

Secretary & Prophet

Recall the secretary problem from last lecture.

we have n candidates for a secretary position and we assume there is a universal ordering of them, i.e. if we compare any two candidate i & j we can say which one is better for the job.

The candidates arrive in a u.r. dist. order; each time we interview we must decide to either **hire** (and terminate the process) or **pass** and continue.

Goal: Find a strategy to maximize the prob. of hiring the best candidate.

We proposed the following algo:

- pass for the first $\frac{n}{e}$ candidates
- Then hire the candidate that is the best seen so far.

Theorem: This algorithm finds/hires the best candidate with prob. $\frac{1}{e}$.

We showed that if we pass k and then hire the best we hire the best with prob. $(1 - o(1)) \frac{k}{n} \ln\left(\frac{n}{k}\right)$ and with $k \approx \frac{n}{e}$ this is maximized.

We can show that in this problem the best strategy is in fact a wait-and-pick strategy like what we described.

Theorem: The strategy that maximizes picking the best candidate is a wait-and-pick strategy

Proof: Consider some fixed optimal strategy.

let P_i : prob. the strategy picks agent at position i

q_i : prob. pick agent at position i conditioned on it being the best seen so far.

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$$\text{So } q_i = \frac{P_i}{\sum_j P_j} = i \cdot P_i$$

$$\begin{aligned} \Pr[\text{Picking the best}] &= \sum_i P_i [i\text{'th agent is the best \& we pick it}] \\ &= \sum_i P_i [i\text{'th agent is the best}] \cdot q_i \\ &= \sum_i \frac{1}{n} q_i = \sum_i \frac{i}{n} P_i \end{aligned}$$

clearly $0 \leq P_i \leq 1$ and we have:

$$\begin{aligned} P_i &= \Pr[\text{pick agent } i \mid i \text{ is the best so far}] \cdot \Pr[i \text{ is best so far}] \\ &\leq \Pr[\text{did not pick } 1 \dots i-1 \mid i \text{ is best so far}] \cdot \frac{1}{i} \end{aligned}$$

But not picking $1 \dots (i-1)$ is independent of " i being the best so far"

$$\text{So } P_i \leq \frac{1}{i} \left(1 - \sum_{j < i} P_j\right)$$

So we can upper-bound the success prob. of this (and any) strategy by the following LP:

$$\begin{aligned} \max \quad & \sum_i \frac{i}{n} \cdot P_i \\ \text{s.t.} \quad & i \cdot P_i \leq 1 - \sum_{j < i} P_j \\ & 0 \leq P_i \leq 1 \end{aligned}$$

It can be verified that:

$$\begin{cases} P_i = 0 & \text{for } i < k \\ (k-1)\left(\frac{1}{i-1} - \frac{1}{i}\right) & k \leq i \leq n \end{cases} \quad \text{is a feasible solution where } k = \text{smallest int s.t. } H_{n-1} - H_{k-1} \leq 1$$

It can be shown that the dual LP has a solution of the same value $\longrightarrow$ must be optimum.

or the same value $\rightarrow$ must be optimum.

We have a wait-and-pick strategy whose value is the same as this LP solution:

For position i , if we have not picked any & this is the best so far, pick with prob. $\frac{i P_i}{1 - \sum_{j < i} P_j}$

then it can be shown that this is picking the best candidate with prob. $\sum_i \frac{1}{n} \cdot P_i$ which is the same as the LP.

Extension: Multiple agents

Suppose we want to hire k agents (or pick k items) instead of just 1.

Goal: maximize the expected sum of the values of these

Say the set of k largest items are $S^* \subseteq [n]$ and their total values is $V^* = \sum_{i \in S^*} a_i$

First approach: Suppose we pass on the first $\frac{n}{2}$ agents.

Note that we expect half ($\sim \frac{k}{2}$) of the largest be in the first half and half ($\sim \frac{k}{2}$) be in the second half.

Suppose we use the value $\tilde{a}$ of the $\frac{(1-\epsilon)k}{2}$ th largest element in the first half as the threshold and pick up to k items from the second half if their values are $\geq \tilde{a}$. We can formalize this.

let $\delta = O(\frac{\log k}{\frac{1}{1-\epsilon}})$ and $\epsilon = \delta/2$. Our goal is an algorithm

let $\delta = O\left(\frac{\log k}{k^{1/3}}\right)$ and $\epsilon = \delta/2$. Our goal is an algorithm

that gives value $V^*(1-\delta)$ (note $\delta \rightarrow 0$ when $k \rightarrow \infty$)

— pass the first δn items

(we expect $\approx k^{2/3} / \log k$ items from S^* in this set)

— let $\tilde{a}$ be the value of $(1-\epsilon)\delta k$ 'th highest among the "passed" items; pick the first k elements in the remaining $(1-\delta)n$ with value $\geq \tilde{a}$

Bad events: E1: if $a' = \min_{i \in S^*} a_i$ is the lowest value of S^* and $\tilde{a} < a'$ (we pick items with lower value)

E2: # of items from S^* in the last $(1-\delta)n$ and greater than $\tilde{a}$ is much smaller than k

Why these bad events happen rarely:

For E1, less than $(1-\epsilon)\delta k$ items from S^* fall in the first δn locations; this requires the # of them is smaller than $(1-\epsilon) \times$ expectation.

