

Admin:

- PSet 5 is out today
 - We will have a post-quiz survey
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Today:

- Game theory
 - Two person zero-sum games
 - Min-Max theorem
 - How to get rich? (Stock market prediction)
 - (Rand.) Weighted majority alg.
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Let's play a game!Prisoner's Dilemma

- Setting:
- Two members of criminal gang are arrested
 - They are put in separate cells
 - ⇒ no means to communicate!
 - Police does not have evidence to convict both of them on the principal charge
 - But: they are able to sentence them on a lesser charge for a year
 - They offer each one of them:
"If you testify against the other, you walk free, and him will go to jail for three years"
 - Catch: If both testify, they both go to prison, but "only" for two years

matrix
Compact representation of possible outcomes:

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Prisoner B:		silent	testify
Prisoner A:	silent	1 year 1 year	0 years 3 years
	testify	3 years 0 years	2 years 2 years

What will the prisoners do?

→ Intuitively: The "optimal" outcome for them is silent/silent
⇒ they get "only" 1 year of jail each

→ But is that what will really happen?

Note: → If both prisoners are silent, then if any one of them switches to testify, he/she decreases his/her jail time from two to zero years!

→ Also, if exactly one testifies then the other one has incentive to testify as well (to go from three to two years)

⇒ The only "stable" outcome: (i.e., no one has incentive to deviate)

Both prisoners testify

Remark: → This behavior is somewhat hard to replicate in real world as this analysis ignores factors like "repeated" nature of the game
(e.g., if I "betray" you now, you will take revenge later)

Games (from game theory perspective):

Thought experiments to help us learn how to predict rational behavior in situations of conflict

↑
Players aim to maximize their own utility (= gain)
(Altruism, masochism, etc. are NOT modelled)

↑
Every player's actions affect the other players' utility
(not necessarily in negative way)

Convenient way to represent two-player game:

Utility matrices: $A =$ utility matrix of Player A
 $B =$ ——— || ——— B

Rows of A (B) = actions of Player A (= Row player)
Columns of A (B) = ——— || ——— B (= Column player)

Given action i of Player A (row) & action j of Player B (column):

A_{ij} = utility of Player A on outcome (i, j)

B_{ij} = ——— || ——— B on outcome (i, j)

Important class of games: (Two-person) zero-sum games

Two-person games in which:

$$A_{ij} = -B_{ij} \quad \forall_{i,j}$$

Note: Fully described by matrix A (or B) alone

⇒ Models direct conflict

(= "your loss is my gain")

⇒ Prisoner's Dilemma is NOT zero-sum

Example: Rock-Paper-Scissors game

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Matrix A:

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

Matrix B:
(= -A)

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

Is there a "stable" outcome?

* No, if consider only ^{pairs of} single action (= deterministic strategy)

If row player chooses rock \rightarrow column player has incentive to switch to paper

\rightarrow But, then row player has incentive to play scissors

\rightarrow But, then column player has incentive to switch to rock...

"infinite loop of switching"

* Yes if we allow randomized strategies!

\Rightarrow If both players randomize uniformly at random over rock, paper & scissors, no one can improve their expected utility by switching to different strategy

\Rightarrow The pair of strategies $(\frac{1}{3}, \frac{1}{3}, \frac{1}{3}), (\frac{1}{3}, \frac{1}{3}, \frac{1}{3})$ is a Nash equilibrium of R-P-S game

Nash Equilibrium: A state of game (= choice of (possibly randomized) strategies for each player) such that no player can improve his/her expected utility by unilaterally changing his/her strategy

[Nash '50]
(= "stable" outcome)

"Fun" fact: "Beautiful Mind" movie got this concept WRONG!

Note: (testify, testify) = pure Nash equilibrium of deterministic prisoner's dilemma game (5)

Fundamental question: Does Nash equilibrium always exist?

Min-Max Theorem: [von Neumann '28]

$$P = \{x \mid x \geq 0 \text{ \& } \sum x_i = 1\}$$

$$Q = \{y \mid y \geq 0 \text{ \& } \sum y_j = 1\}$$

For any matrix A , if

$$V_R := \max_{x \in P} \min_{y \in Q} x A y \quad \& \quad V_C := \min_{y \in Q} \max_{x \in P} x A y$$

then

$$V_R = V_C = V$$

Game theory interpretation:

→ V_R = expected utility of row player if she/he needs to go first (i.e., disclose his/her strategy before the other player discloses his/her)

→ V_C = expected negative utility of column player if he/she goes first

⇒ Row player wants to maximize $x A y$
Column player wants to minimize $x A y$

⇒ $V_R \leq V_C$ as V_R corresponds to row player playing with a handicap
(column player can switch seeing x)
& row player has an advantage in case of V_C

⇒ So, $V_R = V_C$ is surprising!

