

# Prophet Secretary Against the Online Optimal

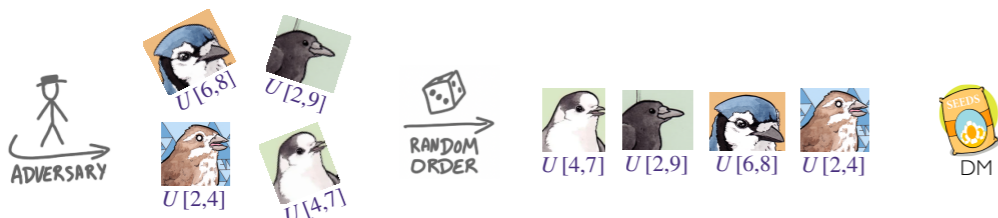
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## Background

- The secretary problem and the prophet inequality are two of the most important optimal stopping problems with many applications.
- We have to decide immediately and irrevocably whether to choose the current item. Secretary problem: **random arrival order**, **adversarial values** for the items. Prophet inequality: **adversarial order**, values drawn from **known distributions**.
- We study the prophet secretary problem [1], a well-studied variant that arises as a natural combination of the two. Typically, we compare our algorithm to the **prophet**, who knows the values and always picks the best. Closing the gap is still open! Current best strategy guarantees 0.669 [2] and UB is 0.7254 [3].
- We turn to a natural, but much less-studied benchmark: the **online optimal algorithm** [4]. This benchmark has the same info as we do at every step, but **infinite computational power**.
- This way, we measure the potential loss that arises due to computational limitations, rather than due to the fact that we have to make decisions online.

## A new benchmark: The online optimal



Optimal strategy can be found via dynamic programming/backward induction → it is in fact a series of **decreasing thresholds**. But DP size is exponential...

Idea: Group variables together into  $g$  types without hopefully losing much in the DP value.

$$\text{OPT}(X, k_1, \dots, k_g) = \mathbb{E} \left[ \max \left( X, \sum_{i \in [g]} \frac{k_i}{k_1 + \dots + k_g} \text{OPT}(X_i, k_1, \dots, k_{i-1}, k_{i+1}, \dots, k_g) \right) \right]$$

Running time is  $O(n^g) \rightarrow O(1)$  types needed for PTAS.

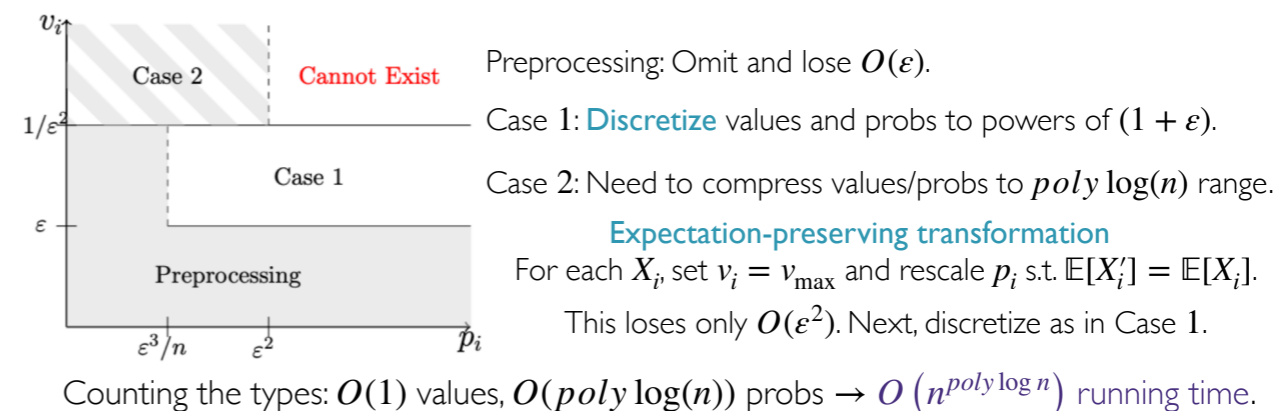
Obsv 1: If we can calculate thresholds that are always within  $(1 - \epsilon)$  of the DP ones, then the strategy that uses these thresholds is a  $(1 - \epsilon)$ -approximation to the online optimal.

Obsv 2: Perturbing the support values and the probs of each  $X_i$  by a bit does not change the DP solution by much.

[1] Esfandiari H., HajiAghayi M., Liaghat V., Monemizadeh M. Prophet Secretary, ESA 2015.  
 [2] Correa J.R., Saona R., Ziliotto B. Prophet Secretary Through Blind Strategies, SODA 2019, Math. Program. 2022.  
 [3] Bubna A., Chiplunkar A. Prophet Inequality: Order selection beats random order, EC 2023.  
 [4] Papadimitriou C., Pollner T., Saberi A., Wajc D. Online Stochastic Max-Weight Bipartite Matching: Beyond Prophet Inequalities, EC 2021.

## Warmup: QPTAS

→ To simplify, think of 2-point distr: with one mass at 0. WLOG, normalize  $\text{OPT} \in [0.5, 1]$ .



→ For general distr: we need more because each  $X_i$  can have multiple big support values. Fact: OPT (the optimal DP) will not set a threshold of more than OPT at any step.

$$\text{Bundling: } X'_i = \begin{cases} x & \text{when } x \leq 1, \text{ w.p. } \Pr[X_i = x] \\ \mathbb{E}[X_i | X_i > 1] & \text{w.p. } \Pr[X_i > 1] \end{cases}$$

The bundling does not change the value of the optimal DP solution!

## Main result: PTAS

- Problem: Each support value can still have  $\Omega(\log n)$  different realization probabilities.
- **Frontloading**: For a sequence of r.v.'s, if their total realization prob. is "small", we can make a decision for the sequence as a whole: **even if we have seen the realization of all such r.v.'s, we do not gain much compared to making a decision upon arrival of each!**

Start from where we left off with the QPTAS and think again of 2-point distr.

