Reward Poisoning Attacks on Offline Multi-Agent Reinforcement Learning

Young Wu, Jeremy McMahan, Xiaojin Zhu, Qiaomin Xie

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How to Manipulate Competitive Agents

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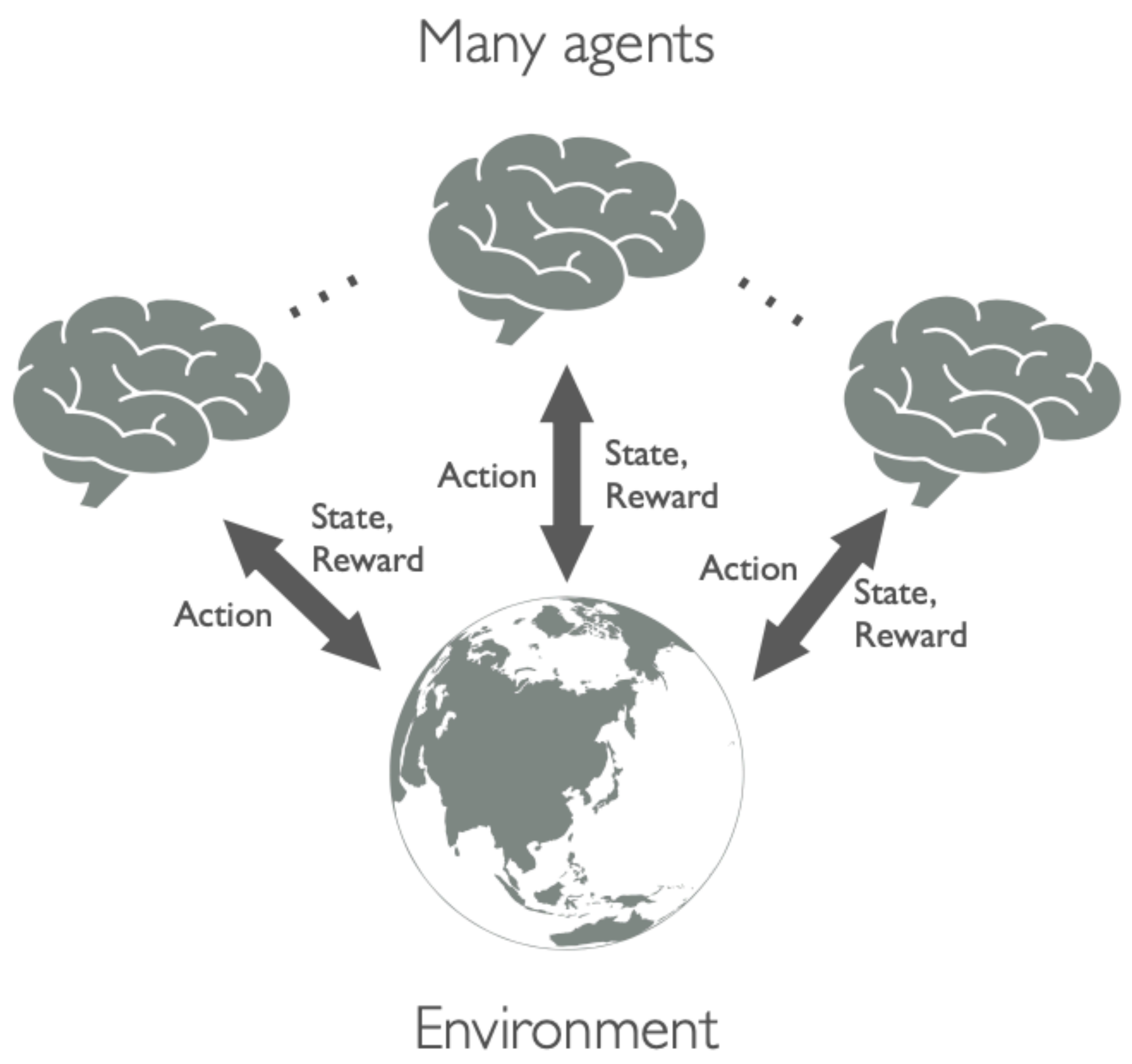
MARL

Learning Goals



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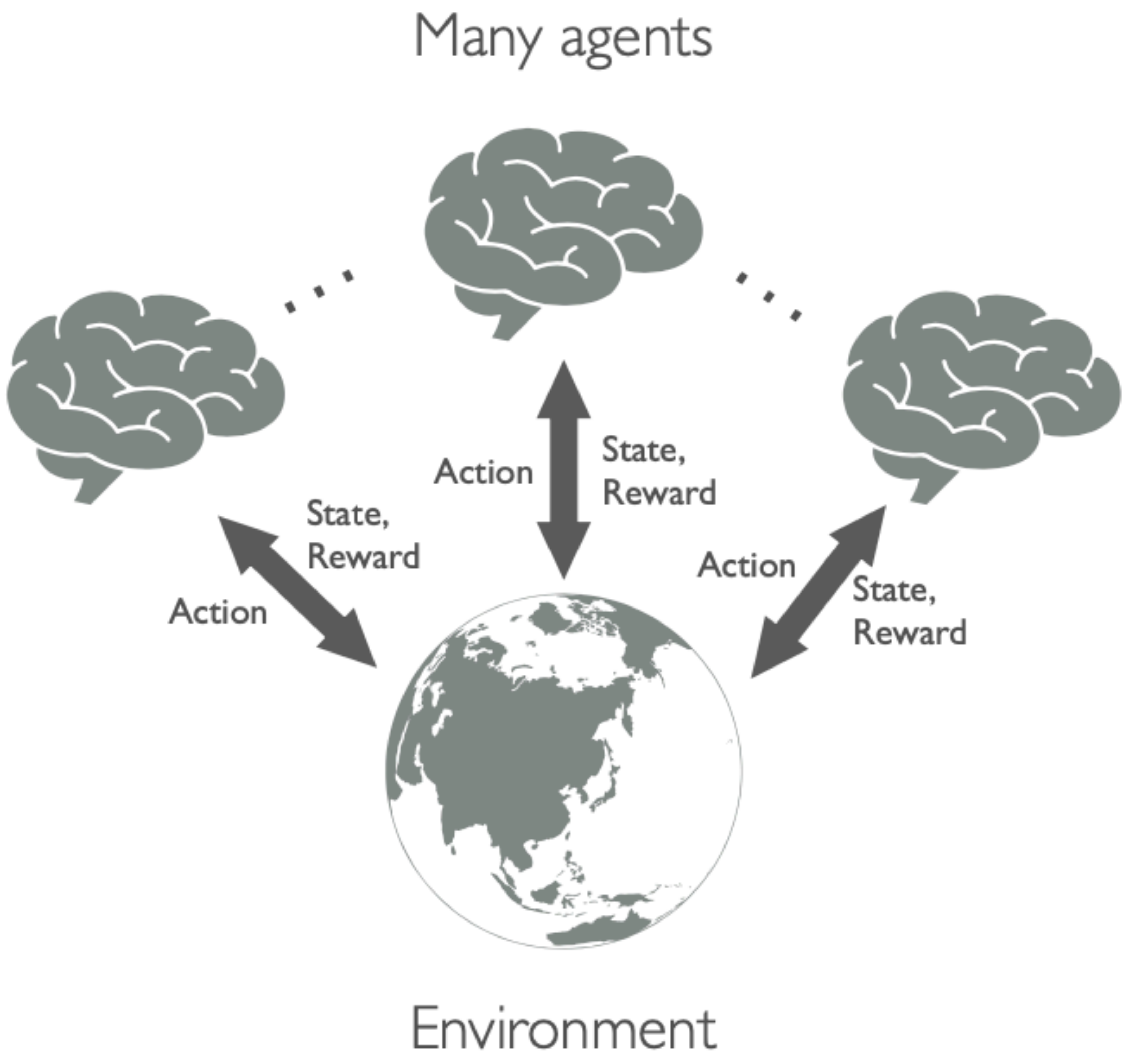
- Agents learn a joint policy $\pi : \mathcal{S} \to \Delta(\mathcal{A})$.



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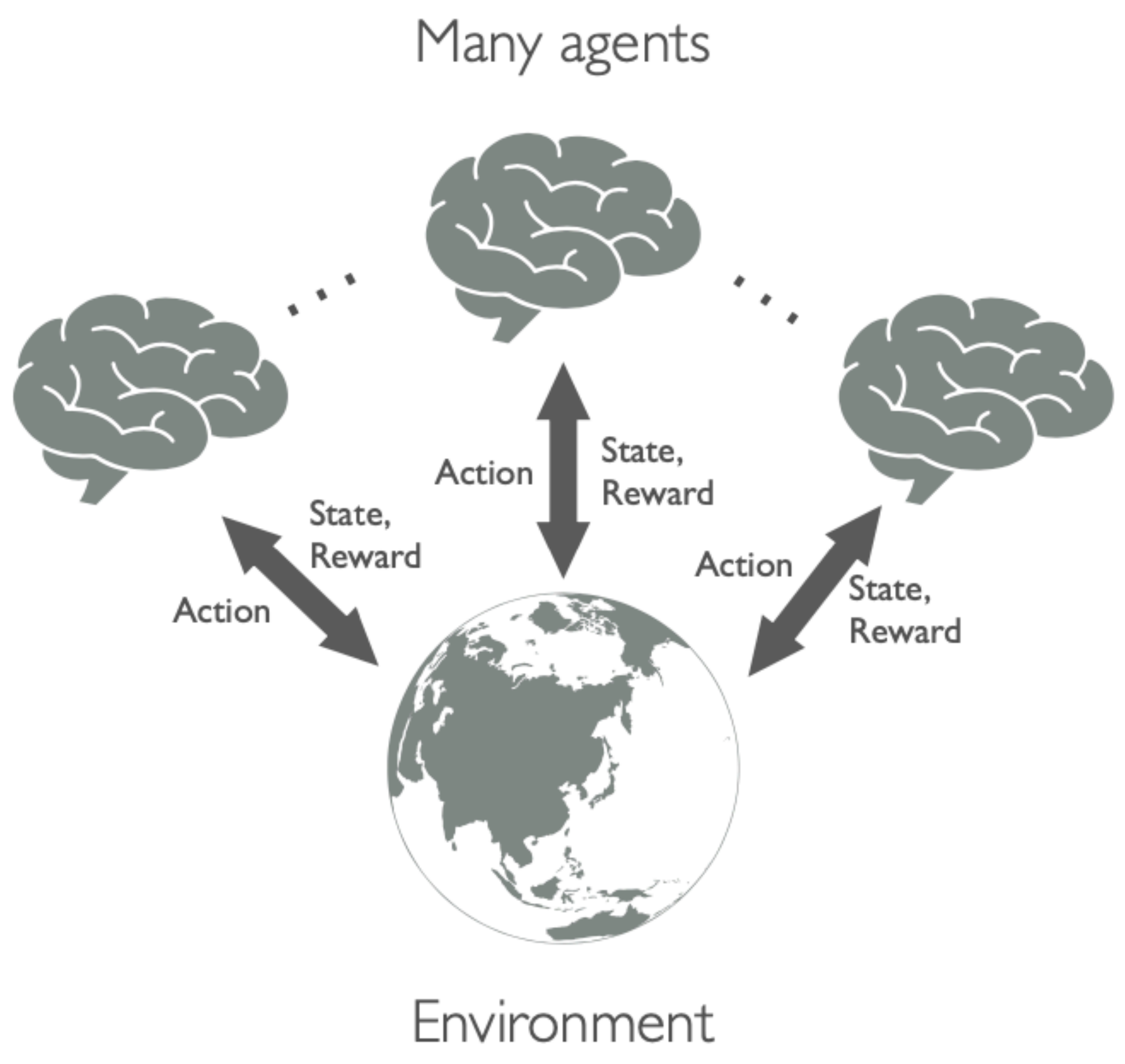
- Agents learn a joint policy $\pi : \mathcal{S} \rightarrow \Delta(\mathcal{A})$.
- π is an "optimal" strategy.



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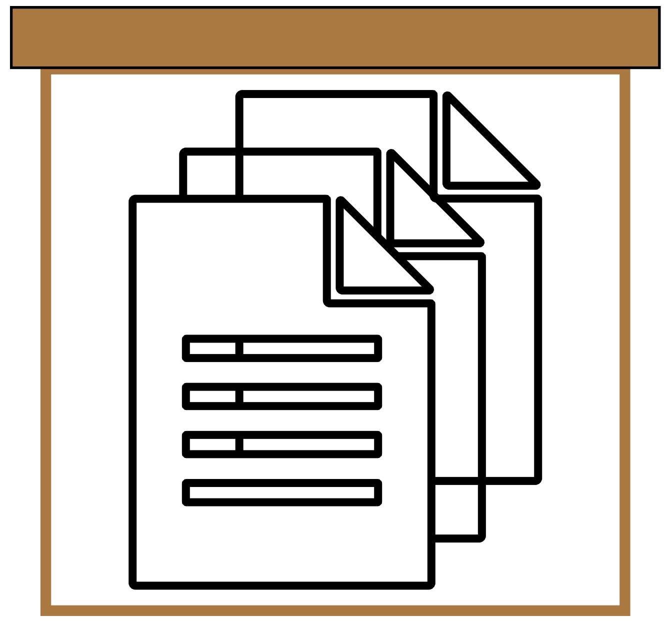

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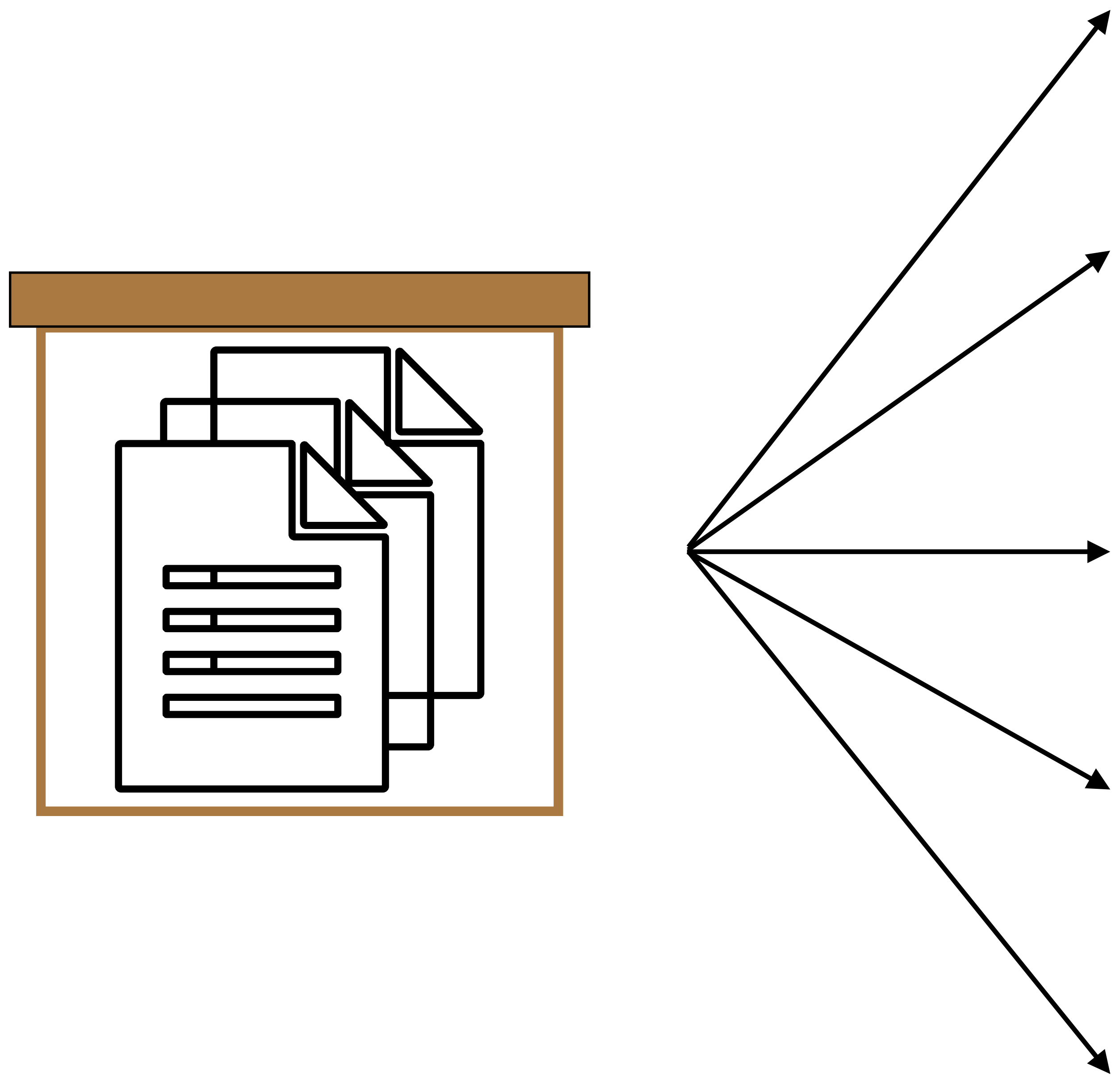

