

Today

Multiplicative Weight
Update Method
(part III)

- Approximately solving
zero-sum games = LPs

CSS.205.1

Toolkit in TCS

- Lecture #17

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Application of MWUM

- Solving zero-sum games

- Solving LPs.

n-experts

$$M^{(t)} = (m_1^{(t)} \dots m_n^{(t)})$$

- loss vector.

$$p^{(t)} = (p_1^{(t)}, \dots, p_n^{(t)}) - \text{prob proportional to weights}$$

$$l^{(t)} = \langle M^{(t)}, p^{(t)} \rangle.$$

Update Rule:

$$\omega_i^{(t+1)} \leftarrow \omega_i^{(t)} (1 - \epsilon m_i^{(t)})$$

(Assumptions: $m_i^{(t)} \in [-1, 1]$
 $\epsilon \in (0, \frac{1}{2}]$)

Thm [MWUM].

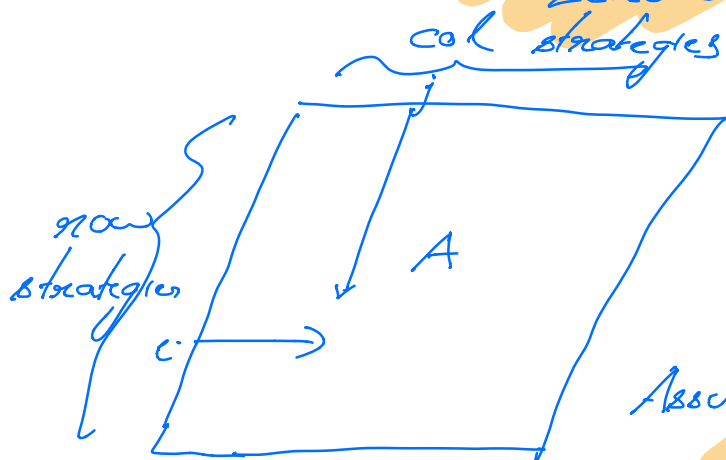
For any expert $e \in [n]$, the expected loss of the MWUM algorithm

$$\begin{aligned} L(T) &= \sum_{t=1}^T l(e) = \sum_{t=1}^T \langle M^{(t)}, p^{(t)} \rangle \\ &\leq \sum_{t=1}^T m_e^{(t)} + \varepsilon \sum_{t=1}^T |m_e^{(t)}| + \frac{\ln n}{\varepsilon} \end{aligned}$$

Cor: p - any distribution on experts

$$\begin{aligned} L(T) &\leq \sum_{t=1}^T \langle M^{(t)}, p \rangle + \varepsilon \sum_{t=1}^T \langle |M^{(t)}|, p \rangle \\ &\quad + \frac{\ln n}{\varepsilon} \end{aligned}$$

Application I: Approximately Solve Zero-Sum Games.



$A(i,j)$ = payoff to the column player

Assume:

$$A(i,j) \in [0, 1]$$

Row player's mixed strategy
 $p \sim$ dist over pure row strategies

Col plays j

$$A(p, j) \triangleq \mathbb{E}_{i \sim p} [A(i, j)]$$

Col player finds that maximizes $A(p, j)$

$$C(p) = \max_j A(p, j)$$

Similarly

q - Col player's mixed strategy
 i - Row player strategy

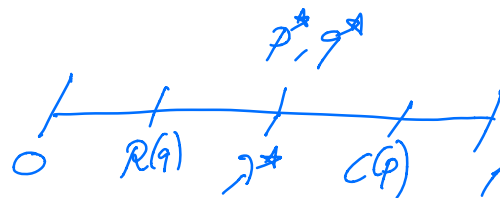
$$A(i, q) \triangleq \mathbb{E}_{j \sim q} [A(i, j)]$$

$$R(q) = \min_i A(i, q)$$

Weak duality: $R(q) \leq C(p)$, $\forall p, q$.

Strong Duality: $\exists \lambda^* \geq p^*, q^*$

$$R(q) \leq R(q^*) = \lambda^* = C(p^*) \leq C(p)$$



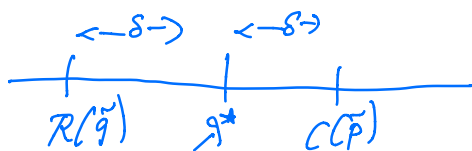
Von-Neumann's MiniMax Theorem

Last time: Non-constructive proof of existence of λ^* , p^* , q^*

Today: Algorithm using MWUM to compute λ^* , p^* , q^* **approximate**

Given $\delta \in (0, 1)$

Will find \tilde{p} , \tilde{q} - Row mixed strategy
Col mixed strategy



i.e., $\lambda^* - \delta \leq R(\tilde{q}) \leq \lambda^*$
 $\lambda^* \leq C(\tilde{p}) \leq \lambda^* + \delta$ } Additive δ -approximation

Experts: - row pure strategies.



