Marketplace Operations: From Resource Allocation to Recommendations

Akshit Kumar

Columbia Business School

Joint work with Omar Besbes and Yash Kanoria

Matching in marketplaces

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Match demand location with fulfillment center

Matching in marketplaces

Match demand location with fulfillment center

Match customers with service providers

Matching in marketplaces

Match demand location with fulfillment center

Recommend movies/songs to consumers

Match customers with service providers

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Match customers with service providers

Match students to college programs

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Matching in marketplaces

Part I

Match demand location with fulfillment center

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Match students to college programs

Matching in marketplaces

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Part I

Research Questions

Recommend movies/songs to consumers

Match students to college programs

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Part I

Research Questions

1. How should platforms allocate limited resources dynamically and efficiently?

Match students to college programs

Matching in marketplaces

Match demand location with fulfillment center

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Part I

Research Questions

1. How should platforms allocate limited resources dynamically and efficiently?

2. What are the fundamental driver of algorithmic performances in these marketplaces?

Matching in marketplaces

Match demand location with fulfillment center

Recommend movies/songs to consumers

Match customers with service providers

Match students to college programs

Matching in marketplaces

Part II

Match demand location with fulfillment center

Recommend movies/songs to consumers

Joint Seat Allocation Authority

Match customers with service providers

Match students to college programs

Matching in marketplaces

Part II

Research Questions

1. What is the value of personalized recommendations in marketplaces?

Recommend movies/songs to consumers

Joint Seat Allocation Authority

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Match students to college programs

Part I in a Nutshell

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We study prototypical models of dynamic resource allocation problem (focus on the multisecretary prob)

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Shape of the reward distribution is a fundamental driver of algorithmic performance

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- Shape of the reward distribution is a fundamental driver of algorithmic performance
- Workhorse policies can be highly suboptimal and near-optimal algorithms are overly specified
- Design a simple and near-optimal policy called Repeatedly Act using Multiple Simulations **(RAMS)**

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- We study a prototypical utility model which comprises of public and private utility components
- Identify subtle interplay of personalized recommendations and capacity constraints on social welfare
- Personalized recos may have *little to no* benefit in markets with uncapacitated supply (think movies, songs)
- Personalized recos unlock *significant* social welfare in capacitated supply settings (think AirBnB, college admits)

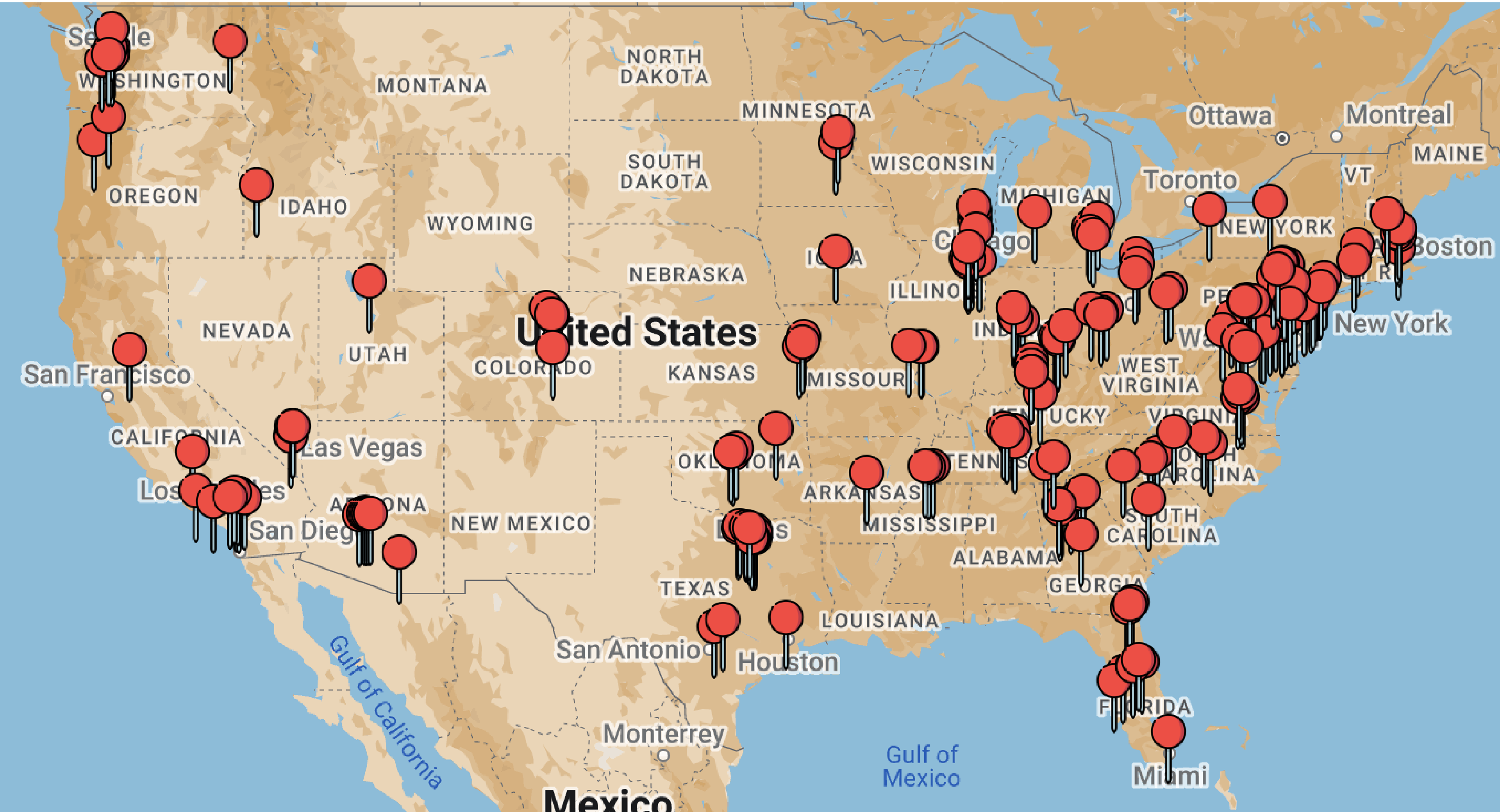
Part I

Dynamic Resource Allocation: Algorithmic Design Principles & Spectrum of Achievable Performances

Forthcoming in Operations Research (2024)

Dynamic Resource Allocation

Algorithmic Design Principles & Spectrum of Achievable Performances



Research Question

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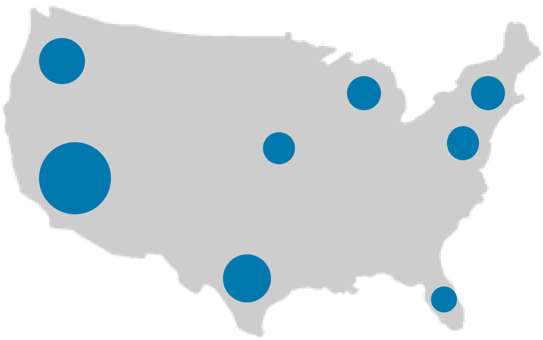
A few (demand) types are present



Theory

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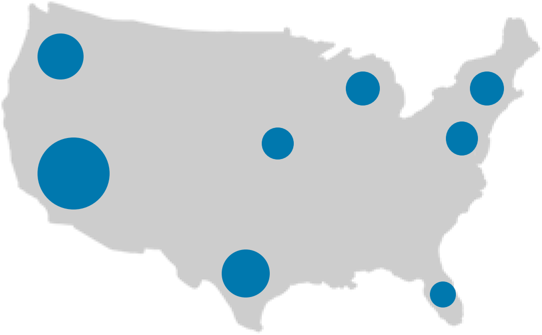

Theory

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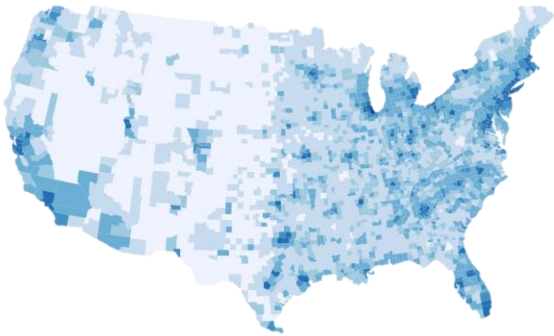

Practice

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Theory

Research Question

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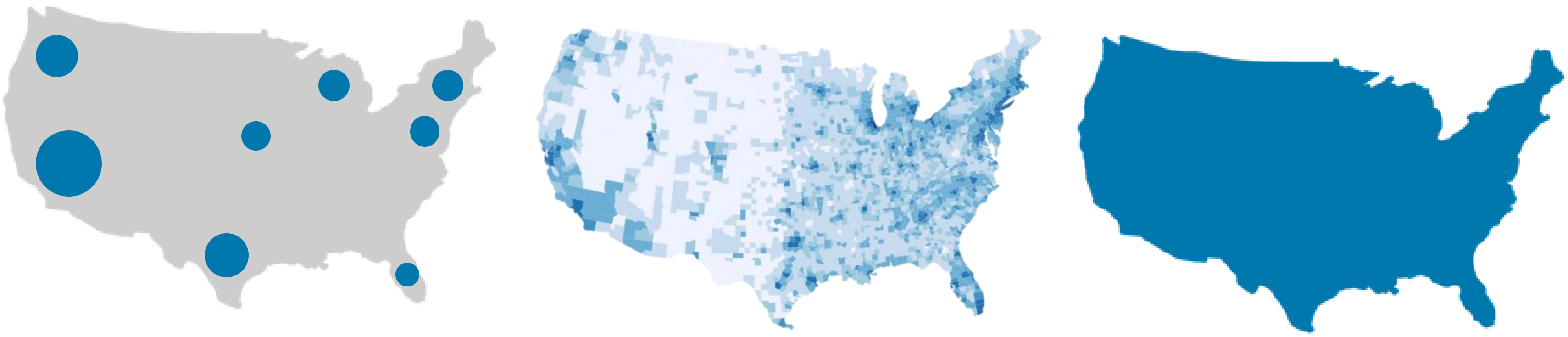

Theory | Practice | Theory

Entire spectrum of how to model (demand) types

Research Question

1. What is the interplay between the distribution of request types and achievable algorithmic performance?

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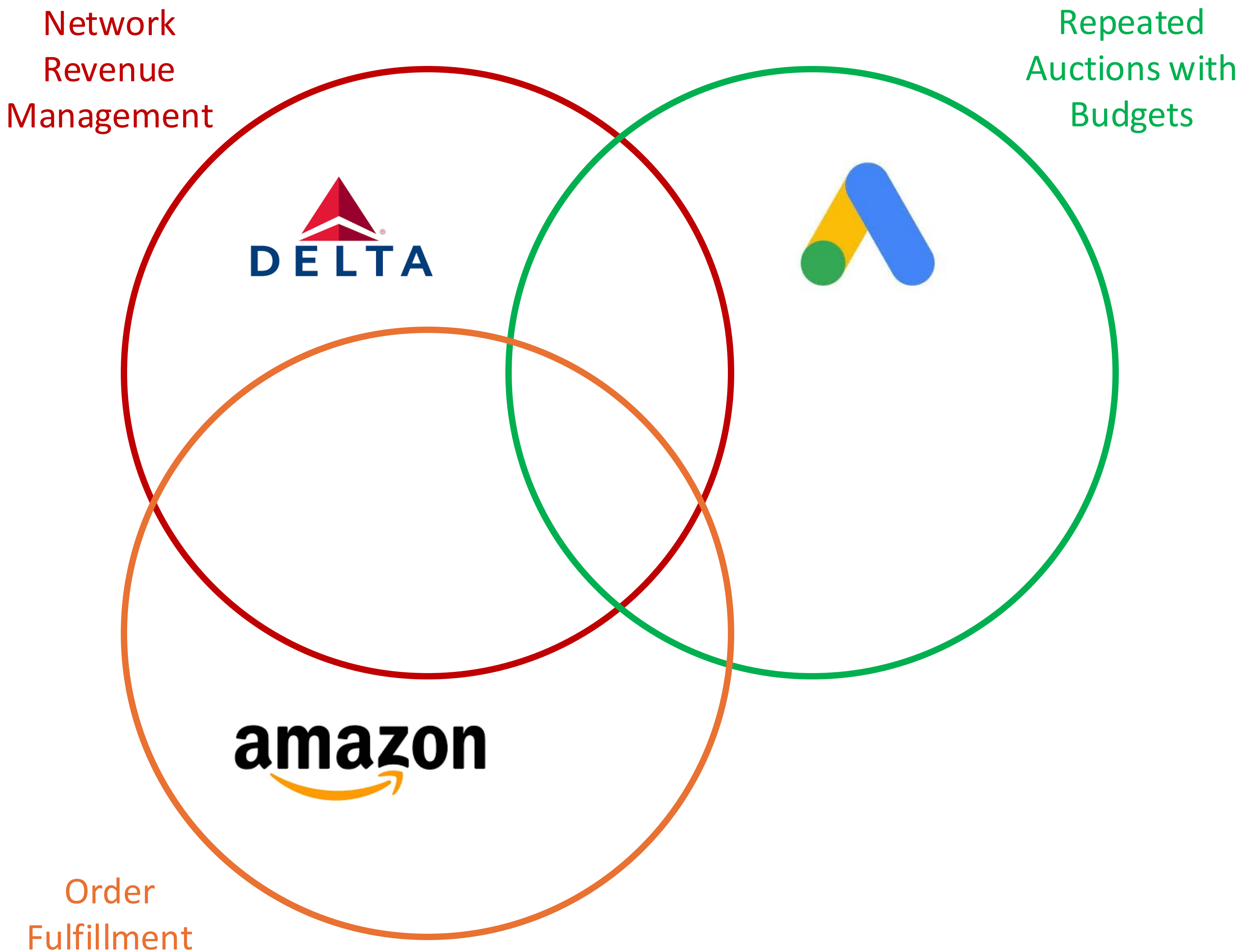
Theory | Practice | Theory

Entire spectrum of how to model (demand) types

1. What is the interplay between the distribution of request types and achievable algorithmic performance?
2. Can we design a **unified**, **simple** and **near-optimal** algorithms which works for all type distributions?

