



Selling Bananas in an Uncertain Environment

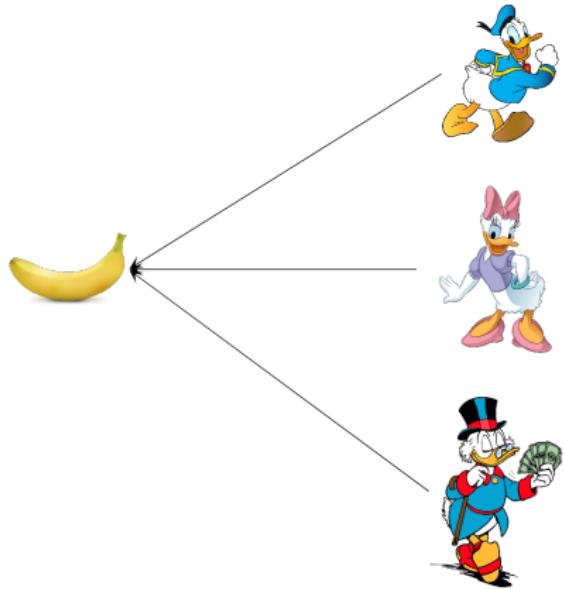
Vasilis Livanos

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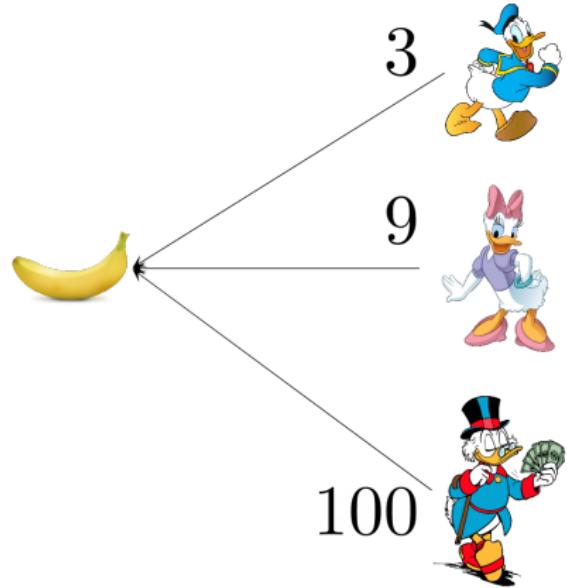
November 29th, 2023



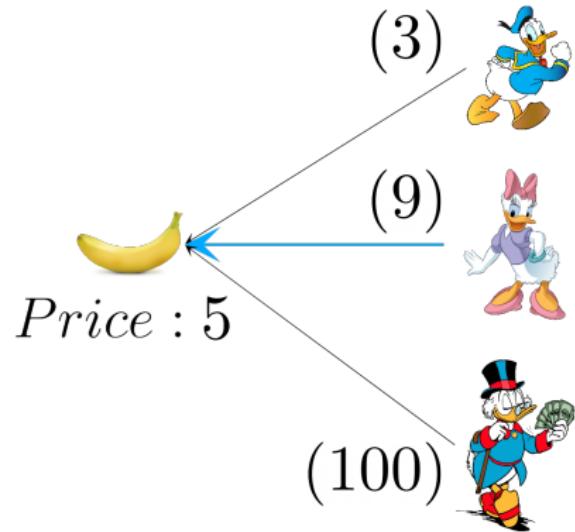
Auction Design



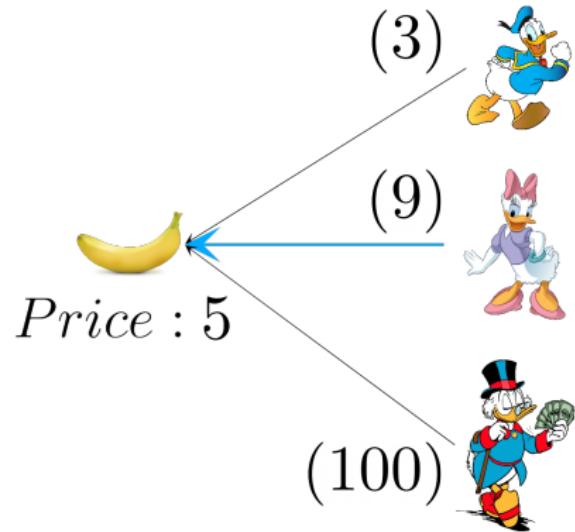
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How to set the price?

