

# MS&E 233

# Game Theory, Data Science and AI

## Lecture 7

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(by courtesy) Computer Science and Electrical Engineering

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# Computational Game Theory for Complex Games

- 1
  - Basics of game theory and zero-sum games (T)
  - Basics of online learning theory (T)
  - Solving zero-sum games via online learning (T)
  - *HW1: implement simple algorithms to solve zero-sum games*
  - Applications to ML and AI (T+A)
  - *HW2: implement boosting as solving a zero-sum game*

- 2
  - Basics of extensive-form games
  - Solving extensive-form games via online learning (T)
  - *HW3: implement agents to solve very simple variants of poker*

- 3
  - **General games, equilibria and online learning (T)**
  - Online learning in general games, multi-agent RL (T+A)
  - *HW4: implement no-regret algorithms that converge to correlated equilibria in general games*

## Data Science for Auctions and Mechanisms

- 4
  - Basics and applications of auction theory (T+A)
  - **Learning to bid in auctions via online learning (T)**
  - *HW5: implement bandit algorithms to bid in ad auctions*

- 5
  - **Optimal auctions and mechanisms (T)**
  - **Simple vs optimal mechanisms (T)**
  - *HW6: calculate equilibria in simple auctions, implement simple and optimal auctions, analyze revenue empirically*

- 6
  - **Optimizing mechanisms from samples (T)**
  - **Online optimization of auctions and mechanisms (T)**
  - *HW7: implement procedures to learn approximately optimal auctions from historical samples and in an online manner*

## Further Topics

- 7
  - **Econometrics in games and auctions (T+A)**
  - **A/B testing in markets (T+A)**
  - *HW8: implement procedure to estimate values from bids in an auction, empirically analyze inaccuracy of A/B tests in markets*

## Guest Lectures

- Mechanism Design and LLMs, Song Zuo, Google Research
- A/B testing in auction markets, Okke Schrijvers, Central Applied Science, Meta

# General Multiplayer Games





Many real-world games are not zero-sum

Are there simple scalable algorithms that compute Nash equilibria or other reasonable solution concepts in general games?



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## Learning to Communicate with Deep Multi-Agent Reinforcement Learning

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Article | Published: 30 October 2019

## Grandmaster level in StarCraft II using multi-agent reinforcement learning

## OpenAI Five



Our team of five neural networks, OpenAI Five, has started to defeat amateur human teams at Dota 2.

# Recent Successes

Much harder to compute equilibria;  
*theory* typically considers relaxed solution  
concepts that are computationally easy  
*practice* typically uses similar algorithms as in  
zero-sum games as good heuristics

# Equilibria in General Games



# Battle of Partners

Partner 2

Partner 1

	Opera (O)	Football (F)
Opera (O)	3, 1	0, 0
Football (F)	0, 0	1, 3

How should partners behave?

# ***Recap:*** Mixed Nash Equilibrium

- A mixed strategy profile  $\sigma = (\sigma_1, \dots, \sigma_n)$  is a Nash equilibrium if no player is better off in expectation, by choosing another strategy  $s'_i$

$$\forall s'_i \in S_i: E_{s_1 \sim \sigma_1, \dots, s_n \sim \sigma_n} [u_i(s_1, \dots, s_n)] \geq E_{s_{-i} \sim \sigma_{-i}} [u_i(s'_i, s_{-i})]$$



By JOHN F. NASH, JR.\*

PRINCETON UNIVERSITY

Communicated by S. Lefschetz, November 16, 1949

# ***Recap:*** Existence of Nash Equilibrium [Nash1950]

Every  $n$  player finite action game has at least one mixed Nash equilibrium



One may define a concept of an  $n$ -person game in which each player has a finite set of pure strategies and in which a definite set of payments to the  $n$  players corresponds to each  $n$ -tuple of pure strategies, one strategy being taken for each player. For mixed strategies, which are probability distributions over the pure strategies, the pay-off functions are the expectations of the players, thus becoming polylinear forms in the probabilities with which the various players play their various pure strategies.

Any  $n$ -tuple of strategies, one for each player, may be regarded as a point in the product space obtained by multiplying the  $n$  strategy spaces of the players. One such  $n$ -tuple counters another if the strategy of each player in the countering  $n$ -tuple yields the highest obtainable expectation for its player against the  $n - 1$  strategies of the other players in the countered  $n$ -tuple. A self-countering  $n$ -tuple is called an equilibrium point.

The correspondence of each  $n$ -tuple with its set of countering  $n$ -tuples gives a one-to-many mapping of the product space into itself. From the definition of countering we see that the set of countering points of a point is convex. By using the continuity of the pay-off functions we see that the graph of the mapping is closed. The closedness is equivalent to saying: if  $P_1, P_2, \dots$  and  $Q_1, Q_2, \dots, Q_n, \dots$  are sequences of points in the product space where  $Q_n \rightarrow Q$ ,  $P_n \rightarrow P$  and  $Q_n$  counters  $P_n$  then  $Q$  counters  $P$ .

Since the graph is closed and since the image of each point under the mapping is convex, we infer from Kakutani's theorem<sup>1</sup> that the mapping has a fixed point (i.e., point contained in its image). Hence there is an equilibrium point.

In the two-person zero-sum case the "main theorem"<sup>2</sup> and the existence of an equilibrium point are equivalent. In this case any two equilibrium points lead to the same expectations for the players, but this need not occur in general.

# Battle of Partners

Partner 2

Partner 1

	Opera (O)	Football (F)
Opera (O)	3, 1	0, 0
Football (F)	0, 0	1, 3

How should partners behave?

## Choose whether you will go to your favorite or your non-favorite activity

Favorite

Non-Favorite



## Choose whether you will go to your favorite or your non-favorite activity

Favorite

Non-Favorite

## Choose whether you will go to your favorite or your non-favorite activity

Favorite

0%

Non-Favorite

0%

# Battle of Partners

		Partner 2	
		Opera (O)	Football (F)
Partner 1	Opera (O)	3, 1	0, 0
	Football (F)	0, 0	1, 3

How should partners behave?

# Battle of Partners

		Partner 2	
		Opera (O)	Football (F)
Partner 1	Opera (O)	3, 1	0, 0
	Football (F)	0, 0	1, 3

How should partners behave?

For a full support NE both rows need to yield the same utility to row player

$3y_1 + 0y_2 = 0y_1 + 1y_2 \Rightarrow y_2 = 3y_1$   
and columns need to yield the same utility to column player

$$1x_1 + 0x_2 = 0x_1 + 3x_2 \Rightarrow x_1 = 3x_2$$

# Battle of Partners

		Partner 2	
		1/4 Opera (O)	3/4 Football (F)
Partner 1	3/4 Opera (O)	3, 1	0, 0
	1/4 Football (F)	0, 0	1, 3

How should partners behave?

For a full support NE both rows need to yield the same utility to row player

$3y_1 + 0y_2 = 0y_1 + 1y_2 \Rightarrow y_2 = 3y_1$   
and columns need to yield the same utility to column player

$$1x_1 + 0x_2 = 0x_1 + 3x_2 \Rightarrow x_1 = 3x_2$$



# Battle of Partners

		Partner 2	
		1/4 Opera (O)	3/4 Football (F)
Partner 1	3/4 Opera (O)	$\frac{3}{4} \cdot \frac{1}{4}$ 3, 1	$\frac{3}{4} \cdot \frac{3}{4}$ 0, 0
	1/4 Football (F)	$\frac{1}{4} \cdot \frac{1}{4}$ 0, 0	$\frac{1}{4} \cdot \frac{3}{4}$ 1, 3

What is the expected payoff to each player at the mixed Nash?

Column:

$$\frac{3}{4} \frac{1}{4} 1 + \frac{3}{4} \frac{3}{4} 0 + \frac{1}{4} \frac{1}{4} 0 + \frac{1}{4} \frac{3}{4} 3 = \frac{12}{16}$$

Row:

$$\frac{3}{4} \frac{1}{4} 3 + \frac{3}{4} \frac{3}{4} 0 + \frac{1}{4} \frac{1}{4} 0 + \frac{1}{4} \frac{3}{4} 1 = \frac{12}{16}$$

# ***Recap:*** Intractability of Mixed Nash Equilibrium

- If we know the supports of the player strategies then we can easily calculate a mixed Nash equilibrium
- For games with many actions, we cannot enumerate all possible supports (combinatorial explosion)
- Turns out there is no easy way to side-step this
- Computing a mixed NE in two player games is “intractable”
- It is provable as hard as computing a “fixed point” ( $f(x) = x$ ) of an arbitrary function  $f$ , which is considered an intractable problem

No learning dynamics will converge to a *Nash Equilibrium*, generically *for every game*, in a reasonable amount of time *in the worst-case*!

Look for other equilibrium concepts

Analyze special classes of games

No learning dynamics will converge to a  
*Nash Equilibrium* in *every game* in a  
reasonable time *in the worst-case!*

Develop heuristics that typically converge fast in practice

Correlated equilibrium, coarse correlated equilibrium

Look for other equilibrium concepts

Zero-sum games, potential games, auction games, strictly monotone games...

Analyze special classes of games

No learning dynamics will converge to a  
*Nash Equilibrium* in *every game* in a  
reasonable time *in the worst-case!*

Develop heuristics that typically converge fast in practice

Fictitious play, EXP, perturbed fictitious play, best-response dynamics, self-play...



# In Search for Other Equilibrium Concepts

# What if we can flip public coins?

Partner 2

Partner 1

	Opera (O)	Football (F)
Opera (O)	$\frac{1}{2}$ 3, 1	0 0, 0
Football (F)	0 0, 0	$\frac{1}{2}$ 1, 3

We flip a coin!