Order
Fulfillment


Network
Revenue
Management
DELTA
amazon
Order
Fulfillment


Network Revenue Management
Repeated Auctions with Budgets
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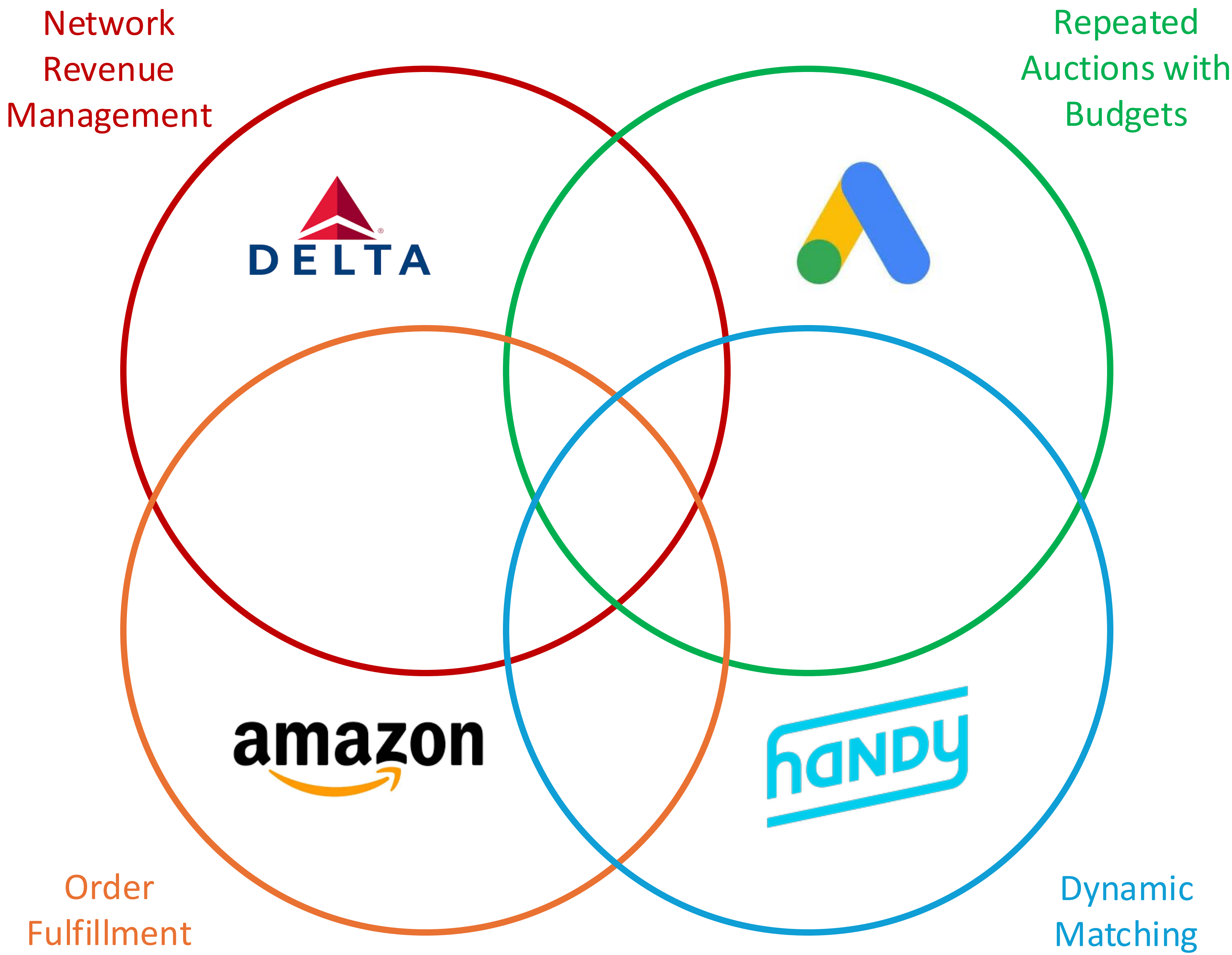
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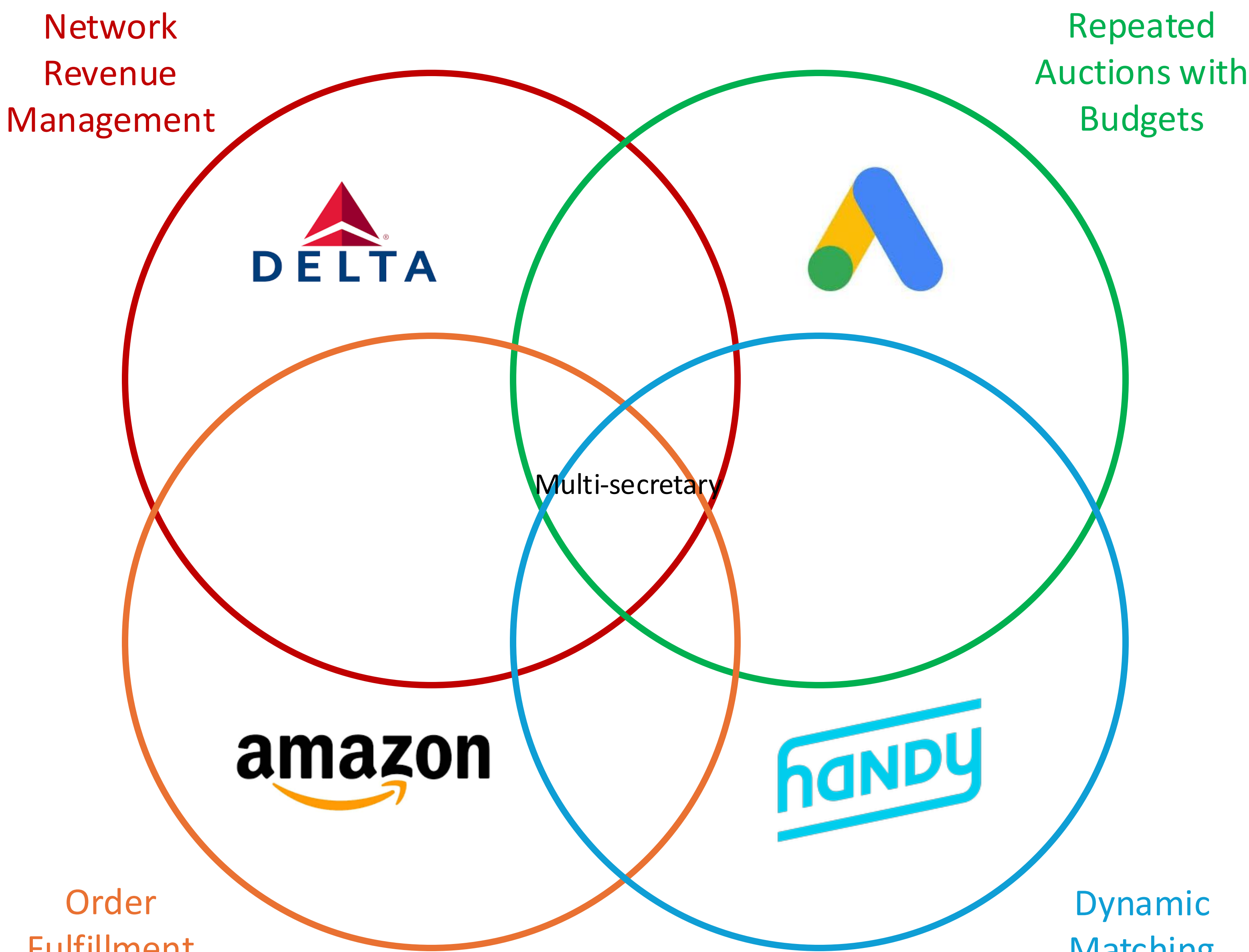
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Multi-secretary Problem

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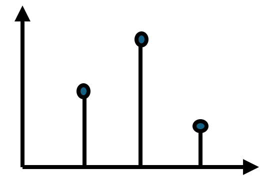

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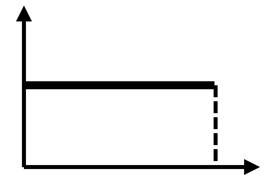

Multi-secretary Problem

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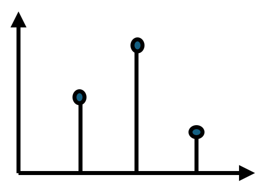
Bounded Regret



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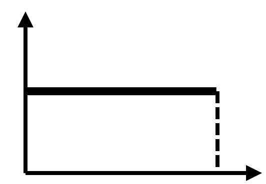
Logarithmic Regret



Regret is the additive gap b/w the value of hindsight opt. and value under some algorithm

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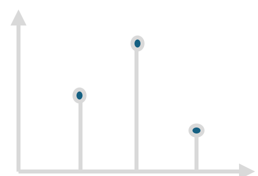

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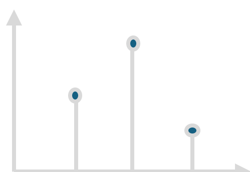

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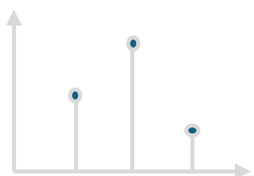

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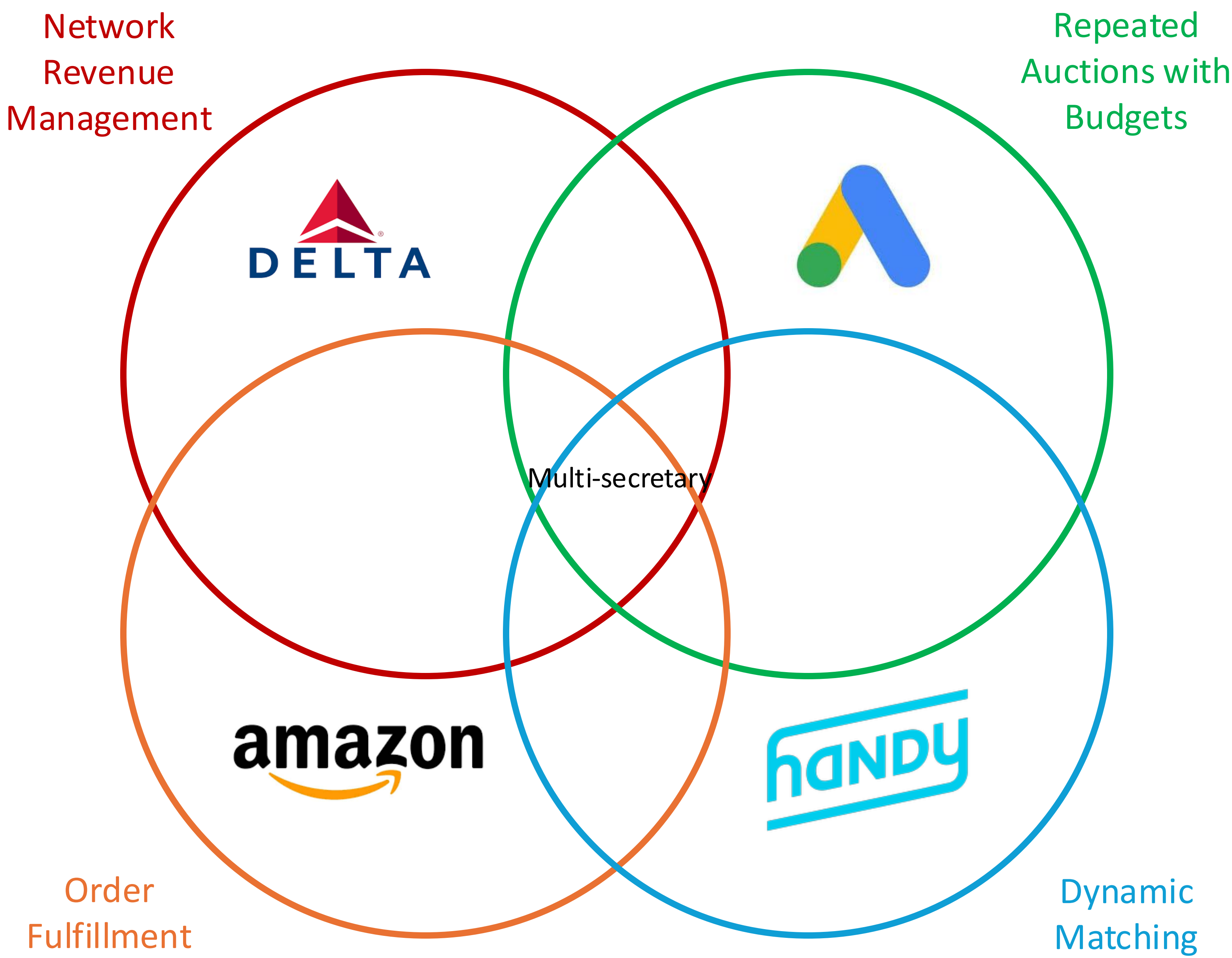
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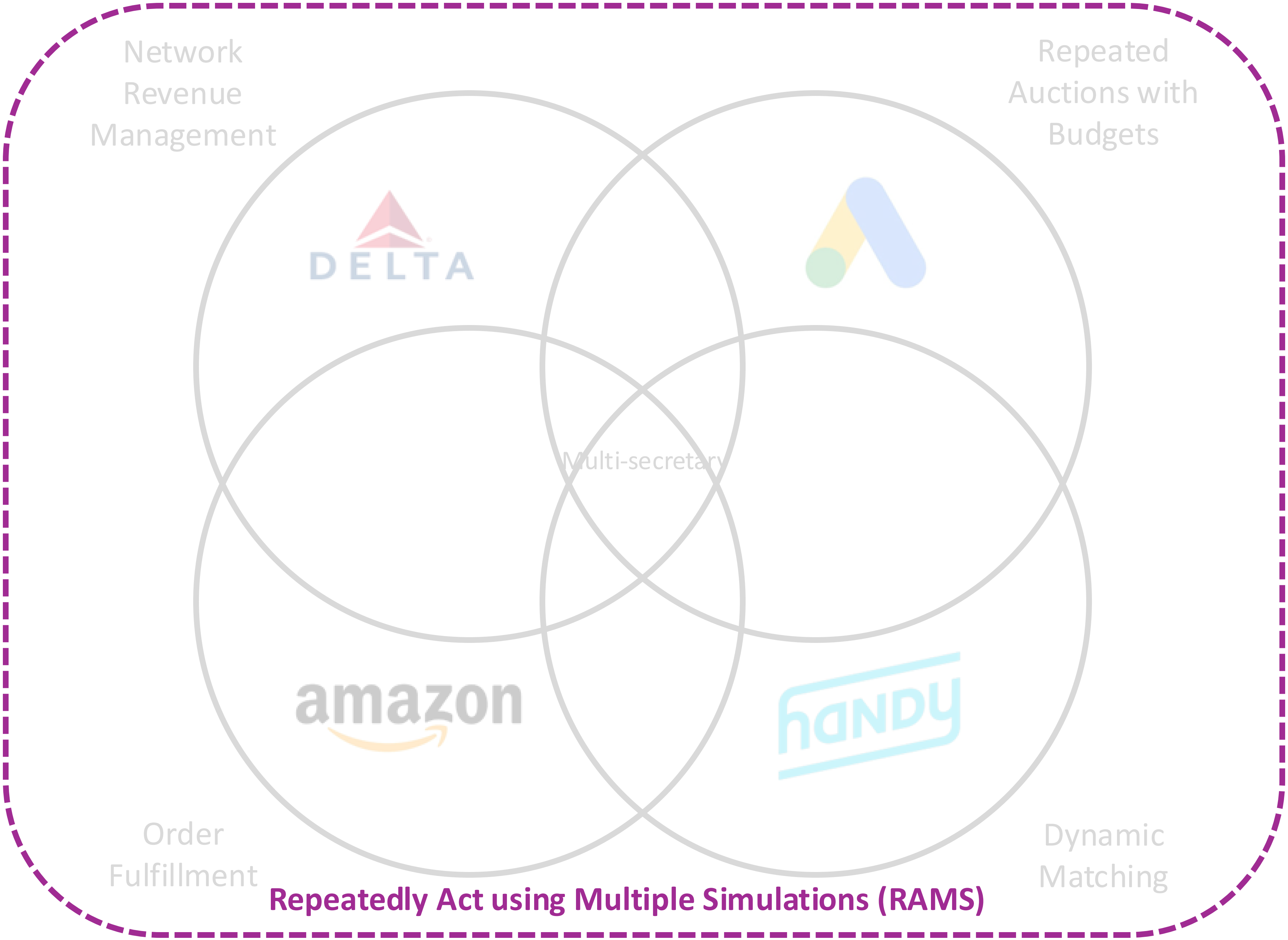
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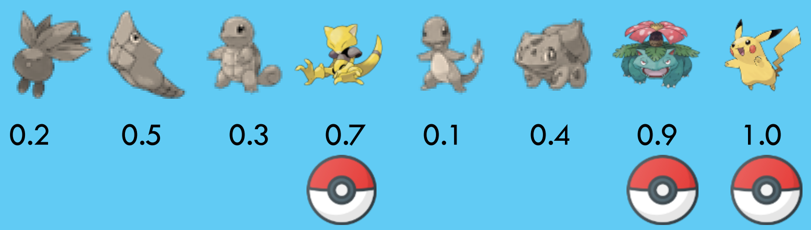

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  Regret$(\pi) =$ (Expected Maximum Value in Hindsight) – (Expected Value under π)

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Value in hindsight = 0.7 + 0.9 + 1.0 = 2.6

