

# ORIE 4154 - Pricing and Market Design

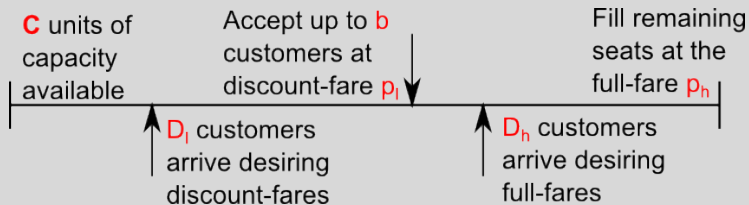
## Module 1: Capacity-based Revenue Management (Intro to Stochastic Dynamic Programming)

Instructor: Sid Banerjee, ORIE



Cornell University

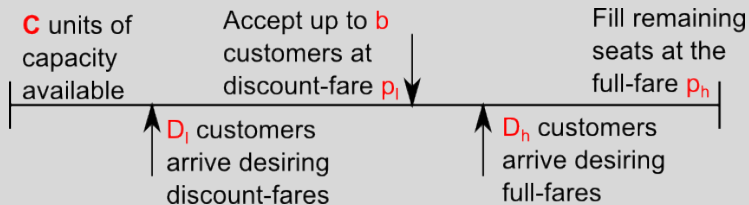
# Single-resource two-stage capacity allocation



$$R(b, D_\ell, D_h) = p_\ell \min\{b, D_\ell\} + p_h \min\{D_h, \max\{C - b, C - D_\ell\}\}$$

**Aim:** Choose  $b^* = \arg \max_{b \in [0, C]} \mathbb{E}[R(b, D_\ell, D_h)]$

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## Littlewood's Rule

Assume  $D_\ell, D_h$  are continuous,  $b$  can be fractional – then optimal booking limit  $b^*$  (or protection level  $C - b^*$ ) satisfies:

$$C - b^* = y^* = F_h^{-1} \left( 1 - \frac{p_\ell}{p_h} \right)$$

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Alternate derivation of Littlewood's rule (Discrete RVs)

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Main Idea: Analyze  $\Delta r(b) = \mathbb{E}[R(b+1, D_\ell, D_h) - R(b, D_\ell, D_h)]$

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$$\begin{aligned} \Delta r(b) = & p_\ell \mathbb{E} \left[ \min\{b+1, D_\ell\} - \min\{b, D_\ell\} \right] + \\ & p_h \mathbb{E} \left[ \min\{D_h, \max\{C - (b+1), C - D_\ell\}\} - \right. \\ & \left. \min\{D_h, \max\{C - b, C - D_\ell\}\} \right] \end{aligned}$$

## Littlewood's Rule (Discrete RVs)

- $\min\{b+1, D_\ell\} - \min\{b, D_\ell\} = \begin{cases} 1 & \text{if } D_\ell \geq b+1 \\ 0 & \text{o.w.} \end{cases}$

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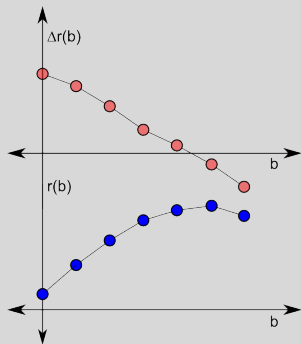
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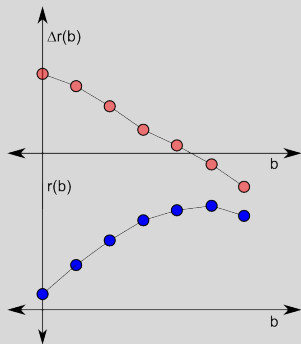
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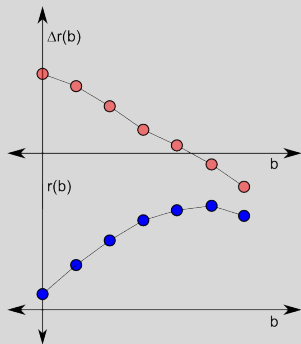


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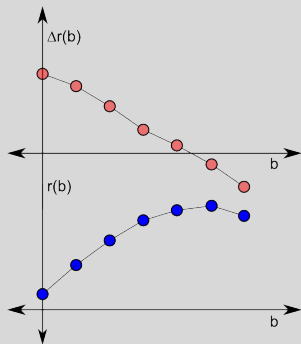
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 Why is  $y^*$  independent of  $C$ ?  
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 Perfect segmentation + dynamics

## Problem: Single-resource three-stage capacity allocation

- Seller constraints:
  - (Setting)  $C$  seats, 3 fare-classes with prices  $p_1 > p_2 > p_3$
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**Idea:** If an oracle gave us  $X_3$ , the number of lowest-fare class seats sold – then we have a two fare-class problem with  $C - X_3$  seats!

## First, let us play a game

- Setup: A pile of 10 toothpicks
- You will be playing against an oblivious random adversary (called Computer).
- A Sequence of Events in Each Iteration:
  - You start first. You can take either 1 or 2 toothpicks from the pile.
  - After you make the decision, I will flip a random fair coin. If the coin lands HEAD, the Computer will remove 1 toothpick from the pile. Otherwise, the Computer will remove 2 toothpicks.
- The game proceeds until all toothpicks are removed from the pile.
- If you end up holding the last toothpick, you win \$20. Otherwise, you get nothing.