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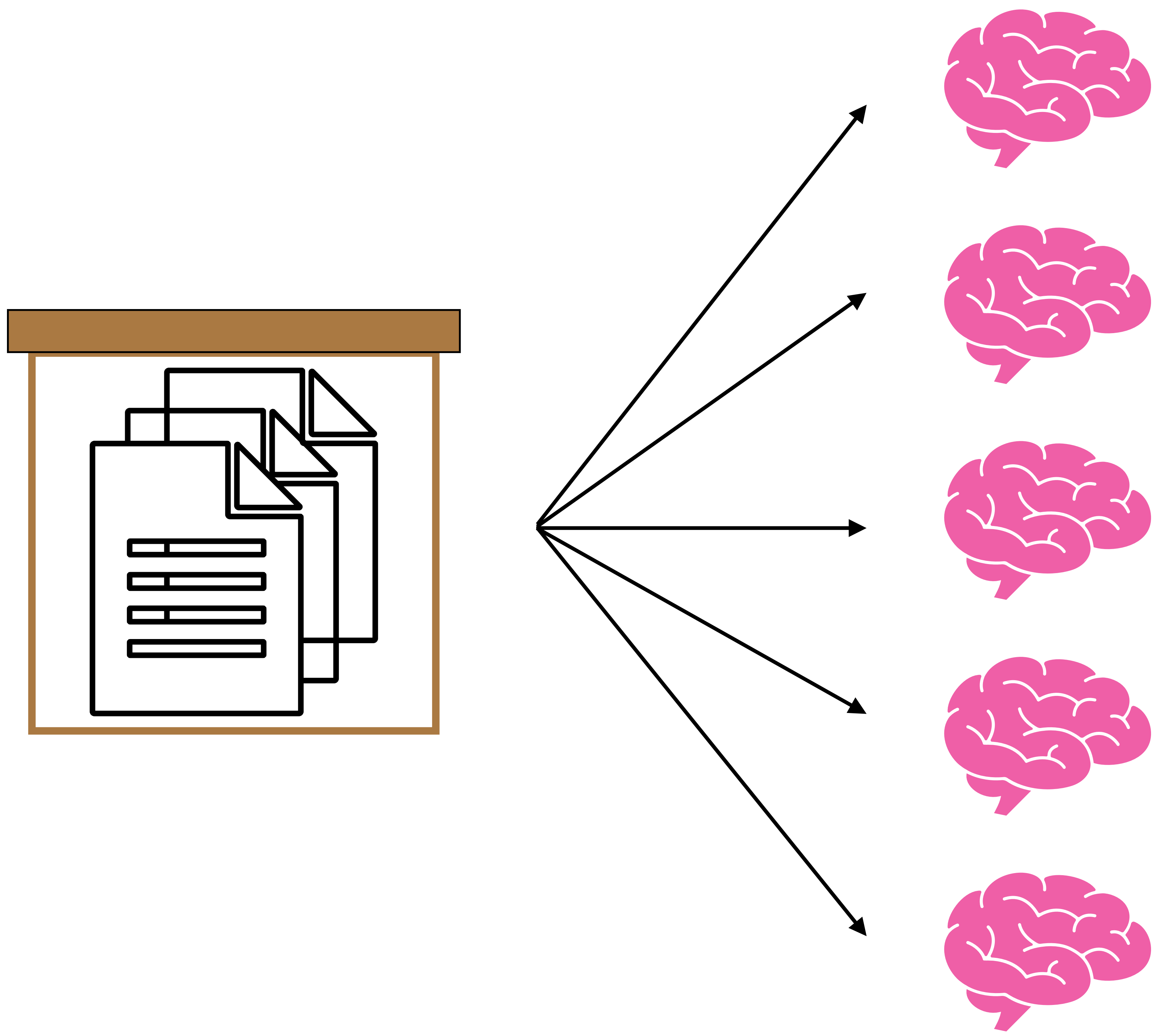

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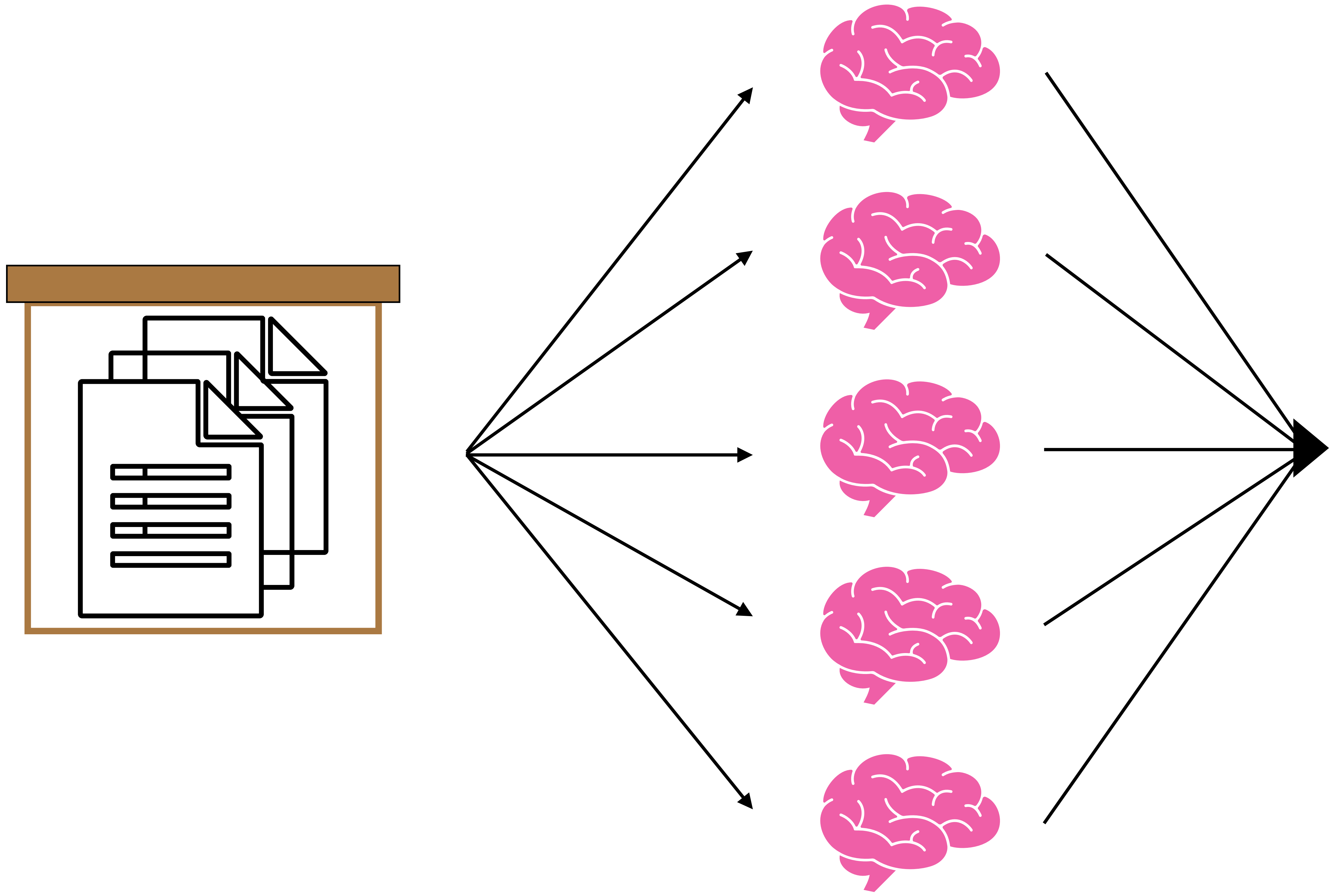

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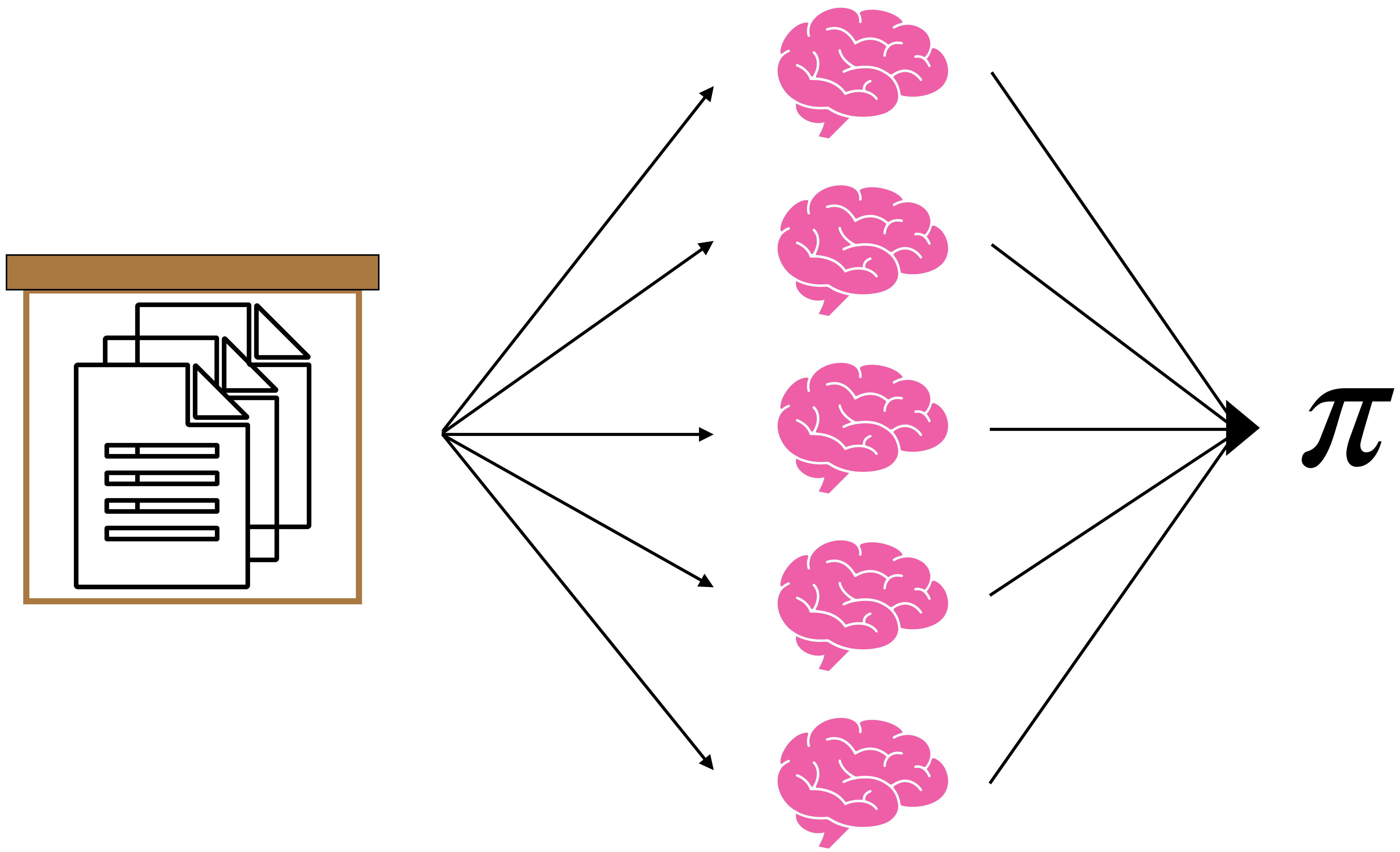

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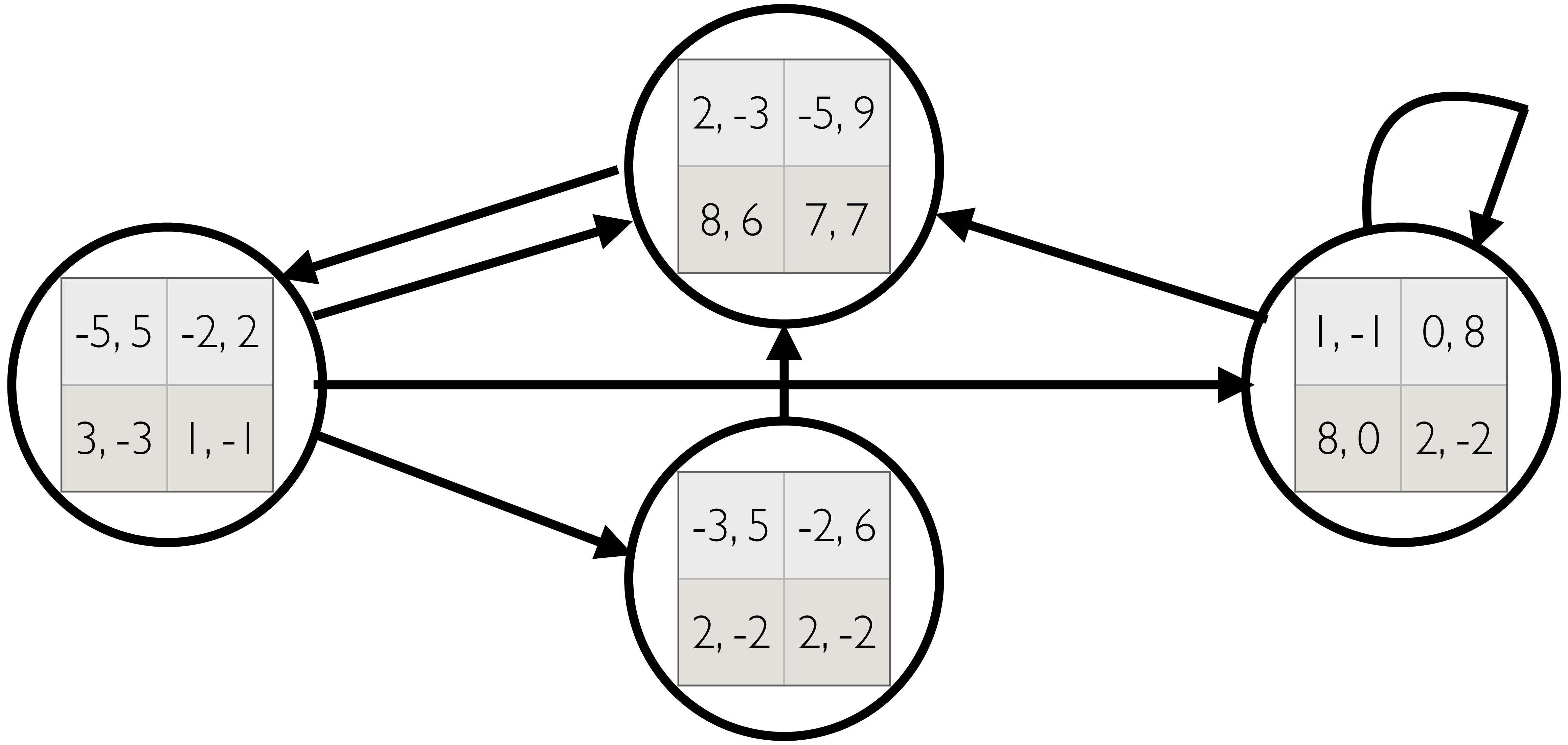