Heads we choose (O, O)

Tails we choose (F, F)

# What if we can flip public coins?

Partner 2

Partner 1

	Opera (O)	Football (F)
Opera (O)	$\frac{1}{2}$ 3, 1	0 0, 0
Football (F)	0 0, 0	$\frac{1}{2}$ 1, 3

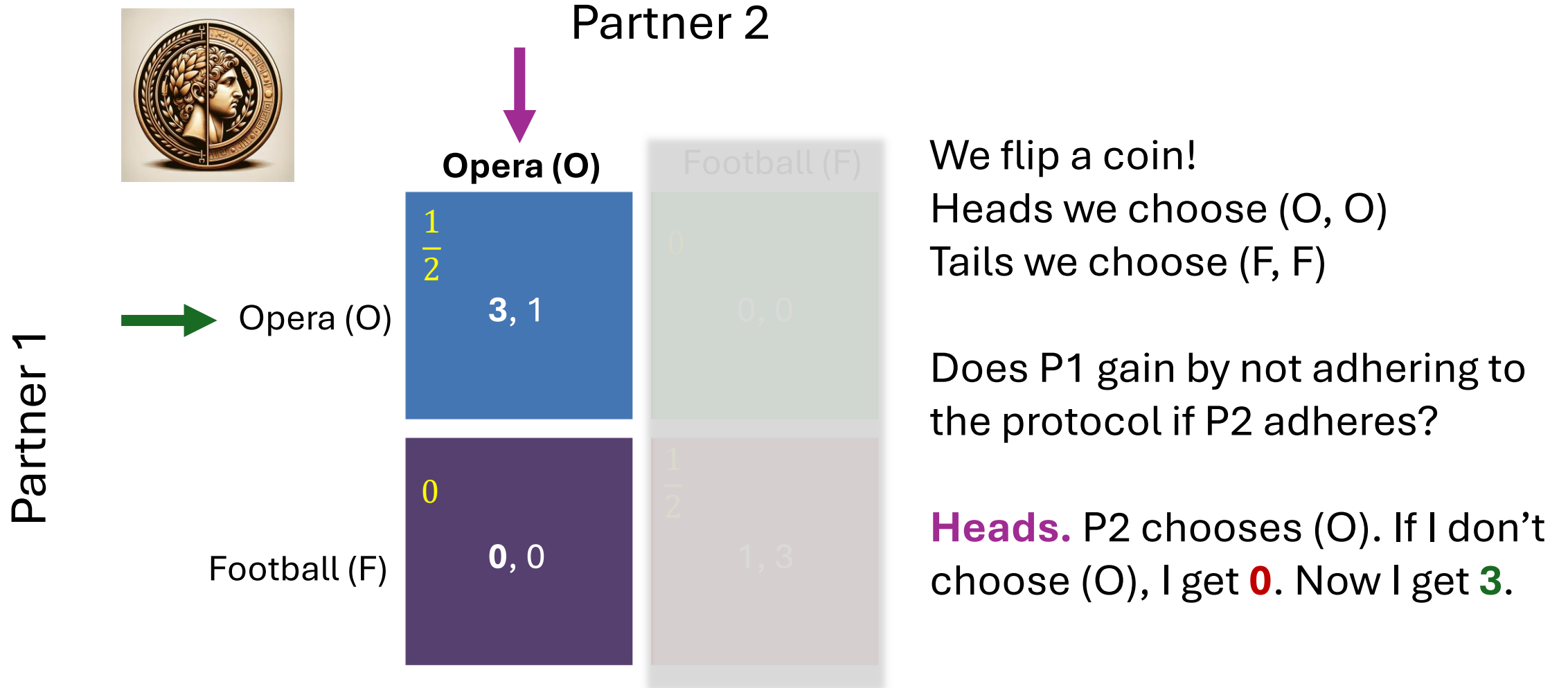
We flip a coin!

Heads we choose (O, O)

Tails we choose (F, F)

Does P1 gain by not adhering to the protocol if P2 adheres?

# What if we can flip public coins?



# What if we can flip public coins?



		Partner 2	
Partner 1	Opera (O)	<div>Opera (O)</div> <div><math>\frac{1}{2}</math></div> <div>3, 1</div>	<div>Football (F)</div> <div>0</div> <div>0, 0</div>
	Football (F)	<div>0</div> <div>0, 0</div>	<div><math>\frac{1}{2}</math></div> <div>1, 3</div>

We flip a coin!

Heads we choose (O, O)

Tails we choose (F, F)

Does P1 gain by not adhering to the protocol if P2 adheres?

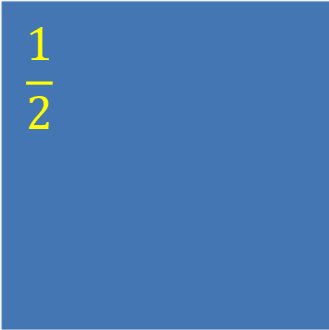
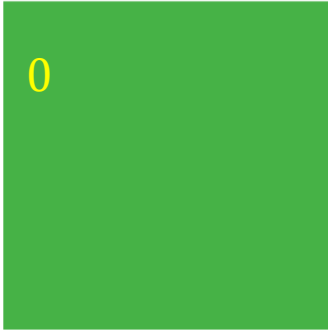


**Heads.** P2 chooses (O). If I don't choose (O), I get **0**. Now I get **3**.

**Tails.** P2 chooses (F). If I don't choose (F), I get **0**. Now I get **1**.



# Structure of equilibrium distributions

P2

		P2	
		(A)	(B)
P1	(A)		
	(B)		

Consider a new game

You don't know the utilities

The yellow numbers depict the probability distribution over outcomes (strategy profiles)

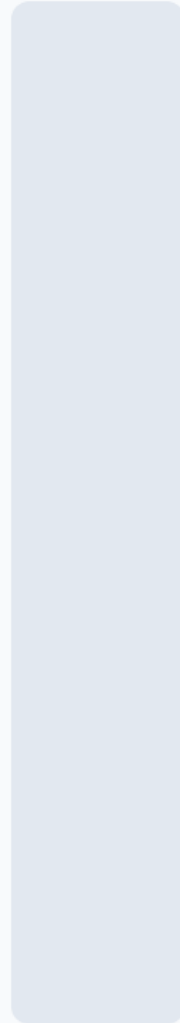
This distribution over pairs of strategies can be the result of a mixed Nash equilibrium?

True

False

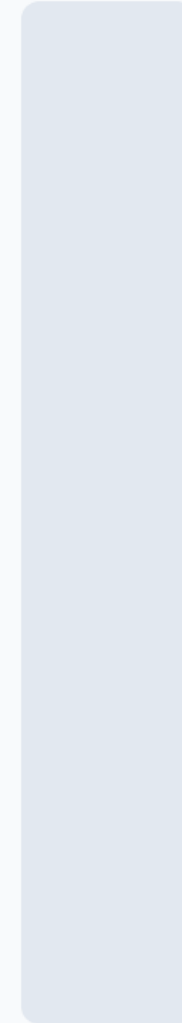
This distribution over pairs of strategies can be the result of a mixed Nash equilibrium?

0%



True

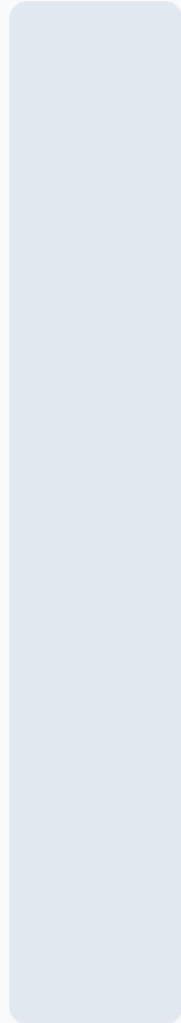
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False

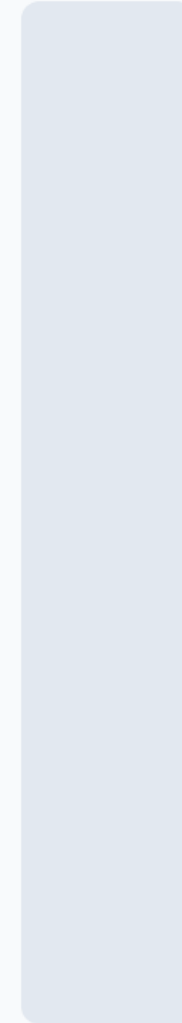
This distribution over pairs of strategies can be the result of a mixed Nash equilibrium?

0%



True

0%



False

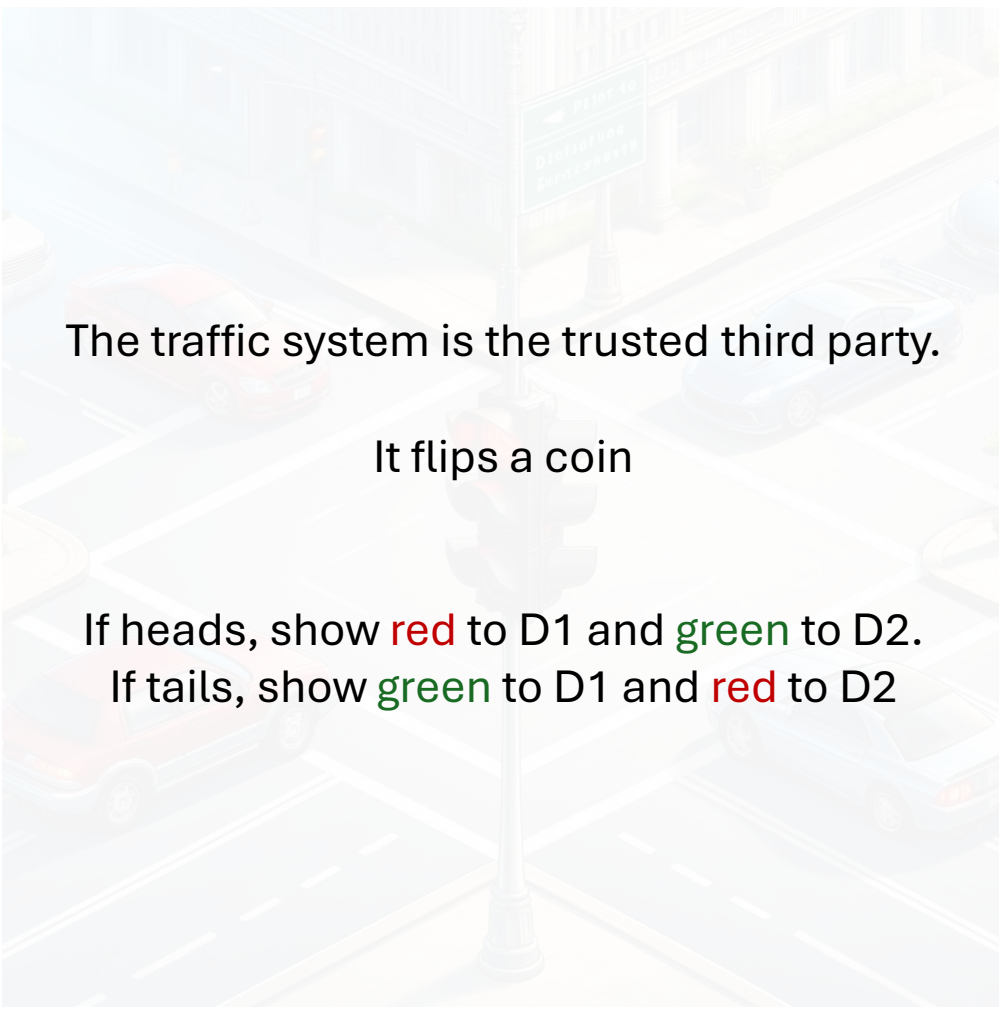
# The Junction Game

		Driver 2	
		$\frac{1}{101}$ Pass (P)	$\frac{100}{101}$ Not Pass (N)
Driver 1	$\frac{1}{101}$ Pass (P)	-100, -100	1, 0
	$\frac{100}{101}$ Not Pass (N)	0, 1	0, 0



