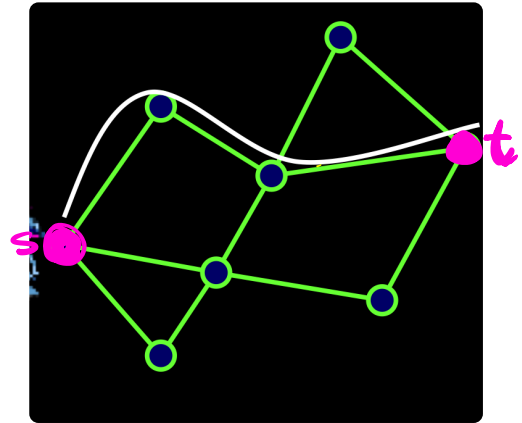


Repeated Online Decision Making and the Multiplicative Weights Algorithm

A set of possible actions $|A|=n$
 T a time horizon $A=\{1,2,\dots,n\}$

Setup:

- At each time step $t=1..T$
 - a decision maker picks an action $a_t \in A$ where $p_t^i = \Pr(a_t = i)$
 $\vec{p}^t = (p^t(1), p^t(2), \dots, p^t(n))$
 - an adversary picks reward vector $\vec{r}^t = (r^t(1), r^t(2), \dots, r^t(n))$ where $r^t(i) =$ reward to alg. if picked action i
- decision maker learns r^t



Goal of alg: maximize total exp reward.

$$= \sum_{t=1}^T \sum_{i=1}^n p^t(i) r^t(i)$$

$\underbrace{\hspace{10em}}_{\vec{p}^t \cdot \vec{r}^t}$

Examples:

- Choosing a route
- Choosing stocks to buy

	Expert 1		Expert 2		Expert 3	
	$p^t(1)$	$r^t(1)$	$p^t(2)$	$r^t(2)$	$p^t(3)$	$r^t(3)$
$t=1$						
$t=2$						
$t=3$						

$\vec{p}^t \cdot \vec{r}^t$

Alg total reward = $\sum_{t=1}^T \vec{p}^t \cdot \vec{r}^t =$



Totals

Exp 1 Exp 2 Exp 3

Best possible result

$$\text{total reward} = \sum_{t=1}^T \max_i r^t(i) \quad (*)$$

Observation: this benchmark is too strong

Ex: $A = \{1, 2\}$

Adv: $y \quad p^t(1) \geq \frac{1}{2} \Rightarrow \begin{cases} r^t(1) = -1 \\ r^t(2) = 1 \end{cases}$

$$p^t(1) + p^t(2) = 1$$

$y \quad p^t(1) < \frac{1}{2} \Rightarrow \begin{cases} r^t(1) = 1 \\ r^t(2) = -1 \end{cases}$

$$E(\text{reward}) \leq 0 \quad \text{whenever} \quad (*) = T$$

To make progress, weaken benchmark

$$\text{Regret}(\vec{p}^1, \dots, \vec{p}^T) = \underbrace{\max_{a \in A} \sum_{t=1}^T r_t(a)}_{\text{best reward possible if you use same action every day}} - \underbrace{\sum_{t=1}^T \vec{p}^t \cdot \vec{r}^t}_{\text{alg total exp reward}}$$

$$\text{Avg Regret} = \frac{1}{T} \text{Regret}$$

Goal: Avg regret $\rightarrow 0$

Most obvious thing to try to minimize Regret

"Follow the Leader": set $p^t(i) = \begin{cases} 1 & \sum_{\tau=1}^{t-1} r_{\tau}(i) > \sum_{\tau=1}^{t-1} r_{\tau}(j) \\ 0 & \text{o.w.} \end{cases} \quad \forall j \neq i$
(break ties arbitrarily)

Claim: no good. In fact, no det alg good

adversary sets $r^+(a) = \begin{cases} 0 & \text{if alg chooses action } a \\ 1 & \text{o.w.} \end{cases}$

Alg total reward = $\max_{a \in A} \sum_{t=1}^T r^+(a) = ?$

How well can we do with a randomized alg?

simple lower bound.

$n=2$ $r^+_t = \begin{cases} (1, -1) & \text{wp. } \frac{1}{2} \\ (-1, 1) & \text{wp. } \frac{1}{2} \end{cases}$

$E[\text{reward of any alg}] =$

What about best action in hindsight?

if $H > T \Rightarrow$ choose action 1
else action 2

reward of best action

can extend to n actions & show

every alg has regret $\Omega(\sqrt{T \log n})$

avg regret $\Omega\left(\frac{\log n}{T}\right)$

Theorem:

\exists online alg (MWU, Hedge, ...) s.t.

$$\max_a \sum_t r_t(a) - E(\text{reward of online alg}) \leq 2\sqrt{T \ln n}$$

$$\equiv \text{avg per-step reward of online alg} \geq \text{avg reward of best action} - 2\sqrt{\frac{\ln n}{T}}$$