Key implication:

$$x^* := \operatorname{argmax}_x \min_y x A y$$

$$y^* := \operatorname{argmin}_y \max_x x A y$$

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$\Rightarrow (x^*, y^*)$ is always a Nash equilibrium of the two-person zero-sum game described by A
(If there was an incentive to deviate from x^* or y^* it would contradict that $V_R = V_C$)

\Rightarrow Nash equilibrium always exists for two-person zero-sum games

How about general games?

[Nash '51]: Any game with a finite number of players and finite number of possible actions per player has a Nash equilibrium

Proof of Min-Max Theorem:

Key idea: Let's express V_R (& V_C) as an LP!

Recall: $V_R = \max_x \min_y x A y$

\Rightarrow if $z = V_R$ and x is the strategy corresponding to V_R , we have to have that, for any column action j , the expected utility we get if column player plays j has to be $\geq z$
(otherwise col. player could switch to playing j and thus contradict that $z = V_R$)

\Rightarrow In other words:

$$\sum_i A_{ij} x_i \geq z \quad \forall_j$$

→ Also, as x is a randomization over actions

$$\sum_i x_i = 1 \quad \& \quad x_i \geq 0 \quad \forall_i$$

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As, z is the expected utility we are guaranteed to get in this case, we can write:

$$V_R = \max z$$
$$\left(\sum_{i,j} A_{ij} x_i \right) - z \geq 0 \quad \forall_j$$
$$\sum_i x_i = 1$$
$$x_i \geq 0$$

(R)

By similar reasoning (taking into account col. player wants to min. $x A y$)

$$V_C = \min u$$
$$\left(\sum_{i,j} A_{ij} y_j \right) - u \leq 0 \quad \forall_i$$
$$\sum_j y_j = 1$$
$$y_j \geq 0$$

(C)

Key observation: (R) & (C) are dual to each other!

(See next page)

⇒ By strong LP duality:

$$V_R = \underset{\substack{\uparrow \\ \text{Def of (R)}}}{\text{OPT}(R)} = \underset{\substack{\uparrow \\ \text{Def of (C)}}}{\text{OPT}(C)} = V_C$$

⇒ Strong LP duality implies Min-Max Thm.

(In fact, one can show these two are equivalent!)

{ }

"Missing" calculations:

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→ (R) in standard form:

$$\max z^+ - z^-$$

$$-\sum_j A_{ij} x_j + z^+ - z^- \leq 0 \quad \forall_i$$

$$\sum_i x_i \leq 1$$

$$-\sum_i x_i \leq -1$$

$$x, z^+, z^- \geq 0$$

$$(y_j)$$

$$(u^+)$$

$$(u^-)$$

→ Dual of (R)

$$\min u^+ - u^-$$

$$-\sum_j A_{ij} y_j + u^+ - u^- \geq 0 \quad \forall_i$$

$$\sum_j y_j \geq 1$$

$$-\sum_j y_j \geq -1$$

$$y, u^+, u^- \geq 0$$

$$\left. \begin{array}{l} \sum_j y_j \geq 1 \\ -\sum_j y_j \geq -1 \end{array} \right\} \sum_j y_j = 1$$

→ Taking $u = u^+ - u^-$ and multiplying \geq by (-1) gives us (C) !

□

How to get rich (if you have good advice)

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(Very simple) stock market model:

- X_t = stock market index on day t (e.g., value of Dow Jones at day t)
- Initially, $X_0 = 0$
- Each day t :

- You have to predict if $X_t = X_{t-1} + 1$ (UP) or $X_t = X_{t-1} - 1$ (DOWN)
- Only then, X_t is revealed
 - ⇒ If your prediction was correct, gain \$1M
 - otherwise, lose \$1M

How well can you do if you don't know how X_t evolves?

- Best we can do: flip a coin
 - ⇒ Expected gain is 0

⇒ Additional element: n "experts"

Each day t : Before you have to make a prediction, you get UP/DOWN advice from each expert

Note: This advice does not need to be consistent. Some might say UP, some might claim DOWN.

← "experts" as in "they have an opinion", but not necessarily know what they are talking about
⇒ Think: Financial advisors in CNN, WSJ, etc.

Problem: This advice might be wrong or even misleading!

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Goal: Do well if at least one expert is consistently providing decent advice

Measure of quality:

$$\text{Regret} = (\# \text{ of } \underline{\text{our}} \text{ mis predictions}) - (\# \text{ of mistakes of the } \underline{\text{best}} \text{ expert})$$

→ Think: How much better off would we be, if we followed advice of the best expert from the start

Key difficulty: We know who the best expert is only in hindsight! (and then it's too late)

How to approach this problem?

① Easier case: The best expert makes NO mistakes

→ Halving algorithm:

→ Maintain a pool S of "trustworthy" experts

→ At first, S = all experts

→ At day:

→ Go with majority prediction of only experts in S

→ After seeing X_t , remove from S , all experts that mis predicted
(Pruning of S)

Exercise: How good is this alg. if we never prune S ?

