Announcements

- HW 2 will be due this Saturday.
  - Can chat with me after today's class if any help is needed
- Project proposals are all well-done!
- HW 3, about online learning, will be out this Saturday
  - Will be lighter
  - Please focus more on project from now on

Goals for Today

Wrap up online learning by designing learning algorithms

✓Against stronger benchmark

✓Under partial/bandit feedback

CMSC 35401: The Interplay of Economics and ML (Winter 2024)

Swap Regret and Convergence to CE

Instructor: Haifeng Xu

Outline

- (External) Regret vs Swap Regret
- Convergence to Correlated Equilibrium
- Converting No Regret to No Swap Regret

Recap: Online Learning

At each time step $t = 1, \cdots, T$, the following occurs in order:

1. Learner picks a distribution p_t over actions $[n]$
2. Adversary picks cost vector $c_t \in [0,1]^n$
3. Action $i_t \sim p_t$ is chosen and learner incurs cost $c_t(i_t)$
4. Learner observes c_t (for use in future time steps)

Recap: (External) Regret

- External regret

$$R_T = \mathbb{E}_{i_t \sim p_t} \sum_{t \in [T]} c_t(i_t) - \boxed{\min_{j \in [n]} \sum_{t \in [T]} c_t(j)}$$

- Benchmark $\min_{j \in [n]} \sum_t c_t(j)$ is the learner utility had he known $c_1, \cdots, c_T$ and is allowed to take the best single action across all rounds
- Describes how much the learner regrets, had he known the cost vector $c_1, \cdots, c_T$ in hindsight

Recap: (External) Regret

➢ A closer look at external regret

$$R_T = \mathbb{E}_{i_t \sim p_t} \sum_{t \in [T]} c_t(i_t) - \min_{j \in [n]} \sum_{t \in [T]} c_t(j)$$

$$= \sum_{t \in [T]} \sum_{i \in [n]} c_t(i) p_t(i) - \min_{j \in [n]} \sum_{t \in [T]} c_t(j)$$

$$= \max_{j \in [n]} \left[\sum_{t \in [T]} \sum_{i \in [n]} c_t(i) p_t(i) - \sum_{t \in [T]} c_t(j) \right]$$

$$= \max_{j \in [n]} \sum_{t \in [T]} \sum_{i \in [n]} [c_t(i) - c_t(j)] p_t(i)$$

Many-to-one action swap

Recap: (External) Regret

- A closer look at external regret

$$R_T = \mathbb{E}_{i_t \sim p_t} \sum_{t \in [T]} c_t(i_t) - \min_{j \in [n]} \sum_{t \in [T]} c_t(j)$$

$$= \sum_{t \in [T]} \sum_{i \in [n]} c_t(i) p_t(i) - \min_{j \in [n]} \sum_{t \in [T]} c_t(j)$$

$$= \max_{j \in [n]} \left[\sum_{t \in [T]} \sum_{i \in [n]} c_t(i) p_t(i) - \sum_{t \in [T]} c_t(j) \right]$$

$$= \max_{j \in [n]} \sum_{t \in [T]} \sum_{i \in [n]} \boxed{[c_t(i) - c_t(j)]} p_t(i)$$

- In external regret, adversary is allowed to swap to a single action j and can choose the best j in hindsight

Swap Regret

- A closer look at external regret

$$R_T = \max_{j \in [n]} \sum_{t \in [T]} \sum_{i \in [n]} [c_t(i) - c_t(j)] p_t(i)$$

$c_t(s(i))$

- Swap regret allows many-to-many action swap
  - E.g., $s(1) = 2, s(2) = 1, s(3) = 4, s(4) = 4$
- Formally,

$$swR_T = \max_{s} \sum_{t \in [T]} \sum_{i \in [n]} [c_t(i) - c_t(s(i))] p_t(i)$$

where $\max$ is over all possible swap functions

- Each action i has n choices to swap to, so n^n many swap functions
- Quiz: how many many-to-one swaps?

