Advanced Algorithms (Fall 2026)

Multiplicative Weight Update

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Outline

1. Learning with Expert Advice
2. The Multiplicative Weight Update Theorem
3. Solving Zero-Sum Games
4. Approximate LP Feasibility
5. Optional Material
   - Halving and Weighted Majority

- Focus of this lecture: learning with experts online
- how to dynamically choose from among a set of "experts" in a way that compares favorably to the best expert
- Use it to solve 0-sum game and linear programs approximately

Learning with Experts Online

- m experts, indexed by $[m]$
- a two-outcome event on each of following T days: up or down
  - Example: stock goes up or down? rain or not?

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  - algorithm makes a prediction, knowing the predictions of the m experts
  - the outcome of day t reveals

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- Goal: minimize the number of mistakes
  - Ideally, not too bad compared to the best expert.

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The General Setting

1: **for** $t \leftarrow 1, 2, \cdots, T$ **do**
2: algorithm chooses a distribution $p^t = (p_1^t, p_2^t, \cdots, p_m^t)$ over experts
3: the penalty vector $M^t \in [-1, 1]^m$ is revealed
4: each expert i pays penalty M_i^t
5: algorithm pays penalty $\langle p^t, M^t \rangle = \sum_{i=1}^m p_i^t M_i^t$

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- Note: penalty can be negative: negative penalty = reward

Theorem Let $\epsilon \in (0, 1]$. If $T \geq \frac{\ln m}{\epsilon^2}$, then there is an algorithm that satisfies:

$$\frac{1}{T}\sum_{t=1}^{T}\langle p^t, M^t\rangle \leq \frac{1}{T}\sum_{t=1}^{T} M_i^t + 2\epsilon, \forall i \in [m].$$

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Algorithm for the General Setting

1: $w_i^0 \leftarrow 1$ for every $i \in [m]$
2: **for** $t \leftarrow 1, 2, \cdots, T$ **do**
3: choose $p^t \leftarrow \frac{w^{t-1}}{|w^{t-1}|_1}$
4: the penalty vector $M^t \in [-1, 1]^m$ is revealed
5: each expert i pays penalty M_i^t
6: algorithm pays penalty $\langle p^t, M^t\rangle = \sum_{i=1}^{m} p_i^t M_i^t$
7: **for** every $i \in [m]$ **do**: $w_i^t \leftarrow w_i^{t-1} \cdot e^{-\epsilon \cdot M_i^t}$

Analysis of Algorithm

- $p_i^t = w_i^{t-1}/\Phi^{t-1}$, where $\Phi^t := \sum_{i=1}^m w_i^t$.

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$$\begin{aligned}
\Phi^t &= \Phi^{t-1} \sum_i p_i^t e^{-\epsilon M_i^t} \\
&\leq \Phi^{t-1} \sum_i p_i^t \left(1 - \epsilon M_i^t + \epsilon^2 (M_i^t)^2\right) \\
&\leq \Phi^{t-1} \left(1 - \epsilon \langle p^t, M^t \rangle + \epsilon^2\right).
\end{aligned}$$

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- $e^z \leq 1 + z + z^2$ for $z \in [-1, 1]$.
- Here $0 < \epsilon \leq 1$, $|M_i^t| \leq 1$, and $\sum_i p_i^t = 1$.

Analysis of Algorithm

$$\begin{aligned}\Phi^t &\leq (1+\epsilon^2)\Phi^{t-1} - \epsilon \cdot \Phi^{t-1} \cdot \langle p^t, M^t \rangle \\ &= \left(1 + \epsilon^2 - \epsilon \cdot \langle p^t, M^t \rangle\right) \cdot \Phi^{t-1} \\ &\leq \exp\left(- \epsilon \cdot \langle p^t, M^t \rangle + \epsilon^2\right) \cdot \Phi^{t-1} \\ &\qquad\qquad\qquad\qquad\qquad\qquad \text{as } 1 - x \leq e^{-x},\ \forall x \in \mathbb{R}\end{aligned}$$

$$\begin{aligned}\Phi^T &\leq \exp\left(\sum_{t=1}^{T} \left(- \epsilon \cdot \langle p^t, M^t \rangle + \epsilon^2\right)\right) \cdot \Phi^0 \\ &= \exp\left(- \epsilon \cdot \sum_{t=1}^{T} \langle p^t, M^t \rangle + T\epsilon^2\right) \cdot \Phi^0\end{aligned}$$