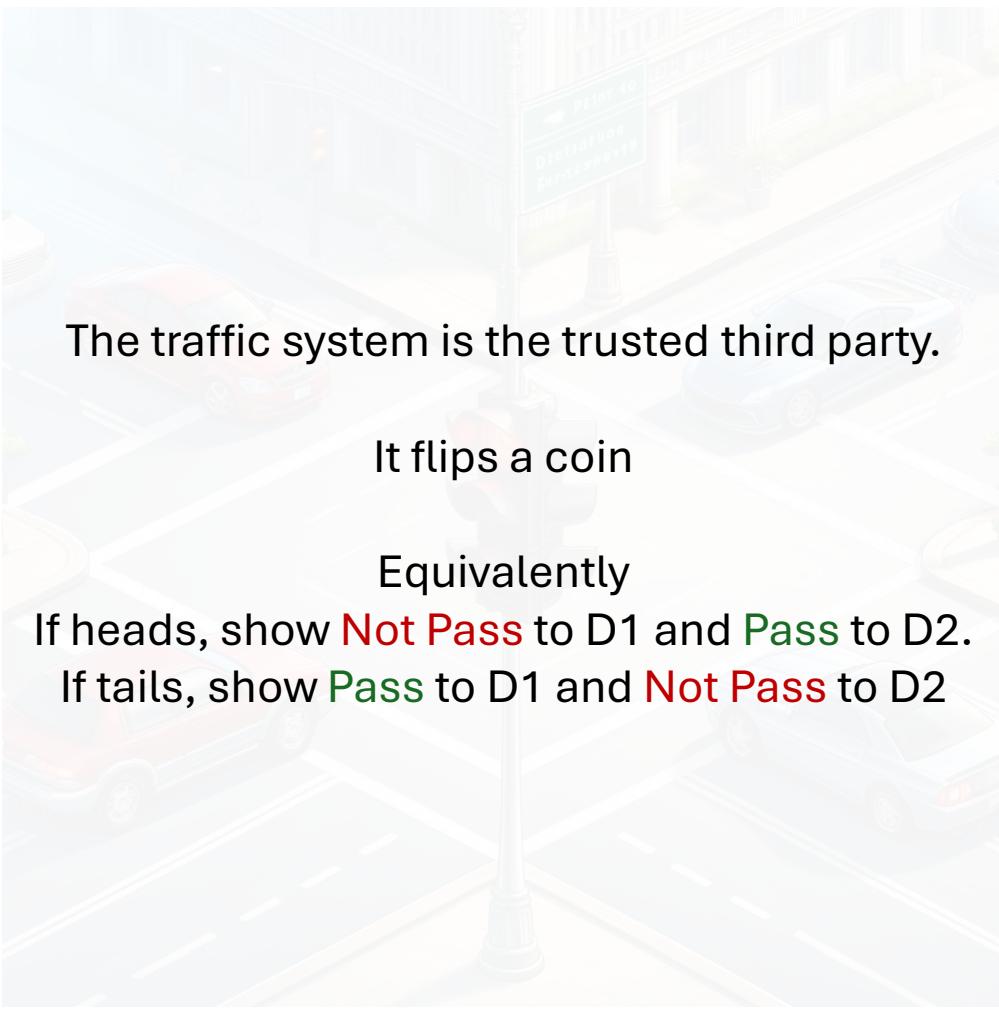
# What if we have a trusted third party that can flip coins?

		Driver 2	
		Pass (P)	Not Pass (N)
Driver 1	Pass (P)	-100, -100	1, 0
	Not Pass (N)	0, 1	0, 0



# What if we have a trusted third party that can flip coins?

		Driver 2	
		Pass (P)	Not Pass (N)
Driver 1	Pass (P)	<div>0</div> <div>-100, -100</div>	<div><math>\frac{1}{2}</math></div> <div>1, 0</div>
	Not Pass (N)	<div><math>\frac{1}{2}</math></div> <div>0, 1</div>	<div>0</div> <div>0, 0</div>





# Correlated Equilibrium

- A **trusted third party** draws strategy profiles  $s = (s_1, \dots, s_n)$  of the game from some distribution  $D$
- Communicates to each participant **their part of the profile**, i.e., the **recommended strategy  $s_i$**
- The distribution  $D$  is a **correlated equilibrium** if participants don't have incentive to deviate from their **recommended strategy**

$$\forall s_i, s'_i \in S_i: \quad \underbrace{E_{s \sim D}[u(s) \mid s_i]}_{\text{Expected utility of choosing } s_i \text{ when recommended } s_i} \geq \underbrace{E_{s \sim D}[u(s'_i, s_{-i}) \mid s_i]}_{\text{Expected utility of deviating to } s'_i \text{ when recommended } s_i}$$

For any recommendation  $s_i$   
and possible deviation  $s'_i$

Expected utility of choosing  $s_i$   
when recommended  $s_i$

$\geq$

Expected utility of deviating to  $s'_i$   
when recommended  $s_i$

# Correlated Equilibria are Tractable

- Define a variable  $\pi(s)$  for every strategy profile  $s \in S_1 \times \cdots \times S_n$
- The variables encode a distribution

$$\sum_s \pi(s) = 1$$

- The distribution  $\pi$  is a correlated equilibrium if participants don't have incentive to deviate from their recommended strategy

$$\forall s_i, s'_i \in S_i: \sum_{s_{-i}} \frac{\pi(s)}{\Pr(s_i)} u(s_i, s_{-i}) \geq \sum_{s_{-i}} \frac{\pi(s)}{\Pr(s_i)} u(s'_i, s_{-i})$$

For any recommendation  $s_i$   
and possible deviation  $s'_i$

Expected utility of choosing  $s_i$   
when recommended  $s_i$

$\geq$

Expected utility of deviating to  $s'_i$   
when recommended  $s_i$

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$$\forall s_i, s'_i \in S_i: \sum_{s_{-i}} \frac{\pi(s)}{\Pr(s_i)} u(s_i, s_{-i}) \geq \sum_{s_{-i}} \frac{\pi(s)}{\Pr(s_i)} u(s'_i, s_{-i})$$

By Bayes rule this is the conditional distribution  $s \sim \pi|s_i$ , i.e.,  $\Pr_\pi(s | s_i) = \frac{\pi(s)}{\sum_{\tilde{s}_{-i}} \pi(s_i, \tilde{s}_{-i})}$

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$$\forall s_i, s'_i \in S_i: \sum_{s_{-i}} \pi(s) u(s_i, s_{-i}) \geq \sum_{\tilde{s}_{-i}} \pi(s) u(s'_i, s_{-i})$$

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- The distribution  $\pi$  is a correlated equilibrium if participants don't have incentive to deviate from their recommended strategy

$$\forall s_i, s'_i \in S_i: \sum_{s_{-i}} \pi(s_i, s_{-i}) \left( u(s_i, s_{-i}) - u(s'_i, s_{-i}) \right) \geq 0$$

# Correlated Equilibria are Tractable

- Define a variable  $\pi(s)$  for every strategy profile  $s \in S_1 \times \cdots \times S_n$
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$$\forall s_i, s'_i \in S_i: \sum_{s_{-i}} \pi(s) \left( u(s_i, s_{-i}) - u(s'_i, s_{-i}) \right) \geq 0$$

A known quantity  $\Delta_i(s, s'_i)$ : utility gain for player  $i$  when switching from  $s_i \rightarrow s'_i$  when others play  $s_{-i}$

# Correlated Equilibria are Tractable

- Define a variable  $\pi(s)$  for every strategy profile  $s \in S_1 \times \cdots \times S_n$
- The variables encode a distribution

$$\sum_s \pi(s) = 1$$

- The distribution  $\pi$  is a correlated equilibrium if participants don't have incentive to deviate from their recommended strategy

$$\forall s_i, s'_i \in S_i: \sum_{s_{-i}} \pi(s) \Delta_i(s, s'_i) \geq 0$$

- A Linear Program with variables  $\pi(s)$



## Why do correlated equilibria always exist?

Nobody has responded yet.

Hang tight! Responses are coming in.