Value for policy π = 0.5 + 0.4 + 0.9 = 1.8

A tale of two FCs

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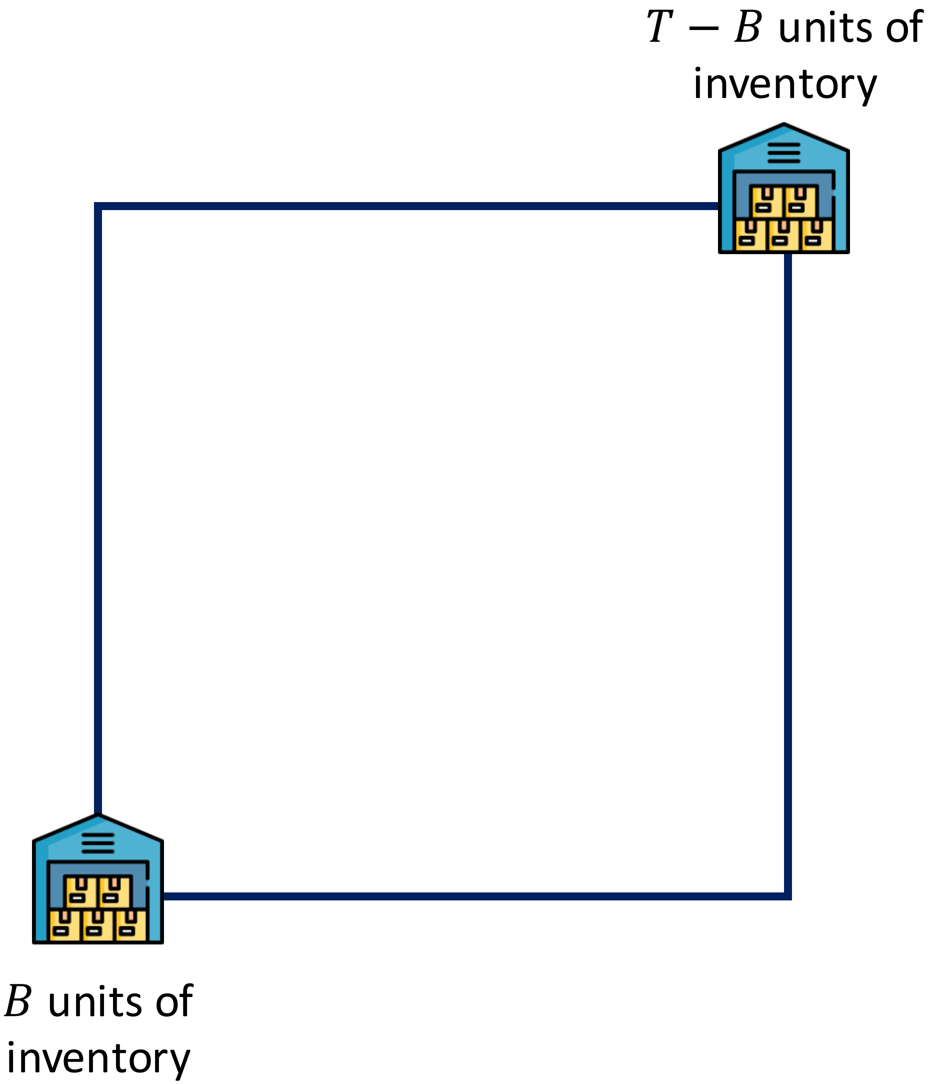

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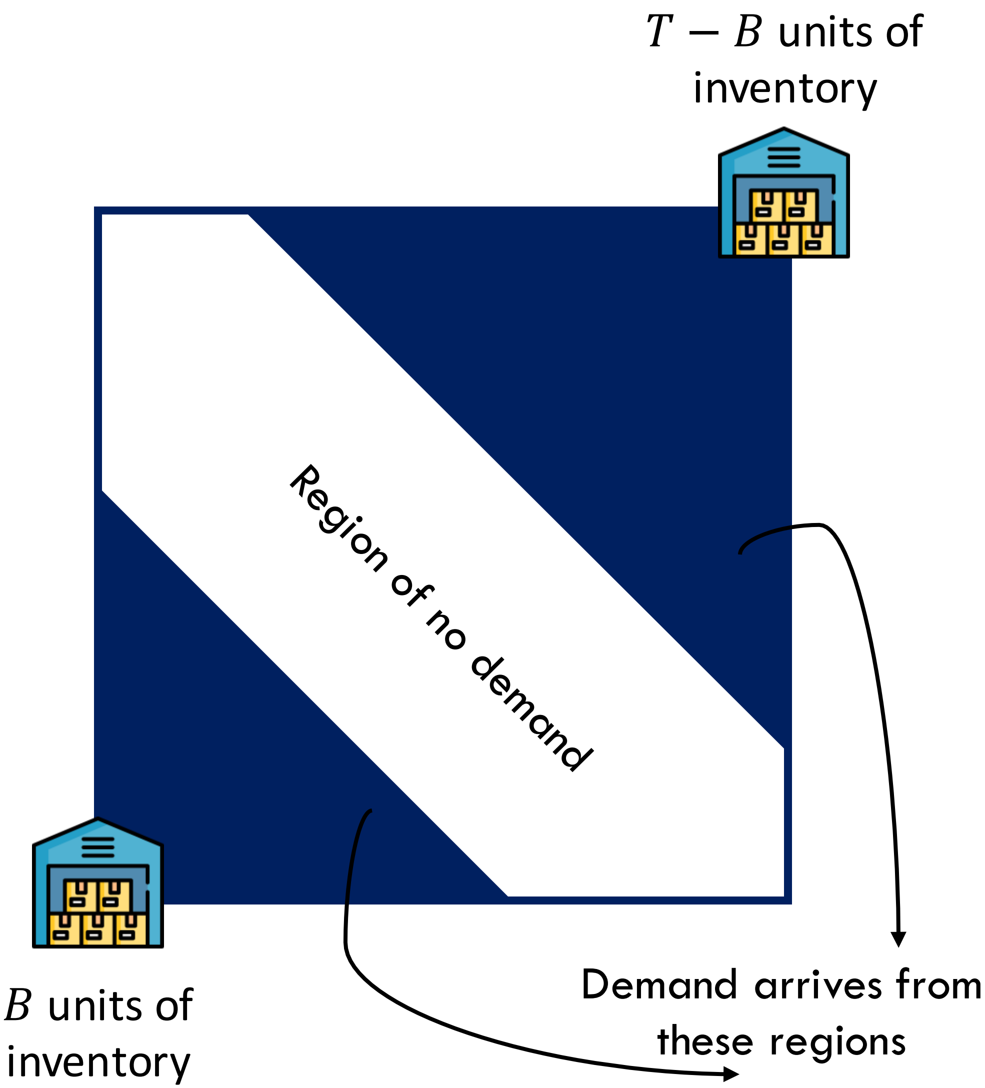

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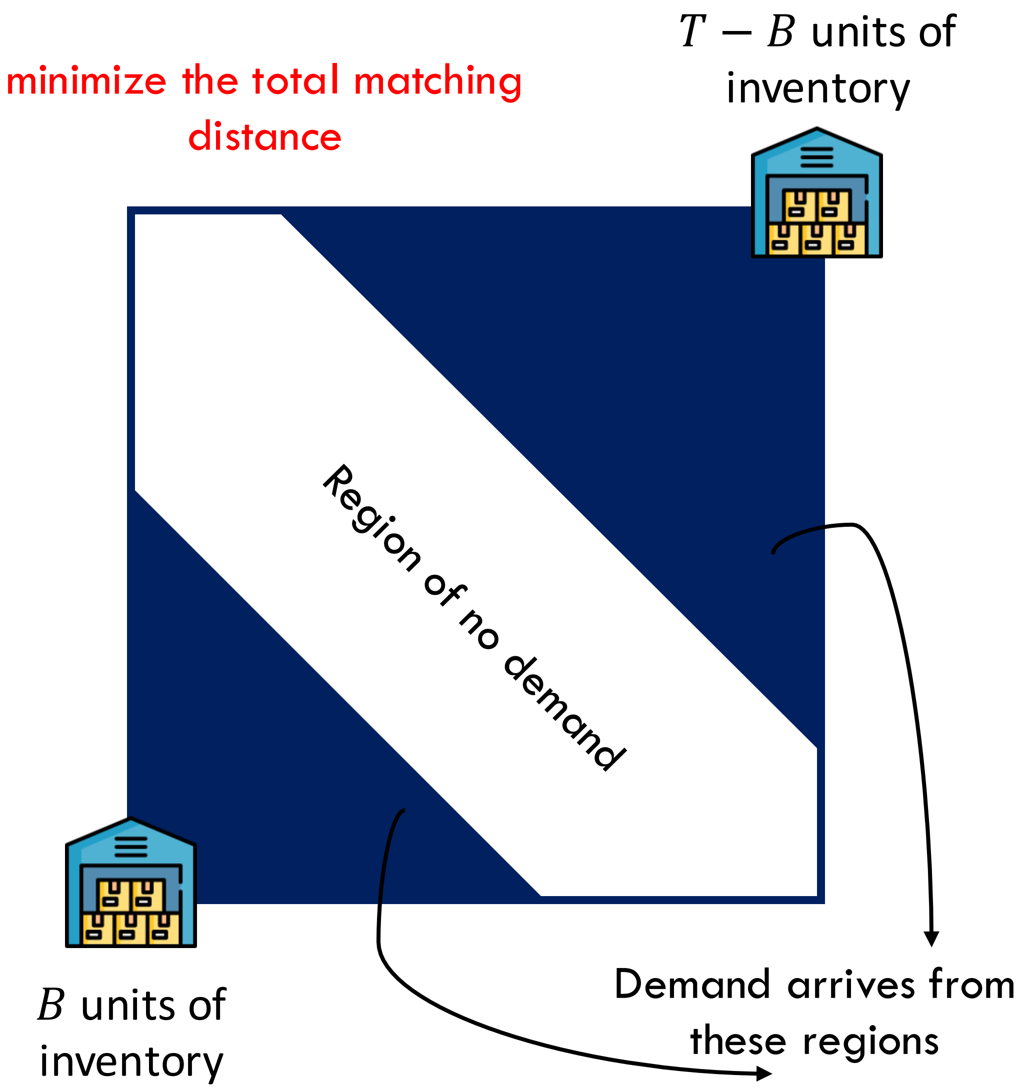
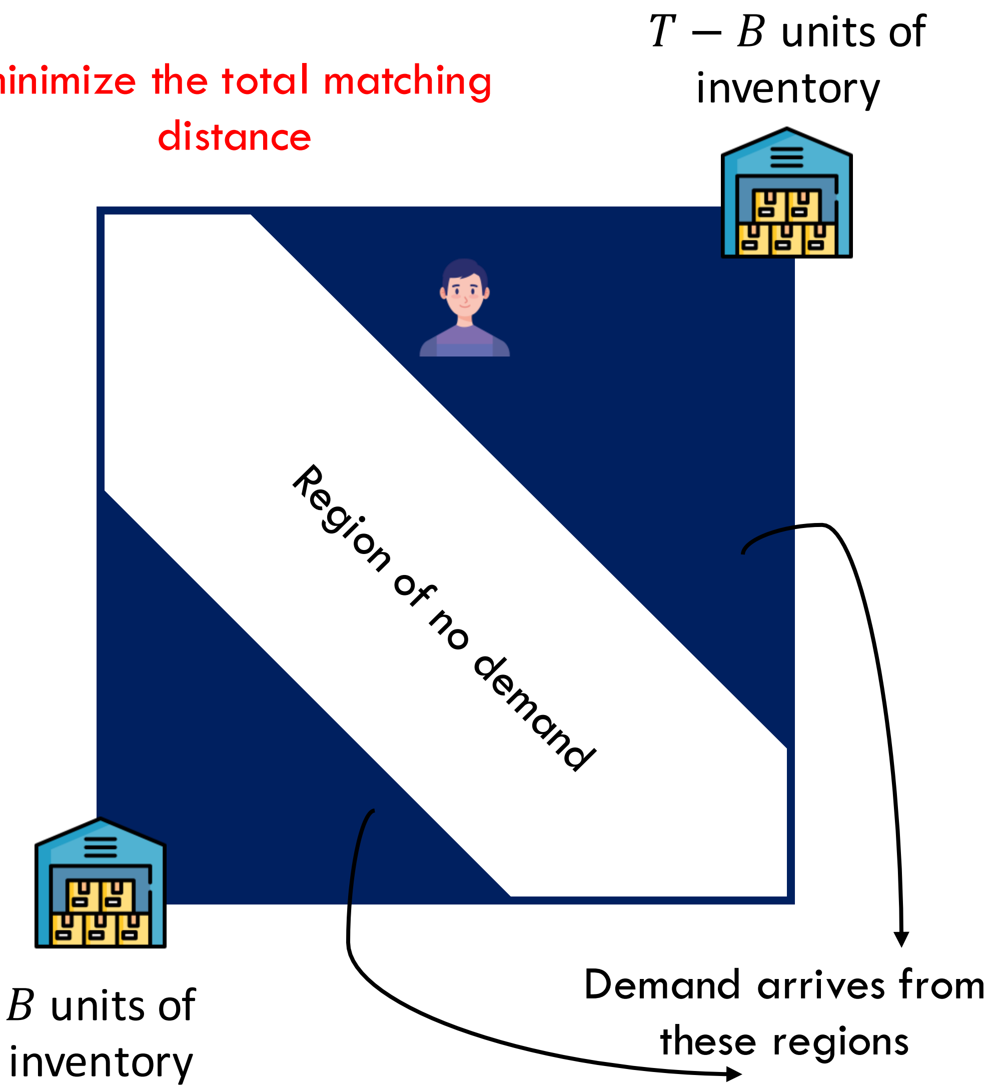


A tale of two FCs

minimize the total matching distance



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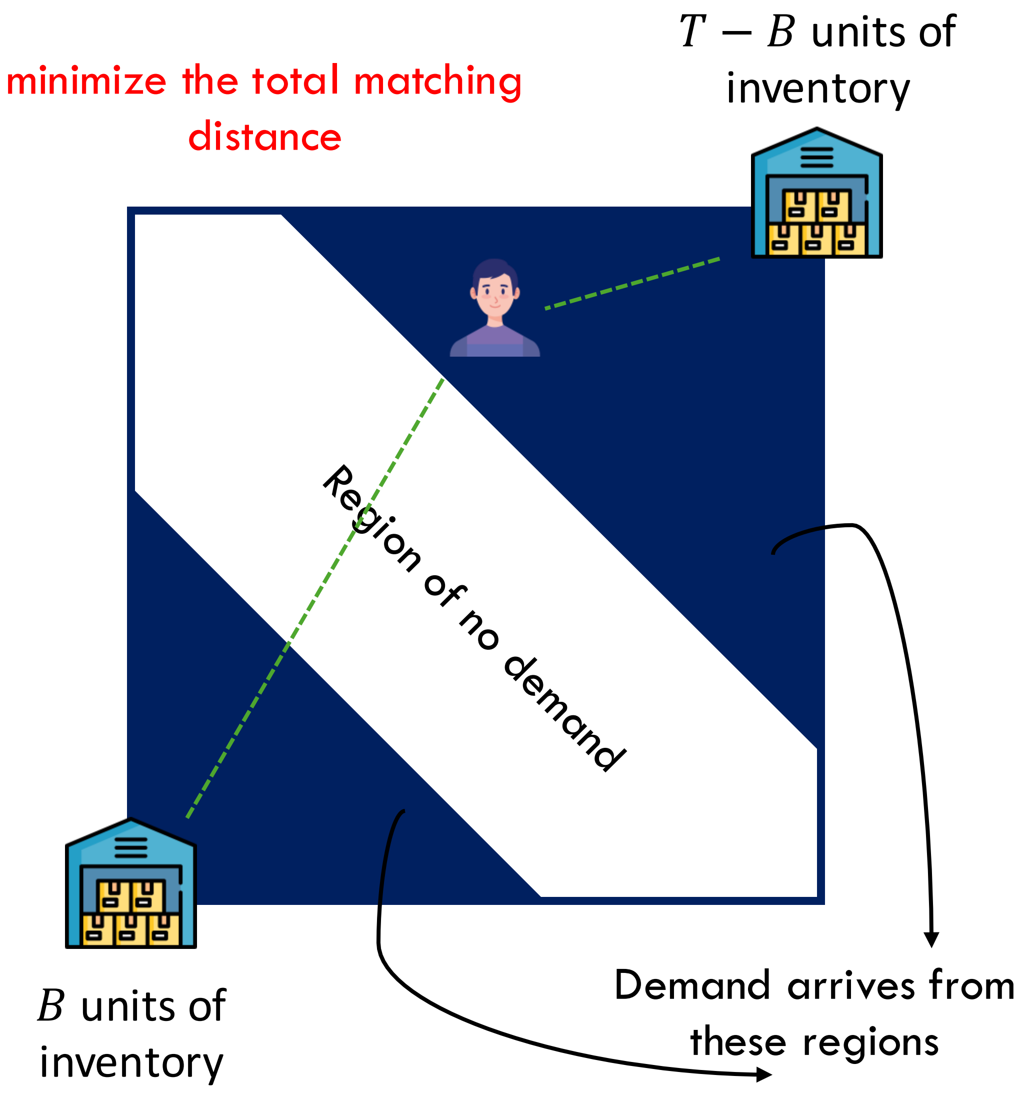