Using Chernoff-Hoeffding this prob $\leq e^{-\epsilon^2 \delta k} \approx \frac{1}{\text{poly}(k)}$

For E2 to happen, more than $(1-\epsilon)\delta k$ of the top $(1-\delta)k$ from S^* must be in the first δn elements.

This means the # of them exceeds $(1+\alpha(\epsilon))$ times the expectation, again has probability $\leq e^{-\epsilon^2 \delta k} = \frac{1}{\text{poly}(k)}$

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$1 - O(\frac{1}{\sqrt{k}})$ competitive ratio for the k -Secretary & this is best possible.

The Prophet inequality

- The setting and the goal of this is slightly different

- We have a distribution for the value of each item but don't know the actual value until the candidate is sampled (interviewed).

The arrival of candidates/items is not random but adversarial!

Formally: An ordered set of random variables $X_1, \dots, X_n$, with known distribution.

At each step i we sample $x_i \sim X_i$ and get its value: can decide to accept (terminate) or pass (continue).

Goal: maximize the expected value of chosen item compared to $\max_i X_i$

i.e. find an algorithm A st. $\mathbb{E}[A] \geq \alpha \cdot \mathbb{E}[\max_i X_i]$

while maximizing α .

First we show we cannot have $\alpha > \frac{1}{2}$

Suppose X_1 is always 1 while $X_2 = 0$ with prob $1 - \epsilon$

and $X_2 = \frac{1}{\epsilon}$ with prob. ϵ . Then

$$\mathbb{E}[\max\{X_1, X_2\}] = (1 - \epsilon) \cdot 1 + \epsilon \cdot \frac{1}{\epsilon} = 2 - \epsilon$$

Any strategy either picks X_1 (which has always value 1) or picks X_2 and in either case $\mathbb{E}[\text{algorithm}] = 1$

So we cannot have $\alpha > \frac{1}{2}$, but surprisingly we can get $\alpha = \frac{1}{2}$

Theorem (Krengel, Sucheston, Garling) There is a strategy with $\alpha = \frac{1}{2}$

proof: The idea is similar to the secretary problem, however because the arrival is not random (could be adversarial) we cannot ignore a fixed collection of values.

Define $X_{\max} = \max X_i$ and let $\tau = \frac{1}{2} \mathbb{E}[X_{\max}]$.

The algorithm is: Select the first X_i s.t. $\geq \tau$

i.e. the first time we sample a value $\geq \tau$.

For any random var Y let $Y^+ = \max\{Y, 0\}$

$$\begin{aligned} \mathbb{E}[X_{\max}] &= \mathbb{E}[\tau + X_{\max} - \tau] \\ &= \tau + \mathbb{E}[(X_{\max} - \tau)^+] \quad \text{since } (X_{\max} - \tau)^+ \geq X_{\max} - \tau \\ &\leq \tau + \mathbb{E}\left[\sum_i (X_i - \tau)^+\right] \\ &= \tau + \sum_i \mathbb{E}[(X_i - \tau)^+] \quad (*) \end{aligned}$$

let q be the prob. that the alg. returns some value

$$q = \Pr[\exists i: X_i \geq \tau] = 1 - \Pr[\forall i: X_i < \tau]$$

$$\mathbb{E}[\text{Alg}] = \sum_i \underbrace{\Pr\left[\bigwedge_{j < i} (X_j < \tau) \wedge (X_i \geq \tau)\right]}_{\text{Alg} = X_i} \cdot \mathbb{E}\left[X_i \mid \bigwedge_{j < i} (X_j < \tau) \wedge (X_i \geq \tau)\right]$$

since X_i 's ind

$$= \sum_i \Pr\left[\bigwedge_{j < i} (X_j < \tau)\right] \cdot \underbrace{\Pr[X_i \geq \tau]}_{X_i \text{ ind of } X_j} \cdot \mathbb{E}[\tau + (X_i - \tau)^+ \mid X_i \geq \tau]$$

$$\sum_i \Pr \left[\bigwedge_{j < i} (X_j < c) \right] \cdot \underbrace{\Pr[X_i \geq c] \cdot \mathbb{E}[c + (X_i - c) \mid X_i \geq c]}_{c + \mathbb{E}[(X_i - c)^+]} = \sum_i \Pr \left[\bigwedge_{j < i} (X_j < c) \right] \cdot \mathbb{E}[(X_i - c)^+]$$