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- For any expert $i \in [m]$, $\Phi^T \geq w_i^T = \exp\Big(-\epsilon \sum_{t=1}^{T} M_i^t\Big)$.
- So, for every $i \in [m]$, we have (note that $\Phi^0 = m$)

$$\begin{aligned}
-\epsilon \cdot \sum_{t=1}^{T} M_i^t &\leq -\epsilon \cdot \sum_{t=1}^{T} \langle p^t, M^t \rangle + T\epsilon^2 + \ln m \\
\sum_{t=1}^{T} \langle p^t, M^t \rangle &\leq \sum_{t=1}^{T} M_i^t + T\epsilon + \frac{\ln m}{\epsilon} \\
\frac{1}{T} \sum_{t=1}^{T} \langle p^t, M^t \rangle &\leq \frac{1}{T} \sum_{t=1}^{T} M_i^t + \epsilon + \frac{\ln m}{T\epsilon} \\
&\leq \frac{1}{T} \sum_{t=1}^{T} M_i^t + 2\epsilon \qquad \Big[T \geq \frac{\ln m}{\epsilon^2}\Big]
\end{aligned}$$

Theorem Let $\epsilon \in (0, 1]$. If $T \geq \frac{\ln m}{\epsilon^2}$, then there is an algorithm that satisfies:

$$\frac{1}{T}\sum_{t=1}^{T}\langle p^t, M^t\rangle \leq \frac{1}{T}\sum_{t=1}^{T} M_i^t + 2\epsilon, \forall i \in [m].$$

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Coro. Suppose each penalty in the game is in $[-\rho, \rho]$ (instead of $[-1, 1]$) for some $\rho > 0$. Let $\epsilon \in \big(0, 2\rho\big]$. If $T \geq \frac{4\rho^2 \ln m}{\epsilon^2}$, then there is an algorithm that satisfies

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Proof.

- scale penalties by $\frac{1}{\rho}$ so that each penalty is in $[-1, 1]$
- $+\epsilon$ before scaling $= +\frac{\epsilon}{\rho}$ after scaling

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Proof.

- scale penalties by $\frac{1}{\rho}$ so that each penalty is in $[-1, 1]$
- $+\epsilon$ before scaling $= +\frac{\epsilon}{\rho}$ after scaling
- Need $T \geq \frac{\ln m}{(\epsilon/2\rho)^2} = \frac{4\rho^2 \ln m}{\epsilon^2}$ and $\frac{\epsilon}{2\rho} \leq 1 \iff \epsilon \leq 2\rho$ □

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Recall:

0-Sum Game

Input: a payoff matrix $M \in \mathbb{R}^{m \times n}, m, n \geq 1$,

two players: row player R, column player C

Output: R plays a row $i \in [m]$, C plays a column $j \in [n]$

payoff of game is M_{ij}

R wants to minimize M_{ij}, C wants to maximize M_{ij}

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Rock-Scissor-Paper Game

payoff	R	S	P
R	0	-1	1
S	1	0	-1
P	-1	1	0

- By scaling, assume $M \in [-1, 1]^{m \times n}$ and $0 < \epsilon \leq 2$.

player	objective	game term	number	distribution
row player	minimize	expert	m	x
column player	maximize	event	n	y

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Multiplicative weight update for 0-sum games

let $w_i^0 = 1$ for every $i \in [m]$
for $t \leftarrow 1$ to T, where $T = \max\{1, \lceil 4 \ln m/\epsilon^2 \rceil\}$ **do**
    algorithm chooses distribution $x^t = \frac{w^{t-1}}{|w^{t-1}|_1}$
    let j^t be the $j \in [n]$ that maximizes $M(x^t, j)$
    event j^t happens:
        expert $i \in [m]$ pays penalty $M(i, j^t)$
        algorithm pays penalty $M(x^t, j^t)$
    $w_i^t \leftarrow w_i^{t-1} \cdot e^{-\epsilon \cdot M(i, j^t)/2}$ for every $i \in [m]$

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- Since $T \geq \frac{4 \ln m}{\epsilon^2}$, we have

$$\frac{1}{T} \sum_{t=1}^{T} M(x^t, j^t) \quad \leq \quad \min_{i \in [m]} \frac{1}{T} \sum_{t=1}^{T} M(i, j^t) + \epsilon$$

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- $\hat{t}$: the $t \in [T]$ with minimum $M(x^t, j^t)$ $\qquad \hat{x} := x^{\hat{t}}$