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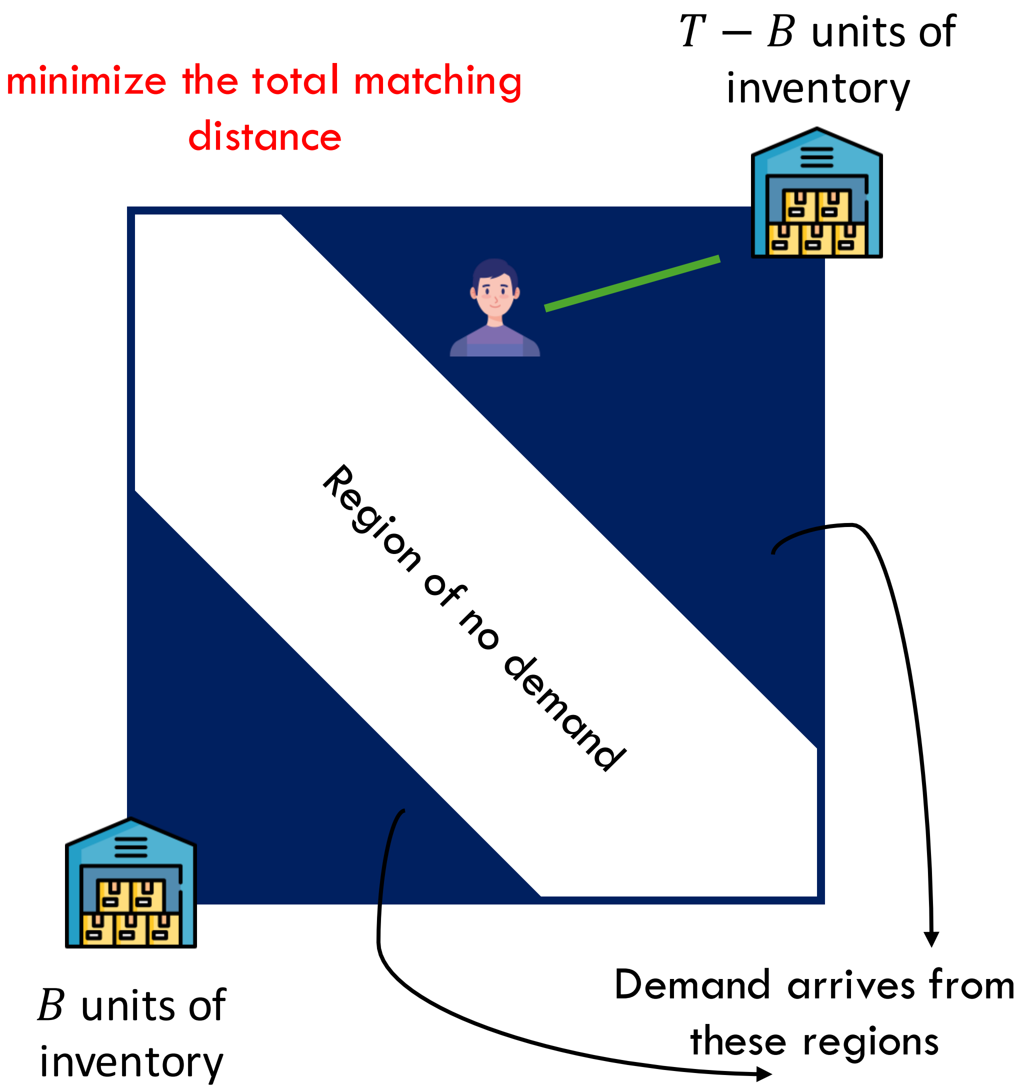

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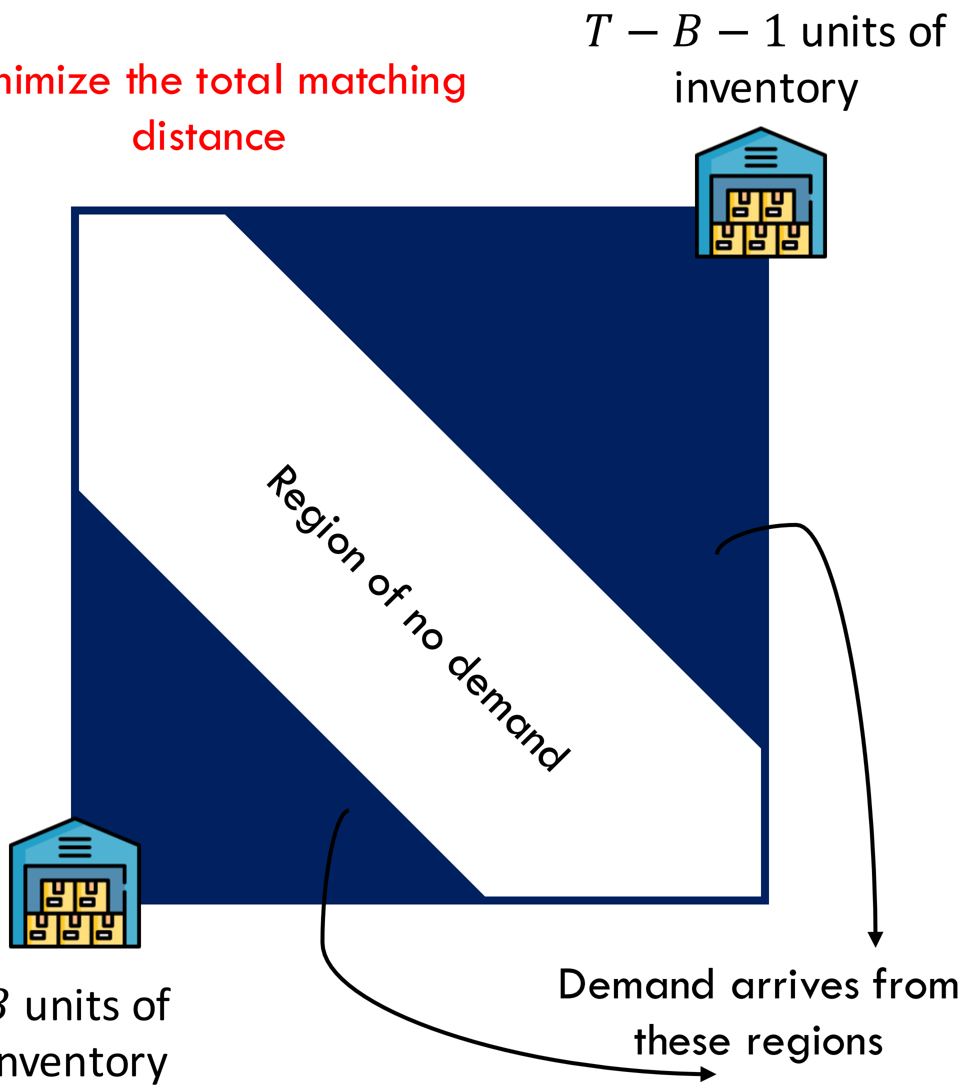

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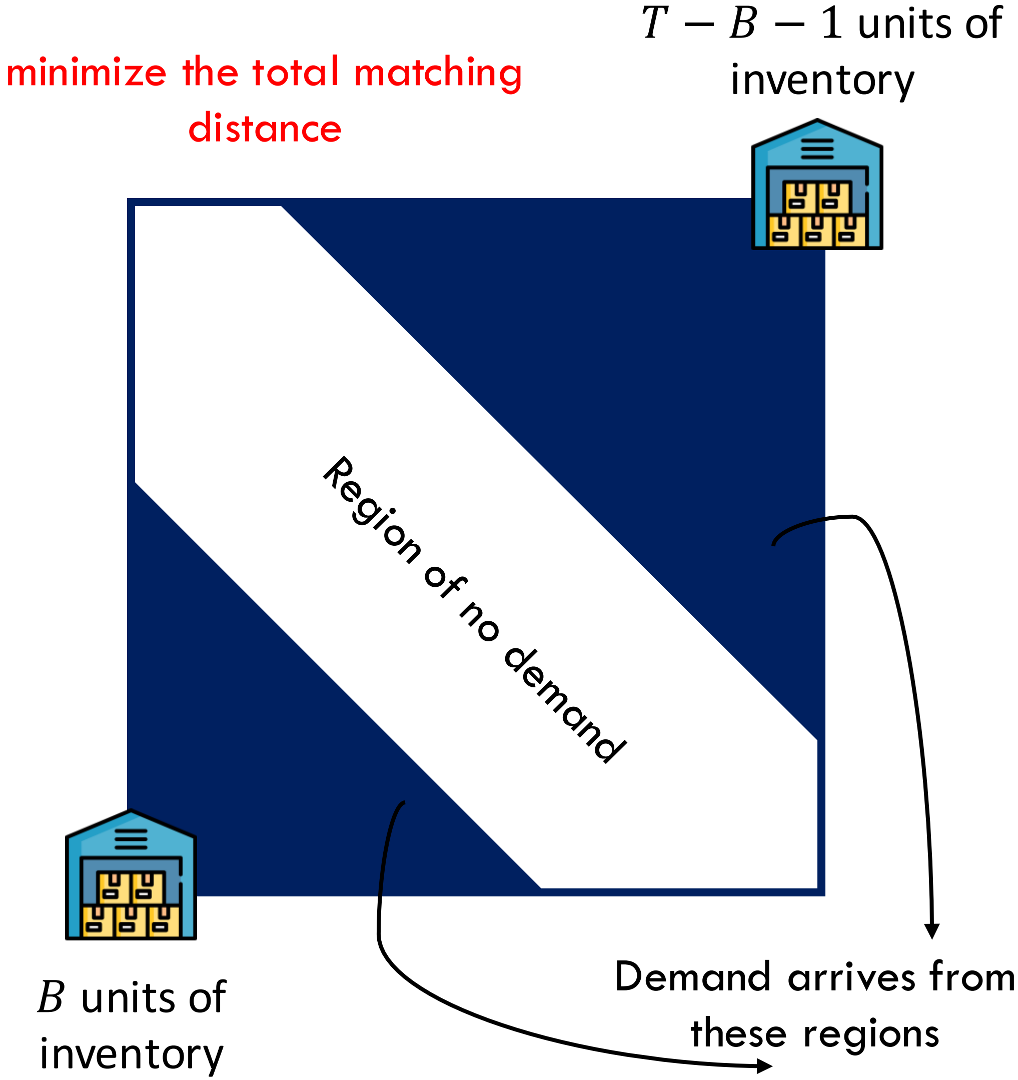

A tale of two FCs

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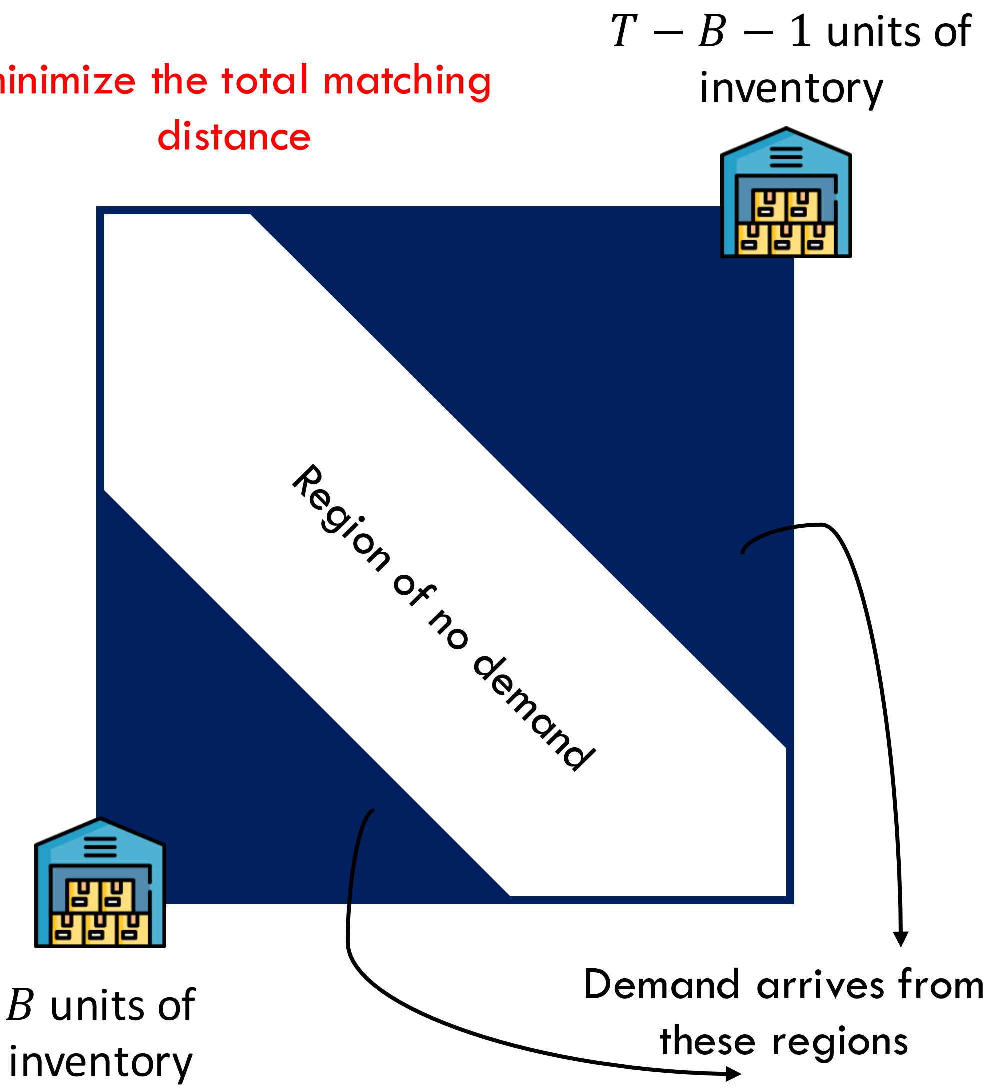