Overview

1. Distribution-optimal prophet inequalities

[L., Mehta '22, L. '23]

- ▶ Unified proof for both max and min I.I.D prophet inequality
- ▶ Competition complexity

2. Oracle-augmented prophet inequalities

[Har-Peled, Harb, L. '23]

- ▶ Connection with top-1-of- k model
- ▶ Upper-lower bounds for I.I.D. case
- ▶ Upper-lower bounds for general case (adversarial order)

3. Optimal greedy OCRSs [L., '22]

- ▶ $1/e$ -selectable greedy OCRS for single-item
- ▶ $1/e$ hardness
- ▶ Extension to transversal matroids

4. Submodular prophet inequalities [Chekuri, L. '21]

- ▶ Small constant SPI via OCRS
- ▶ Generalized framework for several constraints
- ▶ Correlation gap

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Optimal Stopping: The Prophet Inequality

[Krengel, Sucheston, Garling '77]

$X_1, X_2, \dots, X_n \sim (\text{known}) \mathcal{D}_1, \mathcal{D}_2, \dots, \mathcal{D}_n$
arrive in *adversarial* order.

- ▶ Design *stopping time* to maximize selected value.
- ▶ Compare against all-knowing *prophet*: $\mathbb{E}[\max_i X_i]$.

$\mathcal{U}[13, 14]$ $\mathcal{U}[7, 16]$ $\mathcal{U}[0, 20]$

$$\begin{cases} 1000 & \text{w.p. } \frac{1}{100} \\ 0 & \text{otherwise} \end{cases}$$

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$$X_4 = 0$$

$$\mathbb{E}[\max \{X_1, X_2, X_3, X_4\}] \approx 24.66$$

$$\mathbb{E}[OPTALG \{X_1, X_2, X_3, X_4\}] \approx 13.37$$

Optimal strategy was to select X_1 .

Prophet Inequality [Krengel, Sucheston, Garling '77, '78]

\exists stopping strategy that achieves $1/2 \cdot \mathbb{E}[\max_i X_i]$,
and this is tight.

$$X_1 = 1 \quad \text{w.p. 1, and } X_2 = \begin{cases} 1/\varepsilon & \text{w.p. } \varepsilon \\ 0 & \text{w.p. } 1 - \varepsilon \end{cases}$$

$\mathbb{E}[\text{ALG}] = 1$ for all algorithms.

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

- ▶ $\frac{\mathbb{E}[\text{ALG}]}{\mathbb{E}[\max_i X_i]}$: Competitive Ratio

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[Kleinberg, Weinberg '12]

Two proofs in one??



For any T ,

$$\mathbb{E}[ALG] \geq \Pr[\max_i X_i \geq T] T + \sum_i \Pr[\text{We reach } i] \mathbb{E}[\max \{X_i - T, 0\}]$$

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[\[Esfandiari, Hajiaghayi, Liaghat, Monemizadeh '15\]](#)
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No hope for universal bound: [\[Lucier '22\]](#)

$\mathcal{D} : F(x) = 1 - 1/x$, with $x \in [1, +\infty)$ (Equal-revenue distribution).

$$\mathbb{E}[X] = 1 + \int_1^\infty (1 - F(x)) dx = +\infty, \text{ but}$$

$$\mathbb{E}[\min\{X_1, X_2\}] = 1 + \int_1^\infty (1 - F(x))^2 dx < +\infty.$$

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For any \mathcal{D} , \exists threshold stopping strategy $\tau_1, \tau_2, \dots, \tau_n$ that achieves $\beta \cdot \mathbb{E}[\max_i X_i]$, where $\beta \approx 0.745$, and this is tight.

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For any \mathcal{D} , \exists a single threshold τ such that selecting the first $X_i \geq \tau$ achieves $(1 - 1/e) \cdot \mathbb{E}[\max_i X_i] \approx 0.632 \cdot \mathbb{E}[\max_i X_i]$.

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- ▶ Minimization?

Intuition:

Set $T = c \cdot \mathbb{E}[\min_i X_i]$.

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Intuition False Intuition:

Doesn't work! $\Pr[\text{We are forced to select } X_n] \geq c$.

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Worst-case instance for Max: $n \rightarrow \infty \implies$ Fix \mathcal{D} and take $n \rightarrow \infty$.