MWU algorithm

initialize $w^1(a) = 1 \quad \forall a \in A$

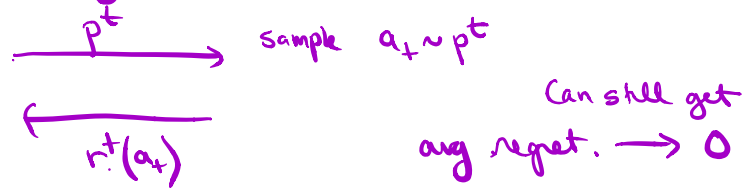
for $t = 1$ to T

pick action a with probability proportional to $w^t(a)$

given r^t update wts as follows:

$$w^{t+1}(a) = w^t(a) \cdot (1 + \eta r^t(a))$$

Another interesting setting: "bandits".



Application domain	Action	Reward
medical trials	which drug to prescribe	health outcome.
web design	<i>e.g.</i> , font color or page layout	#clicks.
content optimization	which items/articles to emphasize	#clicks.
web search	search results for a given query	1 if the user is satisfied.
advertisement	which ad to display	revenue from ads.
recommender systems	<i>e.g.</i> , which movie to watch	1 if follows recommendation.
sales optimization	which products to offer at which prices	revenue.
procurement	which items to buy at which prices	#items procured
auction/market design	<i>e.g.</i> , which reserve price to use	revenue
crowdsourcing	which tasks to give to which workers, and at which prices	1 if task completed at sufficient quality.
datacenter design	<i>e.g.</i> , which server to route the job to	job completion time.
Internet	<i>e.g.</i> , which TCP settings to use?	connection quality.
radio networks	which radio frequency to use?	1 if successful transmission.
robot control	a "strategy" for a given task	job completion time.

Minimax Theorem

Let A be $m \times n$ payoff matrix for zero-sum game

$[a_{ij}]$: gain of row player when row player plays i & col player plays j
 = loss of col player

Nature flips
 coins
 submit dish

Let $\vec{x} \in \mathbb{R}^m$ $\sum_{i=1}^m x_i = 1, x_i \geq 0$ be mixed strategy for row player

$\vec{y} \in \mathbb{R}^n$ $\sum_{j=1}^n y_j = 1, y_j \geq 0$ be mixed strategy for col player

$$\max_{\vec{x} \in \Delta_m} \min_{\vec{y} \in \Delta_n} \vec{x}^T A \vec{y} = \min_{\vec{y} \in \Delta_n} \max_{\vec{x} \in \Delta_m} \vec{x}^T A \vec{y}$$

$V = V_R = V_C$ called "value" of game
 x^*, y^* called "optimal" strategies



FIGURE 2.6. Von Neumann explaining duality to Dantzig.

Proof of Minimax Thm using MWU thm (sketch)

(assume $a_{ij} \in [-1, 1]$ just scale)

Thought experiment

Fix $\epsilon > 0$ (eventually we'll take $\epsilon \rightarrow 0$)
for $t = 1 \dots T = \frac{4 \ln(\max(n, m))}{\epsilon^2}$

each player is "adversary" for other

Imagine row player & col player
using MWU alg to play
T rounds of game

$$\Rightarrow \vec{p}^t, \vec{q}^t, \quad t = 1 \dots T$$

where in each round

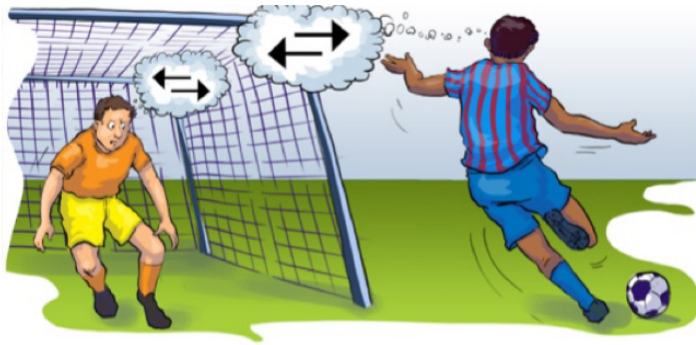
$$\text{row player rewards} \quad r^t = A \vec{q}^t$$

$$\text{col player rewards} \quad r^t = -(\vec{p}^t)^T A$$

$$\text{Let } \hat{x} = \frac{1}{T} \sum_{t=1}^T \vec{p}^t$$
$$\hat{y} = \frac{1}{T} \sum_{t=1}^T \vec{q}^t$$

$$\text{Let } V = \frac{1}{T} \sum_{t=1}^T (\vec{p}^t)^T A \vec{q}^t$$

avg exp payoff of row player over T rounds



Is it predictive?

Penalty Kicks.

		col player goalie	
		L	R
row player kicker	L	0.58	0.95
	R	0.93	0.7

Based on actual data on 1417 penalty kicks from professional games in Europe

	Kicker	Goalie
Optimal strategies	(0.38, 0.62)	(0.42, 0.58)
Observed frequencies	(0.40, 0.60)	(0.423, 0.577)