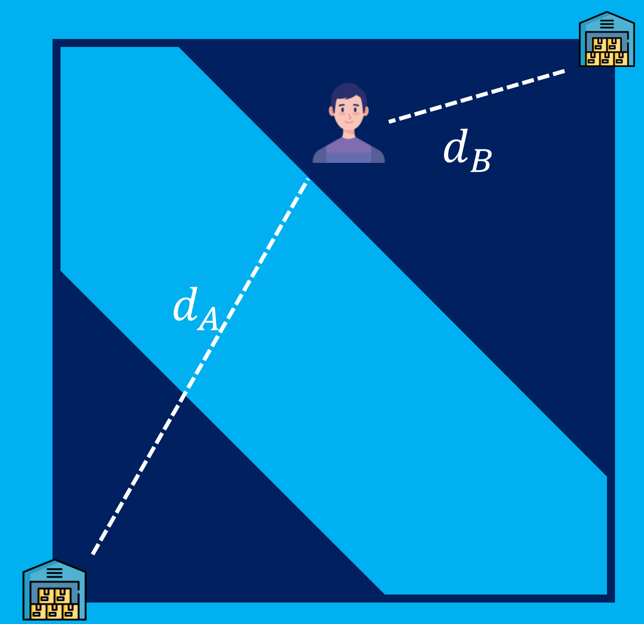

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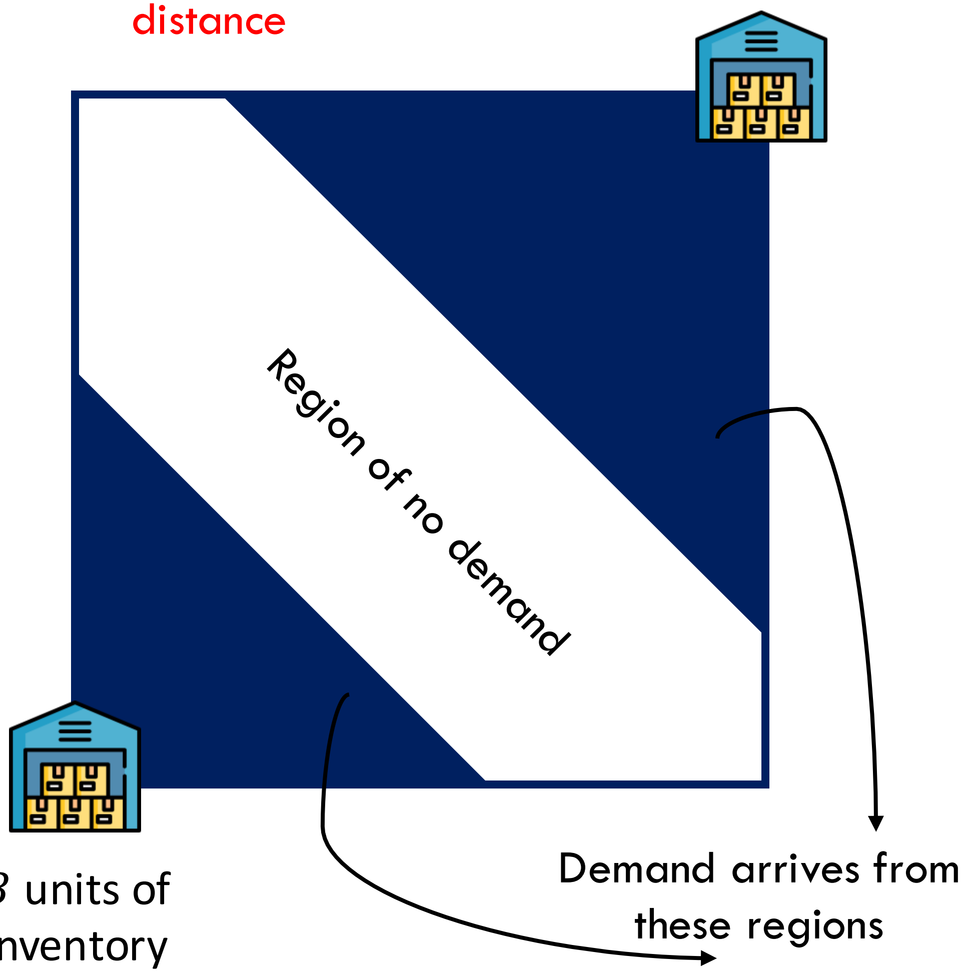
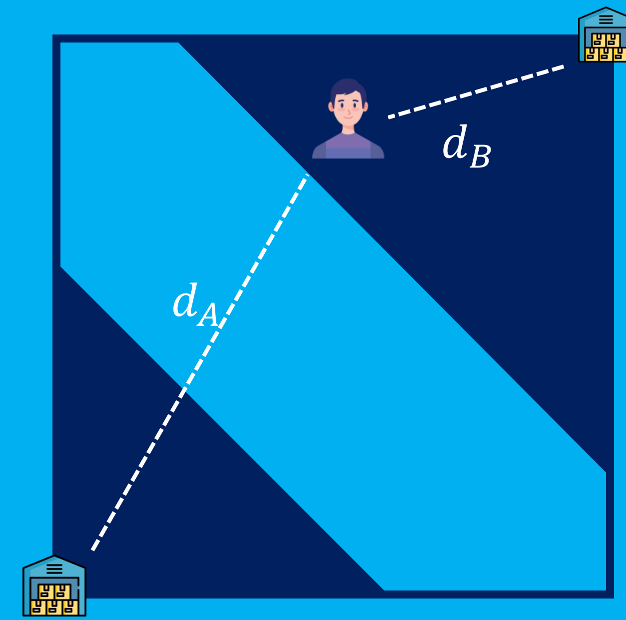




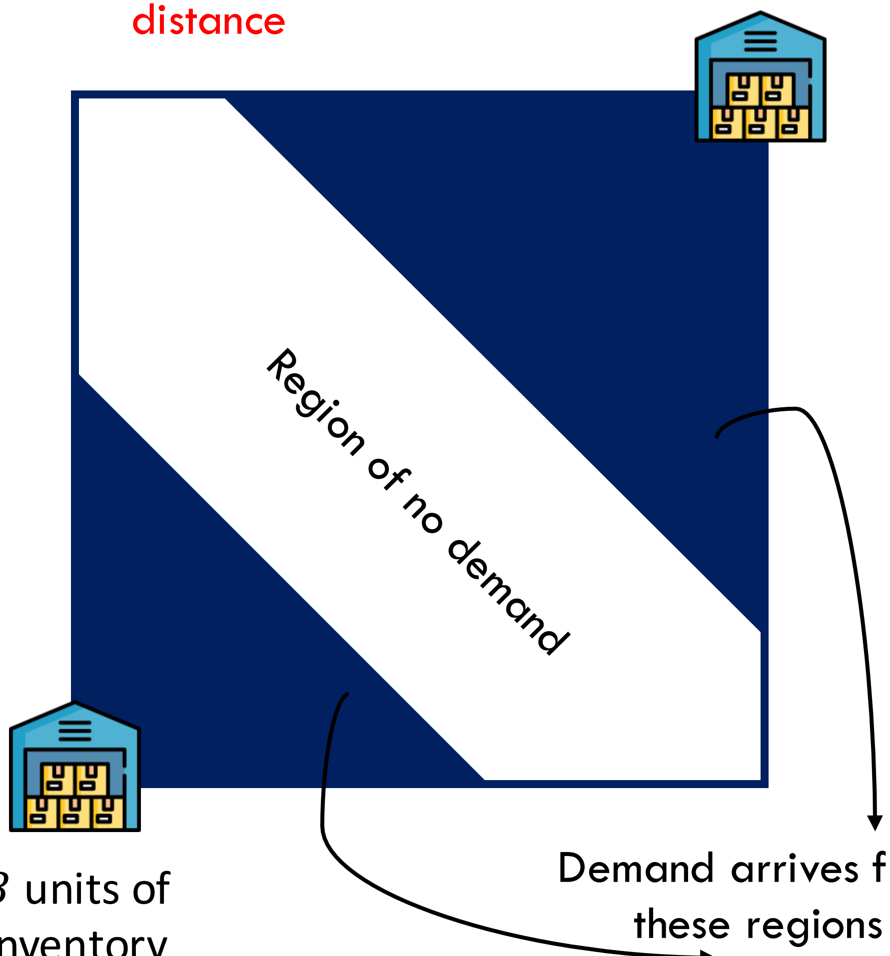
$$r = d_B - d_A + L$$

minimize total matching distance $\equiv$ maximize total matching reward

A tale of two FCs

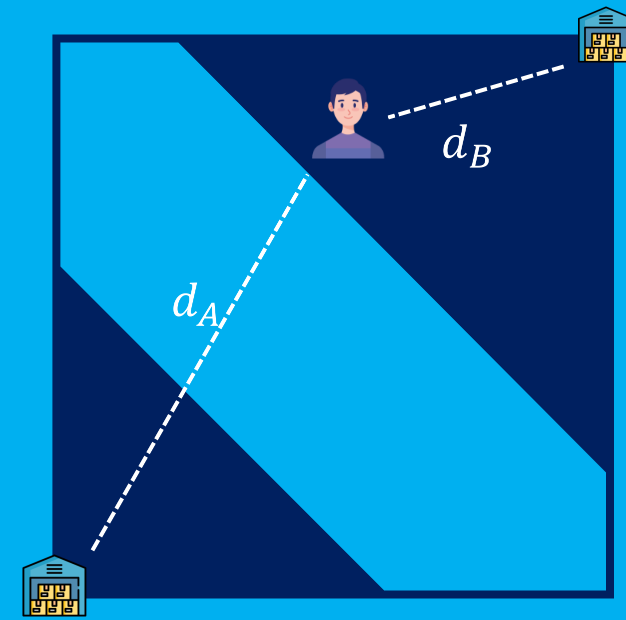
minimize the total matching distance

$T - B - 1$ units of inventory



B units of inventory

Demand arrives from these regions



$$r = d_B - d_A + L$$

minimize total matching distance $\equiv$ maximize total matching reward

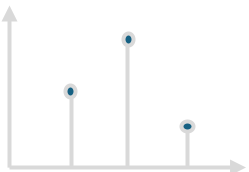
Dynamically choose the highest B reward values, given the reward distribution

maximize total matching reward $\equiv$ multi-secretary problem

Multi-secretary Problem

A few types are present

Bounded Regret



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Complete Characterization of the Multi-secretary Problem

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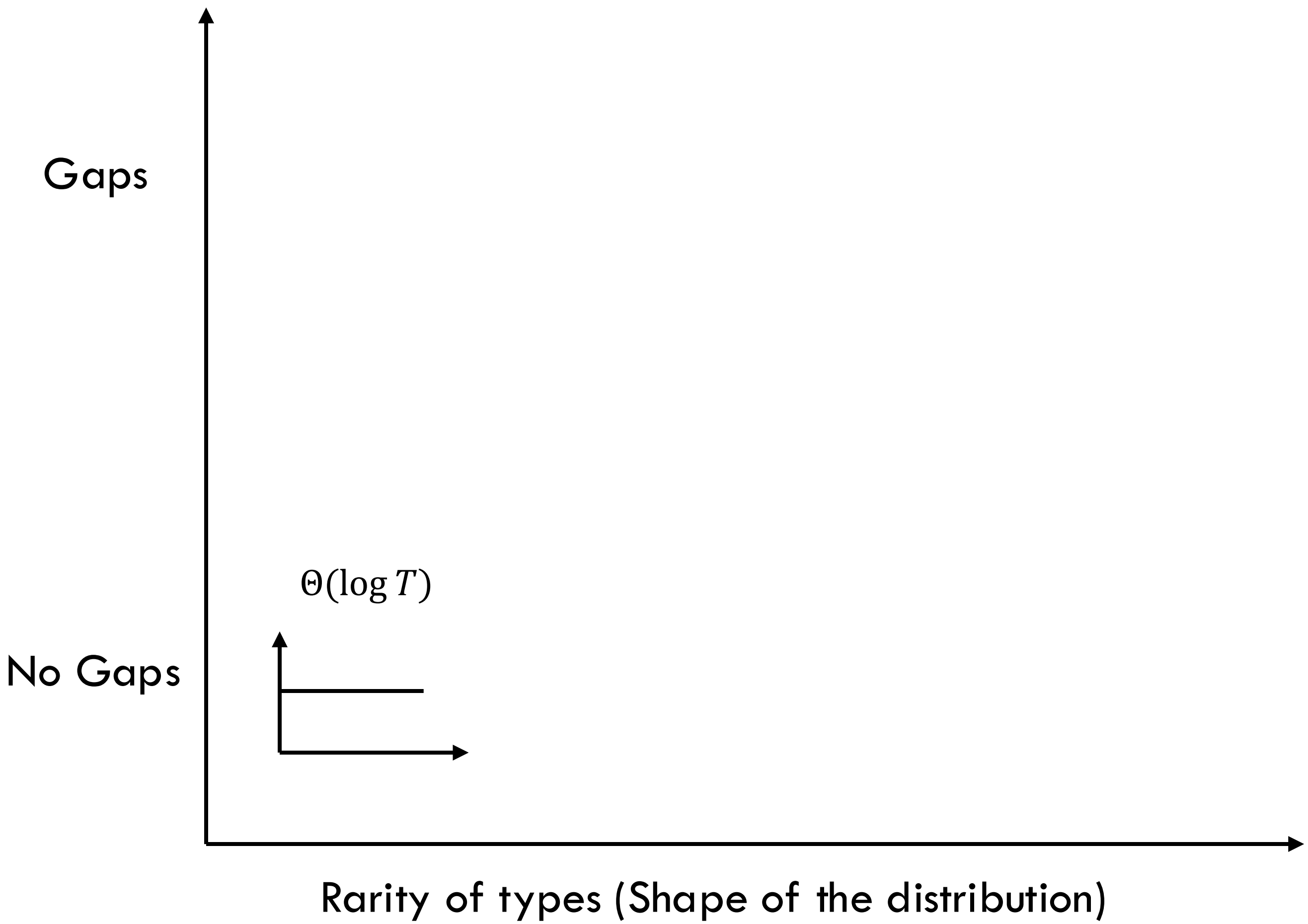

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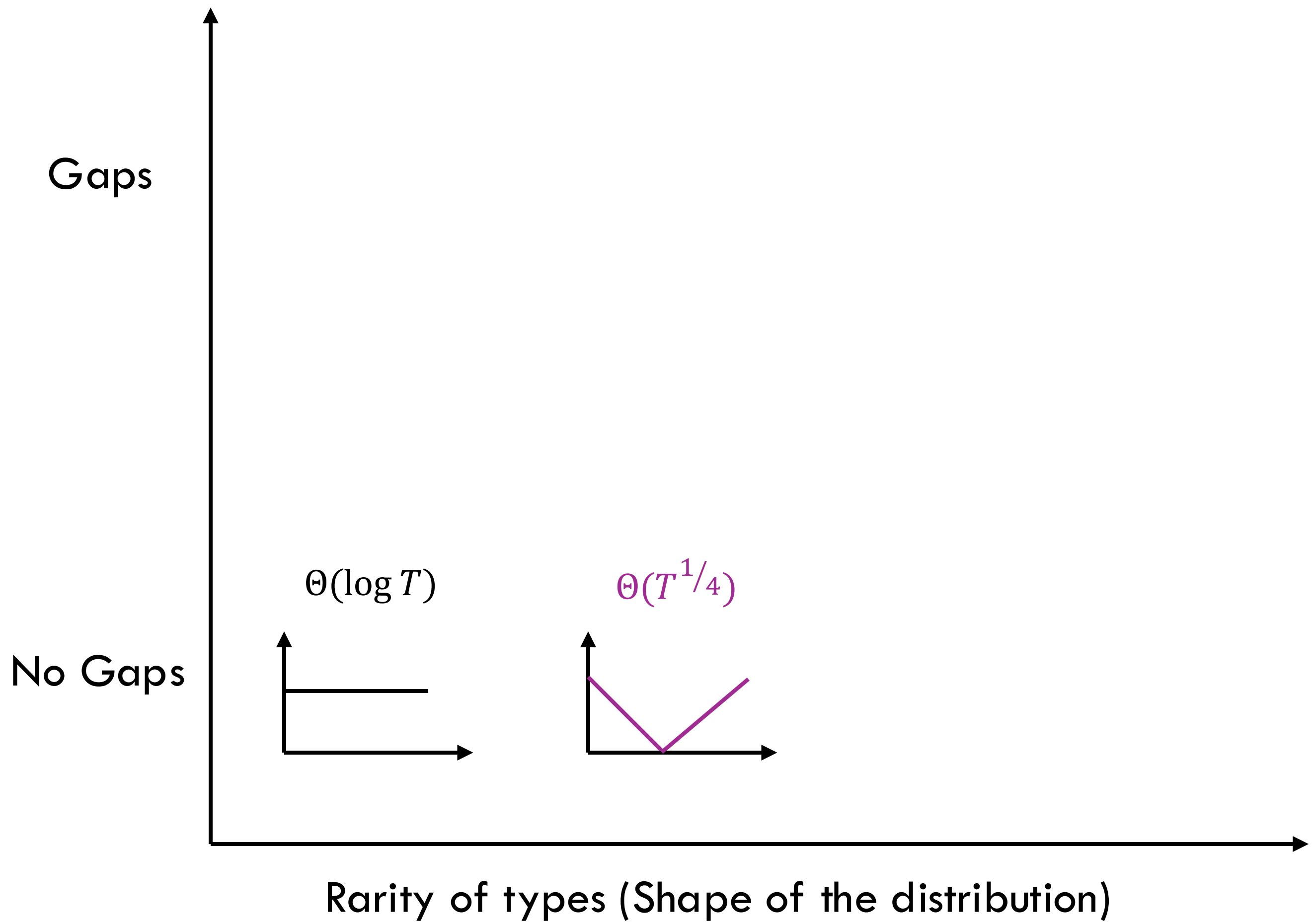