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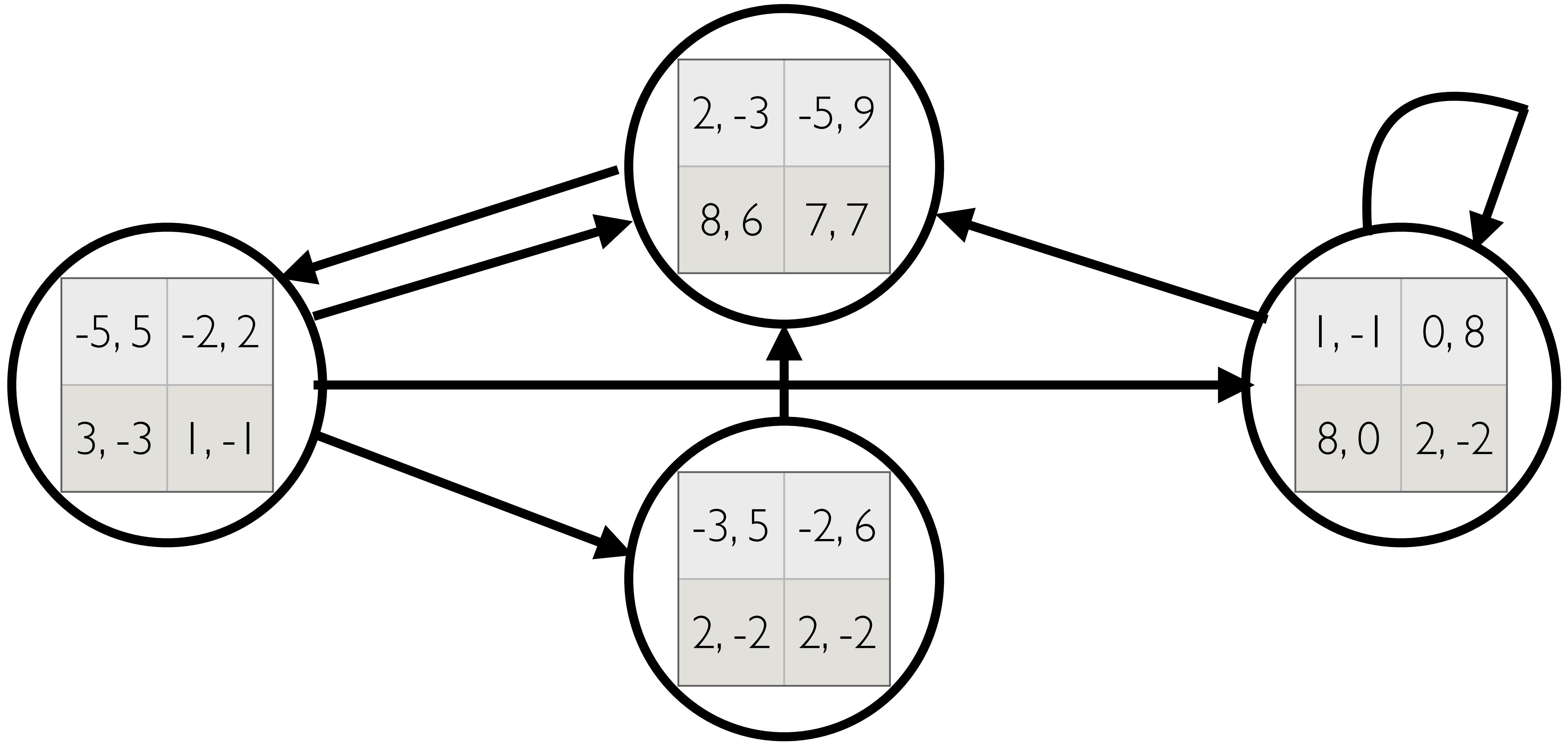

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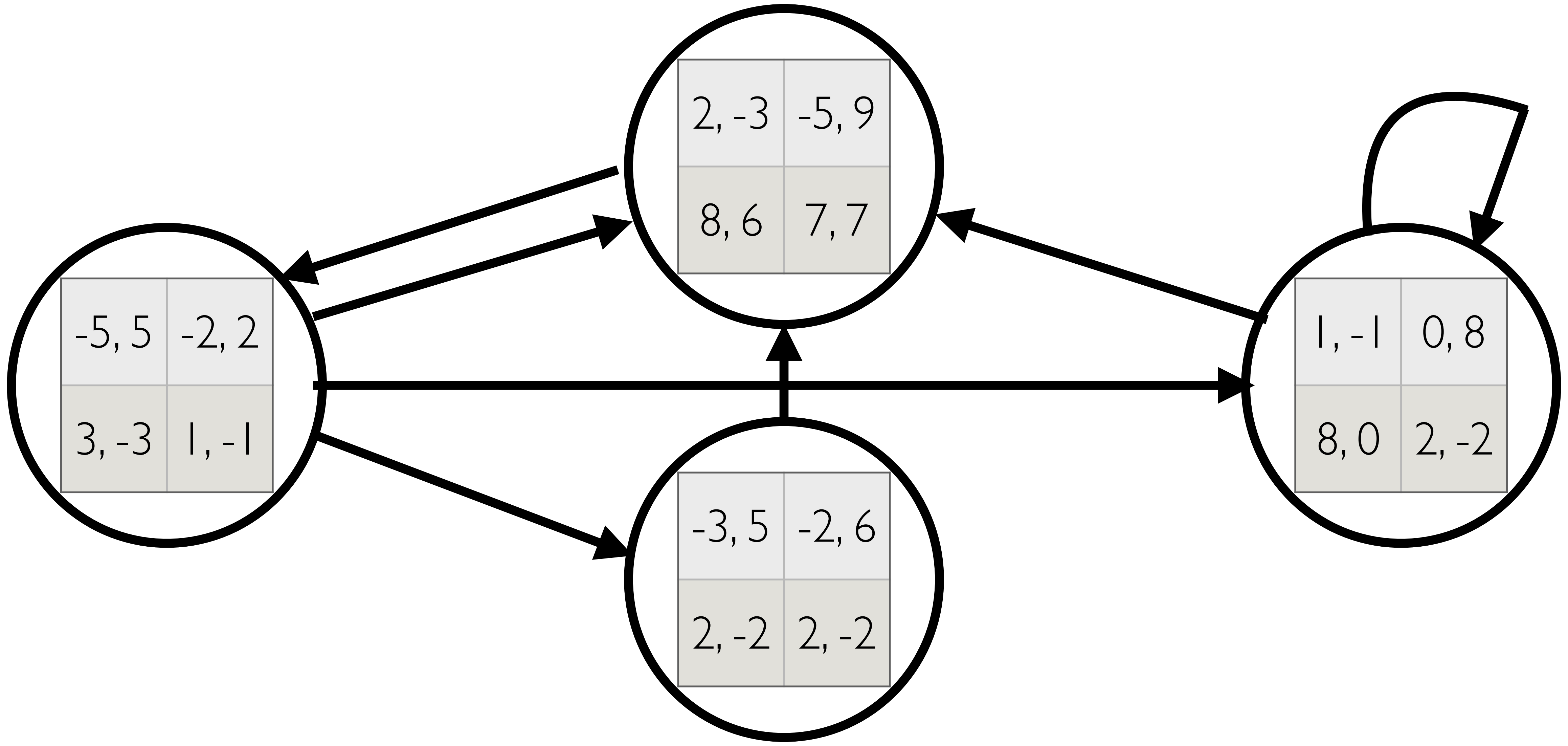

Transition depends on actions of all players.

Solution Concepts

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- Solution to a game takes form of an Equilibrium.

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- Examples: NE, DSE, CCE

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- Strict Markov Perfect Dominant Strategy Equilibrium (MPDSE) is the corresponding equilibrium concept.

Key Fact: Rational agents always play the MPDSE if it exists.

Robust Learners

Plausible Games

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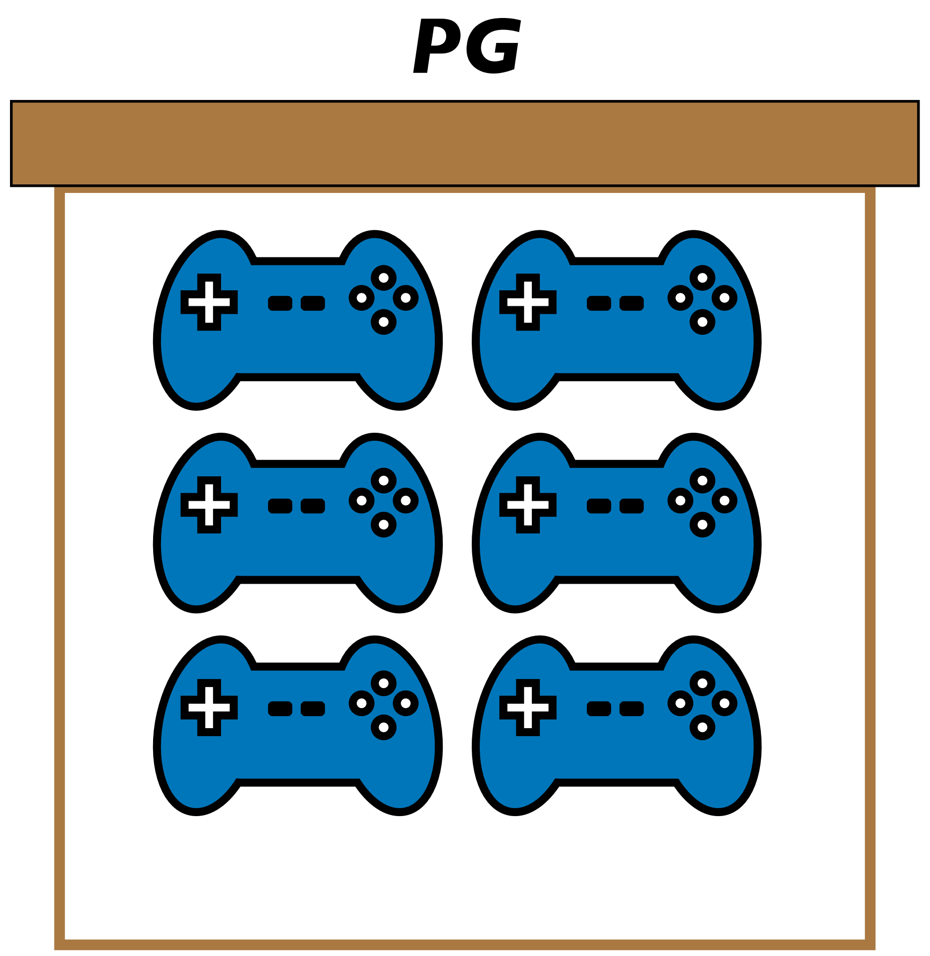

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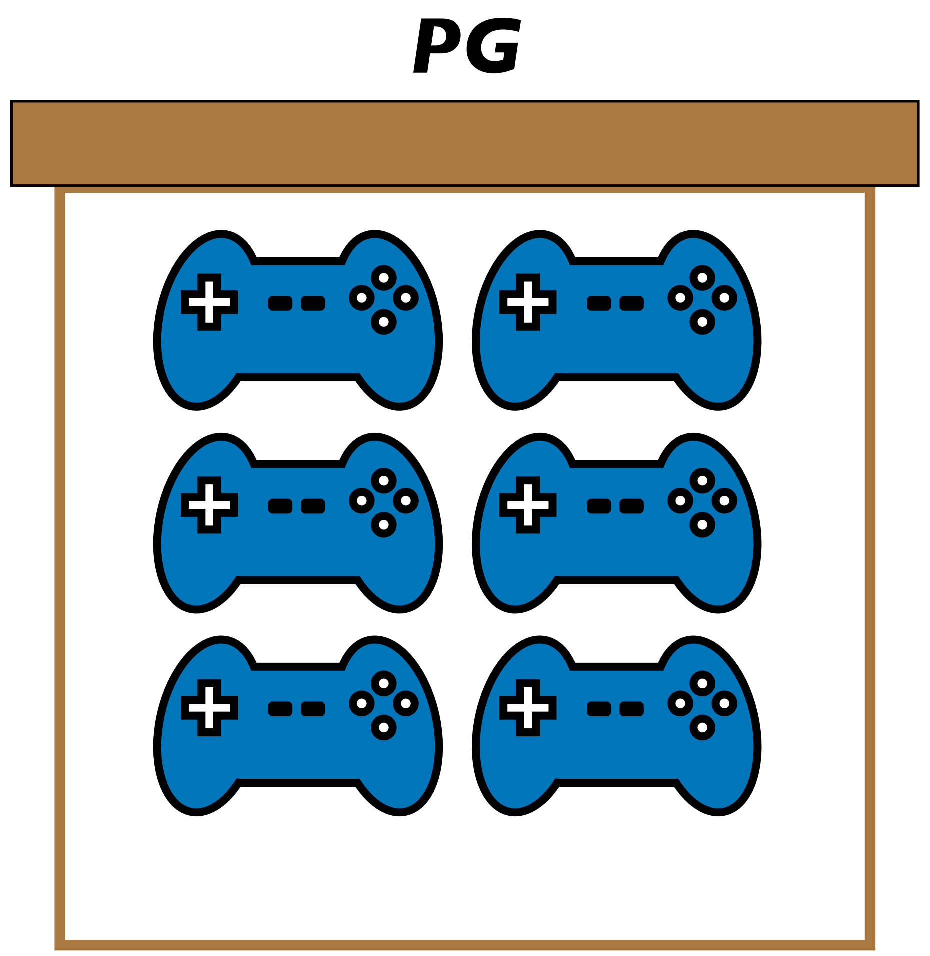