Asymptotic Competitive Ratio (ACR)

$$\lambda_{\min} = \lim_{n \rightarrow \infty} \frac{\mathbb{E}[ALG(n)]}{\mathbb{E}[\min_{i=1}^n X_i]}.$$

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- ▶ $\lim_{n \rightarrow \infty} M_n = +\infty, \quad \lim_{n \rightarrow \infty} m_n = 0 \implies$ Re-scaling

Technique: Extreme Value Theory

Extreme Value Theorem [Fisher, Tippett '28, Gnedenko '43]

Assume there exist sequences $a_n > 0, b_n \in \mathbb{R}$ such that

$$\lim_{n \rightarrow \infty} F_{M_n}(a_n x + b_n) = G_\gamma^+(x).$$

Then,

$$G_\gamma^+(x) = \begin{cases} \exp(-(1 + \gamma x)^{-1/\gamma}), & \text{if } \gamma \neq 0 \\ \exp(-\exp(-x)), & \text{if } \gamma = 0 \end{cases}.$$

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- ▶ G : Extreme Value Distribution, γ : Extreme Value Index
- ▶ Three distinct G_γ^+ 's:
 - ▶ $\gamma < 0$: Reverse Weibull
 - ▶ $\gamma = 0$: Gumbel
 - ▶ $\gamma > 0$: Fréchet

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- ▶ Conditions $\implies \mathcal{D}$ follows EVT.

IID PI via Extreme Value Theory

Theorem [L., Mehta '22, L. '23]

$$\Gamma(x) = (x - 1)!$$

Assume there exist sequences $a_n > 0, b_n \in \mathbb{R}$ such that

$$\lim_{n \rightarrow \infty} F_{M_n}(a_n x + b_n) = G_\gamma^+(x)$$

for some γ

$$\lim_{n \rightarrow \infty} F_{m_n}(a_n x + b_n) = G_\gamma^-(x)$$

for some γ

Then, the optimal DP achieves a competitive ratio, as $n \rightarrow \infty$, of

$$ACR_{Max} = \min \left\{ \frac{(1 - \gamma)^{-\gamma}}{\Gamma(1 - \gamma)}, 1 \right\}.$$

$$ACR_{Min} = \max \left\{ \frac{(1 - \gamma)^{-\gamma}}{\Gamma(1 - \gamma)}, 1 \right\}.$$

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$$ACR_{Max} = \min \left\{ \frac{(1 - \gamma)^{-\gamma}}{\Gamma(1 - \gamma)}, 1 \right\}.$$

$$ACR_{Min} = \max \left\{ \frac{(1 - \gamma)^{-\gamma}}{\Gamma(1 - \gamma)}, 1 \right\}.$$

- ▶ Distribution-optimal closed form!
- ▶ Unified analysis of competitive ratio for both Max and Min.

IID PI via Extreme Value Theory

Theorem [L., Mehta '22, L. '23]

$$\Gamma(x) = (x - 1)!$$

Assume there exist sequences $a_n > 0, b_n \in \mathbb{R}$ such that

$$\lim_{n \rightarrow \infty} F_{M_n}(a_n x + b_n) = G_\gamma^+(x)$$

for some γ

$$\lim_{n \rightarrow \infty} F_{m_n}(a_n x + b_n) = G_\gamma^-(x)$$

for some γ

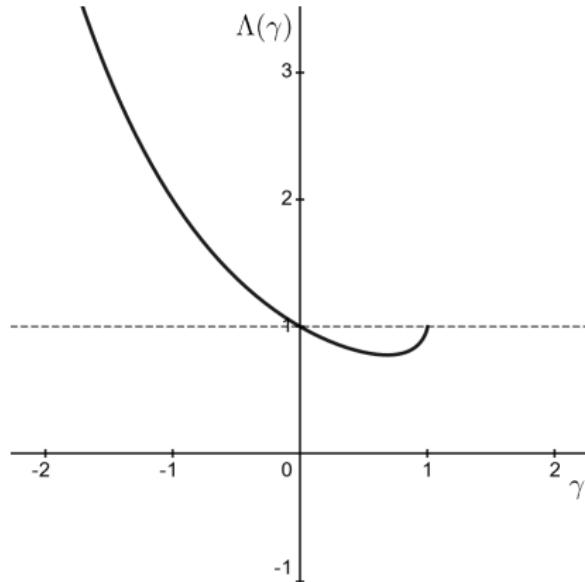
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- ▶ \mathcal{D} MHR $\implies ACR_{Max} = 1 \quad \& \quad ACR_{Min} \leq 2$