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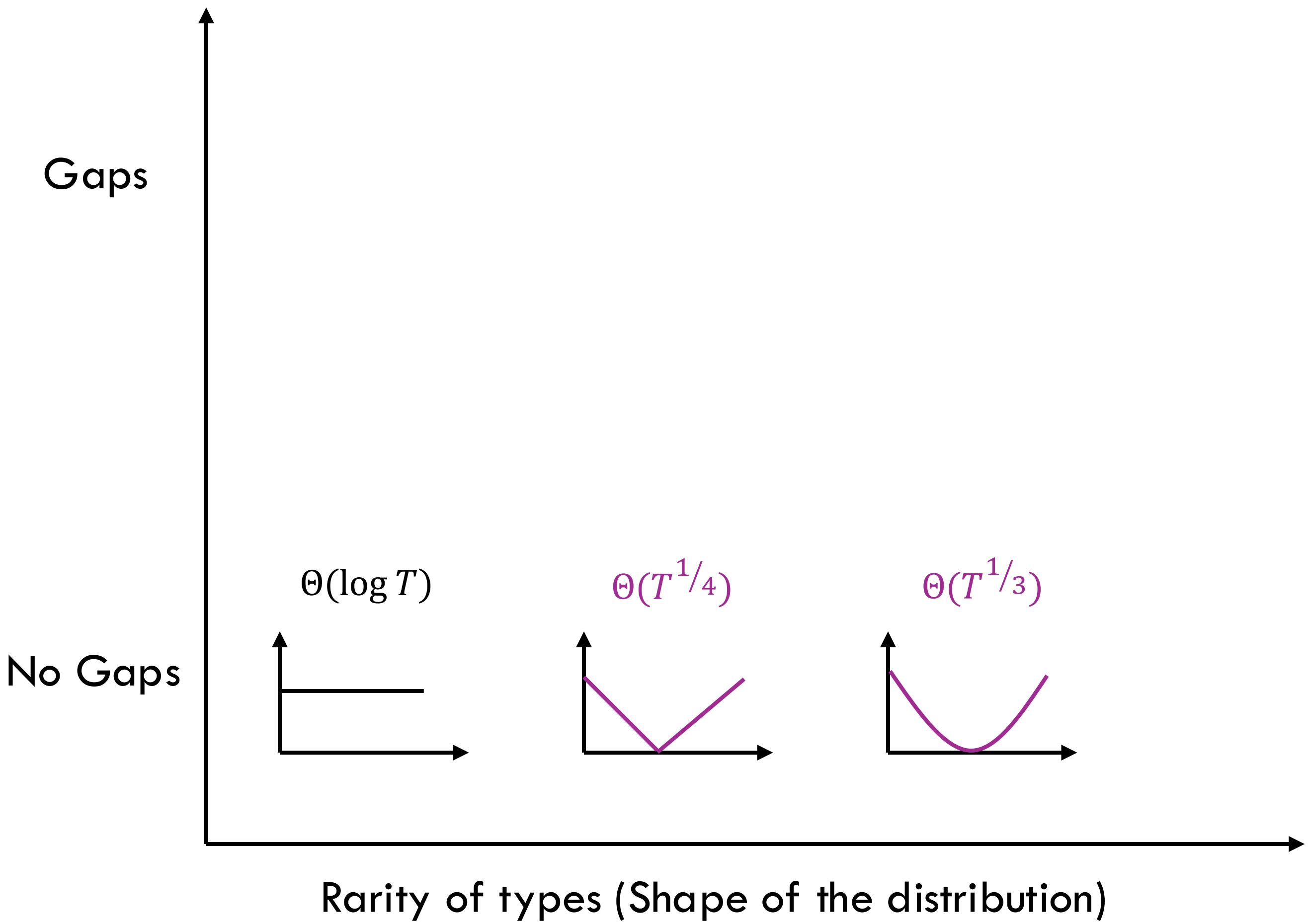

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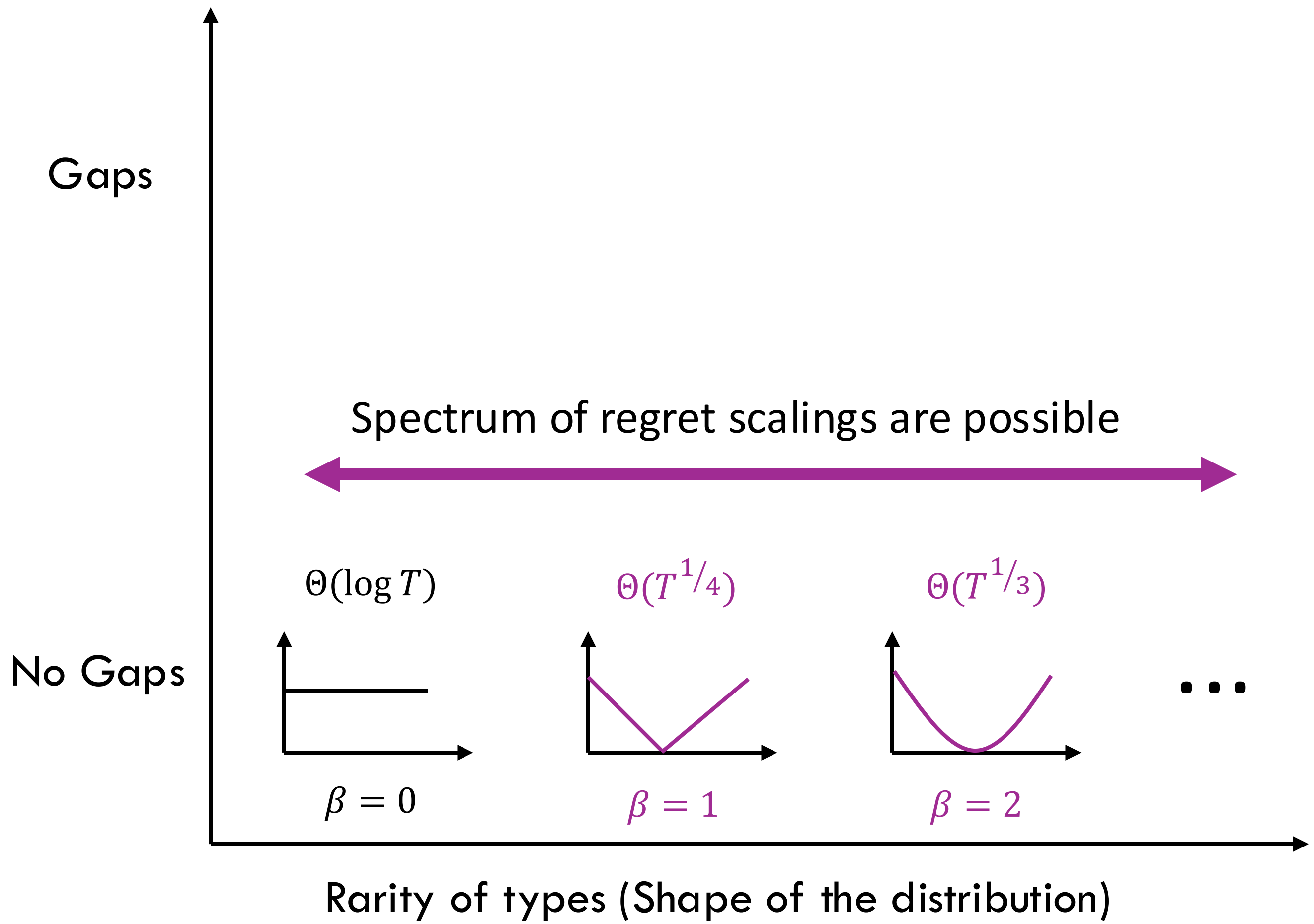

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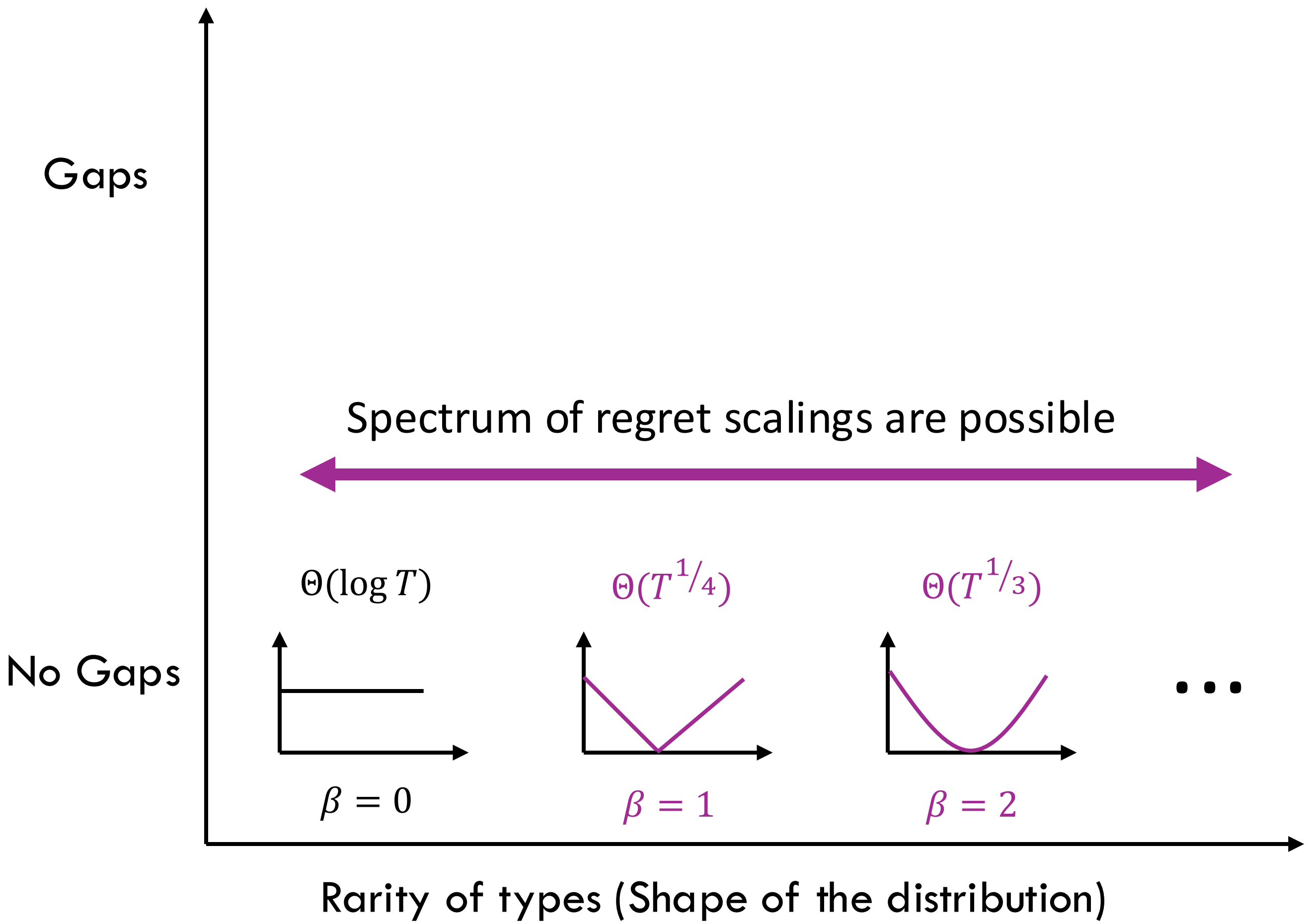

Distribution shape is a fundamental driver of performance

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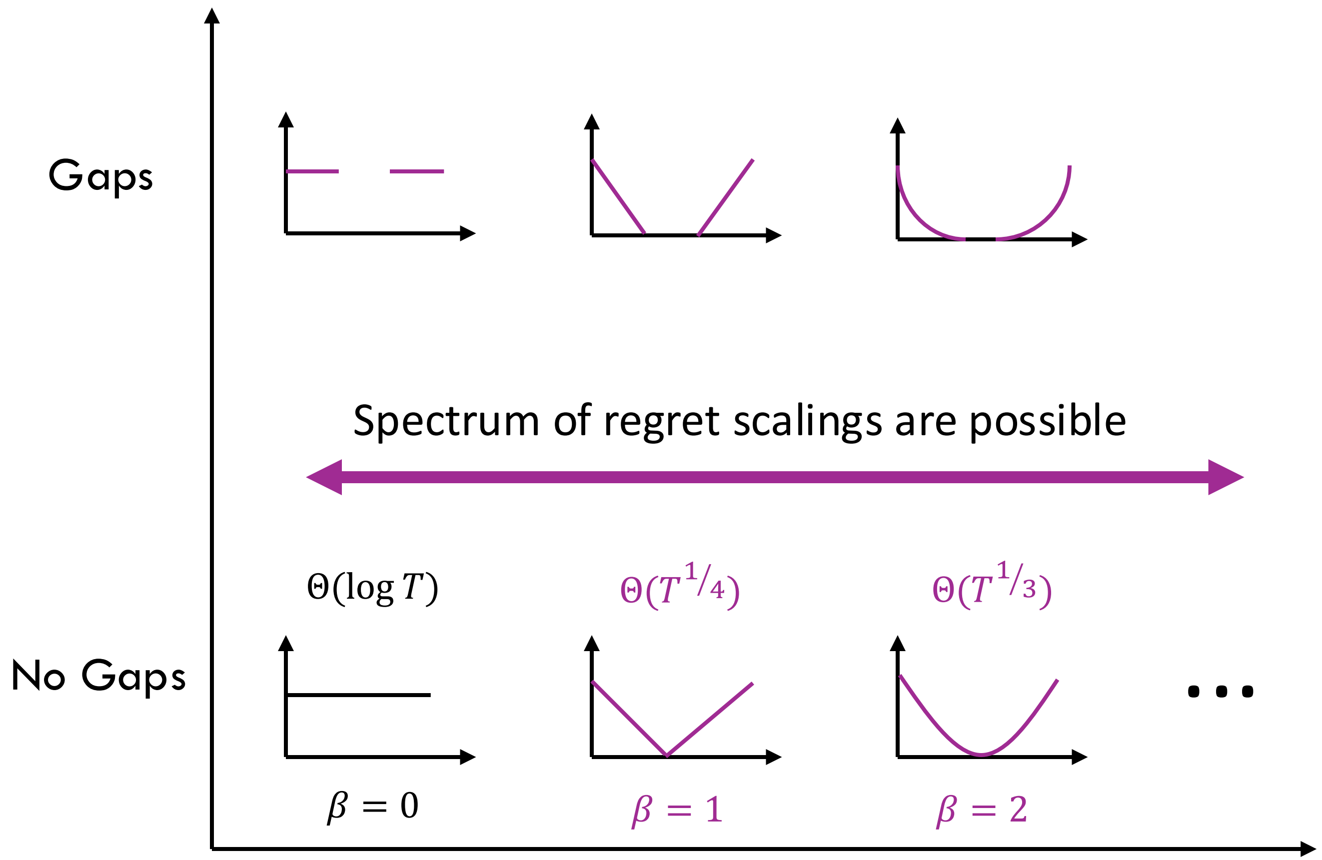