Useful Facts about Swap Regret

Fact 1. For any algorithm: $swR_T \geq R_T$

Fact 2. For any algorithm execution $p_1, \cdots, p_T$, the optimal swap function s^* satisfies, for any i,

$$s^*(i) = \arg\max_{j \in [n]} \sum_{t \in [T]} [c_t(i) - c_t(j)] p_t(i)$$

Recall swap regret

$$swR_T = \max_s \sum_{t \in [T]} \sum_{i \in [n]} [c_t(i) - c_t(s(i))] p_t(i)$$

Proof:

- $s(i)$ only affects term $\sum_{t \in [T]} [c_t(i) - c_t(s(i))] p_t(i)$, so should be picked to maximize this term

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$$s^*(i) = \arg\max_{j \in [n]} \sum_{t \in [T]} [c_t(i) - c_t(j)] p_t(i)$$

Remarks:

- The optimal swap can be decided "independently" for each i

Useful Facts about Swap Regret

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$$s^*(i) = \arg\max_{j \in [n]} \sum_{t \in [T]} [c_t(i) - c_t(j)] p_t(i)$$

Remarks:

- Benchmark of swap regret depends on the algorithm execution $p_1, \cdots, p_T$, but benchmark of external regret does not.
- This raises a subtle issue: an algorithm minimize swap regret does not necessarily minimize the total loss
  - An algorithm may intentionally take less actions so the benchmark does not have many opportunities to swap

Useful Facts about Swap Regret

Fact 1. For any algorithm: $swR_T \geq R_T$

Fact 2. For any algorithm execution $p_1, \cdots, p_T$, the optimal swap function s^* satisfies, for any i,

$$s^*(i) = \arg\max_{j \in [n]} \sum_{t \in [T]} [c_t(i) - c_t(j)] p_t(i)$$

pick worst i

$$\max_{i \in [n]} \max_{j \in [n]} \sum_{t \in [T]} [c_t(i) - c_t(j)] p_t(i)$$

is also called the *internal regret*

Note: internal regret $\leq$ swap regret $\leq n \times$ internal regret

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- (External) Regret vs Swap Regret
- Convergence to Correlated Equilibrium
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Recap: Normal-Form Games and CE

- n players, denoted by set $[n] = \{1, \cdots, n\}$
- Player i takes action $a_i \in A_i$
- Player utility depends on the outcome of the game, i.e., an action profile $a = (a_1, \cdots, a_n)$
  - Player i receives payoff $u_i(a)$ for any outcome $a \in \Pi_{i=1}^{n} A_i$
- Correlated equilibrium is an action recommendation policy

A recommendation policy π is a **correlated equilibrium** if

$$\sum_{a_{-i}} u_i(a_i, a_{-i}) \cdot \pi(a_i, a_{-i}) \geq \sum_{a_{-i}} u_i(a'_i, a_{-i}) \cdot \pi(a_i, a_{-i}), \forall a_i, a'_i \in A_i, \ \ \forall i.$$

- That is, for any recommended action a_i, player i does not want to “swap” to another a_i'

Repeated Games with No-Swap-Regret Players

- The game is played repeatedly for T rounds
- Each player uses an online learning algorithm to select a mixed strategy at each round t
- For any player i's perspective, the following occurs in order at t
  - Picks a mixed strategy $x_i^t \in \Delta_{|A_i|}$ over actions in A_i
  - Any other player $j \neq i$ picks a mixed strategy $x_j^t \in \Delta_{|A_j|}$
  - Player i receives expected utility $u_i(x_i^t, x_{-i}^t) = \mathbb{E}_{a \sim (x_i^t, x_{-i}^t)} u_i(a)$
  - Player i learns x_{-i}^t (for future use)

From No Swap Regret to Correlated Equ

Theorem. If all players use no-swap-regret learning algorithms with strategy sequence $\{x_i^t\}_{t\in[T]}$ for i. The following recommendation policy π^T converges to a CE: $\pi^T(a) = \frac{1}{T}\sum_t \Pi_{i\in[n]} x_i^t(a_i)$, $\forall\, a \in A$.

Remarks:

- In mixed strategy profile $(x_1^t, x_2^t, \cdots, x_n^t)$, prob. of a is $\Pi_{i\in[n]} x_i^t(a_i)$
- $\pi^T(a)$ is simply the average of $\Pi_{i\in[n]} x_i^t(a_i)$ over T rounds

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Proof:

- Derive player i's expected utility from π^T

$$\sum_{a\in A} \left[\frac{1}{T}\sum_t \Pi_{i\in[n]} x_i^t(a_i)\right] \cdot u_i(a)$$

$$= \frac{1}{T}\sum_t \sum_{a\in A} \Pi_{i\in[n]} x_i^t(a_i) \cdot u_i(a)$$

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$$= \frac{1}{T}\sum_t u_i(x_i^t, x_{-i}^t)$$

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$$= \frac{1}{T}\sum_t u_i(x_i^t, x_{-i}^t)$$

$$= \frac{1}{T}\sum_{a_i\in A_i} \sum_{t=1}^{T} u_i\left(a_i, x_{-i}^t\right) \cdot x_i^t(a_i)$$