# ***Recap:*** Mixed Nash Equilibrium

- A mixed strategy profile  $\sigma = (\sigma_1, \dots, \sigma_n)$  is a Nash equilibrium if no player is better off in expectation, by choosing another strategy  $s'_i$

$$\forall s'_i \in S_i: E_{s_i \sim \sigma_i, s_{-i} \sim \sigma_{-i}}[u_i(s_i, s_{-i})] \geq E_{s_{-i} \sim \sigma_{-i}}[u_i(s'_i, s_{-i})]$$



# **Recap:** Mixed Nash Equilibrium

- A mixed strategy profile  $\sigma = (\sigma_1, \dots, \sigma_n)$  is a Nash equilibrium if no player is better off in expectation, by choosing another strategy  $s'_i$

$$\forall s_i \in \text{support}(\sigma_i), s'_i \in S_i: E_{s_{-i} \sim \sigma_{-i}}[u_i(s_i, s_{-i})] \geq E_{s_{-i} \sim \sigma_{-i}}[u_i(s'_i, s_{-i})]$$

Due to independence of strategies,  $\sigma_{-i}$  is also the conditional distribution  $s_{-i} \mid s_i$



# Learning Dynamics and Correlated Equilibria

# Learning in General Games

At each period  $t$ :

- Each player  $i$  picks a strategy  $s_i^t$

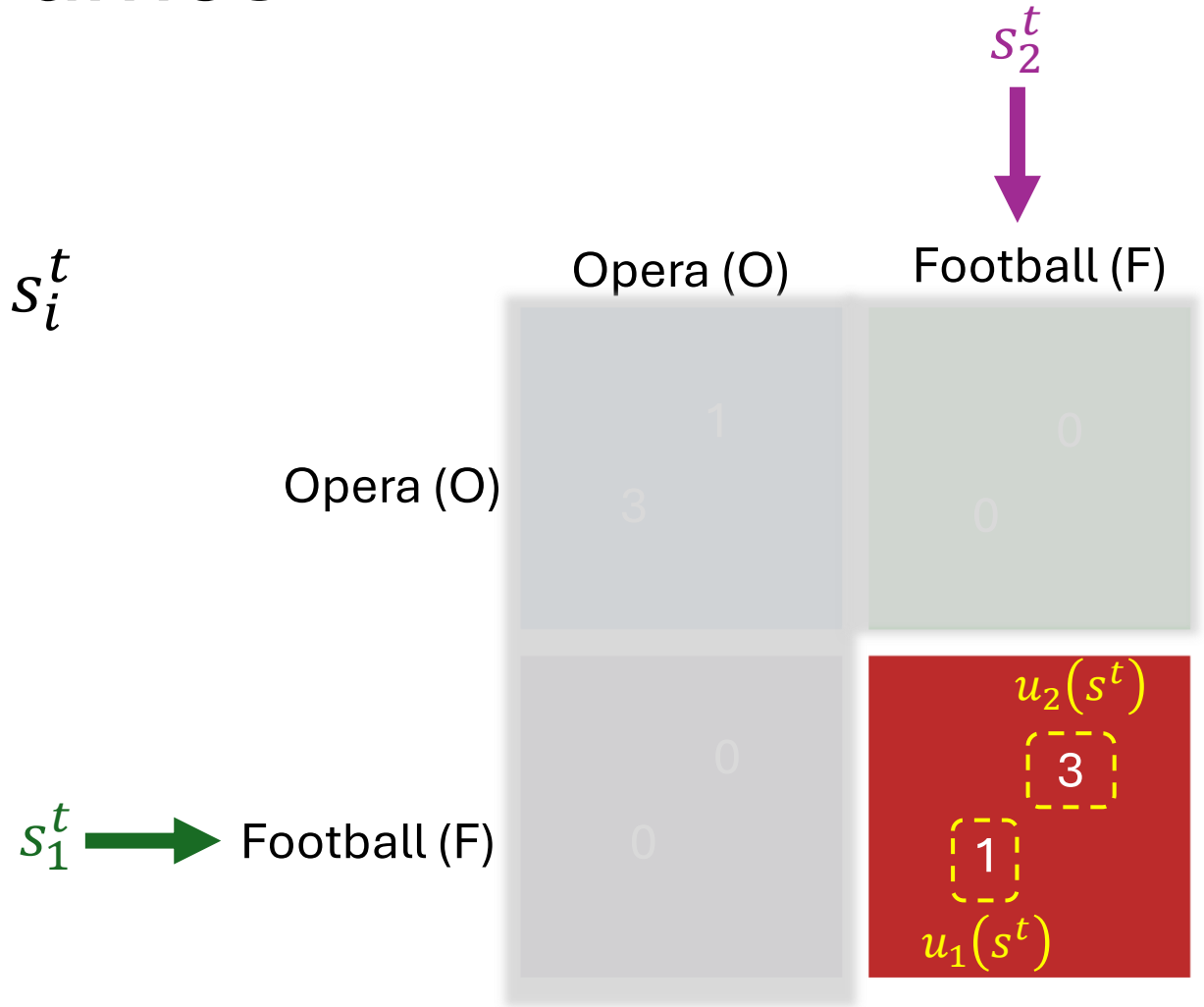
	Opera (O)	Football (F)
Opera (O)	<div>1 3</div>	<div>0 0</div>
Football (F)	<div>0 0</div>	<div>3 1</div>

# Learning in General Games

At each period  $t$ :

- Each player  $i$  picks a strategy  $s_i^t$
- Receives a payoff

$$u_i(s^t) = u_i(s_1^t, \dots, s_n^t)$$



# Learning in General Games

At each period  $t$ :

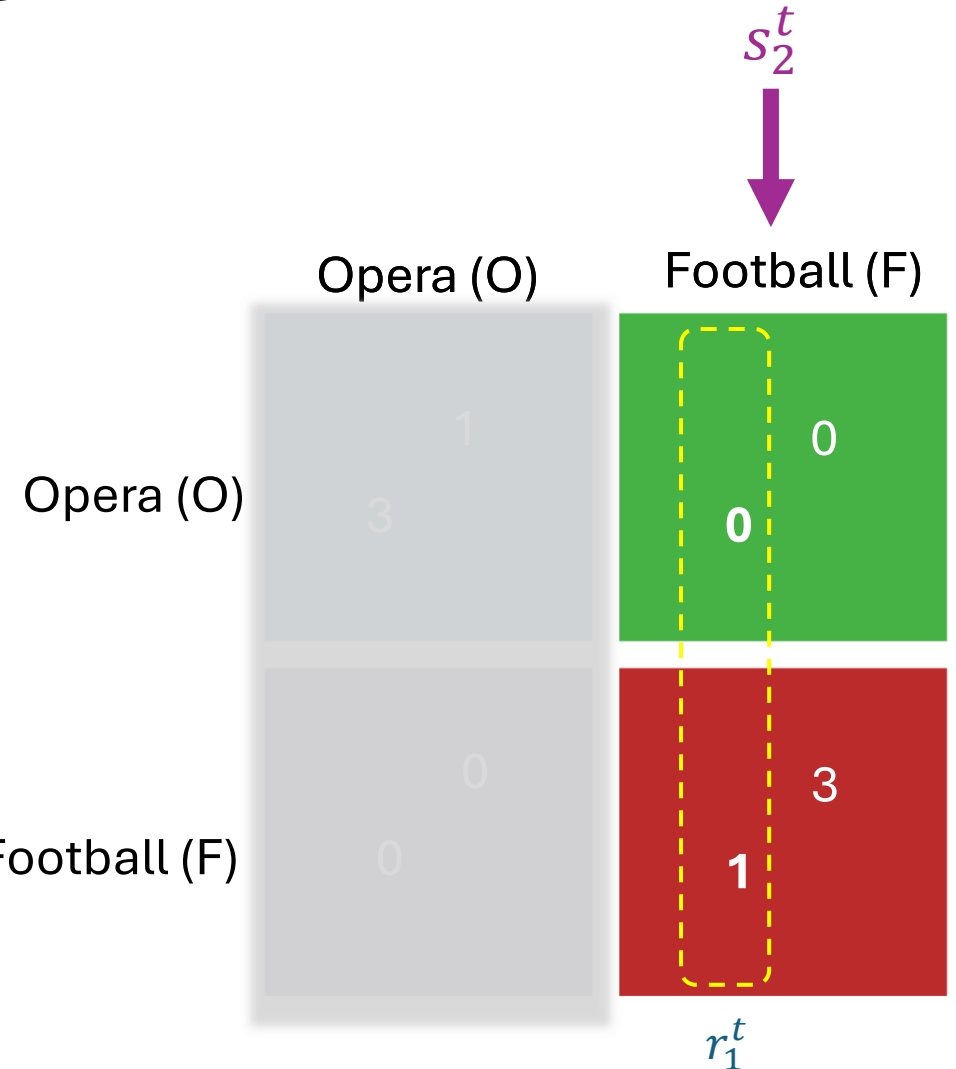
- Each player  $i$  picks a strategy  $s_i^t$
- Receives a payoff

$$u_i(s^t) = u_i(s_1^t, \dots, s_n^t)$$

- Observes utility they would have received from every other action

$$r_i^t = \left( u_i(s_i, s_{-i}^t) \right)_{s_i \in S_i}$$

$s_1^t \longrightarrow$  Football (F)



# Learning in General Games

At each period  $t$ :

- Each player  $i$  picks a strategy  $s_i^t$
- Receives a payoff

$$u_i(s^t) = u_i(s_1^t, \dots, s_n^t)$$

- Observes utility they would have received from every other action

$$r_i^t = \left( u_i(s_i, s_{-i}^t) \right)_{s_i \in S_i}$$

$s_1^t \longrightarrow$  Football (F)

	Opera (O)	Football (F)
Opera (O)	1 3	0 0
Football (F)	0 0	3 1

$s_2^t$

$s_1^t$

$r_2^t$



# No-Regret Learning in General Games

What if all players use a no-regret algorithm to choose  $s_i^t \sim \sigma_i^t$ , which guarantees for some  $\epsilon(T) \rightarrow 0$

$$\frac{1}{T} \sum_{t=1}^T E[u_i(s^t)] \geq \max_{s'_i \in S_i} \frac{1}{T} \sum_{t=1}^T E[u_i(s'_i, s_{-i}^t)] - \epsilon(T)$$

# No-Regret Learning in General Games

What if all players use a no-regret algorithm to choose  $s_i^t \sim \sigma_i^t$ , which guarantees for some  $\epsilon(T) \rightarrow 0$