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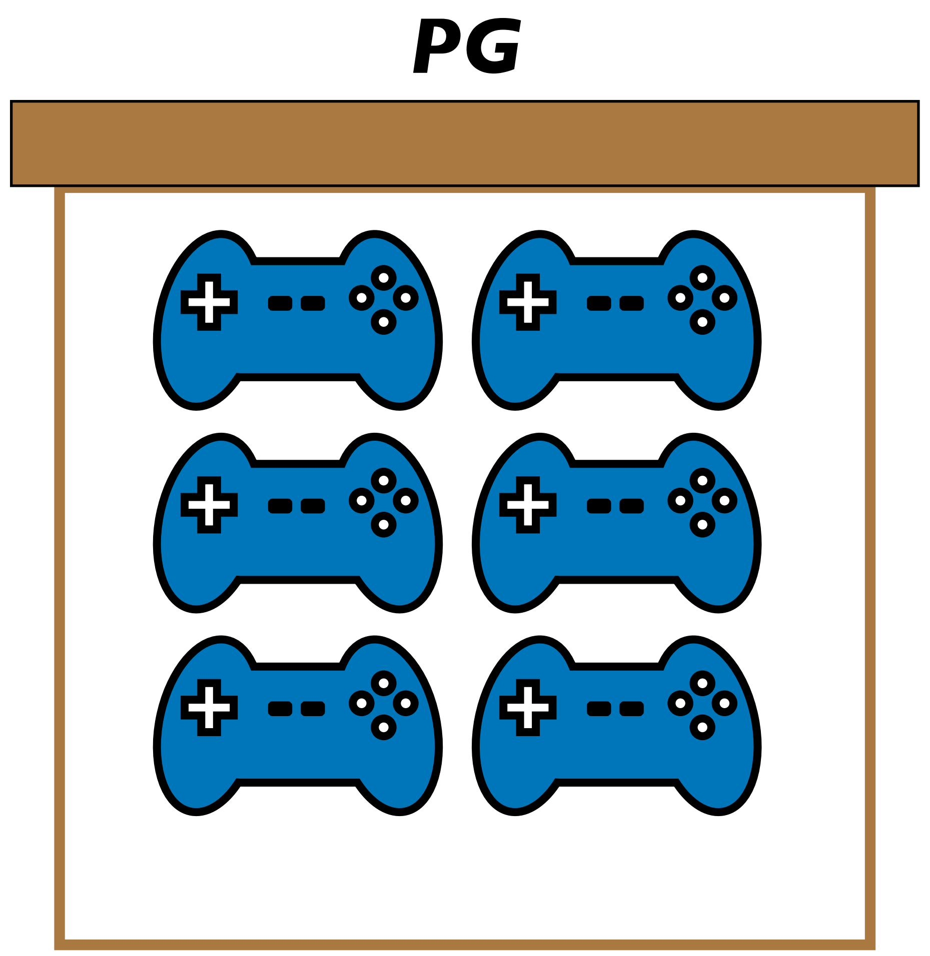
- Example: Confidence Bounded Learners (CBL) assume that $CI_i^R(s,a) = \left\{ R_i(s,a) \in [-b,b] \mid |R_i(s,a) - \hat{R}_i(s,a)| \le \rho^R(s,a) \right\}$.



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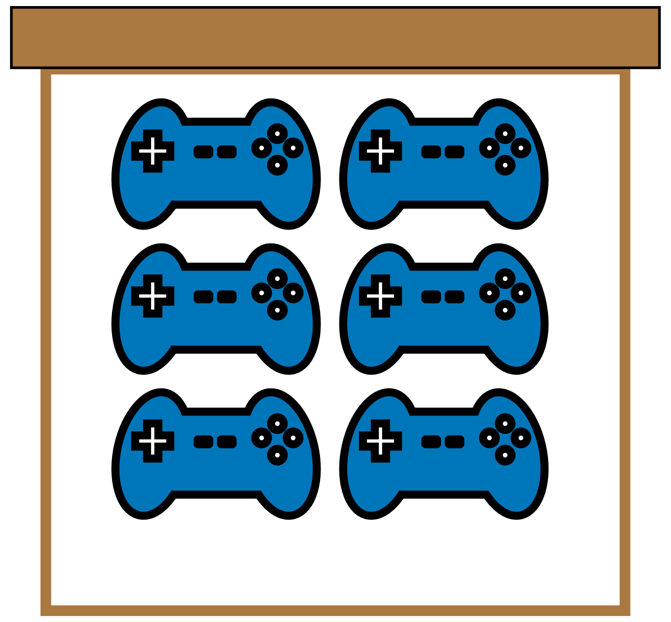
Sol () $= \boldsymbol{\pi}$

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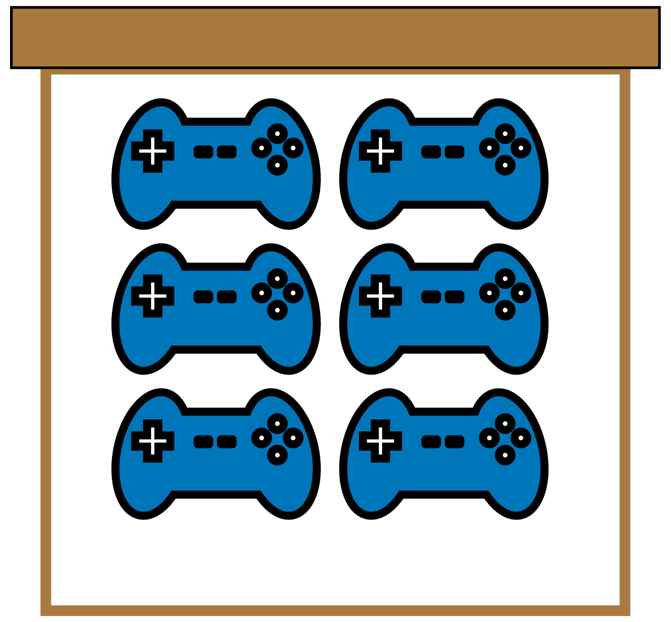
Sol () $= \pi$

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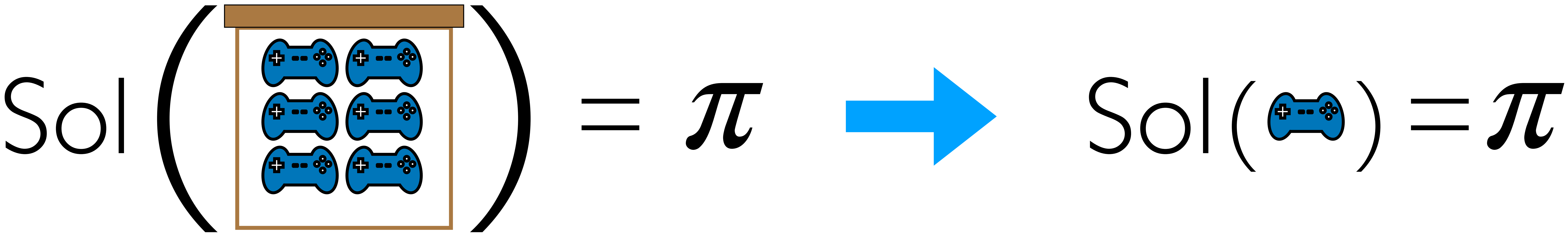
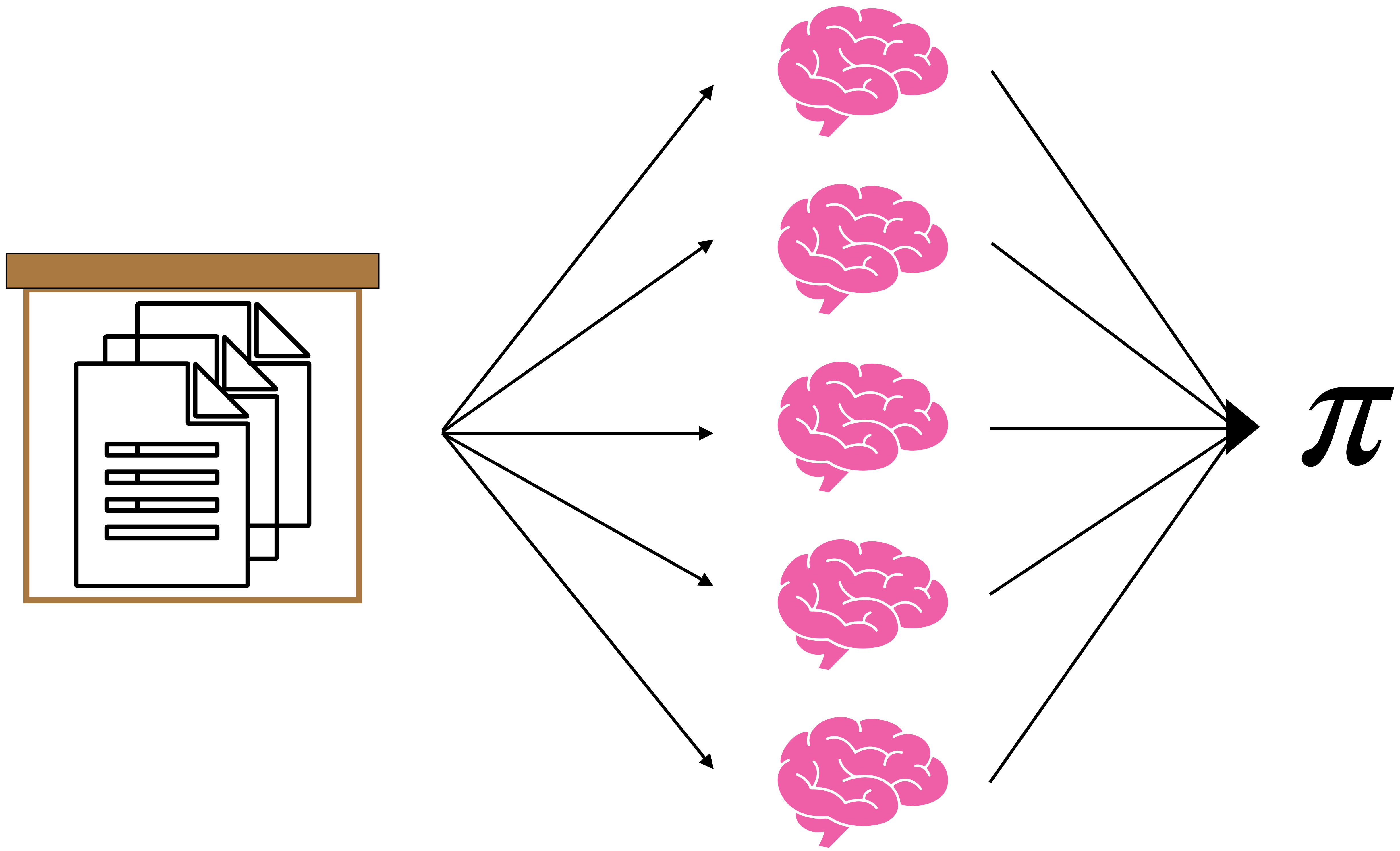


Poisoning

Offline Poisoning



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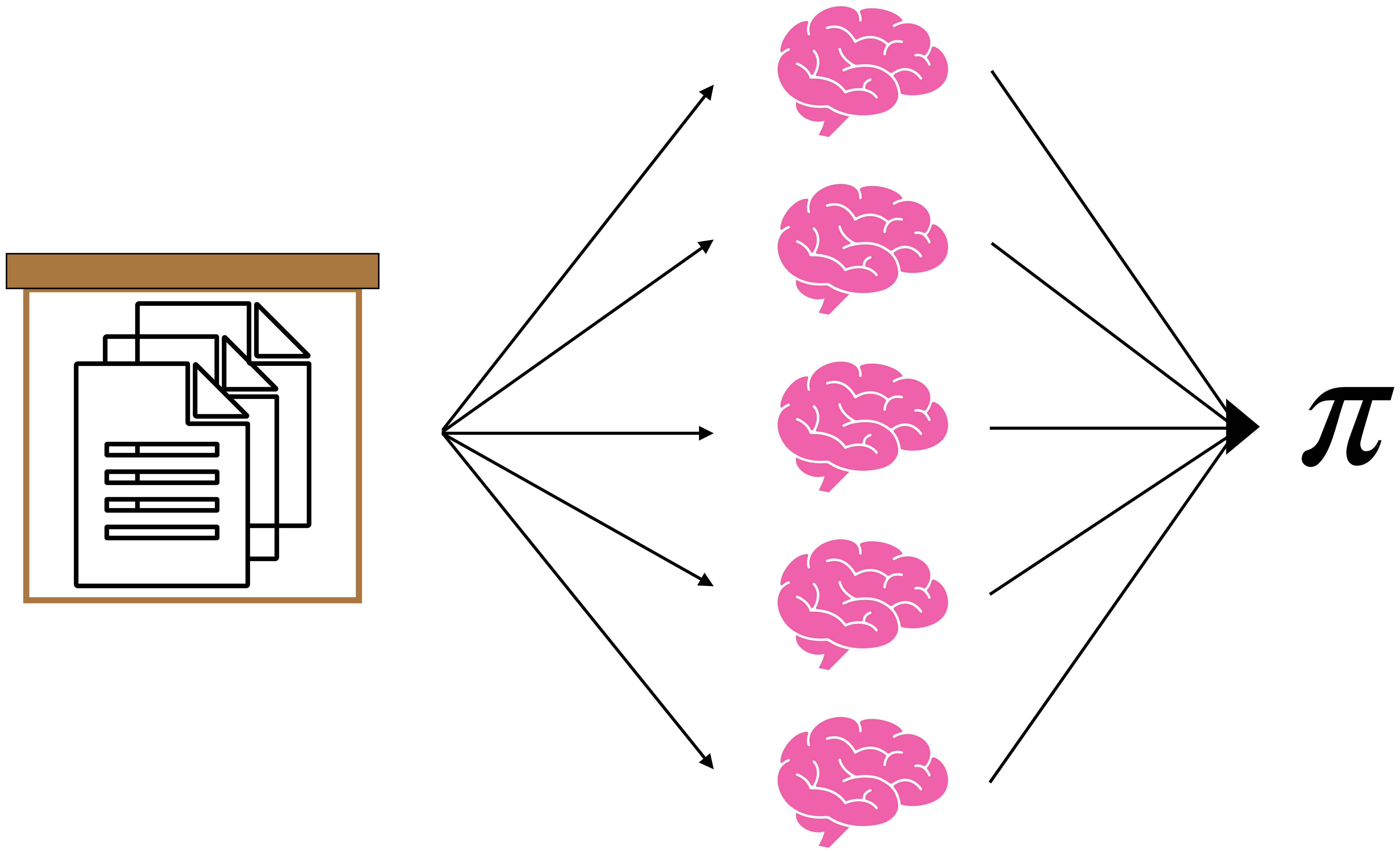
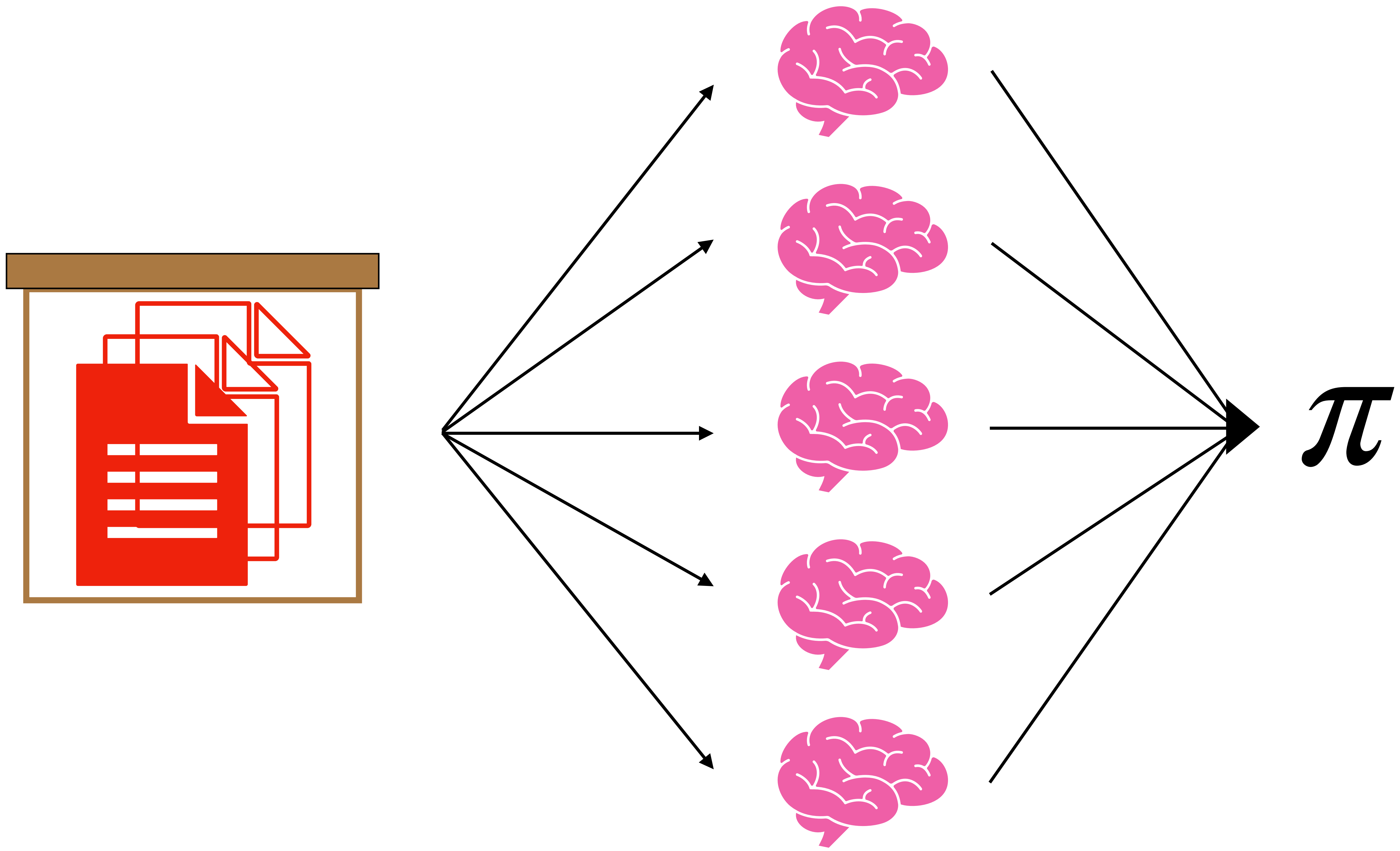