At each step of MWUM,
alg o/p a prob dist over n_i experts.
- p -mixed row strategy.

Oracle: Given any mixed row strategy p , find the best column response.

$$p \mapsto j \text{ s.t. } C(p) = A(p, j)$$

Best-vector: Column corresponding to the j^{th} column in the payoff matrix.

$$p^{(1)} \leftarrow \text{uniform}$$

At any step $t \leftarrow 1..T$

Row player plays accg to prob dist $p^{(t)}$.

$j^{(t)} \triangleq$ Best column response.

$M^{(t)} = j^{(t)}$ -column of payoff matrix.

$p^{(t+1)} \leftarrow$ updated appropriately using $p^{(t)}$, ϵ , & $M^{(t)}$.

MWUM Theorem.

$$\sum_{t=1}^T \langle M^{(t)}, p^{(t)} \rangle \leq (1+\epsilon) \sum_{t=1}^T \langle M^{(t)}, p \rangle + \frac{\ln n}{\epsilon}$$

for any mixed row strategy p .

Writing this in terms of payoff matrix.

$$\sum_{i=1}^T A(p^{(k)}, j^{(k)}) \leq (1+\epsilon) \sum_{i=1}^T A(p, j^{(k)}) + \frac{\ln n}{\epsilon}$$

$j^{(k)}$ is the best col response for $p^{(k)}$

$$\text{Hence } A(p^{(k)}, j^{(k)}) \geq \lambda^*$$

Hence, (since $A_{ij} \leq 1 \forall i, j$)

$$\lambda^* \leq \frac{1}{T} \sum_{i=1}^T A(p^{(k)}, j^{(k)}) \leq \frac{1}{T} \sum_{i=1}^T A(p, j^{(k)}) + \epsilon + \frac{\ln n}{\epsilon T}$$

In particular, it is true for $p = p^*$ for any mixed row strategy p .

$$\lambda^* \leq \frac{1}{T} \sum_{i=1}^T A(p^{(k)}, j^{(k)}) \leq \lambda^* + \epsilon + \frac{\ln n}{\epsilon T}$$

$$\text{Set } \epsilon = \delta/2 ; T = \left\lceil \frac{4 \ln n}{\delta^2} \right\rceil$$

$$\lambda^* \leq \frac{1}{T} \sum_{i=1}^T A(p^{(k)}, j^{(k)}) \leq \lambda^* + \delta.$$

① Approximate Value of Game $\tilde{\lambda}$

$$\tilde{\lambda} \triangleq \frac{1}{T} \sum_{\epsilon=1}^T A(p^{(\epsilon)}, j^{(\epsilon)})$$

$$\lambda^* \leq \tilde{\lambda} \leq \lambda^* + \delta.$$

② Approximate mixed row strategy \tilde{p} :

$$\tilde{p} = \frac{1}{T} \sum p^{(\epsilon)}, \quad j - \text{best response to } \tilde{p}$$

$$\begin{aligned} C(\tilde{p}) &= A(\tilde{p}, j) = \frac{1}{T} \sum_{\epsilon=1}^T A(p^{(\epsilon)}, j) \\ &\leq \frac{1}{T} \sum_{\epsilon=1}^T A(p^{(\epsilon)}, j^{(\epsilon)}) \\ &\leq \lambda^* + \delta. \end{aligned}$$

$j^{(\epsilon)}$ - best response to $p^{(\epsilon)}$

③ Approximate mixed Col. strategy \tilde{q} :

$$\tilde{q}(j) = \frac{|\{\epsilon \mid j^{(\epsilon)} = j\}|}{T}$$

We had proved the following for any p .

$$\lambda^* \leq \frac{1}{T} \sum_{\epsilon=1}^T A(p^{(\epsilon)}, j^{(\epsilon)}) \leq \frac{1}{T} \sum_{\epsilon=1}^T A(p, j^{(\epsilon)}) + \epsilon + \frac{\ln n}{\epsilon T}$$

Applying it to p -pure strategy i :

$$\lambda^* \leq \frac{1}{T} \sum_{t=1}^T A(i, j^{(t)}) + \delta$$
$$= A(i, \tilde{q}) + \delta$$

$$A(i, \tilde{q}) \geq \lambda^* - \delta, \quad \forall i$$

Hence, $R(\tilde{q}) \geq \lambda^* - \delta$.

