003

- Describes an algorithm to extend Q-learning (and VI) to multiagent settings
- Uses "solution concepts" because "max" no longer makes sense
  - Friend/F

    proof of convergance

But agents in the real world have more options...

  - Correlated (Greenwald, Hall, 2003) no proof of convergance

Hot Dog Stand Game

B

A	beach	park
park	120, 40	240, 200
beach	600, 80	300, 100

Coco Value

B

A	beach	park
park	120, 40	240, 200
beach	600, 80	300, 100

$$\frac{A+B}{2}, \frac{A+B}{2}$$

Cooperative

	beach	park
park	130, 130	220, 220
beach	340, 340	200, 200

$$\frac{A-B}{2}, \frac{B-A}{2}$$

Competitive

	beach	park
park	45, -45	20, -20
beach	270, -270	100, -100

Coco Value Solution

Cooperative

	beach	park
park	130, 130	220, 220
beach	340, 340	200, 200

COCO value =(340+100, 340+-100)=(440,240)

But one could calculate many such values...

park	45, -45	20, -20
beach	270, -270	100, -100

A

		park
park	120, 40	240, 200
beach	600, 80	300, 100

A then pays B $240

Cooperation In Strategic Games, Revisited

Kalai and Kalai, 2011

Axioms

1. Pareto Optimality: max sum of values

2. Payoff dominance: if an agent always dominate, value greater

3. Shift invariance: additive shift by c changes value by c

4. Redundant mixed strategies: convex combinations of moves can be removed with no effect on the value

5. Monotonicity in strategies: adding a strategy can only increase your value

Also: unique and efficiently computable and the **only** value that satisfies 1-5

Original Table:

Figure 2. Convergence in the grid games: all algorithms are converging. The CE-Q algorithm shown is uCE-Q.

Grid Games	GG1	GG2	GG3
Algorithm			
Q			
Foe-Q			
Friend-Q			
uCE-Q			
eCE-Q			
rCE-Q			
lCE-Q			

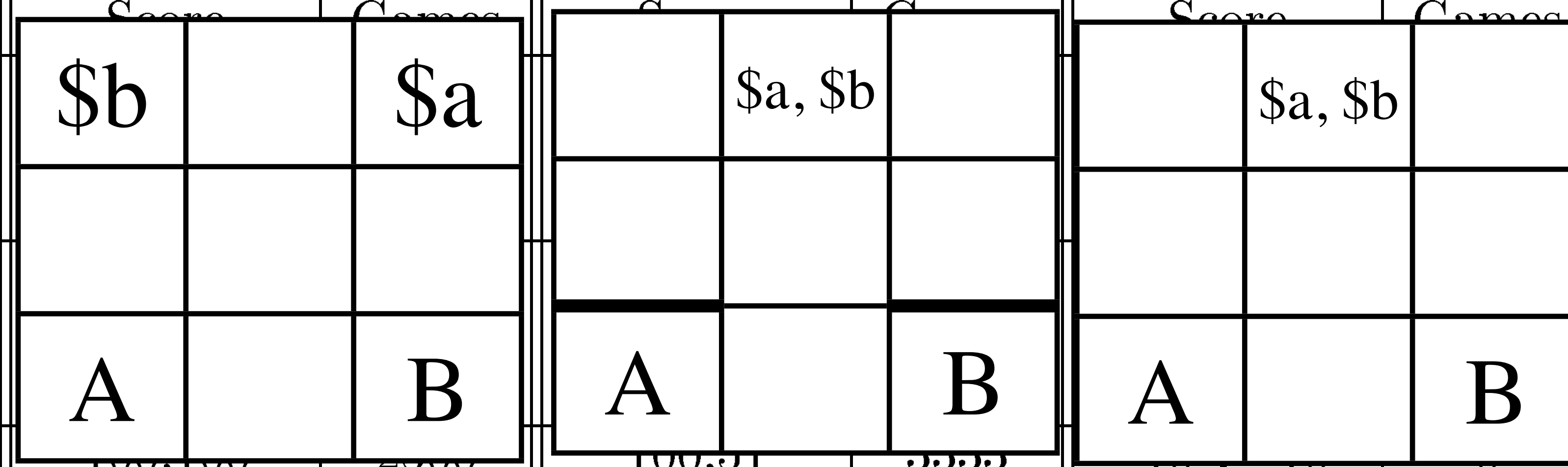

Table 2. Grid Games played repeatedly, allowing 10^4 moves. Average scores are shown. The number of games played varied with the agents' policies: some move directly to the goal, while others digress.

Original Table:

Figure 2. Convergence in the grid games: all algorithms are converging. The CE-Q algorithm shown is uCE-Q.