What the agent sees.

Offline Poisoning



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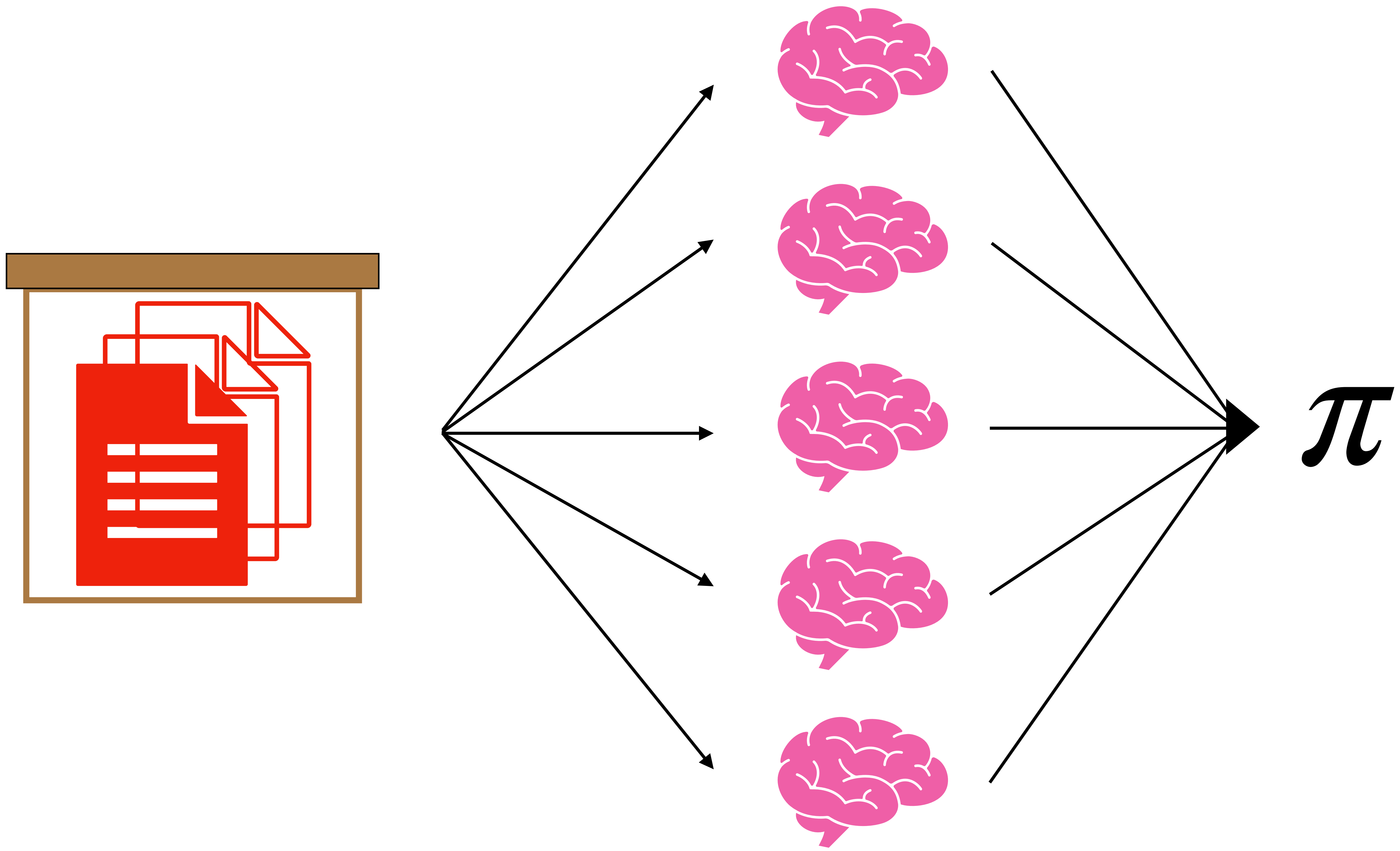
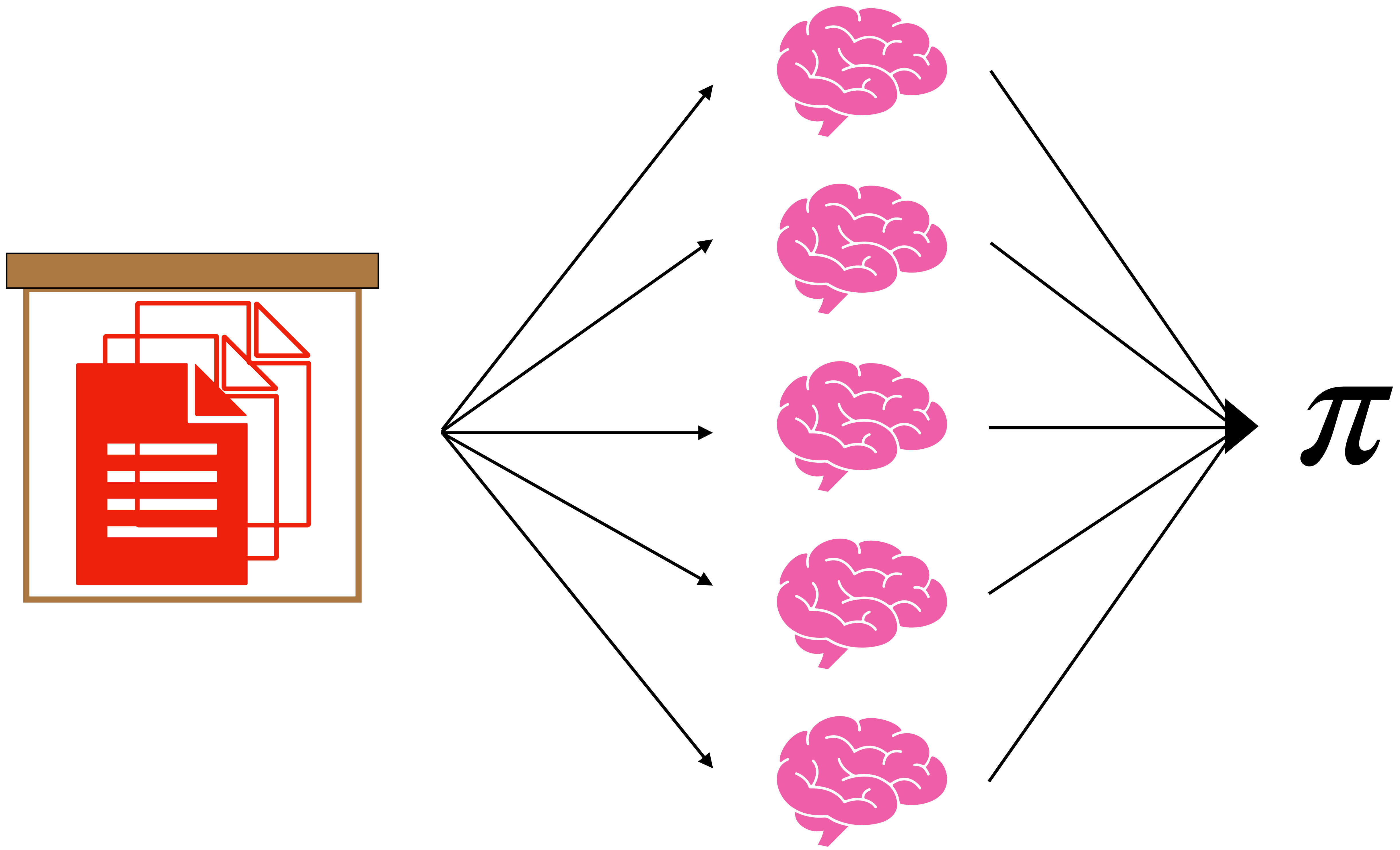


The Data is Corrupted!

Offline Poisoning



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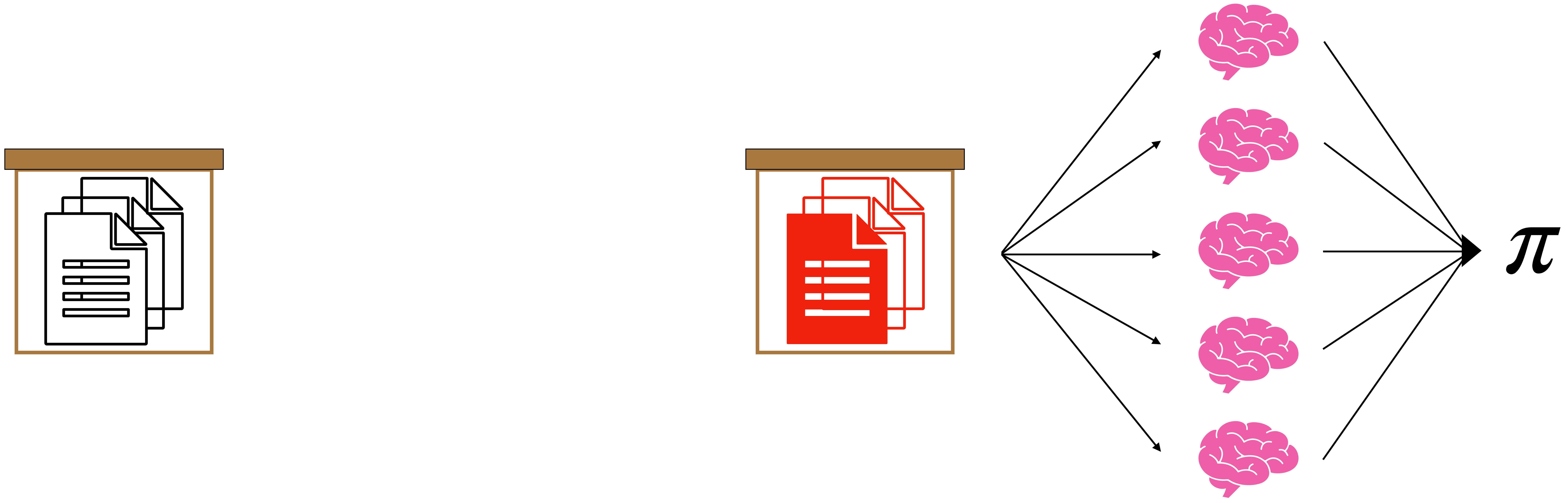

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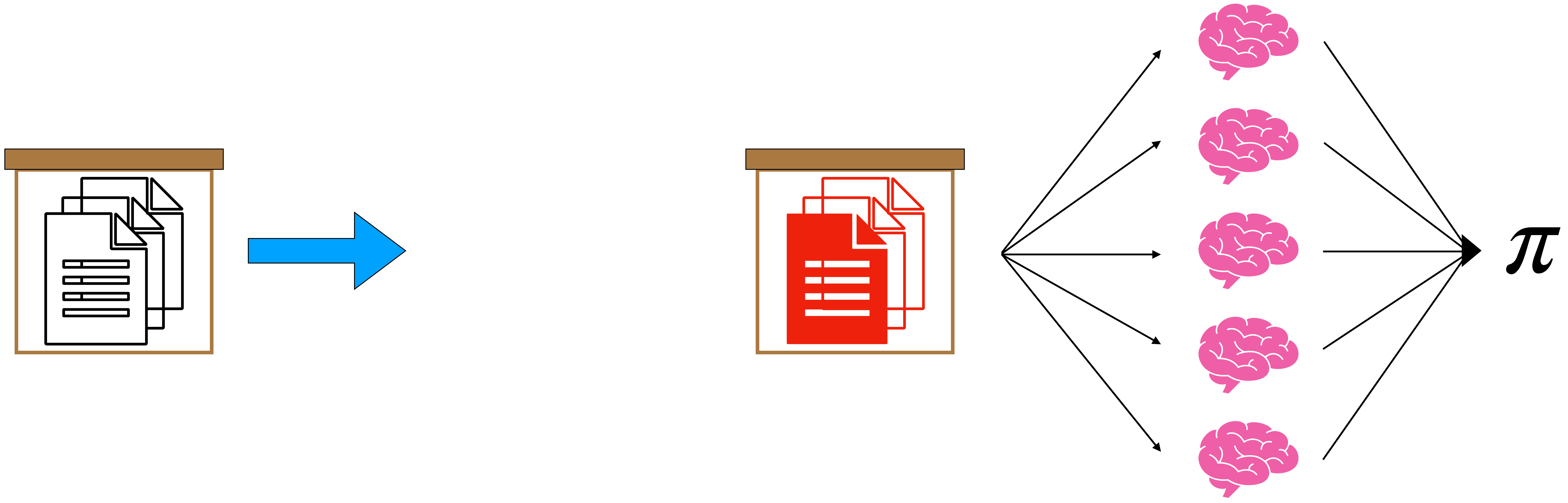