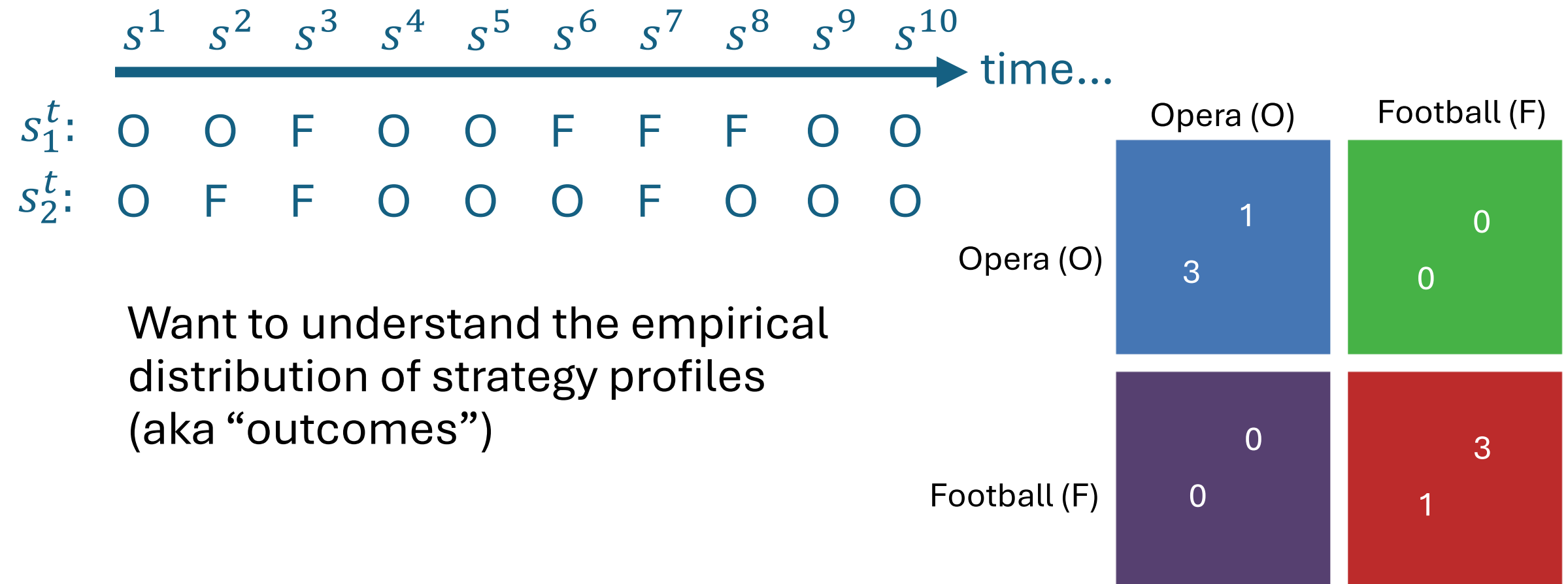
$$\frac{1}{T} \sum_{t=1}^T E[u_i(s^t)] \geq \max_{s'_i \in S_i} \frac{1}{T} \sum_{t=1}^T E[u_i(s'_i, s_{-i}^t)] - \epsilon(T)$$

Using standard Martingale concentration inequalities, this also implies that with high probability  $1 - \delta$ , for some  $\tilde{\epsilon}(T, \delta) \rightarrow 0$ :

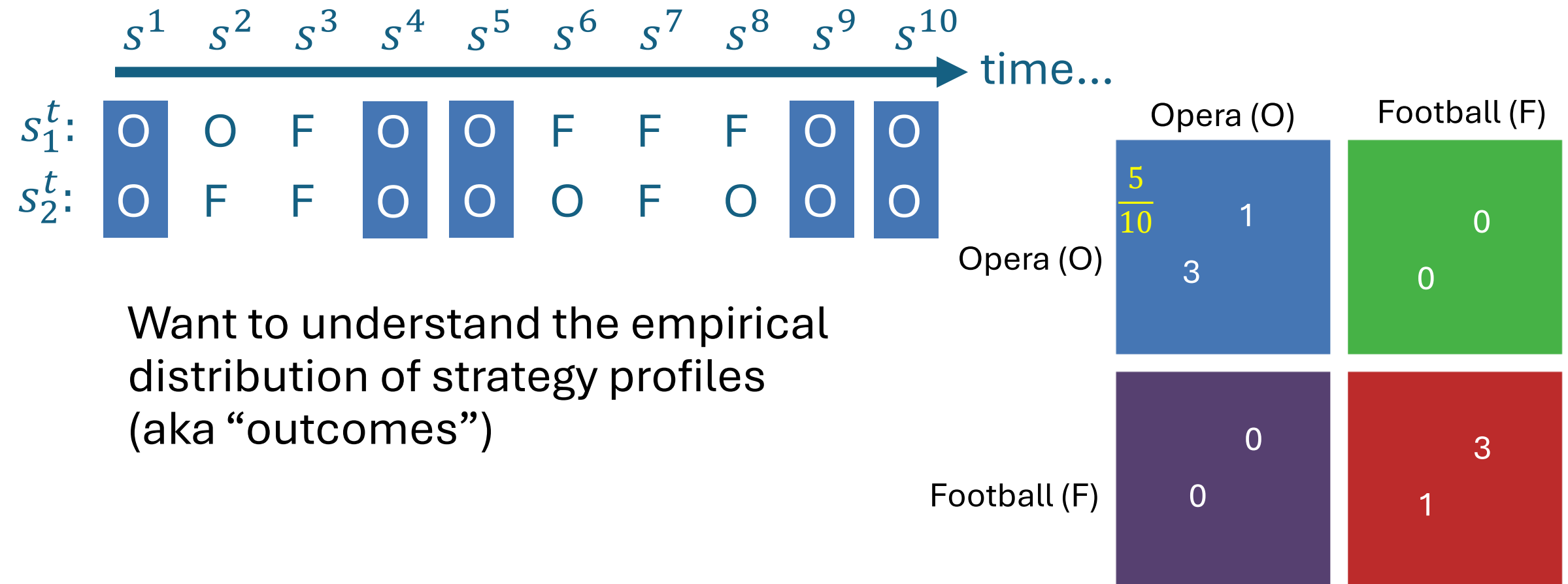
$$\frac{1}{T} \sum_{t=1}^T u_i(s^t) \geq \max_{s'_i \in S_i} \frac{1}{T} \sum_{t=1}^T u_i(s'_i, s_{-i}^t) - \tilde{\epsilon}(T, \delta)$$

What can we say about the empirical distribution of outcomes of such learning dynamics?

