

# Prophet Secretary Against the Online Optimal

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EC, London UK, July 2023

# The Prophet Problem



$$X_1 \sim \mathcal{D}_1$$



$$X_2 \sim \mathcal{D}_2$$



$$X_3 \sim \mathcal{D}_3$$



$$X_4 \sim \mathcal{D}_4$$



$$X_5 \sim \mathcal{D}_5$$

- ▶ **Algorithm:** irrevocably select or discard at each step
- ▶ **Goal:** maximize the value selected
- ▶ **Benchmark:** all knowing Prophet:  $\mathbb{E} [\max_i X_i]$

# The Prophet Problem



35 ~  $\mathcal{D}_1$



13 ~  $\mathcal{D}_2$

Stop here!



42 ~  $\mathcal{D}_3$



24 ~  $\mathcal{D}_4$



17 ~  $\mathcal{D}_5$

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# The Prophet *Secretary* Problem

Random permutation!



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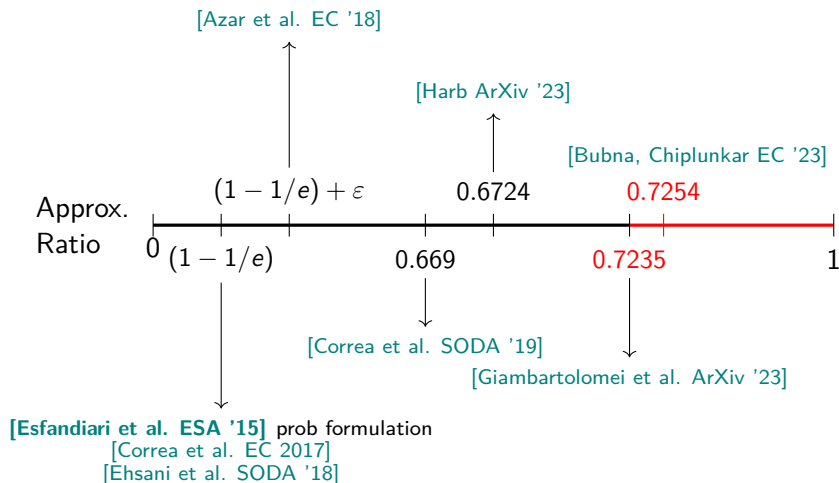


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Best value!

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# State of the Art



# Our Question

## Our Benchmark: Online Optimal

Remaining variables

$$\text{OPT}(X|\mathcal{B}) = \mathbb{E} \left[ \max(X, \frac{1}{|\mathcal{B}|} \sum_{X_i \in \mathcal{B}} \text{subproblem without } X_i) \right]$$

Current variable

## Original benchmark: Prophet ( $\mathbb{E} [\max_i X_i]$ )

- ▶ Pessimistic benchmark!
- ▶ Many problems use Online Optimal (e.g. Matching [Papadimitriou et al. '21, Braverman et al. '21, Naor et al. '23], Prophet Inequalities [Niazadeh et al. '18], Pandora's Box-type problems [Weitzman '79, Chakraborty et al. '10, Fu et al '18, Singla & Segev '21, Liu et al. '21 ])

Can we compete against the Online Optimal?

Yes!

## PTAS

There exists an algorithm with

- ▶  $(1 - \varepsilon)$ -approximation
- ▶ running time  $n^{f(\varepsilon)}$

# Our Results

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Yes!

## QPTAS

There exists an algorithm with

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- ▶ running time  $n^{f(\varepsilon) \cdot \text{polylog } n}$

against the Online Optimal.

## PTAS

There exists an algorithm with

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against the Online Optimal.

**This presentation: First QPTAS, then PTAS**

# Online Optimal Revisited

**DP for Online Optimal:**

$$\text{OPT}(X|\mathcal{B}) = \mathbb{E} \left[ \max(X, \frac{1}{|\mathcal{B}|} \sum_{X_i \in \mathcal{B}} \text{subproblem without } X_i) \right]$$

Size is  $n!$

**Key observation:** for constantly many different “types” (groups), DP size is polynomial

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$k_i$ : variables remaining in group  $i$

$\text{OPT}(X|k_1, \dots, k_g) =$

$$\mathbb{E} \left[ \max \left( X, \frac{1}{K} \sum_{i \in [g]} k_i \cdot (\text{subproblem with } k_i - 1) \right) \right]$$