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$$= \frac{1}{T}\sum_t u_i(x_i^t, x_{-i}^t)$$

$$= \frac{1}{T}\sum_{a_i\in A_i}\sum_{t=1}^T u_i\left(a_i, x_{-i}^t\right)\cdot x_i^t(a_i)$$

- Player i's expected utility conditioned on being recommended a_i is

$$\frac{1}{T}\sum_{t=1}^T u_i\left(a_i, x_{-i}^t\right)\cdot x_i^t(a_i)$$ (normalization factor omitted)

From No Swap Regret to Correlated Equ

Theorem. If all players use no-swap-regret learning algorithms with strategy sequence $\{x_i^t\}_{t\in[T]}$ for i. The following recommendation policy π^T converges to a CE: $\pi^T(a) = \frac{1}{T}\sum_t \Pi_{i\in[n]} x_i^t(a_i)$, $\forall\, a \in A$.

Proof:

- To verify CE, need to show for all player i and all $a_i \in A_i$

$$\geq \frac{1}{T}\sum_{t=1}^{T} u_i\big(s(a_i), x_{-i}^t\big) \cdot x_i^t(a_i), \quad \forall s(a_i) \in A_i$$

- Let s^* be the optimal swap function in the swap regret:

$$swR_T^i = \max_s \sum_{t=1}^{T} \sum_{a_i\in A_i} [u_i(s(a_i), x_{-i}) - u_i\big(a_i, x_{-i}^t\big)] \cdot x_i^t(a_i)$$

$$= \sum_{a_i}\Big(\sum_{t=1}^{T} [u_i(s^*(a_i), x_{-i}) - u_i\big(a_i, x_{-i}^t\big)] \cdot x_i^t(a_i) \Big)$$

$$\geq \sum_{t=1}^{T} \big[u_i(s^*(a_i), x_{-i}) - u_i\big(a_i, x_{-i}^t\big)\big] \cdot x_i^t(a_i), \quad \forall a_i$$

$$\frac{1}{T}\sum_{t=1}^{T} u_i\big(a_i, x_{-i}^t\big) \cdot x_i^t(a_i)$$

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Theorem. If all players use no-swap-regret learning algorithms with strategy sequence $\{x_i^t\}_{t\in[T]}$ for i. The following recommendation policy π^T converges to a CE: $\pi^T(a) = \frac{1}{T}\sum_t \Pi_{i\in[n]} x_i^t(a_i), \forall\, a \in A$.

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- From **Fact 2** before, optimal swap function s^* satisfies

$$s^*(a_i) = \arg\max_{s(a_i)\in A_i} \sum_{t=1}^{T}\left[u_i(s(a_i), x_{-i}) - u_i\left(a_i, x_{-i}^t\right)\right] \cdot x_i^t(a_i)$$

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Proof:

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➢ Let s^* be the optimal swap function in the swap regret:

$$swR_T^i \geq \sum_{t=1}^{T}\left[u_i(s^*(a_i), x_{-i}) - u_i\left(a_i, x_{-i}^t\right)\right] \cdot x_i^t(a_i), \quad \forall a_i$$

➢ From **Fact 2** before, optimal swap function s^* satisfies

$$s^*(a_i) = \arg\max_{s(a_i)\in A_i} \sum_{t=1}^{T}\left[u_i(s(a_i), x_{-i}) - u_i\left(a_i, x_{-i}^t\right)\right] \cdot x_i^t(a_i)$$

➢ This implies

Thm follows by diving both sides by $T (\rightarrow \infty)$

$$swR_T^i \geq \sum_{t=1}^{T}\left[u_i(s(a_i), x_{-i}) - u_i\left(a_i, x_{-i}^t\right)\right] \cdot x_i^t(a_i), \quad \forall a_i \text{ and } s(a_i)$$

Outline

- (External) Regret vs Swap Regret
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Good External Regret $\neq$ Good Swap Regret

- An algorithm with small swap regret also has small external regret
- The reverse is not true – an algorithm with small external regret does not necessarily have small swap regret
  - Examples are not difficult to construct

Does online learning algorithm with sublinear no swap regret exist?

Theorem. Any online algorithm A with external regret R can be converted to another online algorithm H swap regret nR.

$n =$ number of actions

- H utilizes A but is different and more complicated
- There exists no-swap-regret online learning algorithm
  - Since there exists online algorithm with $O(\sqrt{T \ln n})$ regret

Theorem. Any online algorithm A with external regret R can be converted to another online algorithm H swap regret nR.