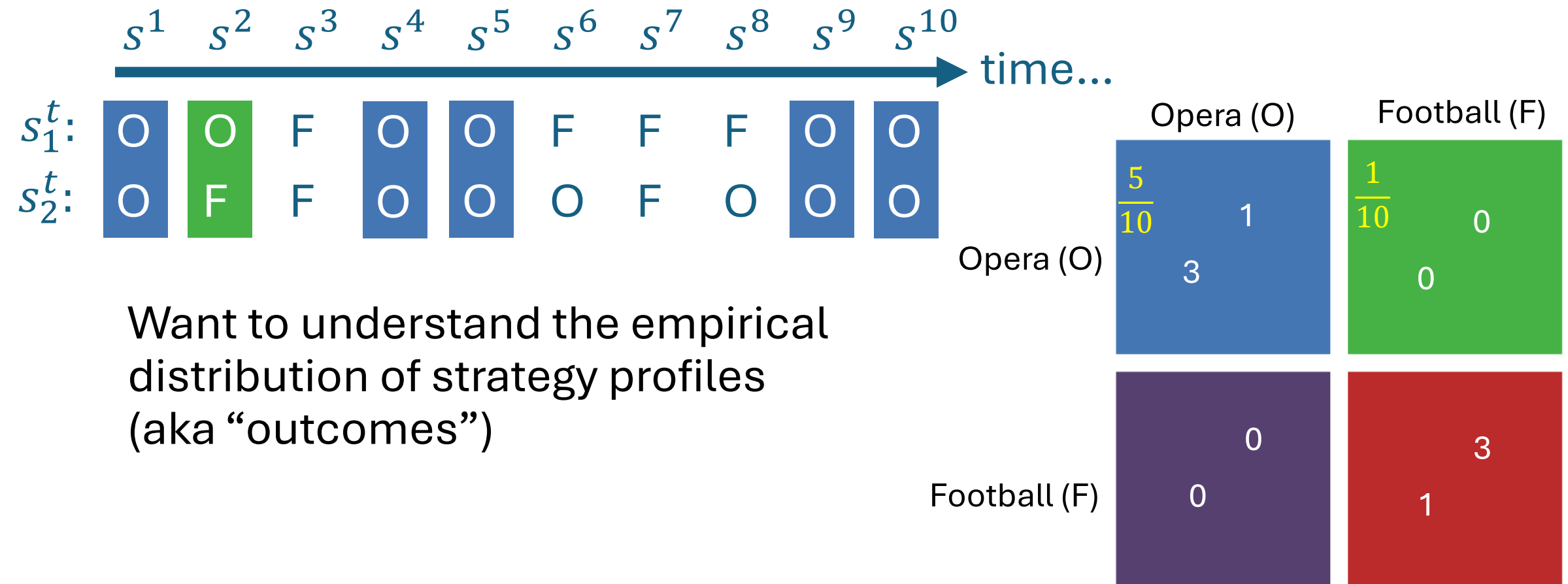
# Empirical Distribution of Outcomes



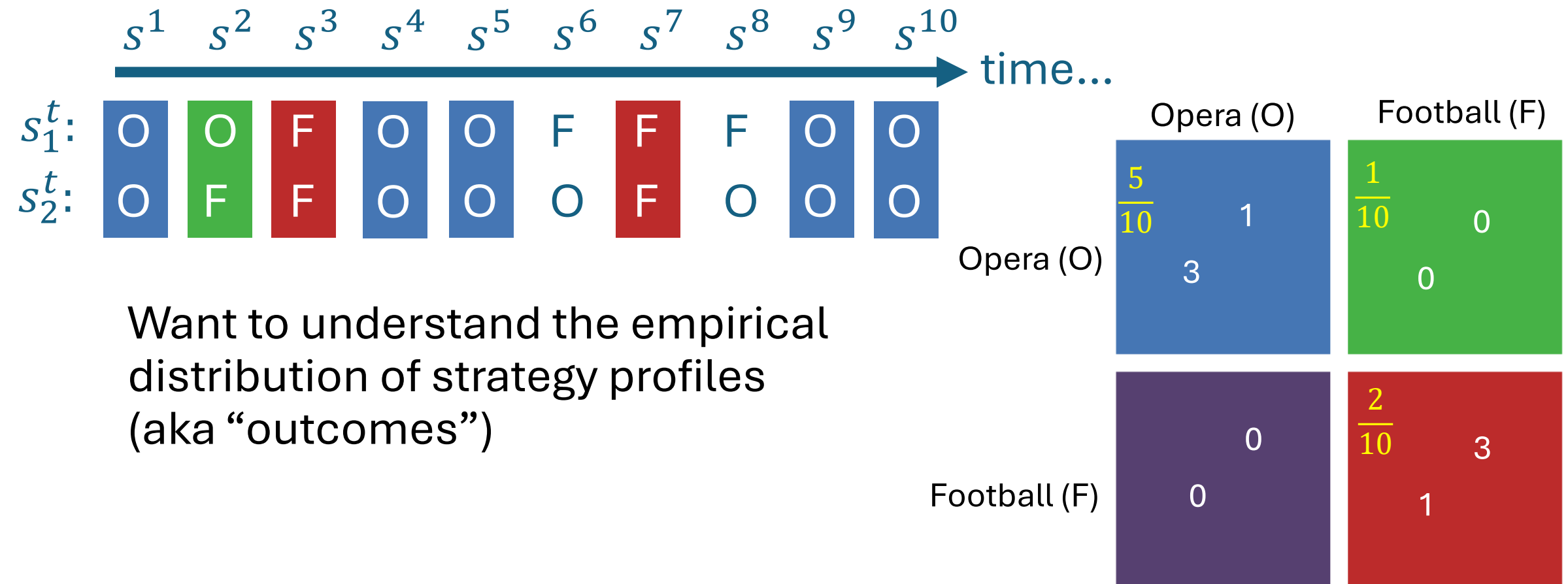
# Empirical Distribution of Outcomes



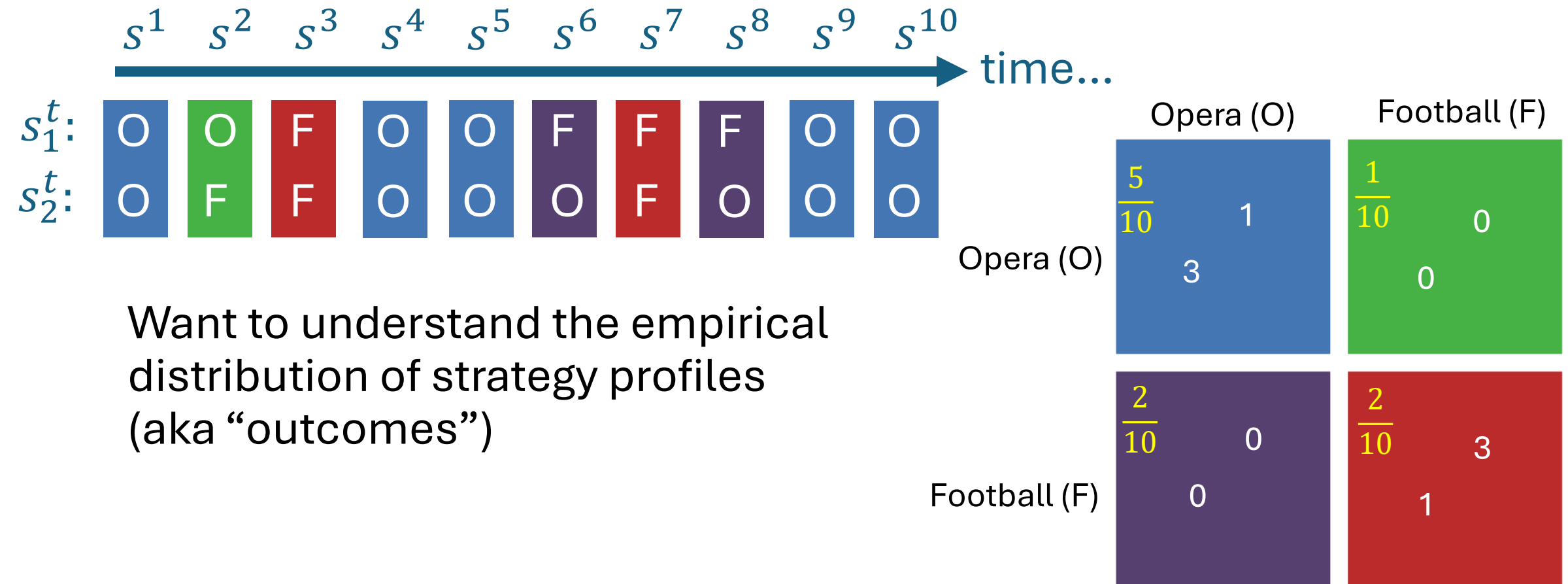
# Empirical Distribution of Outcomes



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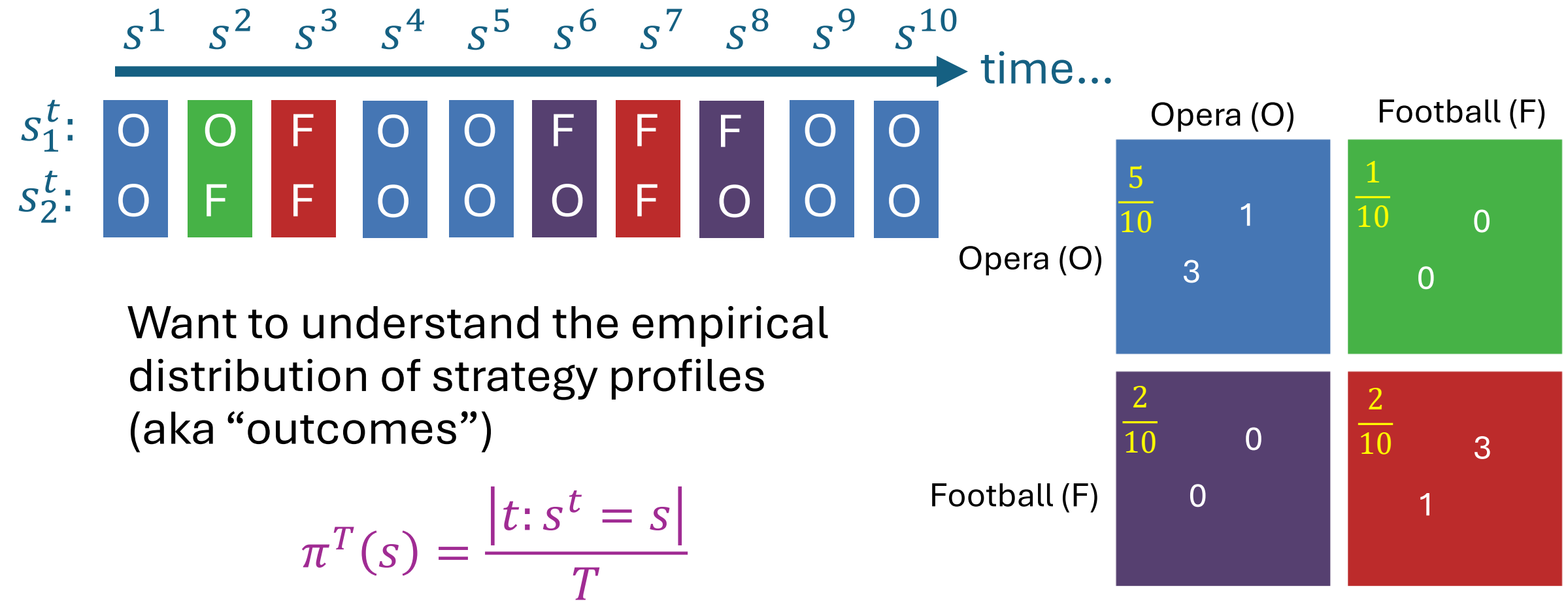


# Empirical Distribution of Outcomes





# Empirical Distribution of Outcomes



# Empirical Distribution of Outcomes

- For zero-sum games, looked at empirical distribution of marginals

$$\rho_i^T(s_i) = \frac{|t: s_i^t = s_i|}{T}$$

- The product of empirical marginals converges to Nash

$$\tilde{\pi}^T(s) = \rho_1^T(s_1) \cdot \rho_2^T(s_2) \rightarrow \text{Nash equilibrium}$$

- Now we look at the empirical joint distribution

$$\pi^T(s) = \frac{|t: s^t = s|}{T}$$

# Correlation of Outcomes

- Players observe a shared history, their actions are correlated
- Shared history plays the role of the “correlating public coin flip”
- Maybe in some games, eventually the play de-correlates
- If mixed strategies of the players converge (typically not the case)  
$$\sigma_i^T \rightarrow \sigma_i^*$$
- *Other players must choose approximate best-response strategies to have vanishing regret*
- Each player’s mixed strategy  $\rightarrow$  best response to opponents’
- Empirical distribution  $\pi^T \rightarrow \sigma_1^* \times \cdots \times \sigma_N^*$  which is a Nash

# Correlation of Outcomes

- Players observe a shared history, their actions are correlated
- Shared history plays the role of the “correlating public coin flip”
- Maybe in some games, eventually the play de-correlates

Even if play doesn't decorrelate and the mixed strategies of the players don't converge, can we argue that empirical distribution converges to some nice set?