Claim: Halving algorithms has regret $\leq \log_2 n$ (11)
(= makes $\leq \log_2 n$ mistakes) (does not depend on length of the sequence)

Can show: This is best possible bound here

Proof: Every time the alg. makes a mistake, we reduce the size of S by at least half (in pruning step)
 \Rightarrow it takes $\leq \log_2 n$ halvings to reduce size of S to 1 (which would be the (unique) perfect expert) $\boxed{?}$

② General setting: Even the best expert makes some m^* mistakes

\rightarrow Iterated halving alg.:

\rightarrow Run halving alg.

Remember: Everyone might make a mistake now

\rightarrow If S becomes empty after pruning

\Rightarrow Replenish S by putting all experts back

\rightarrow Can show: Iterated halving alg. has regret

$$\leq (m^* + 1) \log_2 n$$

\rightarrow This is within $\approx \log_2 n$ of optimum

Can we do better?

Obs 1: Replenishing the set S loses a lot of valuable info. No difference between very bad expert and pretty good but not perfect expert
few mistakes \rightarrow \uparrow tons of mistakes

Obs 2: Classifying experts as either "trustworthy" or not "trustworthy" is too coarse ($\in S$) ($\notin S$)

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Idea: Use weights to capture "trustworthiness" of experts in a more continuous manner

\Rightarrow Update this estimate of our trust by reducing the weight of an expert upon each mistake

\Rightarrow Aggregate predictions by taking a weighted majority of answers

Weighted majority (WM) alg.:

\rightarrow Maintain a weight w_i for each expert:

\rightarrow Initially, $w_i = 1$, for all i

\rightarrow At day t :

\rightarrow Predict by following weighted majority

\rightarrow After X_t is revealed, $w_i \leftarrow \frac{1}{2} w_i$, for each expert i that was wrong

Claim: WM alg. has the regret of

$$\leq 1.4 \cdot m^* + 2.4 \log_2 n$$

Proof:

Let w_i^t = weight of expert i at the end of day t

Consider a potential $W^t := \sum_i w_i^t \Rightarrow W^0 = n$

Each time the alg. makes a mistake

$\Rightarrow \geq \frac{1}{2}$ of total weight of experts gets their w_i halved

i.e. $W^t \leq \frac{3}{4} W^{t-1}$ in such rounds

\Rightarrow If T is the total # of days, and m is the # of mistakes of the WM alg., then

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$$(*) \quad W^T \leq \left(\frac{3}{4}\right)^m W^0 = \left(\frac{3}{4}\right)^m n$$

Note: Even if the alg. makes no mistake on day t , we still have

$$W^t \leq W^{t-1}$$

On the other hand:

If i^* is the best expert and m^* is the # of his/her mistakes, then

$$(**) \quad W_{i^*}^T = \left(\frac{1}{2}\right)^{m^*}$$

Putting $(*)$ & $(**)$ together, we get

$$\left(\frac{1}{2}\right)^{m^*} \leq W_{i^*}^T \leq W^T \leq \left(\frac{3}{4}\right)^m n$$

$$\Rightarrow m^* \log_2 \frac{1}{2} \leq m \log_2 \frac{3}{4} + \log_2 n$$

(Taking $\log_2(\cdot)$ of both sides)

$$\Rightarrow m \leq 2.4 (m^* + \log_2 n)$$

(Use $-\frac{1}{\log_2 \frac{3}{4}} \approx 2.4$)

$$\Rightarrow \text{Regret} = m - m^* \leq 1.4 m^* + 2.4 \log_2 n$$



So, WM alg. gets performance that approaches (when $m^* \rightarrow \infty$) only const. overhead compared to best expert!

In fact: If we make weight reduction by a factor of $(1-\epsilon)^{-1}$ instead of 2, for some $0 < \epsilon \leq \frac{1}{2}$

$$\Rightarrow \text{Regret} \leq (1+\epsilon) m^* + \frac{2}{\epsilon} \log_2 n$$

Can we do even better?

Yes, but have to use randomness

Idea: (Deterministic) weighted majority vote

⇓

Randomized weighted majority sampling

(= when making prediction,
sample a single expert i
proportionally to his/her weight w_i
& follow his/her prediction)

← $\Pr[\text{choose prediction of expert } i] = \frac{w_i}{\sum_j w_j}$

→ This helps with "tie breaking" when the advice is split

Can show: Randomize weighted majority alg. has regret

$$\leq \varepsilon \cdot m^* + \frac{\log_2 n}{\varepsilon}$$

→ This is best possible

→ As $m^* \rightarrow +\infty$ & $\varepsilon \rightarrow 0^+$ (appropriately)

Regret becomes $o(m^*)$!

⇒ Asymptotically, regret is vanishing