Grid Games	GG1		GG2		GG3	
Algorithm	Score	Games	Score	Games	Score	Games
Q	100,100	2500	49,100	3333	100,125	3333
Foe-Q	0,0	0	67,68	3003	120,120	3333
Friend-Q	$-10^4, -10^4$	0	$-10^4, -10^4$	0	$-10^4, -10^4$	0
uCE-Q	100,100	2500	50,100	3333	116,116	3333
eCE-Q	100,100	2500	51,100	3333	117,117	3333
rCE-Q	100,100	2500	100,49	3333	125,100	3333
lCE-Q	100,100	2500	100,51	3333	$-10^4, -10^4$	0

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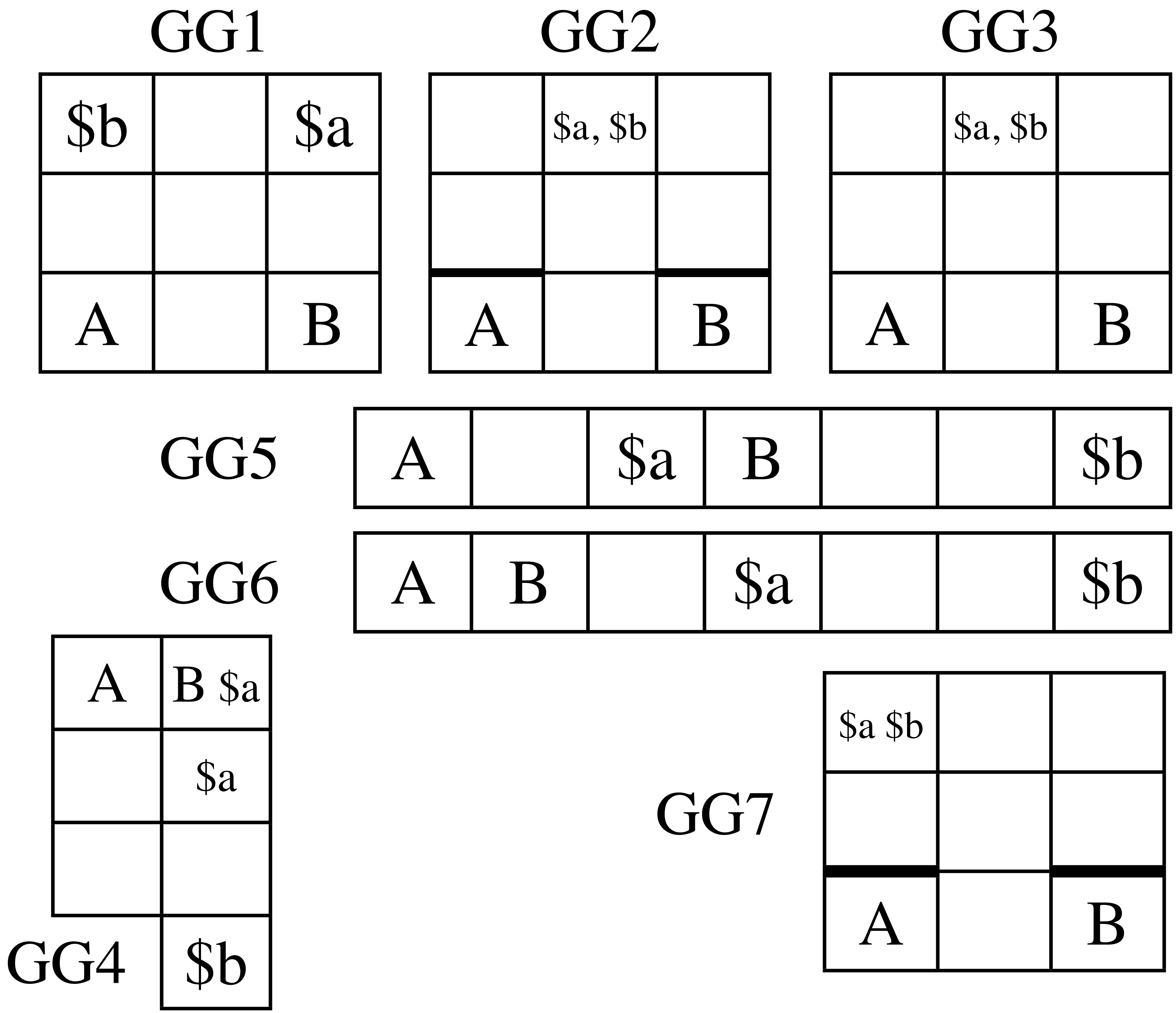
Table 2. Grid Games played repeatedly, allowing 10^4 moves. Average scores are shown. The number of games played varied with the agents' policies: some move directly to the goal, while others digress.