Thm: For any $\delta \in (0, 1)$, δ -additive approximation to the zero-sum game $(\tilde{r}, \tilde{p}, \tilde{q})$ can be obtained by making $O\left(\frac{\log n}{\delta^2}\right)$ calls to the oracle $\approx O(n)$ processing time for each call.

Application II: Approximately Solving Linear Programs.

LP:

$$\exists? x \in \mathcal{P}, Ax \geq b$$

\mathcal{P} -convex set

easy constraint

hard constraint



Guiding Example:

Set Cover: U - universe

$$S_1, \dots, S_m \subseteq U$$

Find smallest sub-collection of sets that covers U .

LP relaxation:

$$\min \sum_S x_S$$

$$\sum_{S \ni e} x_S \geq 1 \quad \forall e \in U$$

$$x_S \geq 0$$

$x_S = 1$ [S is in sub-collection]

$$P = \{x \in \mathbb{R}^m \mid x_S \geq 0; \sum x_S = L\}$$

$$\exists? x \in P \quad \forall e \in U, \sum_{S \ni e} x_S \geq 1$$

$$\exists? x \in P, Ax \geq b \quad \dots \quad (*)$$

Goal: Approximate Solve above Problem

- Either, Find $x \in P$ s.t. for all constraints.

$$A_i x \geq b_i - \delta$$

or

- Declare that (*)
is infeasible.

$$\left\{ \begin{array}{l} \underline{Ax \geq b} \\ A_1 x \geq b_1 \\ A_2 x \geq b_2 \\ \vdots \\ A_m x \geq b_m \end{array} \right\}$$

MWUM - paradigm

m experts - m constraints.

$$p_1 \quad A_1 x \geq b_1$$

$$p_2 \quad A_2 x \geq b_2$$

$$p_m \quad A_m x \geq b_m$$

$$\sum p_i A_i x \geq \sum p_i b_i$$

↪ Single constraint

Assume the existence of an oracle
that solves the single constraint problem

Set cover

$$\sum_{S \in \mathcal{U}} x_S \geq 1 \quad ; e \in U$$

p-prob dist over the elements of

$$\sum_{e \in U} p(e) \sum_{S \in \mathcal{U}} x_S \geq \sum_{e \in U} p_e \cdot 1^{\text{universe}}$$

$$\text{ie } \sum_S x_S \sum_{e \in S} p(e) \geq 1$$

$$\sum_S x_S \cdot p(S) \geq 1 \quad \text{where}$$

$p_S :=$ total prob of all elts in S .

Single Constraint Problem

$$\exists? x \in \mathcal{P}, \quad \sum x_S p(S) \geq 1$$

$$\exists x, \quad x_S \geq 0; \quad \sum x_S = L; \quad \sum x_S p(S) \geq 1.$$

Easy to solve by setting $x_S = \begin{cases} L & \text{if } S = \arg \max p(S) \\ 0 & \text{otherwise} \end{cases}$

Oracle: (L, p) -bounded oracle. ($0 \leq L \leq 1$)

There exists an oracle $\mathcal{O} \pm$
 $I \subseteq [m]$ (subset of constraints) s.t

on input any p - (prob dist over the m constraints), \mathcal{O} outputs

a soln to

$$p^T A x \geq p^T b \quad \text{or declares it infeasible}$$

Whenever, it outputs a soln x , x satisfies

$$-p \leq A_i x - b_i \leq p, \quad \forall i \in I$$

$$-p \leq A_i x - b_i \leq p, \quad \forall i \notin I$$

Set cover:

$$I = [m].$$

$$-1 \leq \sum_{S \in \mathcal{C}} x_S - 1 \leq L-1$$

The oracle we constructed above is a $(1, L-1)$ -bounded oracle.

$$A_1 x \geq b_1$$

$$A_2 x \geq b_2$$

:

$$A_m x \geq b_m$$

m -experts

$$\text{Cost of } i^{\text{th}} \text{ expert} = \frac{[A_i x - b_i]}{p}$$