Rarity of types (Shape of the distribution)

Distribution shape is a fundamental driver of performance

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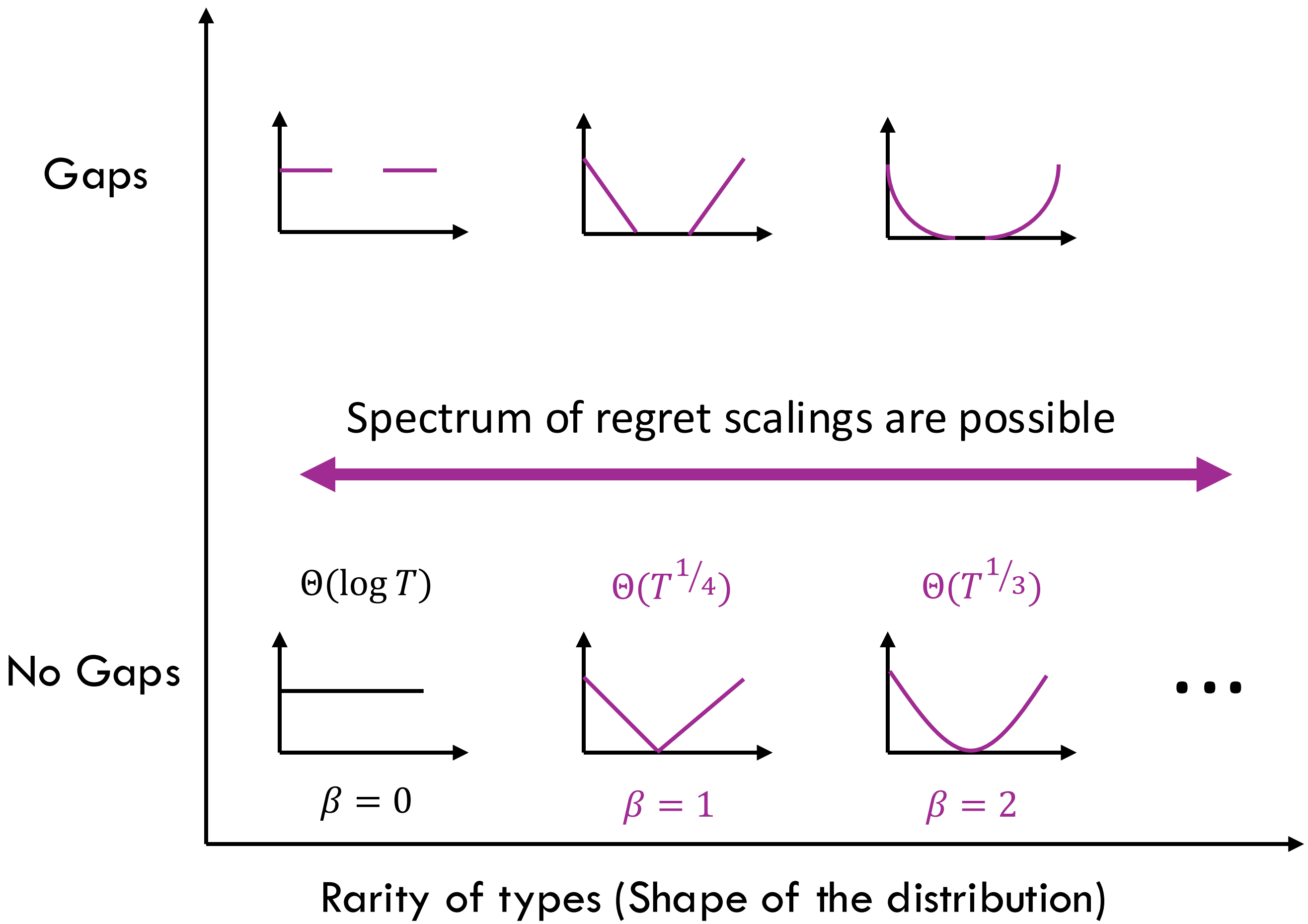

Distribution shape is a fundamental driver of performance

Dealing with gaps in an algorithmic challenge

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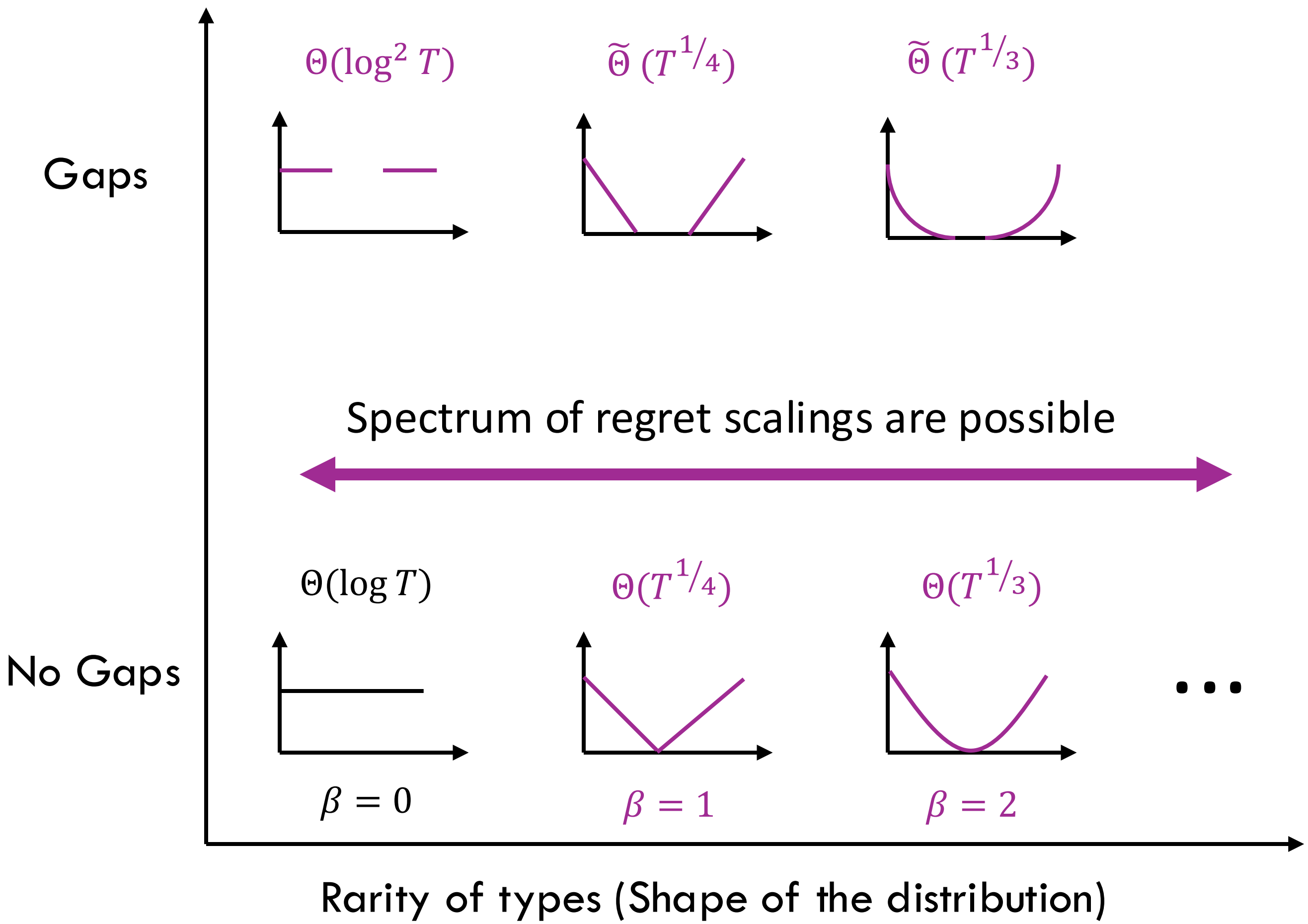

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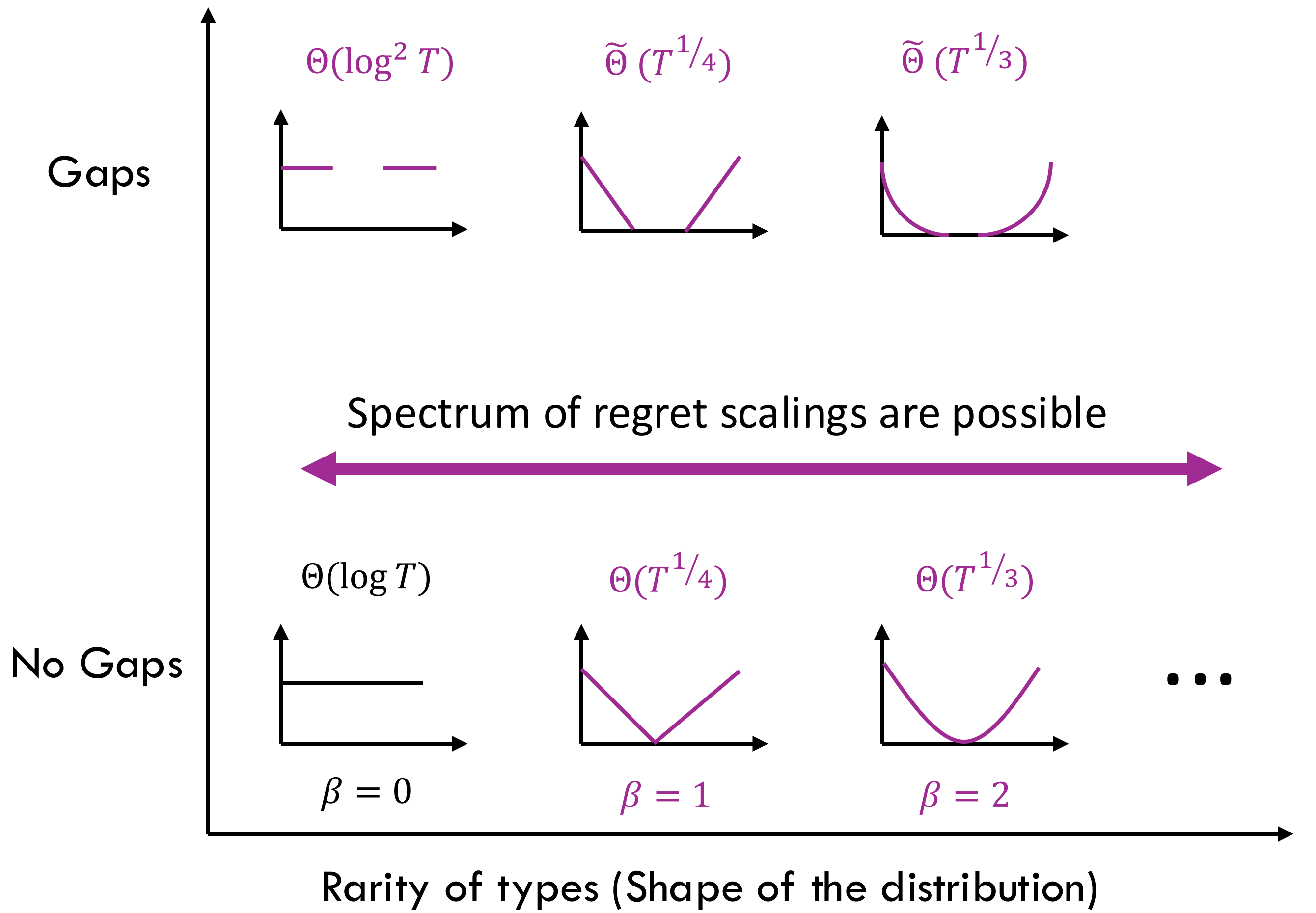

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Use RAMS to operationalize CwG

Multi-secretary Problem

one algorithm to solve them all

Repeatedly Act using Multiple Simulations (RAMS)

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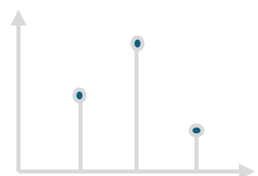

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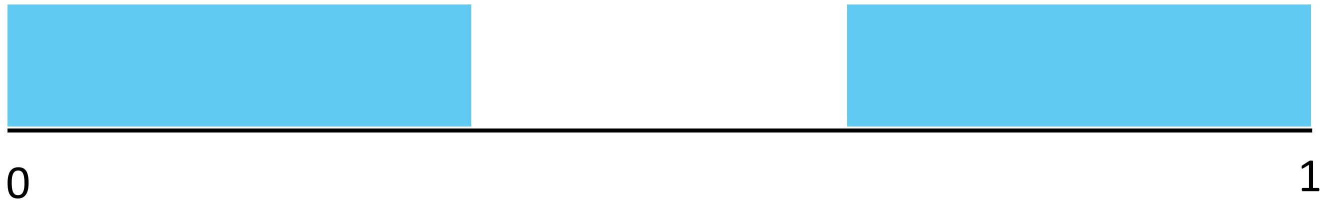

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Certainty Equivalent Control computes the budget ratio

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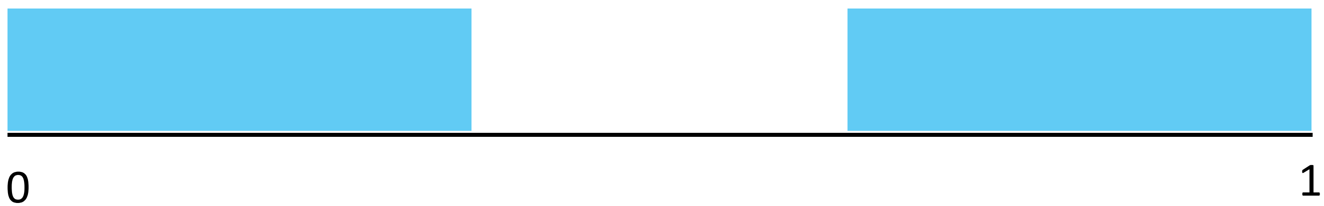
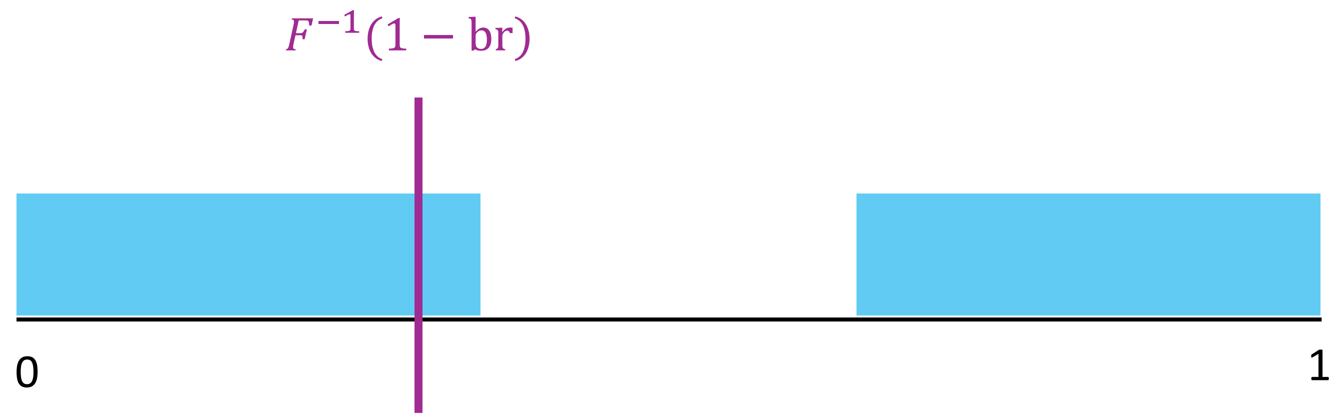


Certainty Equivalent Control computes the budget ratio

br = Budget Ratio = (Remaining Budget) / (Remaining Time)