Our Table:

Grid Games	GG1		GG2		GG3	
Algorithm	Score	Games	Score	Games	Score	Games
Friend-Q	$-10^4, -10^4$	0	$-10^4, -10^4$	0	$-10^4, -10^4$	0
uCE-Q	100,100	2500	50,100	3333	117,117	3333
eCE-Q	100,100	2500	100,50	3333	117,117	3333
rCE-Q	100,100	2500	49,100	3333	100,125	3333
lCE-Q	100,100	2500	52, 100	3333	$-10^4, -10^4$	0

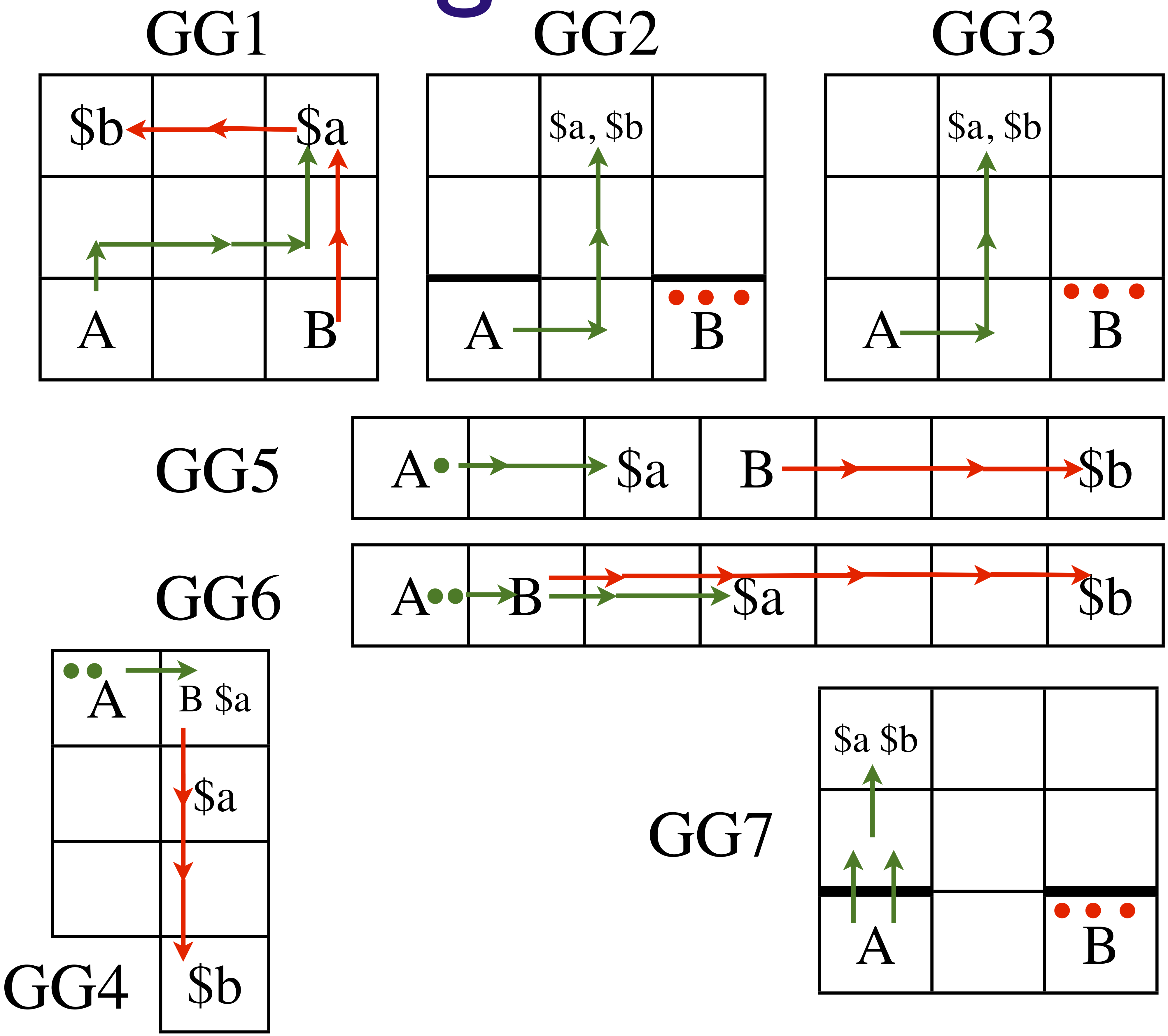
Grid Games


GG1
$b
$a
A
B
GG2
$a, $b
A
B
GG3
$a, $b
A
B
GG5
A
$a
B
$b
GG6
A
B
$a
$b
A
B $a
$a
GG4
$b
$a $b
GG7
A
B

Coco Agents for Grid Games

Coco Results

Coco Agents' Policies



Comparing Solution Concepts

Future work

- What about more than 2 agents?
- Coco in the real world:
  - asymmetric transfer payments?
  - coco vs. negotiation?
- What if humans are allowed (encouraged? forced?) to play games with coco values?

Citations and References

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