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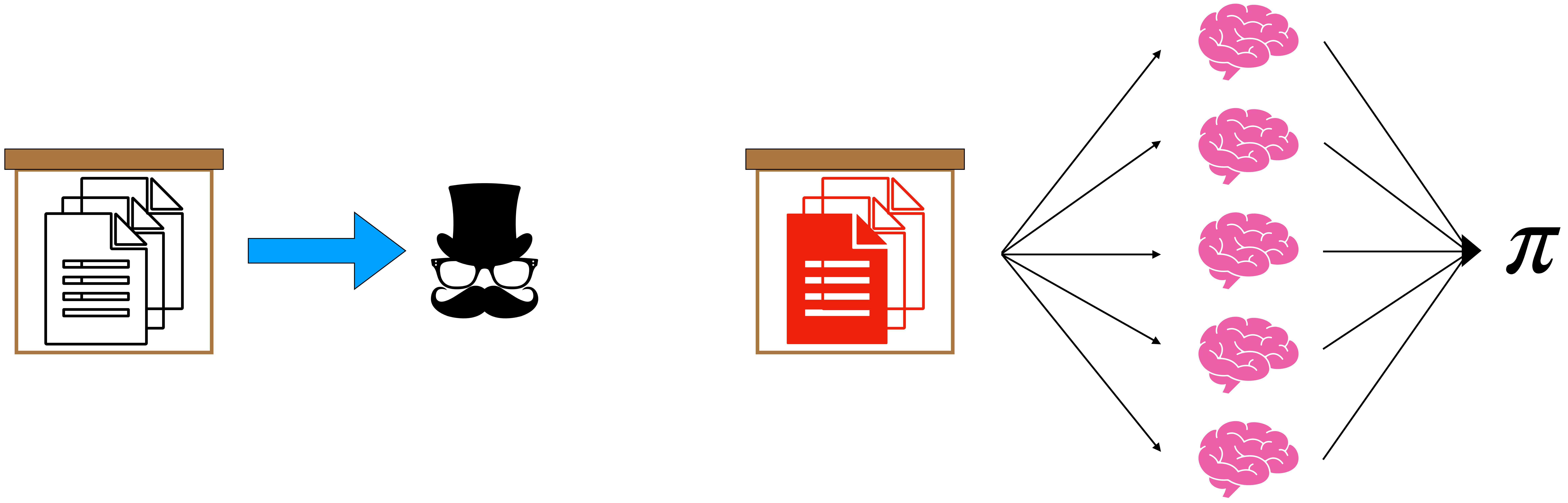

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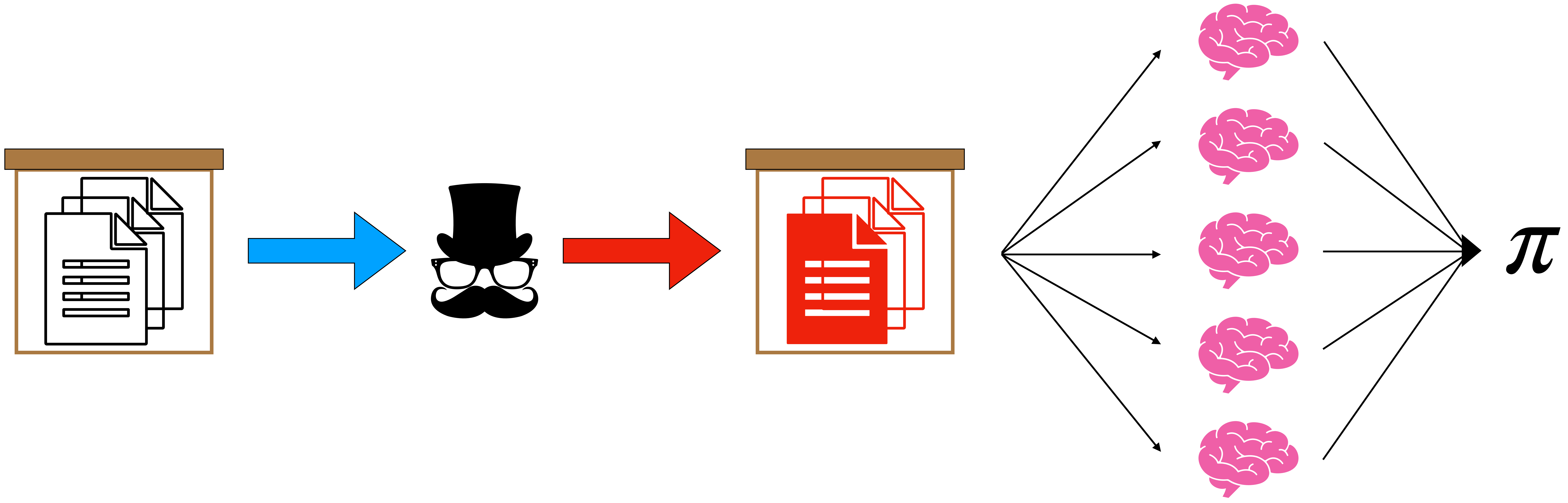

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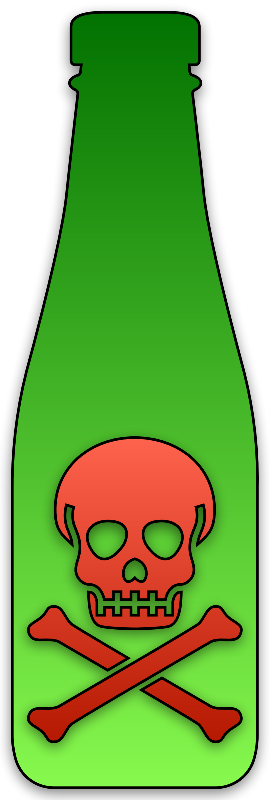

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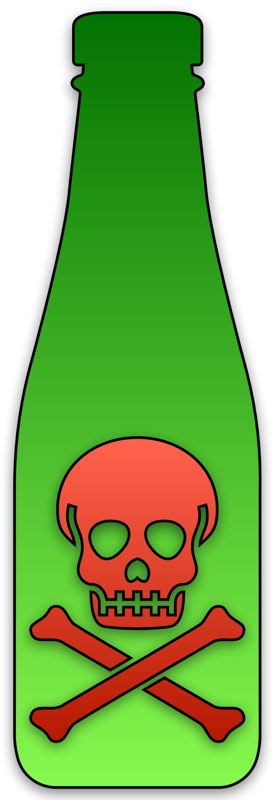
Attacker wants $\pi = \pi^\dagger$.



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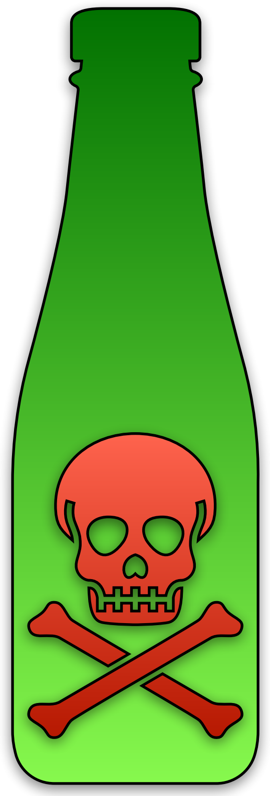

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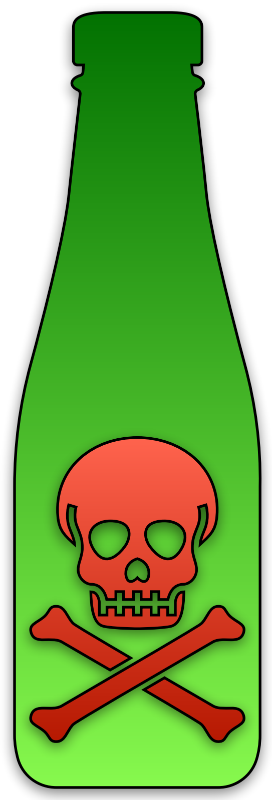

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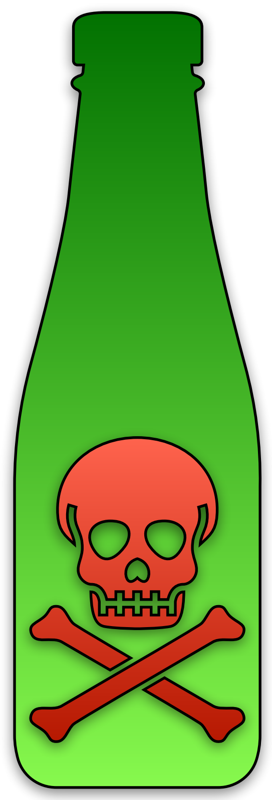
The Attack Problem:

$$\min_{r^\dagger} ||r^0 - r^\dagger||_1$$

s.t. $\pi^\dagger$ is learned from $r^\dagger$



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What can the Attacker do?

Algorithms

Bandit Games

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1, 1	1, 0
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1, 1	1, 1-ε
1-ε, 1	1-ε, 1-ε

Dominance

The *dominance equation* ensures $\boldsymbol{\pi}$ is a strict MPDSE for any game with Q-function $\boldsymbol{Q}$:

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- MPDSE is equivalent to forcing a DSE in each stage game.
  - Boils down to *Optimal Game Design*.

Attacker’s Strategy

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- Let $PQ = \{Q \mid Q = Q_G^{\pi^\dagger}, G \in PG\}$ be the set of plausible Qs.
  - Attacker needs dominance to hold for all $Q \in PQ$.

Complications

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Instead, focus on nice supersets of PQ.

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Where, the Q's are the point-wise extremes:

$$\underline{Q}_i^{\pi^\dagger}(s, a) = \min_{G \in PG} Q_{G,i}^{\pi^\dagger}(s, a)$$

$$\overline{Q}_i^{\pi^\dagger}(s, a) = \max_{G \in PG} Q_{G,i}^{\pi^\dagger}(s, a)$$

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The attacker can efficiently compute minimum cost attacks using a Linear Program

Solutions

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What does this mean?

Coverage Requirements

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Corollary: Poisoning CBL is feasible if the following condition holds:

$$N_h(s,a) \geq \frac{4b^2 (H+1)^2 \log \left(\left(H |S| \, |A| \right) / \delta \right)}{\left(2b - \iota\right)^2} = \tilde{\Omega}(H^2) \, .$$

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This implies: $K \geq H^3SA$.

Cost Analysis

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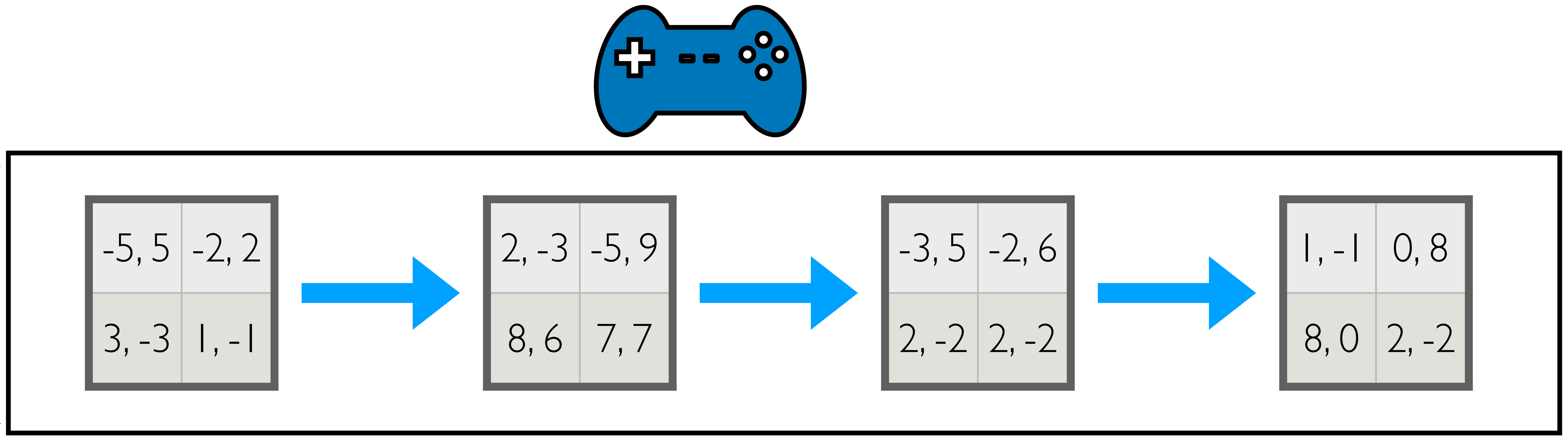
Poison()