Asymptotic Competitive Ratio



For $\gamma \rightarrow -\infty$, by Stirling's approximation

$$\frac{(1-\gamma)^{-\gamma}}{\Gamma(1-\gamma)} \approx e^{-\gamma}.$$

Asymptotic Competitive Ratio

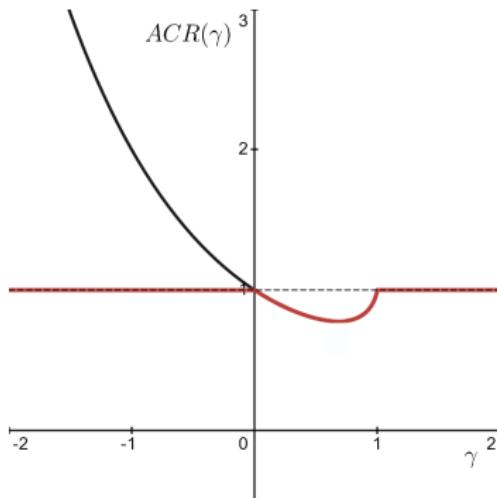


Figure: $ACR(\gamma)$ for MAX

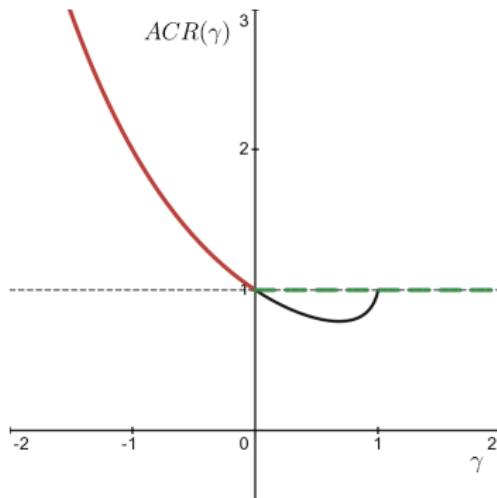


Figure: $ACR(\gamma)$ for MIN

- ▶ “ \mathcal{D} follows EVT”: most general class we expect closed-form.

High-Level Approach

$F(t) = \Pr_{X \sim \mathcal{D}}[X \leq t]$, $F^\leftarrow(p)$: inverse of F (“Quantile function”).

Using EVT and heavy-machinery from theory of regularly-varying functions:

MAX

MIN

High-Level Approach

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Using EVT and heavy-machinery from theory of regularly-varying functions:

$$\mathbb{E}[ALG(n)] \approx F^\leftarrow\left(1 - \frac{1-\gamma}{n}\right)$$

$$\mathbb{E}[ALG(n)] \approx F^\leftarrow\left(\frac{1-\gamma}{n}\right)$$

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What if we want $\mathbb{E}[ALG] \geq \mathbb{E}[\max_i X_i]$ or $\mathbb{E}[ALG] \leq \mathbb{E}[\min_i X_i]$?
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Competition Complexity

For fixed n , the *competition complexity* of a distribution \mathcal{D} is

$$\inf \left\{ c \mid \mathbb{E}[ALG(c \ n)] \geq \mathbb{E}[\max_{i=1}^n X_i] \right\} \quad \mid \quad \inf \left\{ c \mid \mathbb{E}[ALG(c \ n)] \leq \mathbb{E}[\min_{i=1}^n X_i] \right\}$$

for Max for Min

- ▶ For Max and $\mathcal{D} = \mathcal{D}(n)$, it can be unbounded.
[Brustle, Correa, Dütting, Verdugo '22]

Asymptotic Competition Complexity via EVT

What if we fix \mathcal{D} and take $n \rightarrow \infty$?

(Asymptotic Competition Complexity - ACC)

Theorem [L., Verdugo '23]

For every distribution following EVT,

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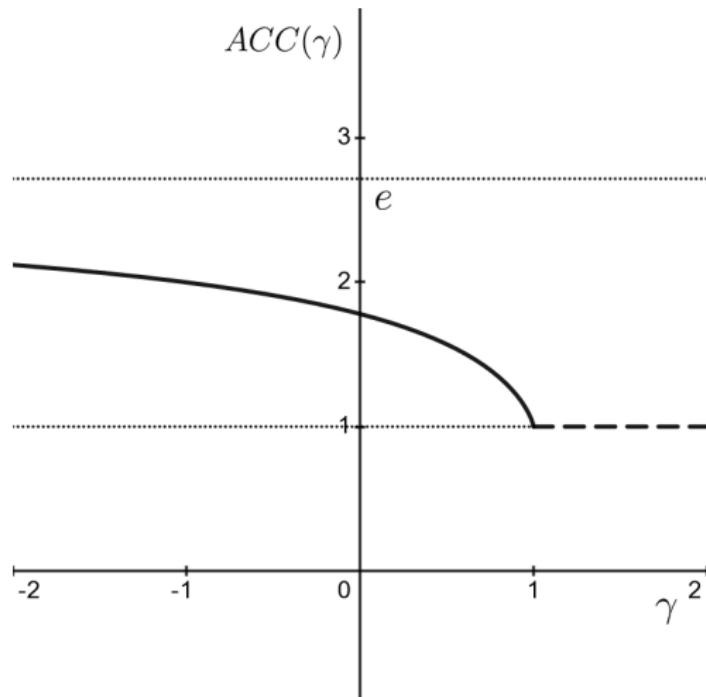
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Asymptotic Competition Complexity