When all players use no-regret algorithms, the empirical distribution converges to a:

Nash Equilibrium

Correlated Equilibrium

Some other equilibrium concept

Nothing interesting

When all players use no-regret algorithms, the empirical distribution converges to a:

Nash Equilibrium

0%

Correlated Equilibrium

0%

Some other equilibrium concept

0%

Nothing interesting

0%

When all players use no-regret algorithms, the empirical distribution converges to a:

Nash Equilibrium

0%

Correlated Equilibrium

0%

Some other equilibrium concept

0%

Nothing interesting

0%

# What does the empirical distribution satisfy?

- No-regret property, for each player  $i$ :

$$\frac{1}{T} \sum_{t=1}^T u_i(s^t) \geq \max_{s'_i \in S_i} \frac{1}{T} \sum_{t=1}^T u_i(s'_i, s_{-i}^t) - \tilde{\epsilon}(T, \delta)$$

- Re-write no-regret property in terms of the empirical distribution

$$\frac{1}{T} \sum_s \sum_{t:s^t=s}^T u_i(s) \geq \max_{s'_i \in S_i} \frac{1}{T} \sum_s \sum_{t:s^t=s}^T u_i(s'_i, s_{-i}) - \tilde{\epsilon}(T, \delta)$$

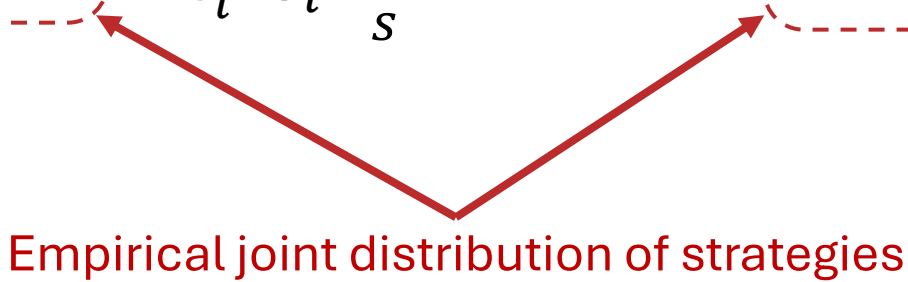


# What does the empirical distribution satisfy?

- No-regret property, for each player  $i$ :

$$\frac{1}{T} \sum_{t=1}^T u_i(s^t) \geq \max_{s'_i \in S_i} \frac{1}{T} \sum_{t=1}^T u_i(s'_i, s_{-i}^t) - \tilde{\epsilon}(T, \delta)$$

- Re-write no-regret property in terms of the empirical distribution

$$\sum_s u_i(s) \frac{|t: s^t = s|}{T} \geq \max_{s'_i \in S_i} \sum_s u_i(s'_i, s_{-i}) \frac{|t: s^t = s|}{T} - \tilde{\epsilon}(T, \delta)$$


Empirical joint distribution of strategies

# What does the empirical distribution satisfy?

- No-regret property, for each player  $i$ :

$$\frac{1}{T} \sum_{t=1}^T u_i(s^t) \geq \max_{s'_i \in S_i} \frac{1}{T} \sum_{t=1}^T u_i(s'_i, s_{-i}^t) - \tilde{\epsilon}(T, \delta)$$

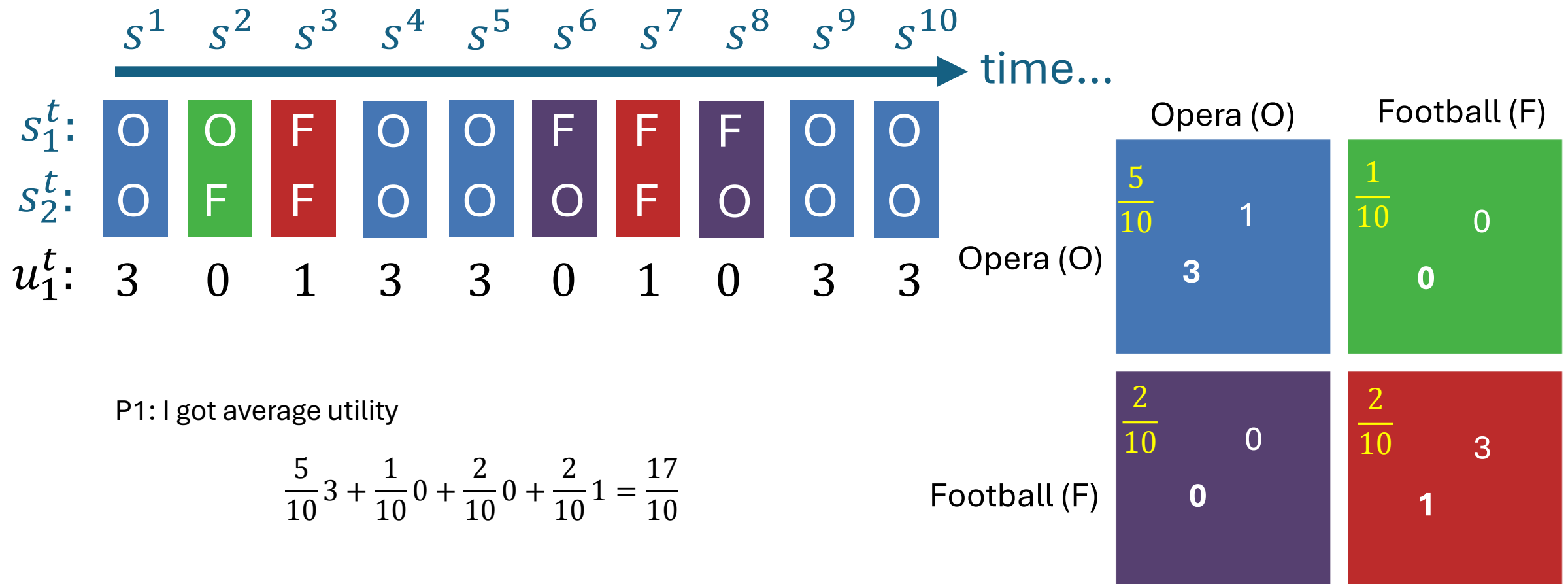
- Re-write no-regret property in terms of the empirical distribution

$$\sum_s \pi^T(s) u_i(s) \geq \max_{s'_i \in S_i} \sum_s \pi^T(s) u_i(s'_i, s_{-i}) - \tilde{\epsilon}(T, \delta)$$

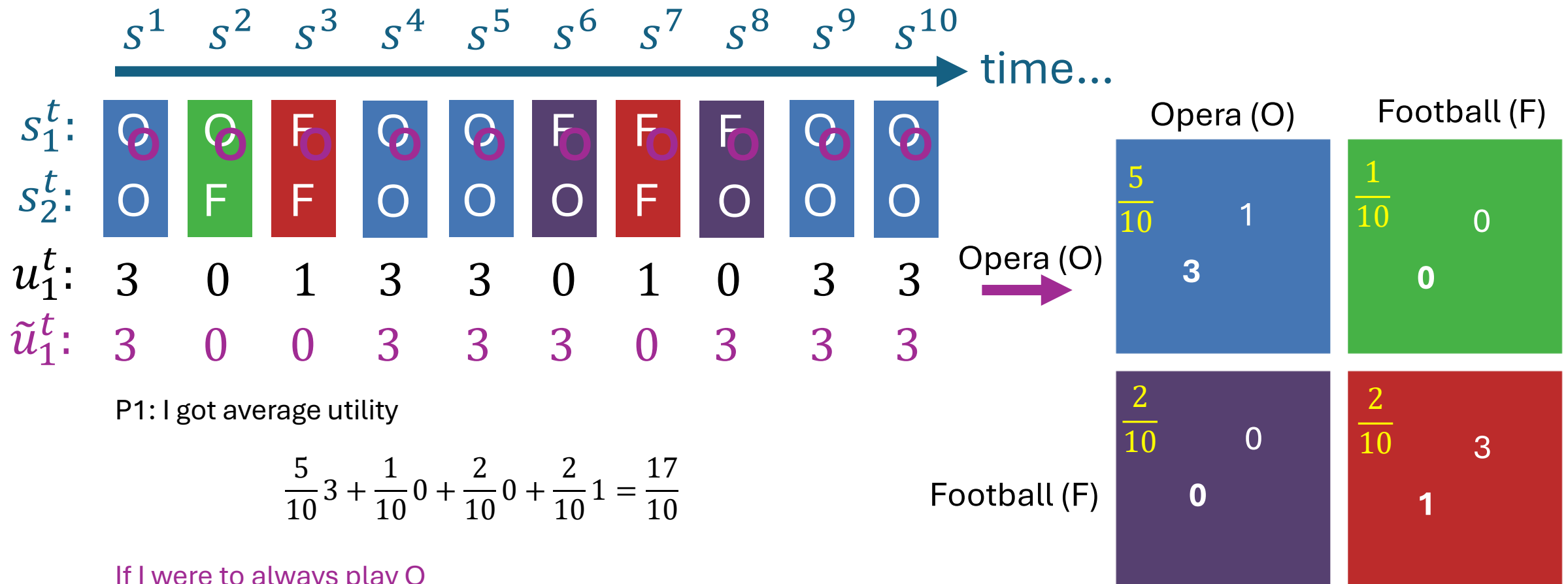
Average utility

Average utility had I  
always played  $s'_i$

# Regret Example



# Regret Example



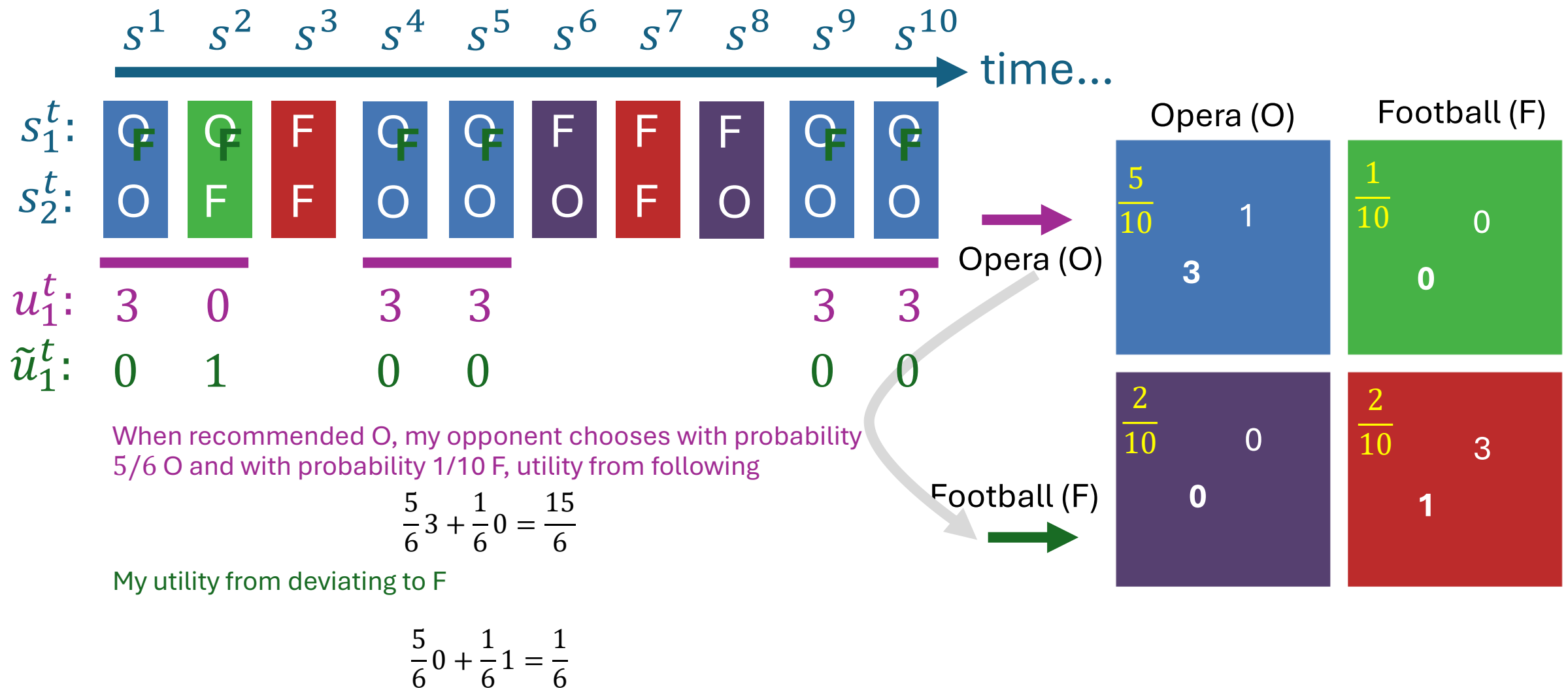
P1: I got average utility

$$\frac{5}{10}3 + \frac{1}{10}0 + \frac{2}{10}0 + \frac{2}{10}1 = \frac{17}{10}$$

