

# Algorithmic game theory

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7th lecture

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# Regret minimization

# Our notation

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- Agent  $A$  with actions  $X = \{1, \dots, N\}$  selects a probability distribution  $p^t = (p_1^t, \dots, p_N^t)$  at every step  $t = 1, \dots, T$ .

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- Given a **comparison class**  $\mathcal{A}_X$  of agents  $A_i$  that select a single action  $i$  in all steps, we let  $L_{min}^T = \min_{i \in X} \{L_{A_i}^T\}$  be the minimum cumulative loss of an agent from  $\mathcal{A}_X$ .

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- We now restrict ourselves to losses from  $\{0, 1\}$ .

## Example

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## No Regret Learning (review)

No single action significantly outperforms the dynamic.



<b>0</b>	<b>1</b>
<b>1</b>	<b>0</b>

Weather					Loss
Algorithm					<b>1</b>
Umbrella					<b>1</b>
Sunscreen					<b>3</b>

# The Randomized greedy algorithm

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**Algorithm 0.2:** RANDOMIZED GREEDY ALGORITHM( $X, T$ )

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*Input* : A set of actions  $X = \{1, \dots, N\}$  and a number of steps  $T$ .

*Output* : A probability distribution  $p^t$  for every  $t \in \{1, \dots, T\}$ .

$p^1 \leftarrow (1/N, \dots, 1/N)$ ,

**for**  $t = 2, \dots, T$

**do** 
$$\begin{cases} L_{min}^{t-1} \leftarrow \min_{j \in X} \{L_j^{t-1}\}, \\ S^{t-1} \leftarrow \{i \in X : L_i^{t-1} = L_{min}^{t-1}\}, \\ p_i^t \leftarrow 1/|S^{t-1}| \text{ for every } i \in S^{t-1} \text{ and } p_i^t \leftarrow 0 \text{ otherwise.} \end{cases}$$

Output  $\{p^t : t \in \{1, \dots, T\}\}$ .

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**Algorithm 0.3:** RANDOMIZED GREEDY ALGORITHM( $X, T$ )

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Output  $\{p^t : t \in \{1, \dots, T\}\}$ .

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## Proposition 2.48

For any sequence of  $\{0, 1\}$ -valued loss vectors, we have

$$L_{RG}^T \leq (1 + \ln N) \cdot L_{min}^T + \ln N.$$





**WHEN YOU FIND THE NASH  
EQUILIBRIUM**





Thank you for your attention.