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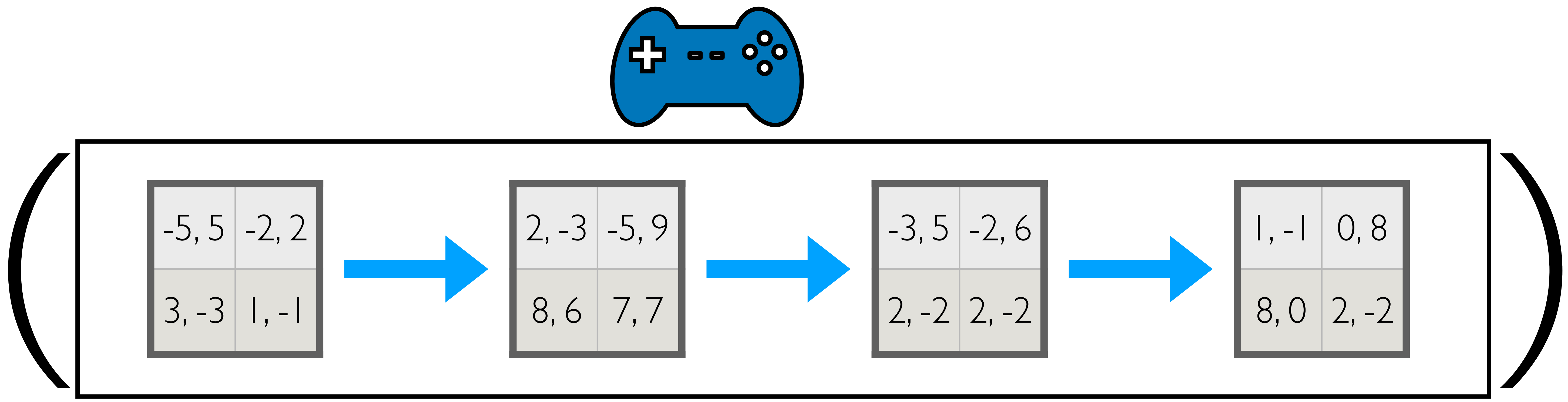
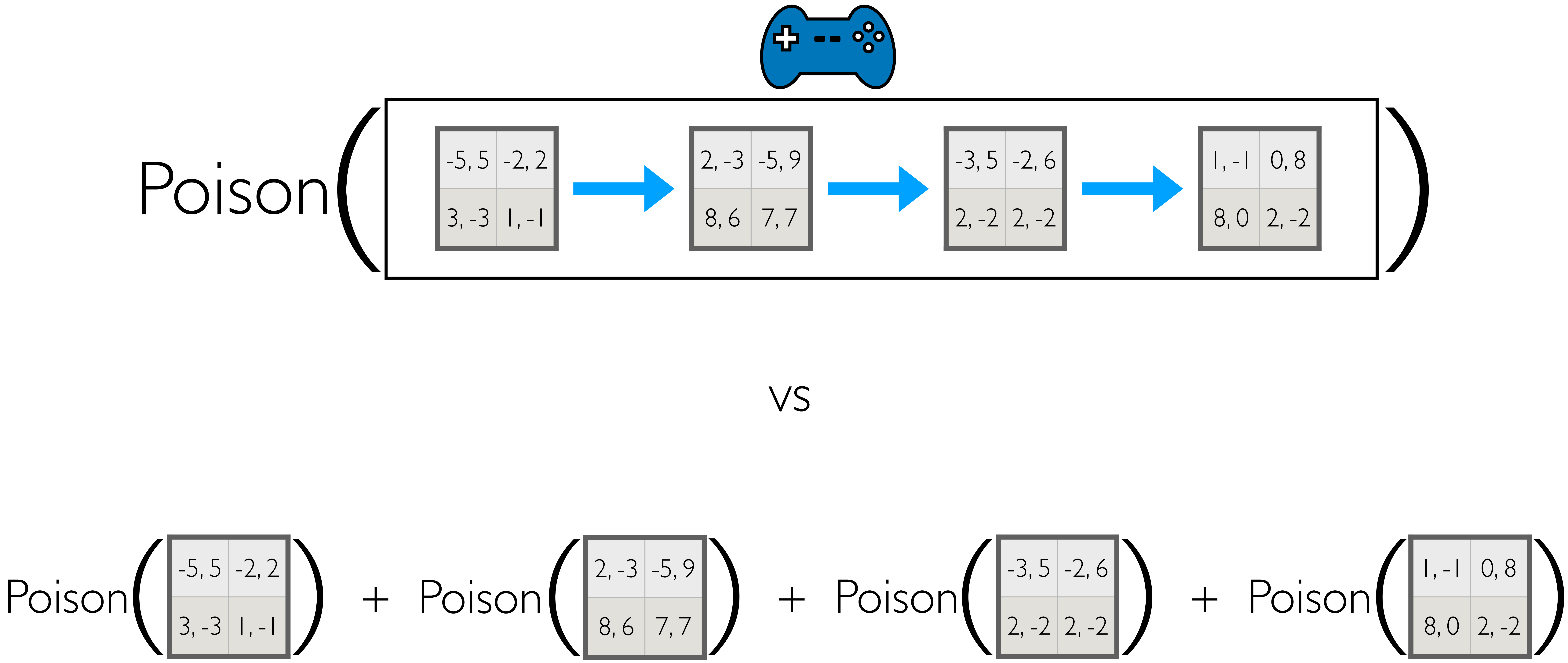


vs

Cost Analysis



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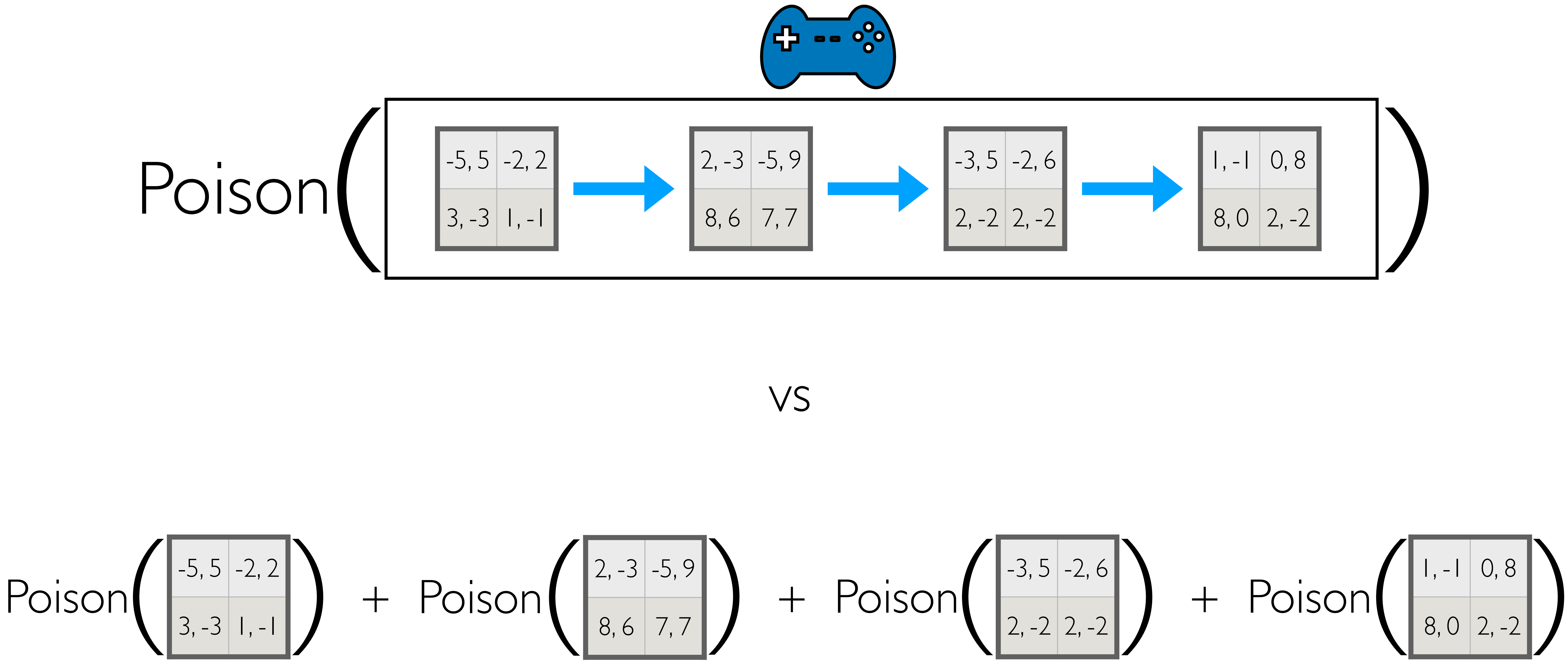

***Poisoning is not separable over stage games.**

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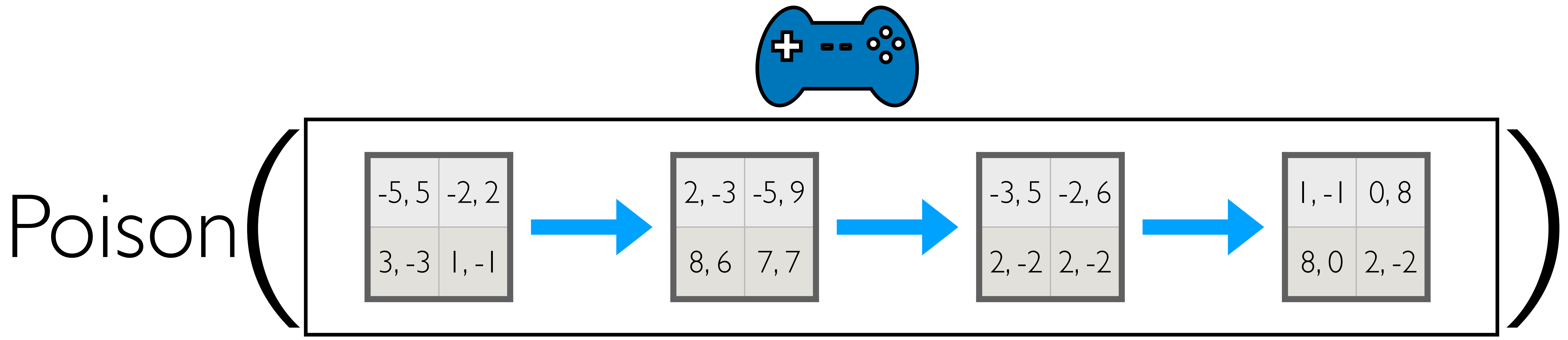

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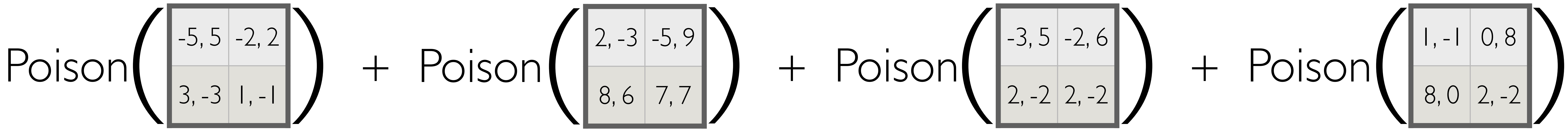

Can exactly characterize!

***Poisoning is not separable over stage games.**

Bound Reduction

Cost Bounds on Optimal Data Poisoning are derived through Bandit Data Poisoning.

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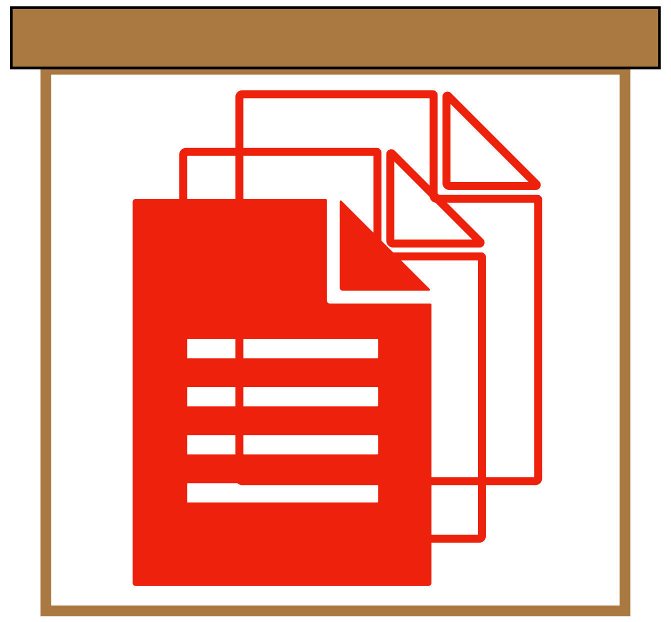

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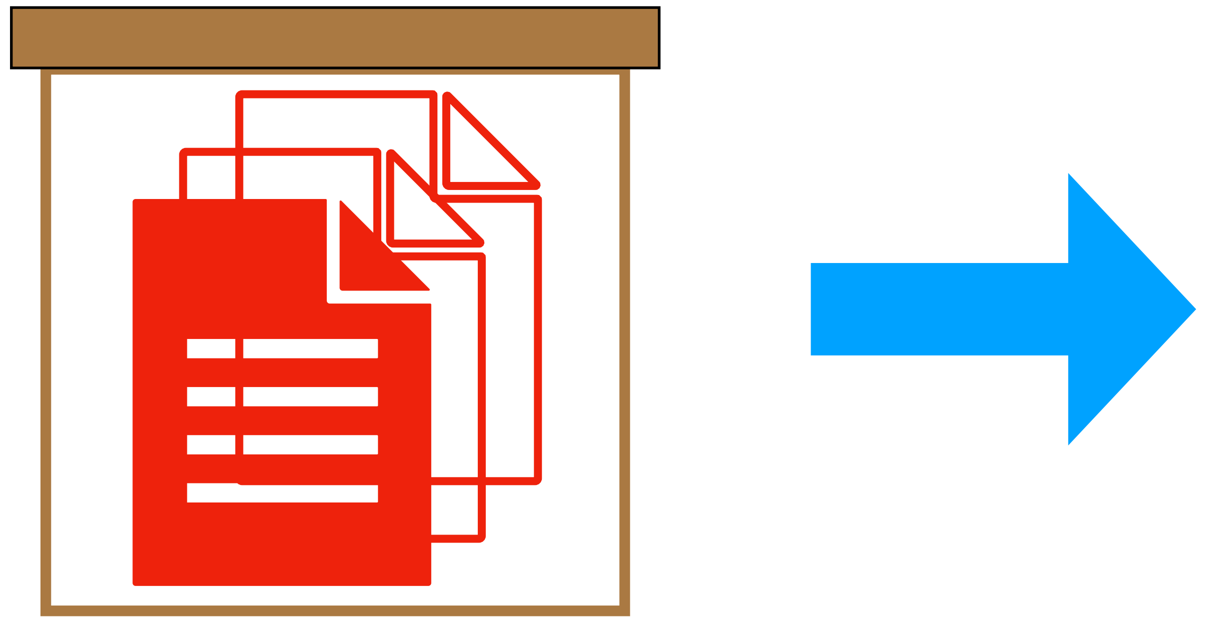

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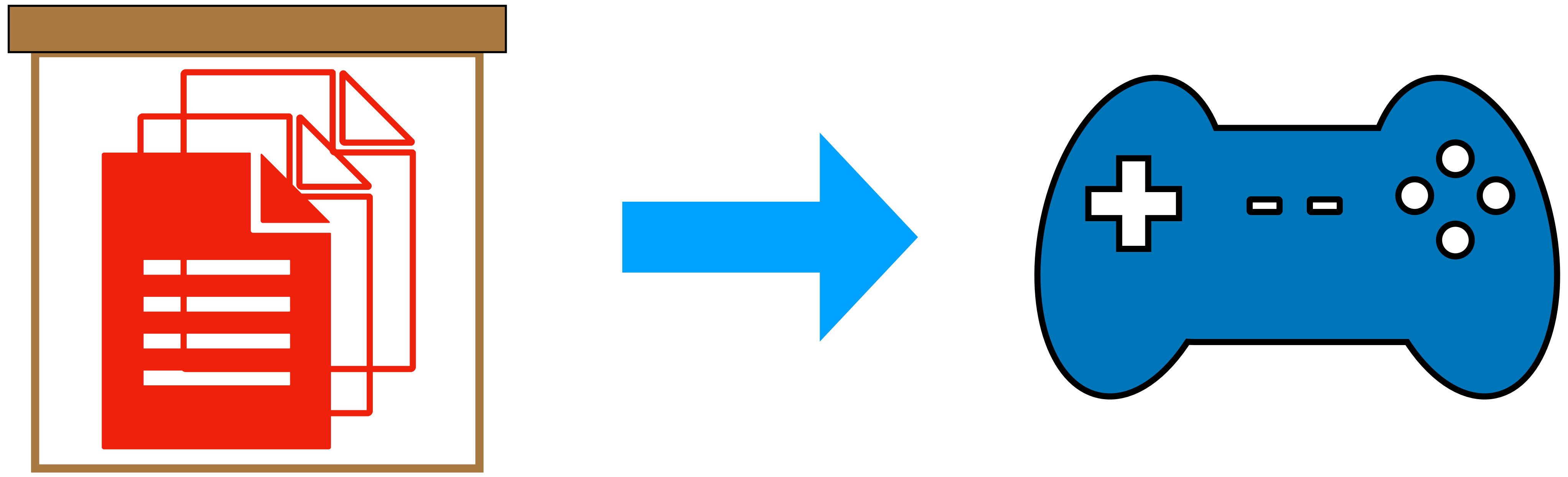