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- $\hat{t}$: the $t \in [T]$ with minimum $M(x^t, j^t)$ $\qquad \hat{x} := x^{\hat{t}}$
- $\hat{y}$: uniform distribution over multi-set $\{j^1, j^2, \cdots, j^T\}$

$$\max_j M(\hat{x}, j) = M(\hat{x}, j^{\hat{t}}) \leq \frac{1}{T} \sum_{t=1}^{T} M(x^t, j^t)$$

$$\leq \min_i \frac{1}{T} \sum_{t=1}^{T} M(i, j^t) + \epsilon = \min_i M(i, \hat{y}) + \epsilon$$

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$$\lambda^* \leq \max_j M(\hat{x}, j) \leq \min_i M(i, \hat{y}) + \epsilon \leq \lambda^* + \epsilon$$

- Therefore $\hat{x}$ and $\hat{y}$ are approximately the optimum strategies for the row and column players.

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Linear Program: Exact Version

Input: An "easy" polytope $K \subseteq \mathbb{R}^n$ (e.g., $K = [0,1]^n$)
normal linear constraints $Ax \geq b$, $\quad A \in \mathbb{R}^{m \times n}, b \in \mathbb{R}^m$

Output: decide if $\{x \in K : Ax \geq b\} = \emptyset$,
if not, then output $x \in K$ with $Ax \geq b$

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or output $x \in K$ with $Ax \geq b - \epsilon \cdot \mathbf{1}$

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Output: either claim $\{x \in K : Ax \geq b\} = \emptyset$,
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- Note: in case there is no exact solution, but an approximate solution, algorithm can respond either way.

What Makes the Polytope K Easy?

- Assume K is nonempty and we can maximize any linear objective over K efficiently. A membership test alone does not suffice.
- Given $y \geq 0$, compute $x \in \arg\max_{z \in K} y^{\mathrm{T}} A z$.
- If $y^{\mathrm{T}} A x < y^{\mathrm{T}} b$, no point of K satisfies all constraints $Az \geq b$. Otherwise x satisfies the aggregated constraint.
- Choose a known width bound $\rho > 0$ with $|A_i x - b_i| \leq \rho$ for every $x \in K$ and every row i.
- The iteration bound is $O(1 + \rho^2 \log(m)/\epsilon^2)$. It is polynomial in ρ/ϵ, which need not be polynomial in the binary input length.

Approximate LP Solver using MWU

row of A	constraint	expert	dual solution y	m
column of A	variable		primal solution x	n

- event $=$ a point in K
- choose $\rho > 0$ with $|A_i x - b_i| \leq \rho$ for all $x \in K$, $i \in [m]$; take $0 < \epsilon \leq 2\rho$

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- event = a point in K
- choose $\rho > 0$ with $|A_i x - b_i| \leq \rho$ for all $x \in K$, $i \in [m]$; take $0 < \epsilon \leq 2\rho$

1: $w_i^0 \leftarrow 1$ for every $i \in [m]$
2: **for** $t \leftarrow 1$ to T, for some T to be decided later **do**
3: $\quad y^t \leftarrow \frac{w^{t-1}}{|w^{t-1}|_1}$
4: $\quad$ **if** $\exists x^t \in K$ s.t $\langle y^t, Ax^t \rangle \geq \langle y^t, b \rangle$ **then** ▷ event x^t happens
5: $\quad\quad$ **for** every $i \in [m]$ **do**
6: $\quad\quad\quad$ expert i gets penalty $A_i x^t - b_i$
7: $\quad\quad\quad$ $w_i^t \leftarrow w_i^{t-1} \cdot e^{-\epsilon \cdot (A_i x^t - b_i)/(2\rho^2)}$
8: $\quad\quad$ our algorithm gets penalty $\langle y^t, Ax^t - b \rangle$
9: $\quad$ **else return** "empty"
10: **return** $\hat{x} = \frac{1}{T} \sum_{t=1}^{T} x^t$

- Counter-intuitive: the more satisfied a constraint is, the more penalty it gets.
- In every iteration, we only need to focus on one "aggregated" linear constraint
- If algorithm returns "empty", then the LP is not feasible

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- $\rho > 0 : \quad \rho \geq \sup_{x \in K} \max_i |A_i x - b_i|, \qquad \epsilon \in (0, 2\rho]$
  $T := \max\{1, \lceil 4\rho^2 \ln m/\epsilon^2 \rceil\}$

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  $T := \max\{1, \lceil 4\rho^2 \ln m/\epsilon^2 \rceil\}$
- $\forall i \in [m]$:

$$0 \leq \frac{1}{T}\sum_{t=1}^{T}\langle y^t, Ax^t - b\rangle \leq \frac{1}{T}\sum_{t=1}^{T}(A_i x^t - b_i) + \epsilon = A_i\hat{x} - b_i + \epsilon$$