Total variables remaining

Size is  $\left(\frac{n}{g}\right)^g$  for  $g$  groups

**QPTAS:**  $g = \text{const} \cdot \text{poly log } n$

**PTAS:**  $g = \text{const}$

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**Idea:** discretize variables into  $g$  groups **while being close** to OPT



# Warmup: Binary Distributions

All variables  $X_i = \begin{cases} v_i & , \text{w.p. } p_i \\ 0 & , \text{w.p. } 1 - p_i \end{cases}$

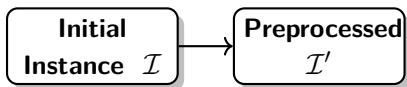
## Algorithm Steps:

**Initial**  
Instance  $\mathcal{I}$

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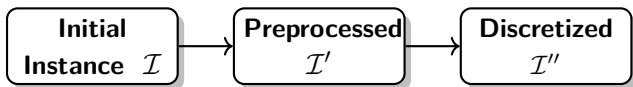


Preprocessing:  
Remove "low" value  $X_i$ 's

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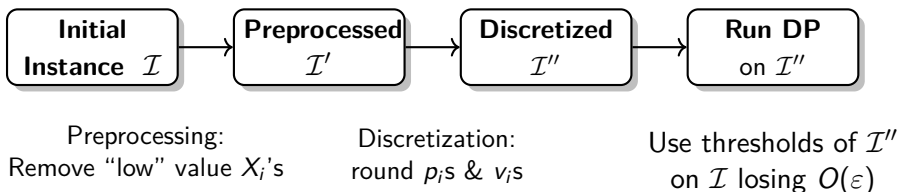
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Discretization:  
round  $p_i$ 's &  $v_i$ 's

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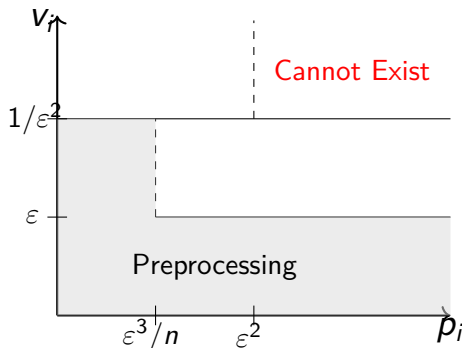
# Preprocessing & Discretization

## Preprocessing

- ▶ Scale optimal s.t.  
 $\mathbb{E}[\max_i X_i] = 1$
- ▶ Remove all  $v_i \leq \epsilon$  or  
 $p_i v_i \leq \epsilon/n$

Total loss:  $(1.5\epsilon)^2 \text{OPT}$ .

Groups created: 0 (disregard  $X_i$ 's)



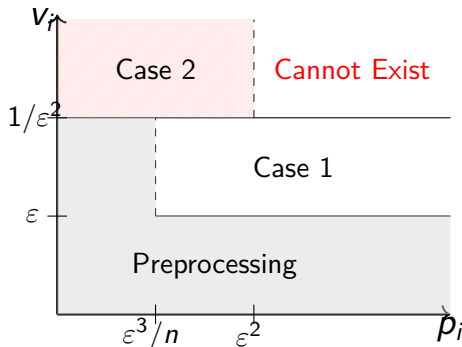
# Preprocessing & Discretization

## Discretization

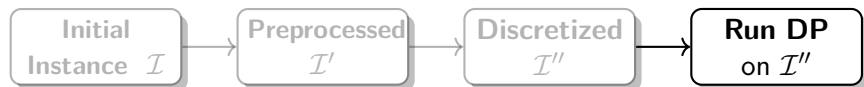
- ▶ **Case 1:** round down  $p_i$  and  $v_i$  to closest  $(1 + \varepsilon)^k$
- ▶ **Case 2:** set  $v'_i = v_{\max}$  & set  $p'_i \leftarrow \frac{v_i p_i}{v_{\max}}$

Total loss:  $\varepsilon^2 \text{OPT}$ .

Groups created:  $O\left(\frac{\log^2 n/\varepsilon}{\log^2(1+\varepsilon)}\right)$ .



# Final Step



## Putting it all together:

- ▶ Loss is  $O(\varepsilon)\text{OPT}$
- ▶ Total groups  $O\left(\frac{\log^2 n/\varepsilon}{\log^2(1+\varepsilon)}\right) \Rightarrow$  runtime is  $n^{\frac{\log^2 n/\varepsilon}{\log^2(1+\varepsilon)}}$

General distributions?