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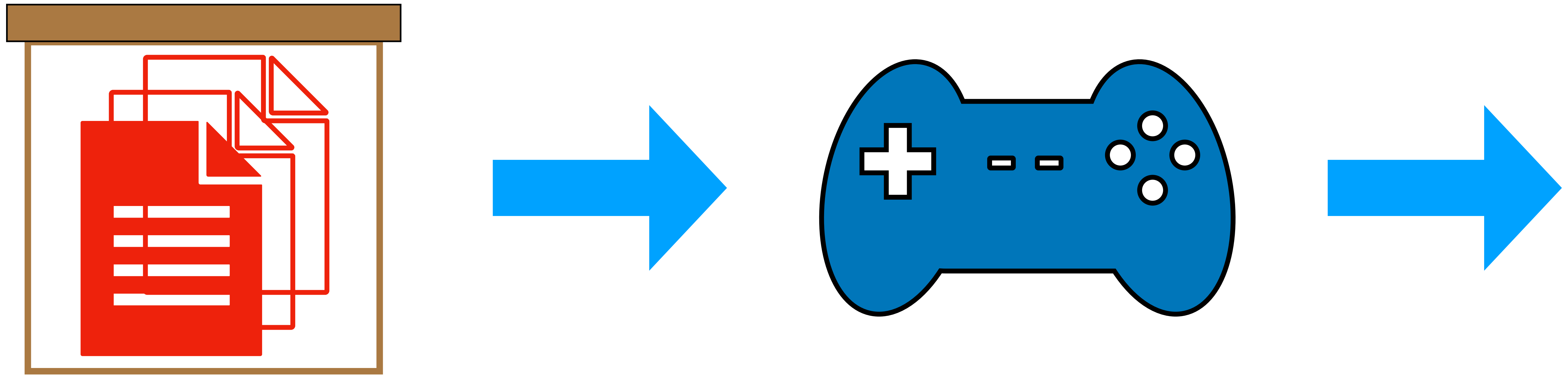

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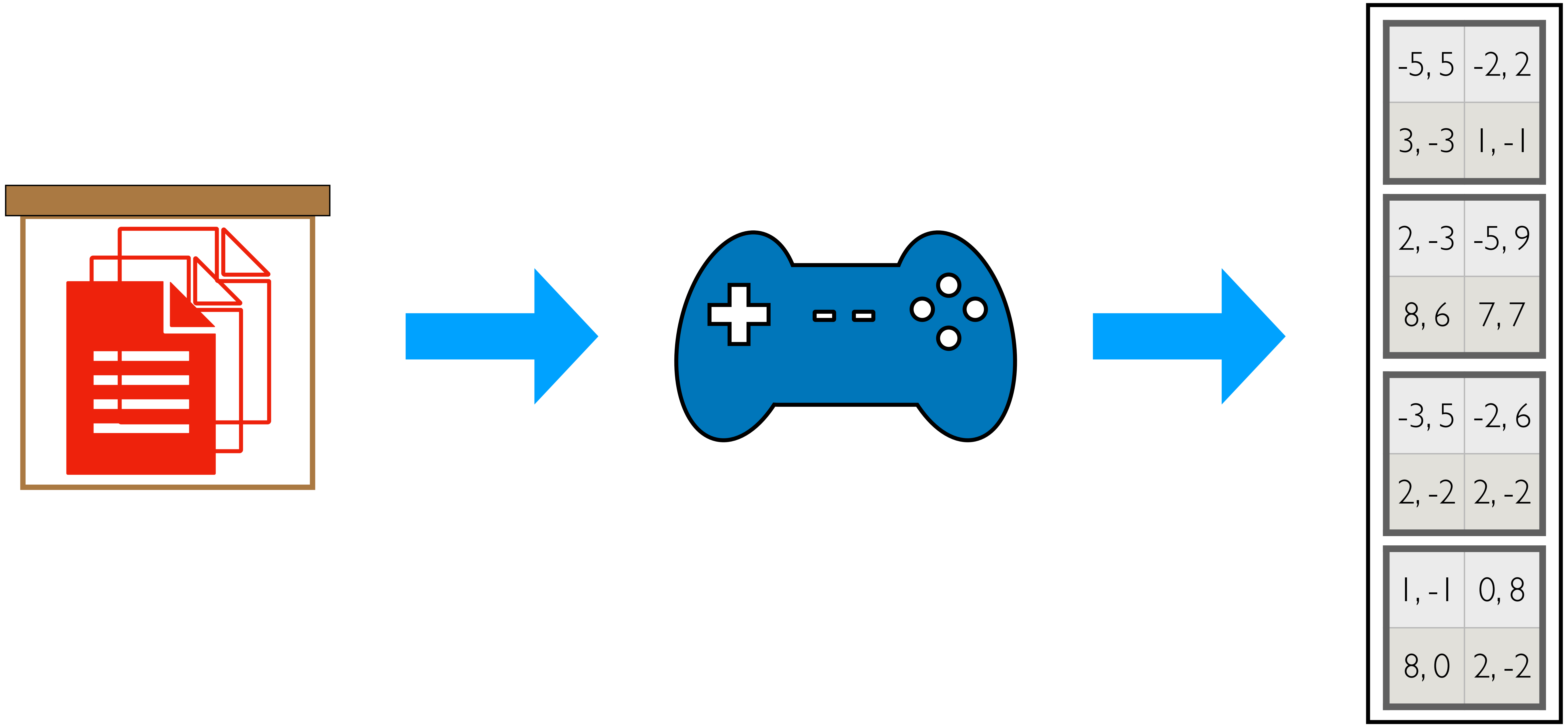

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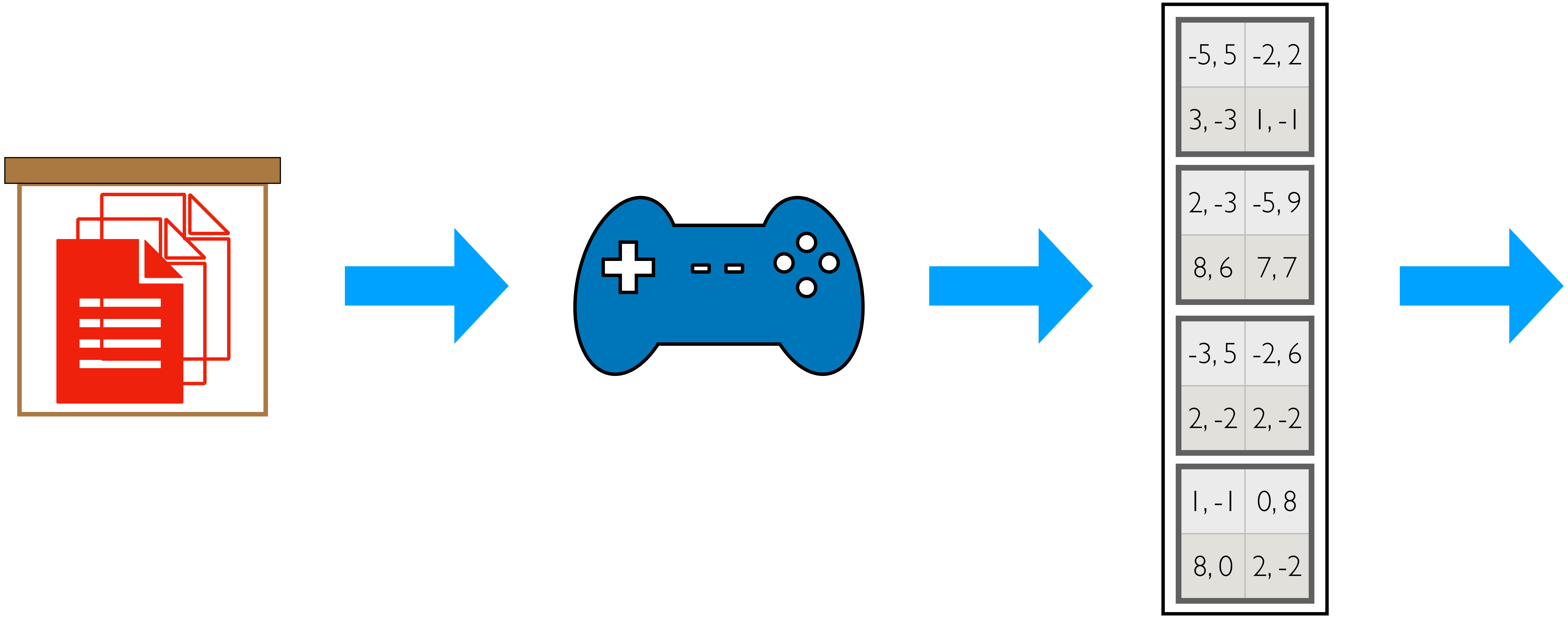

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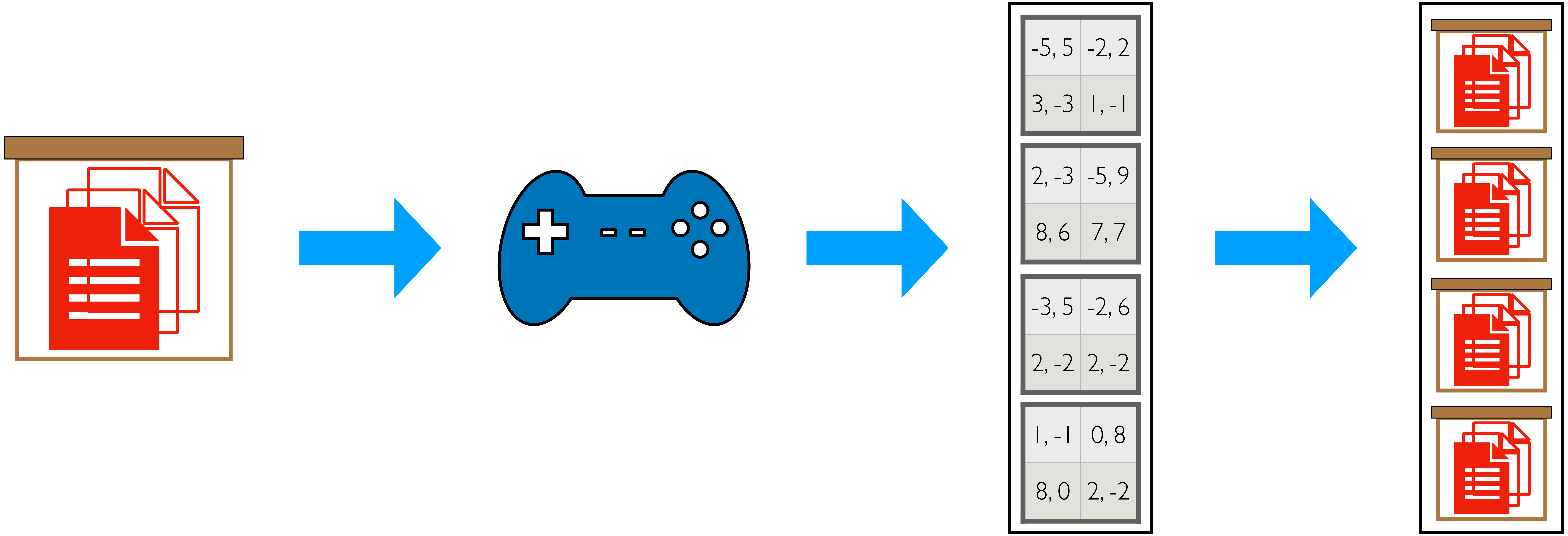

Cost Lower-bounds

Cost Lower-bounds

$\mathcal{A}_1/\mathcal{A}_2$	1	2	...	$\|\mathcal{A}_2\|$
1	$-b, -b$	$-b, b$	...	$-b, b$
2	$b, -b$	b, b	...	b, b
...	...	...	...	...
$\|\mathcal{A}_1\|$	$b, -b$	b, b	...	b, b

Before Attack

Cost Lower-bounds

$\mathcal{A}_1/\mathcal{A}_2$	1	2	...	$\lvert\mathcal{A}_2\rvert$
1	$-b, -b$	$-b, b$	...	$-b, b$
2	$b, -b$	b, b	...	b, b
...	...	...	...	...
$\lvert\mathcal{A}_1\rvert$	$b, -b$	b, b	...	b, b

Before Attack

Cost Lower-bounds

$\mathcal{A}_1/\mathcal{A}_2$	1	2	...	$\lvert\mathcal{A}_2\rvert$
1	$-b, -b$	$-b, b$	...	$-b, b$
2	$b, -b$	b, b	...	b, b
...	...	...	...	...
$\lvert\mathcal{A}_1\rvert$	$b, -b$	b, b	...	b, b

Before Attack

$\mathcal{A}_1/\mathcal{A}_2$	1	2
1	b, b	$b, b-2\rho-\iota$
2	$b-2\rho-\iota, b$	$b-2\rho-\iota, b-2\rho-\iota$
...	...	...
$\lvert\mathcal{A}_1\rvert$	$b-2\rho-\iota, b$	$b-2\rho-\iota, b-2\rho-\iota$

After Attack

Cost Lower-bounds

$\mathcal{A}_1/\mathcal{A}_2$	1	2	...	$\lvert\mathcal{A}_2\rvert$
1	$-b, -b$	$-b, b$	...	$-b, b$
2	$b, -b$	b, b	...	b, b
...	...	...	...	...
$\lvert\mathcal{A}_1\rvert$	$b, -b$	b, b	...	b, b

Before Attack

$\mathcal{A}_1/\mathcal{A}_2$	1	2
1	b, b	$b, b-2\rho-\iota$
2	$b-2\rho-\iota, b$	$b-2\rho-\iota, b-2\rho-\iota$
...	...	...
$\lvert\mathcal{A}_1\rvert$	$b-2\rho-\iota, b$	$b-2\rho-\iota, b-2\rho-\iota$

After Attack

Optimal Attack Cost:

$$H\,|S|\min_{h,s,a} N_h(s,a)\,|A|^{n-1}(2b+2\rho+\iota)$$

Cost Lower-bounds

$\mathcal{A}_1/\mathcal{A}_2$	1	2	...	$\lvert\mathcal{A}_2\rvert$
1	$-b,-b$	$-b,b$	...	$-b,b$
2	$b,-b$	b,b	...	b,b
...	...	...	...	...
$\lvert\mathcal{A}_1\rvert$	$b,-b$	b,b	...	b,b

Before Attack

$\mathcal{A}_1/\mathcal{A}_2$	1	2
1	b,b	$b,b-2\rho-\iota$
2	$b-2\rho-\iota,b$	$b-2\rho-\iota,b-2\rho-\iota$
...	...	...
$\lvert\mathcal{A}_1\rvert$	$b-2\rho-\iota,b$	$b-2\rho-\iota,b-2\rho-\iota$

After Attack

Optimal Attack Cost:

$$H\,|S|\min_{h,s,a} N_h(s,a)\,|A|^{n-1}(2b+2\rho+\iota)$$

Exponential dependency on n!

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The optimal cost could potentially be greater than optimally poisoning each subdataset!

Conclusion

Summary

- In large datasets, poisoning is always feasible, though costly.
- Thus, we illustrate the need for provable defenses against offline reward poisoning.