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  $T := \max\{1, \lceil 4\rho^2 \ln m/\epsilon^2 \rceil\}$
- $\forall i \in [m]$:

$$0 \leq \frac{1}{T}\sum_{t=1}^{T} \langle y^t, Ax^t - b\rangle \leq \frac{1}{T}\sum_{t=1}^{T}(A_i x^t - b_i) + \epsilon = A_i\hat{x} - b_i + \epsilon$$

- Therefore, $A_i\hat{x} \geq b_i - \epsilon, \forall i \in [m] \quad \Longleftrightarrow \quad A\hat{x} \geq b - \epsilon \cdot \mathbf{1}$

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When There Is a Perfect Expert

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Proof.

- The algorithm: only keep the experts who made no mistakes so far.
- Among all the experts, follow the majority.
- observation: when we made a mistake on a day, at least half of the remaining experts made a mistake on that day. □

General Case

- What if there is no perfect expert?

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- Weighted majority: give weights to experts. When an expert made a mistake, halve his weight. In each step, follow the weighted majority.

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Weighted Majority

1: $w_i^0 \leftarrow 1, \forall i \in [m]$
2: **for** $t = 1, 2, \cdots, T$ **do**
3: **if** $\sum_{i:\text{predicts up}} w_i^{t-1} \geq \sum_{i:\text{predicts down}} w_i^{t-1}$ **then**
4: predict "up"
5: **else**
6: predict "down"
7: **for** every expert i **do**
8: **if** i make a mistake **then** $w_i^t \leftarrow \frac{w_i^{t-1}}{2}$ **else** $w_i^t \leftarrow w_i^{t-1}$

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- $\Phi^t := \sum_{i=1}^m w_i^t$.
- $M_i^t \in \{0,1\}, i \in [m], t \in [T]$: whether expert i made a mistake on day t
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- On the other hand, let k be the best expert

$$\Phi^T = \sum_{i=1}^m w_i^T \geq w_k^T \geq \left(\frac{1}{2}\right)^{\sum_{t=1}^T M_k^t}$$

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$$\left(\frac{1}{2}\right)^{\sum_{t=1}^T M_k^t} \leq \Phi^T \leq \left(\frac{3}{4}\right)^{\sum_{t=1}^T M^t} m$$

$$(-\ln 2) \sum_{t=1}^T M_k^t \leq (-\ln \frac{4}{3}) \sum_{t=1}^T M^t + \ln m \qquad \text{(take logs)}$$

$$\sum_{t=1}^T M^t \leq \frac{\ln 2}{\ln 4/3} \sum_{t=1}^T M_k^t + \frac{\ln m}{\ln 4/3}$$

$$\leq 2.41 \sum_{t=1}^T M_k^t + 3.48 \ln m$$

$$\sum_{t=1}^{T} M^t \leq 2.41 \sum_{t=1}^{T} M_k^t + 3.48 \ln m$$

Make the first constant arbitrarily close to 2

- for $0 < \epsilon < 1$, when expert i makes a mistake on day t: $w_i^t \leftarrow w_i^{t-1} \cdot (1 - \epsilon)$
- when algorithm makes a mistake on day t: $\Phi^t \leq \Phi^{t-1} \cdot (1 - \frac{\epsilon}{2})$

$$\Phi^T \leq (1 - \epsilon/2)^{\sum_{t=1}^{T} M^t} \cdot m$$

- $\Phi^T \geq (1 - \epsilon)^{\sum_{t=1}^{T} M_k^t}$

$$\sum_{t=1}^{T} M^t \leq \frac{\ln(1-\epsilon)}{\ln(1-\epsilon/2)} \sum_{t=1}^{T} M_k^t - \frac{\ln m}{\ln(1-\epsilon/2)}$$

$$= (2 + O(\epsilon)) \sum_{t=1}^{T} M_k^t + O\left(\frac{1}{\epsilon}\right) \ln m.$$

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Proof.

- Take $m = 2$: one expert always predicts "up", the other always predicts "down".
- Choose each outcome opposite to the deterministic algorithm's prediction.
- Our algorithm made T mistakes, and the best expert makes at most $T/2$.
- If $T \gg f(m)$, we have $T > (2 - \epsilon) \cdot \frac{T}{2} + f(m)$. □

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- However, if randomness is allowed, we can make multiplicative factor $1 + \epsilon$.