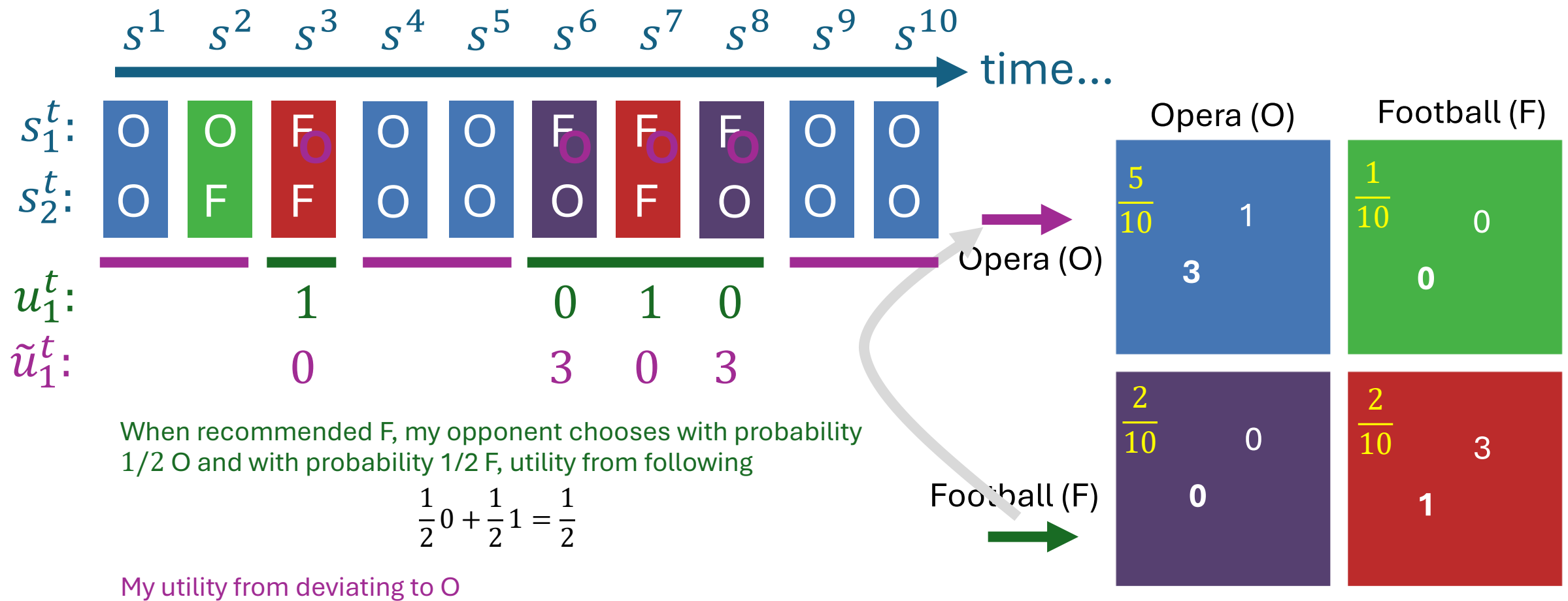
If I were to always play O

$$\frac{5}{10}3 + \frac{1}{10}0 + \frac{2}{10}3 + \frac{2}{10}0 = \frac{21}{10}$$

# The correlated equilibrium calculation?



# The correlated equilibrium calculation?



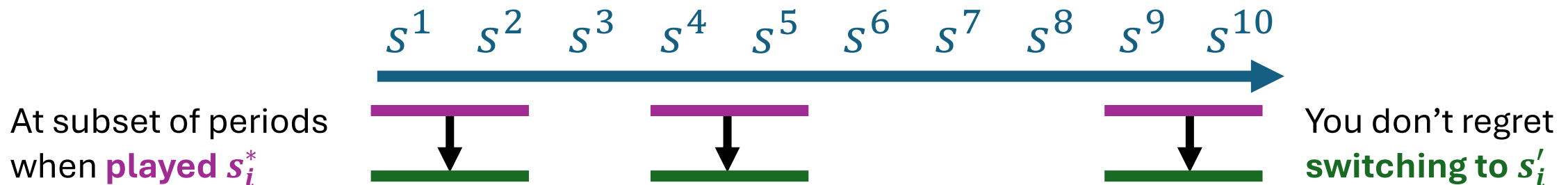
# Regret vs Correlated Equilibrium

- No-regret property, implies

$$\forall s'_i: \sum_s \pi^T(s) \left( u_i(s) - u_i(s'_i, s_{-i}) \right) \geq -\tilde{\epsilon}(T, \delta) \rightarrow 0$$

- Correlated equilibrium requires conditioning on recommendation

$$\forall s_i^*, s'_i: \sum_{s: s_i = s_i^*} \pi^T(s) \left( u_i(s) - u_i(s'_i, s_{-i}) \right) \geq 0$$



# Regret vs Correlated Equilibrium

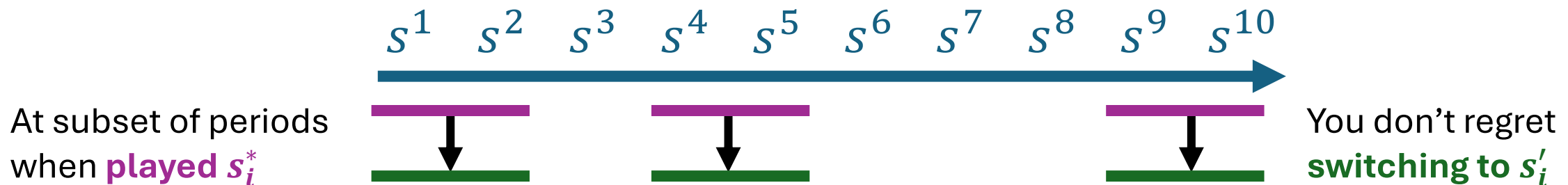
- No-regret property, implies

Distributions that satisfy this are called **Coarse Correlated Equilibria**

$$\forall s'_i: \sum_s \pi^T(s) \left( u_i(s) - u_i(s'_i, s_{-i}) \right) \geq -\tilde{\epsilon}(T, \delta) \rightarrow 0$$

- Correlated equilibrium requires conditioning on recommendation

$$\forall s_i^*, s'_i: \sum_{s: s_i = s_i^*} \pi^T(s) \left( u_i(s) - u_i(s'_i, s_{-i}) \right) \geq 0$$





Need a New Notion of Regret

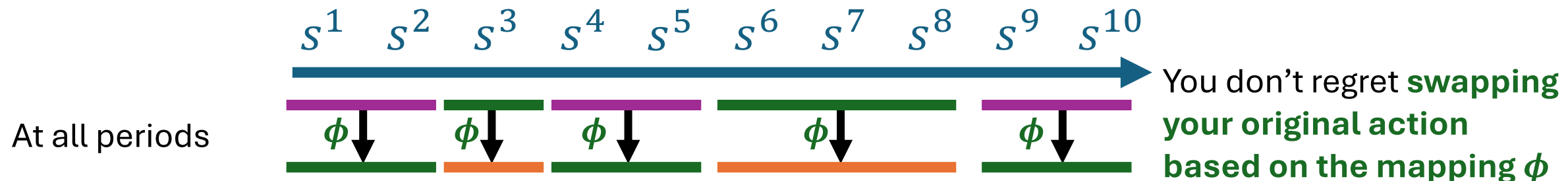
# Swaps and Correlated Equilibrium

- Correlated equilibrium requires conditioning on recommendation

$$\forall s_i^*, s'_i: \sum_{s: s_i = s_i^*} \pi^T(s) \left( u_i(s) - u_i(s'_i, s_{-i}) \right) \geq 0$$

- Equivalently: for any **swap** function  $\phi$  that maps original actions  $s_i$  to deviating actions  $s'_i$  (potentially different for each original  $s_i$ )

$$\sum_s \pi^T(s) \left( u_i(s) - u_i(\phi(s_i), s_{-i}) \right) \geq 0$$



# No-Swap Regret!

- No-regret property requires

$$\frac{1}{T} \sum_{t=1}^T u_i(s^t) \geq \max_{s'_i \in S_i} \frac{1}{T} \sum_{t=1}^T u_i(s'_i, s_{-i}^t) - \tilde{\epsilon}(T, \delta)$$

- No-swap regret property requires

$$\forall \phi: \frac{1}{T} \sum_{t=1}^T u_i(s^t) \geq \frac{1}{T} \sum_{t=1}^T u_i(\phi(s_i^t), s_{-i}^t) - \tilde{\epsilon}(T, \delta)$$

**Theorem.** If all players use **no-swap regret** algorithms, then the **empirical joint distribution** converges to a **Correlated Equilibrium**

Can we construct algorithms with  
vanishing no-swap regret?