# Generalizing to any distribution

- ▶ **Step 1: generalize to support size  $c$  (constant)**
- ▶ **Step 2: the general case**



# Generalizing to any distribution

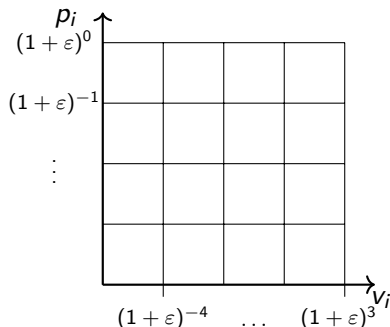
## ▶ Step 1: generalize to support size $c$ (constant)

- ▶ Variables of the form

$$X_i = \begin{cases} v_1 & \text{w.p. } p_1 \\ v_2 & \text{w.p. } p_2 \\ \dots & \\ v_c & \text{w.p. } p_c, \end{cases}$$

- ▶ Variables in same group **if same support** after discretization
- ▶  $k$ : # of (value, probability) pairs
- ▶ Total possible groups  $\binom{c}{k} \approx k^c$

## ▶ Step 2: the general case



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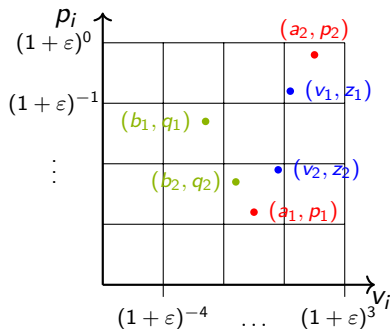
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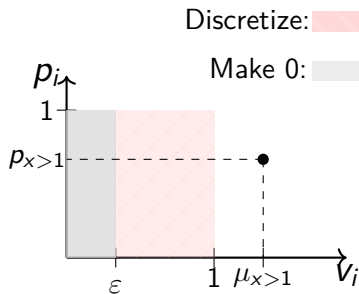
$X_1$  and  $X_2$  **NOT** same group

$X_1$  and  $X_3$  **IN** same group

**Runtime:**  $O\left(n^{f(\epsilon, c)} \cdot \text{poly log } n\right)$

# Generalizing to any distribution

- ▶ Step 1: generalize to support size  $c$  (constant)
- ▶ **Step 2: the general case**
  - ▶ Make 0 all  $v_i \leq \varepsilon$
  - ▶ Collapse support above 1 to single point
  - ▶ Discretize support below 1
  - ▶ Reduce to constant support case with  $c = O\left(\frac{\log 1/\varepsilon}{\log(1+\varepsilon)}\right)$



- ▶  $\mu_{x>1} = \mathbb{E}[X|X > 1]$
- ▶  $p_{x>1} = \mathbf{Pr}[X > 1]$

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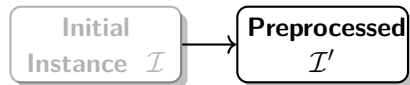
Problem with previous discretization:

# of probability values depends on  $n$

**Initial  
Instance  $\mathcal{I}$**

Problem with previous discretization:

# of probability values depends on  $n$



## Preprocessing:

- ▶ Remove “low” value & low probability  $X_i$ 's
- ▶ Discretize  $X_i$ 's with “high”-er probability

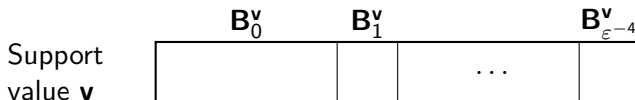
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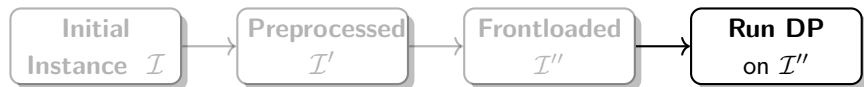
## Frontloading:

- ▶ Split instance into blocks per support value  $\mathbf{v}$
- ▶ At beginning of block  $\mathbf{B}_i^{\mathbf{v}}$  flip coin to decide if accept  $\mathbf{v}$



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Use thresholds from  $\mathcal{I}''$  on initial instance  $\mathcal{I}$  losing  $O(\varepsilon)$ .

**Runtime:**  $n^{(1/\varepsilon)^{\text{poly}1/\varepsilon}}$

## Prophet Secretary against the **Online Optimal**

- ▶ **Result 1 (QPTAS):**  
( $1 - \varepsilon$ ) approximation in time  $n^{f(\varepsilon)} \cdot \text{polylog } n$
- ▶ **Result 2 (PTAS):**  
( $1 - \varepsilon$ ) approximation in time  $n^{f(\varepsilon)}$

**Thank you!**