Note that $q = \sum_i \Pr \left[\bigwedge_{j < i} (X_j < c) \right] \cdot \Pr[X_i \geq c]$

$$\mathbb{E}[\text{Alg}] = q \cdot c + \sum_i \Pr \left[\bigwedge_{j < i} (X_j < c) \right] \cdot \mathbb{E}[(X_i - c)^+]$$

$$\geq q \cdot c + \sum_i (1 - q) \mathbb{E}[(X_i - c)^+]$$

$$\geq q \cdot c + (1 - q) (\mathbb{E}[X_{\max}] - c) \quad \text{using (*)}$$

$$= c$$



LP-based Generalization

The following LP-based approach works for more general settings of prophet inequalities.

Suppose X_i comes from a known dist. and say it will have value $v_i \geq 0$ with prob. P_i and is zero otherwise (for simplicity we are focusing on disc version but the same argument works in general; in general we can have: $\Pr[X_i \geq v_i] = P_i$).

Consider the following LP:

$$\begin{aligned} \max \quad & \sum_i x_i \cdot v_i \\ \forall i \quad & x_i \leq P_i \\ & \sum_i x_i \leq 1 \end{aligned}$$

$$\sum_i x_i \leq 1$$

$$x_i \geq 0$$

let x^* be the opt LP solution

Lemma: $\sum_i x_i^* \cdot v_i \geq \mathbb{E}[X_{\max}]$

proof: we give a feasible sol with obj. value $\mathbb{E}[X_{\max}]$

let q_i be the prob. that X_i is non-zero and is $X_{\max}$

Note $q_i \leq p_i$ and $\sum_i q_i \leq 1$.

Also $\sum_i q_i \cdot v_i = \mathbb{E}[X_{\max}]$. 

Using this lemma we can design a $\frac{1}{4}$ -competitive alg.

Idea: the LP sol x^* suggests how frequently we should accept X_i (x_i^*).

if we had no constraints on how many X_i 's we can accept we could say: accept X_i when it has value v_i with prob. $\frac{x_i^*}{p_i}$, unless we have accepted something

This could have poor performance:

e.g. $X_1 = 1$ w.p. 1 $X_2 = \begin{cases} \frac{1}{\epsilon} & \text{w.p. } \epsilon \\ 0 & \text{o.w.} \end{cases}$

$x^* = (1-\epsilon, \epsilon)$ but an alg. that always accepts X_1 w.p. $1-\epsilon$ reaches X_2 without accepting anything at most ϵ -frac. of time. So

$$\Pr[\text{reach } x_2] \cdot \Pr[X_2 = \frac{1}{\epsilon^2}] = \epsilon^2 \rightarrow$$

Expected value is at most $(1-\epsilon) + \epsilon^2 \cdot \frac{1}{\epsilon^2} = 2 - \epsilon$ but

$$\mathbb{E}[X_{\max}] = \frac{1}{\epsilon}$$

What if we ignore each element we reach with prob. $\frac{1}{2}$? i.e. we don't even look at it!

Alg: let x^* be LP solution.

when looking at item i (assuming nothing is selected)
ignore with prob $\frac{1}{2}$ (w.o. even looking),
else accept with prob x_i

Lemma: The alg achieves a value $\frac{1}{4} \mathbb{E}[X_{\max}]$

proof: we say we reach item i if we have not picked any item before. Note that we pick each i with prob at most $\frac{x_i^*}{2}$ ($\frac{1}{2}$ ignore & then pick w.p. x_i^* if we reach i)

$$\begin{aligned} \mathbb{E}[\text{Alg}] &\geq \sum_{i=1}^n \Pr[\text{reach } i] \cdot \frac{1}{2} \cdot x_i^* \cdot v_i \\ &\geq \sum_{i=1}^n \Pr\left[\bigwedge_{j < i} \text{not picked } j\right] \cdot \frac{x_i^* \cdot v_i}{2} \\ &\geq \sum_{i=1}^n \left(1 - \sum_{j < i} \frac{x_j^*}{2}\right) \frac{x_i^* \cdot v_i}{2} \\ &\geq \sum_{i=1}^n \frac{1}{2} \cdot \frac{x_i^* \cdot v_i}{2} \end{aligned}$$

$$\text{since } \sum_j \frac{x_j^*}{2} \leq \frac{1}{2}$$

$$\geq \frac{1}{4} \mathbb{E}[X_{\max}]$$