- ▶ $ACC \leq e$ for all \mathcal{D} following EVT.

Overview

1. Distribution-optimal prophet inequalities

[L., Mehta '22, L. '23]

- ▶ Unified proof for both max and min I.I.D prophet inequality
- ▶ Techniques: Extreme Value Theory, Regularly-Varying Functions
- ▶ Competition complexity

2. Oracle-augmented prophet inequalities

[Har-Peled, Harb, L. '23]

- ▶ Connection with top-1-of- k model
- ▶ Upper-lower bounds for I.I.D. case
- ▶ Upper-lower bounds for general case (adversarial order)

3. Optimal greedy OCRSs [L., '22]

- ▶ $1/e$ -selectable greedy OCRS for single-item
- ▶ $1/e$ hardness
- ▶ Extension to transversal matroids

4. Submodular prophet inequalities [Chekuri, L. '21]

- ▶ Small constant SPI via OCRS
- ▶ Generalized framework for several constraints
- ▶ Correlation gap

Oracle-Augmented Prophet Inequalities

- ▶ O_k model:
 - ▶ Assume ALG has k calls to O , who knows X_1, \dots, X_n .
- ▶ Step i :
 - 👉 $X_i \geq \max_{j=i+1}^n X_j \implies ALG$ selects X_i
 - 👎 $X_i < \max_{j=i+1}^n X_j \implies ALG$ rejects X_i
- ▶ “Algorithms with predictions”

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[Gilbert, Mosteller '66], [Assaf, Samuel-Cahn '00],
[Assaf, Goldstein, Samuel-Cahn '02]

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- ▶ CR : Maximize $\mathbb{E}[ALG]/\mathbb{E}[\max_i X_i]$
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Results for O_k Model

Theorem [Har-Peled, Harb, L. '23]

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- ▶ General (adversarial order):
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Single-threshold algorithms.

Improves upon $1 - O(e^{-k/6})$ [Ezra, Feldman, Nehama '18]

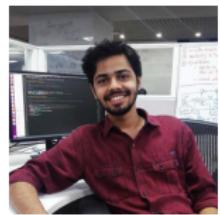
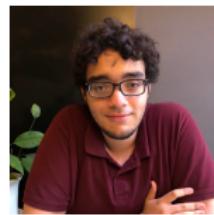
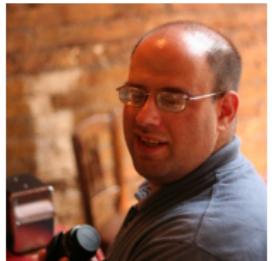
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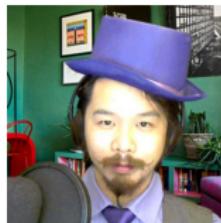
Future Directions

- ▶ Principal wants to delegate a PI instance to k agents.
[Liaw, L., Perlroth, Schwartzman, Wang '24].
- ▶ Beyond the independence assumption.
[L., Patton, Singla '24].
- ▶ Multiple selection minimization PI.
- ▶ Free-Order PI: ALG can choose order of realizations.
Can we get ≈ 0.745 (I.I.D. constant)?

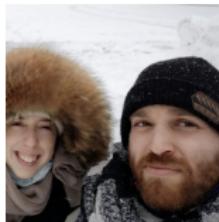
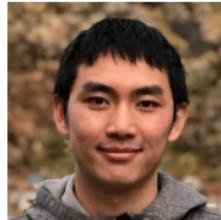
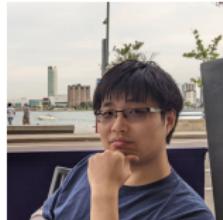
♥ Thank You ♥



♥ Thank You ♥



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Questions?