Proof Overview:

- The idea starts from the following observations

Let s^* be the optimal swap function, then:

$$swR_T = \max_s \sum_{t\in[T]} \sum_{i\in[n]} [c_t(i) - c_t(s(i))] p_t(i)$$
$$= \sum_{i\in[n]} \Big(\sum_{t\in[T]} [c_t(i) - c_t(s^*(i))] p_t(i) \Big)$$

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Let s^* be the optimal swap function, then:

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$$= \sum_{i\in[n]} \Big(\sum_{t\in[T]} [c_t(i) - c_t(s^*(i))]p_t(i) \Big)$$

regret from action i's swap

Two observations:

1. The red terms "looks like" an external regret term
    - Swap to a single action, but $\sum_{t\in[T]} c_t(i)p_t(i)$ does not look quite right yet
2. If the red term is less than R for any i, then we are done

Theorem. Any online algorithm A with external regret R can be converted to another online algorithm H swap regret nR.

Proof Step 1: constructing H

➢ Make n copies of algorithm A as $A_1, \cdots, A_n$

- Intuitively, A_i takes care of the regret from action i's swap

➢ Construction of H

- At round t, H uses algorithm A_i with probability $p_t(i)$ (to be designed)
- Let $q_t^i \in \Delta_n$ be the randomized action of A_i generated at round t
- Choose $p_t(i) \in [0,1]$ to satisfy the following:

$\sum_i p_t(i) = 1$ ⟶ p_t is a distribution

$\sum_i p_t(i) q_t^i(j) = p_t(j), \forall j \in [n]$ ⟶ p_t is stationary

That is, following two ways for H to select actions are equivalent

1. Select algorithm A_i with prob $p_t(i)$, then use A_i to pick an action
2. Select i with probability $p_t(i)$

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  - Intuitively, A_i takes care of the regret from action i's swap
- Construction of H
  - At round t, H uses algorithm A_i with probability $p_t(i)$ (to be designed)
  - Let $q_t^i \in \Delta_n$ be the randomized action of A_i generated at round t
  - Choose $p_t(i) \in [0,1]$ to satisfy the following:

$\sum_i p_t(i) = 1$ → p_t is a distribution

$\sum_i p_t(i) q_t^i(j) = p_t(j), \forall j \in [n]$ → p_t is stationary

  - After observing cost vector c_t, allocate $p_t(i) \cdot c_t$ as the "simulated cost" to algorithm A_i for its future use

Theorem. Any online algorithm A with external regret R can be converted to another online algorithm H swap regret nR.

Proof Step 2: deriving regret bound

- A_i has external regret R, so

$$\sum_{t\in[T]} \sum_j q_t^i(j)\,[p_t(i)c_t(j) - p_t(i)c_t(j')] \leq R \quad \forall j' \in [n] \qquad (1)$$

- Swap regret of H

$$swR_T = \max_s \sum_{t\in[T]} \sum_{j\in[n]} p_t(j)[c_t(j) - c_t(s(j))]$$

Need to somehow relate swR_T to q_t^i's, because Inequality (1) is the only bound we have

By our construction: $\sum_i p_t(i) q_t^i(j) = p_t(j)\,, \forall j \in [n]$

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- A_i has external regret R, so

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- Swap regret of H

$$swR_T = \max_s \sum_{t\in[T]}\sum_{j\in[n]} p_t(j)[c_t(j)-c_t(s(j))]$$

$$= \max_s \sum_{t\in[T]}\sum_{j\in[n]} \sum_i p_t(i)q_t^i(j)\,[c_t(j)-c_t\big(s(j)\big)]$$

$$= \max_s \sum_i \Big(\sum_{t\in[T]}\sum_{j\in[n]} p_t(i)q_t^i(j)[c_t(j)-c_t(s(j))]\Big)$$

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Proof Step 2: deriving regret bound

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- Swap regret of H

$$swR_T = \max_s \sum_{t\in[T]}\sum_{j\in[n]} p_t(j)[c_t(j) - c_t(s(j))]$$

$$= \max_s \sum_{t\in[T]}\sum_{j\in[n]}\sum_i p_t(i)q_t^i(j)\,[c_t(j) - c_t(s(j))]$$

$$= \max_s \sum_i\Big(\sum_{t\in[T]}\sum_{j\in[n]} p_t(i)q_t^i(j)[c_t(j) - c_t(s(j))]\Big)$$

$$\le n\cdot R$$

Thank You

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