Courtesy: Paat Rusmevichientong

(**Aside:** Variant of a game called [Nim](#); see [Youtube video](#) for details)

# Analyzing our game

Divide game into **rounds**: in each round, you go first followed by COMPUTER

In  $k^{\text{th}}$  round, computer picks  $X_k$  toothpicks ( $X_k \sim \text{UNIFORM}\{1,2\}$ )

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- Suppose after  $k - 1$  rounds, game has  $S_k \geq 3$  toothpicks left, and let  $S_{k+1}$  be number of toothpicks left when we play next:
  - If we pick 1 match, then  $S_{k+1} = S_k - 1 - X_k$
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We will now see how to 'solve' this game (i.e., figure out an optimal set of moves) via **Dynamic Programming**.

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$$= \max \left\{ \left( \frac{V(1) + V(0)}{2} \right), \left( \frac{V(0) + V(-1)}{2} \right) \right\} = 10$$

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- $V(3) = \max \{0.5 \cdot (V(1) + V(0)), 0.5 \cdot (V(0) + V(-1))\} = 10$
- $V(4) = \max \{0.5 \cdot (V(2) + V(1)), 0.5 \cdot (V(1) + V(0))\} = 20$
- $V(5) = \max \{0.5 \cdot (V(3) + V(2)), 0.5 \cdot (V(2) + V(1))\} = 20$
- $V(6) = \max \{0.5 \cdot (V(4) + V(3)), 0.5 \cdot (V(3) + V(2))\} = 15$
- $V(7) = \max \{0.5 \cdot (V(5) + V(4)), 0.5 \cdot (V(4) + V(3))\} = 20$
- $V(8) = \max \{0.5 \cdot (V(6) + V(5)), 0.5 \cdot (V(5) + V(4))\} = 20$
- $V(9) = \max \{0.5 \cdot (V(7) + V(6)), 0.5 \cdot (V(6) + V(5))\} = 17.5$
- $V(10) = \max \{0.5 \cdot (V(8) + V(7)), 0.5 \cdot (V(7) + V(6))\} = 20$

## Analyzing our game

$V(x) = \max \mathbb{E}[\text{Reward}]$  if round starts with  $x$  toothpicks

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**Optimal policy:** Move to nearest multiple of 3

We always win if  $x \not\equiv 0 \pmod{3}$

# (Stochastic) Dynamic Programming

General solution paradigm for sequential decision making

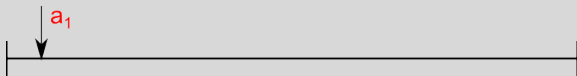
**Problem:**  $\max_{a: \text{“Actions”}} \mathbb{E}_X[f(a, X)]$



# (Stochastic) Dynamic Programming

General solution paradigm for sequential decision making

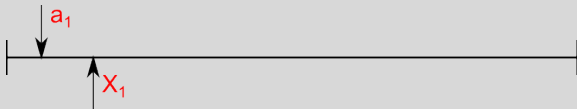
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# (Stochastic) Dynamic Programming

General solution paradigm for sequential decision making

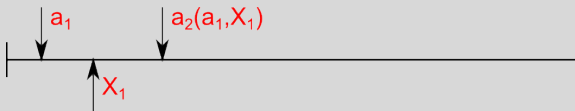
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General solution paradigm for sequential decision making

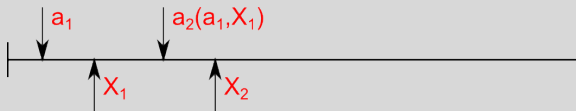
**Problem:**  $\max_{a: \text{“Actions”}} \mathbb{E}_X[f(a, X)]$



# (Stochastic) Dynamic Programming

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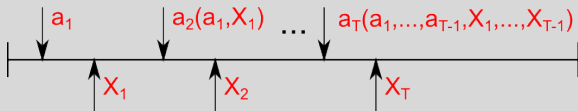
**Problem:**  $\max_{a: \text{“Actions”}} \mathbb{E}_X[f(a, X)]$



# (Stochastic) Dynamic Programming

General solution paradigm for sequential decision making

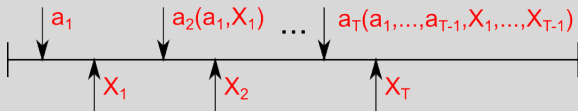
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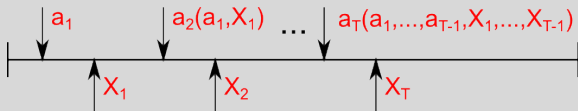


## Main Ideas

# (Stochastic) Dynamic Programming

General solution paradigm for sequential decision making

**Problem:**  $\max_{a: \text{“Actions”}} \mathbb{E}_X[f(a, X)]$



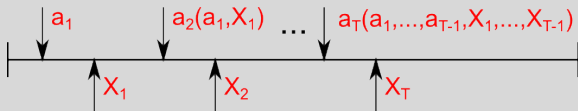
## Main Ideas

- **State:**  $S$  - summary of history

# (Stochastic) Dynamic Programming

General solution paradigm for sequential decision making

**Problem:**  $\max_{a: \text{“Actions”}} \mathbb{E}_X[f(a, X)]$



## Main Ideas

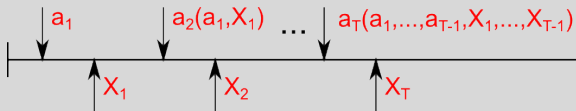
- **State:**  $S$  - summary of history
- **Value function:**  $V(\cdot)$  - 'value-to-go' for given state)



# (Stochastic) Dynamic Programming

General solution paradigm for sequential decision making

**Problem:**  $\max_{a: \text{“Actions”}} \mathbb{E}_X[f(a, X)]$



## Main Ideas

- **State:**  $S$  - summary of history
- **Value function:**  $V(\cdot)$  - 'value-to-go' for given state)
- **Bellman Equation** (or DP equation):

$$V(S_t) = \max_{a_t: \text{actions}} \left\{ R_t(S_t, a_t) + V(S_{t+1}(S_t, a_t)) \right\}$$