Gaps pose an algorithmic challenge



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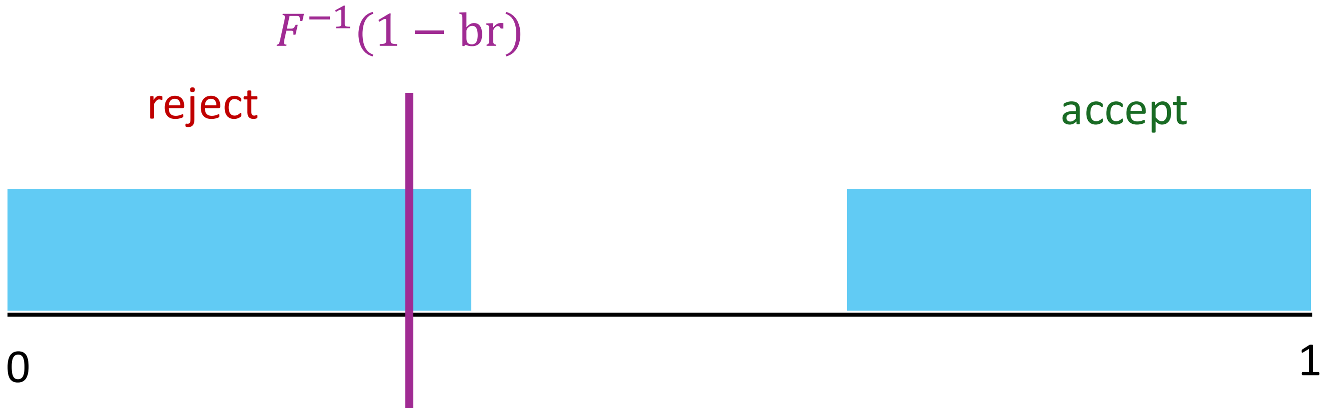

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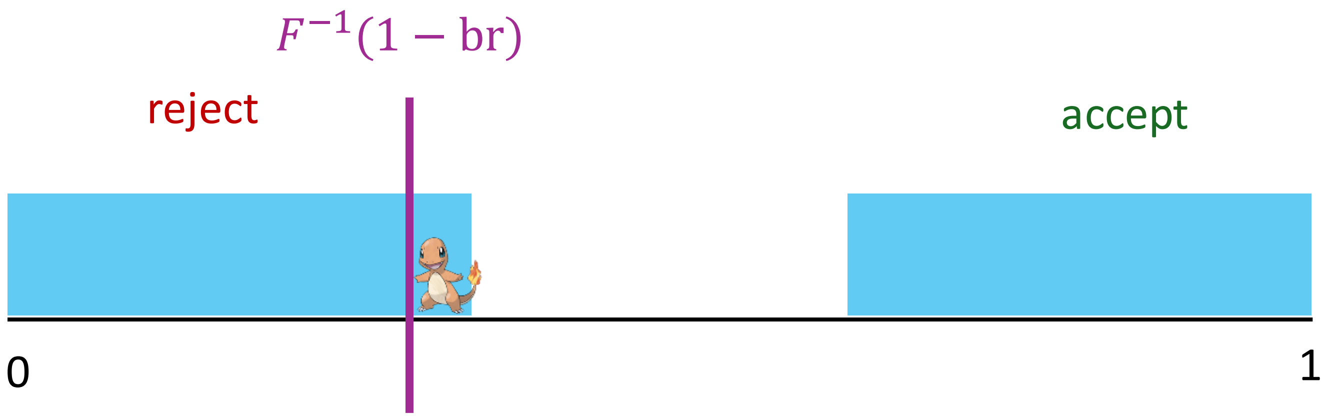

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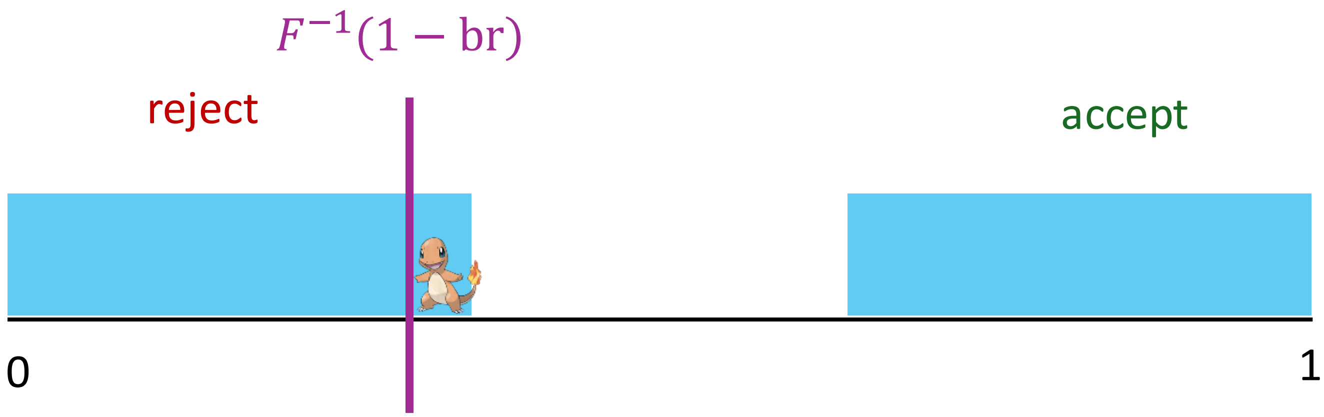

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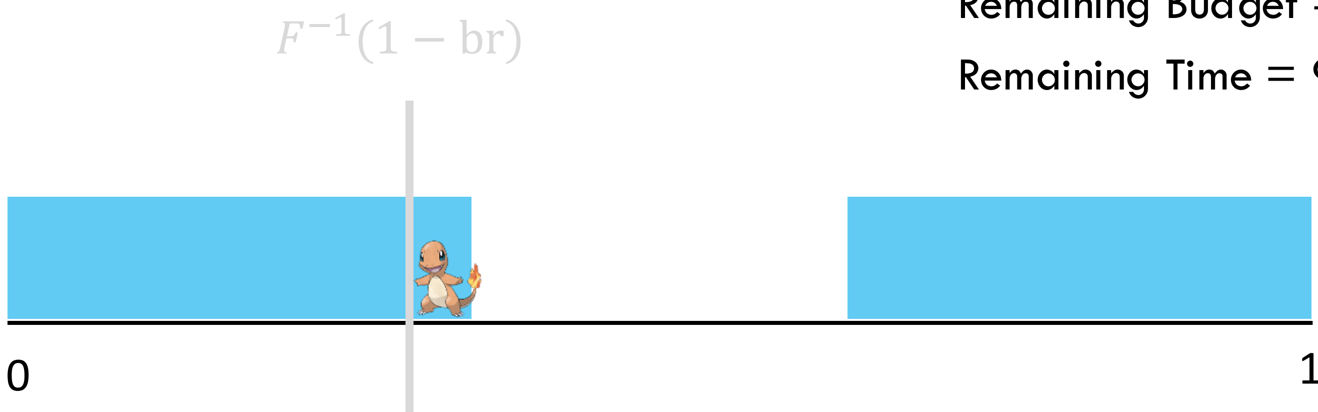
Regret(CE) = $\Omega(\sqrt{T})$ (highly sub-optimal regret scaling)

CwG via multiple simulations

Remaining Budget = 5

Remaining Time = 9



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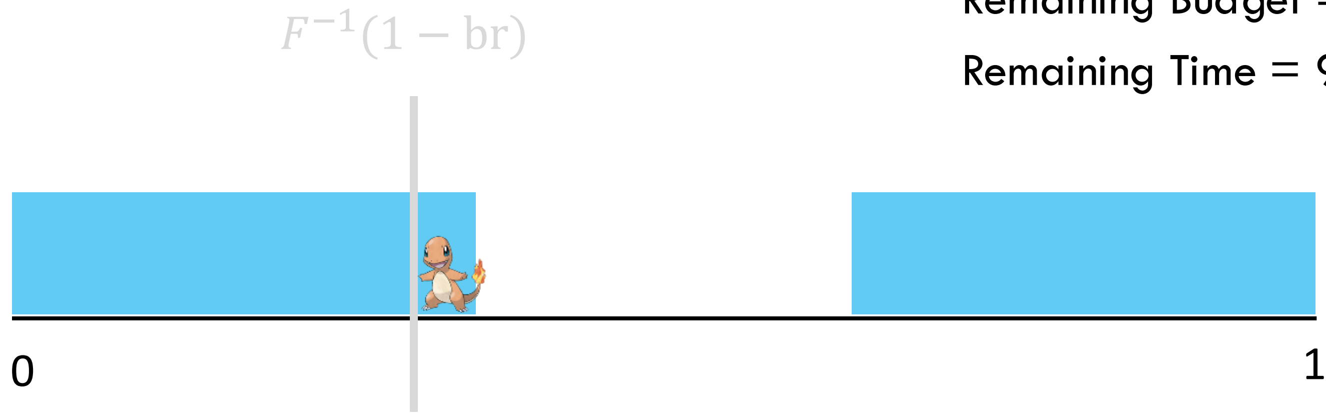

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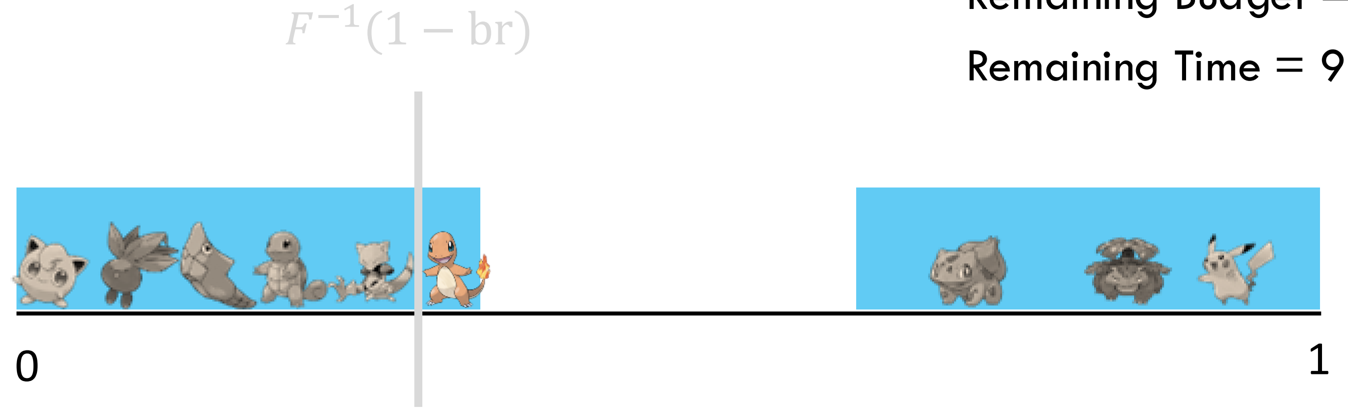

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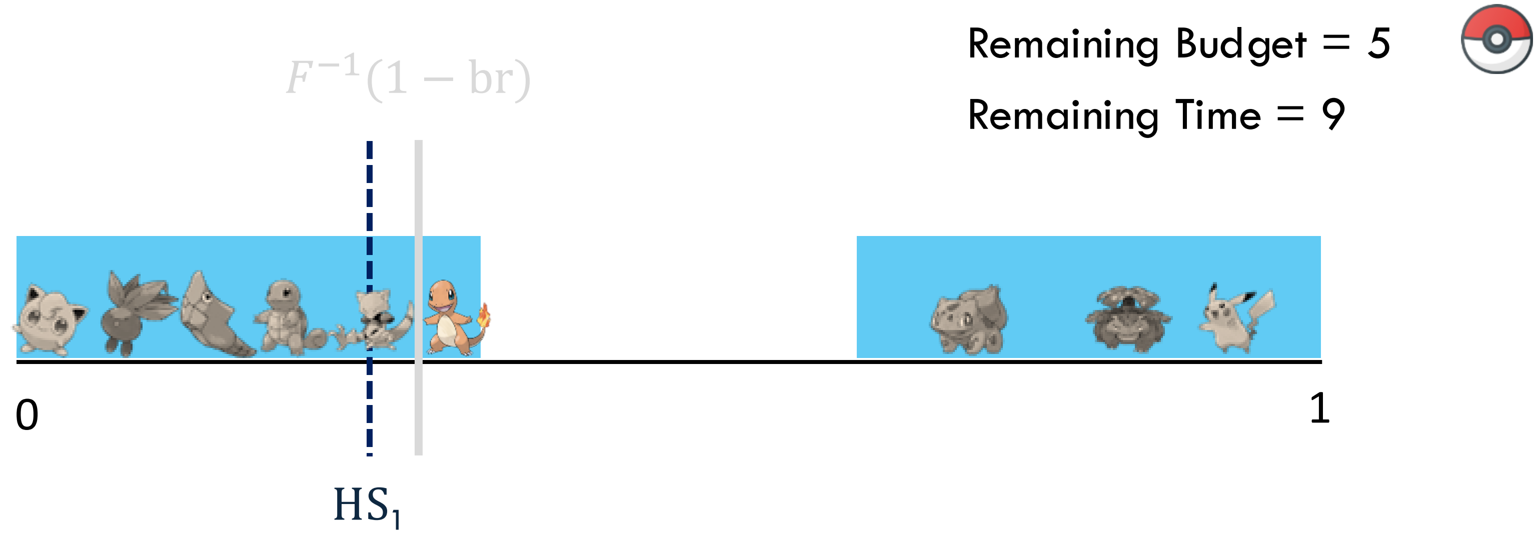

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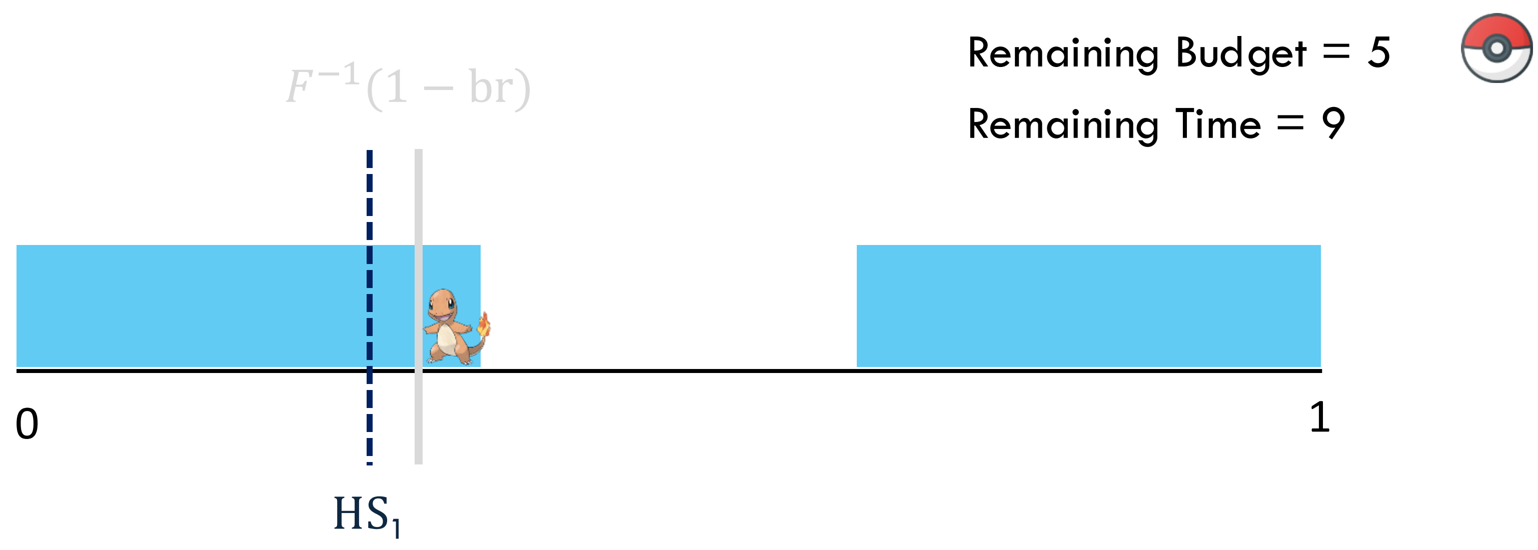

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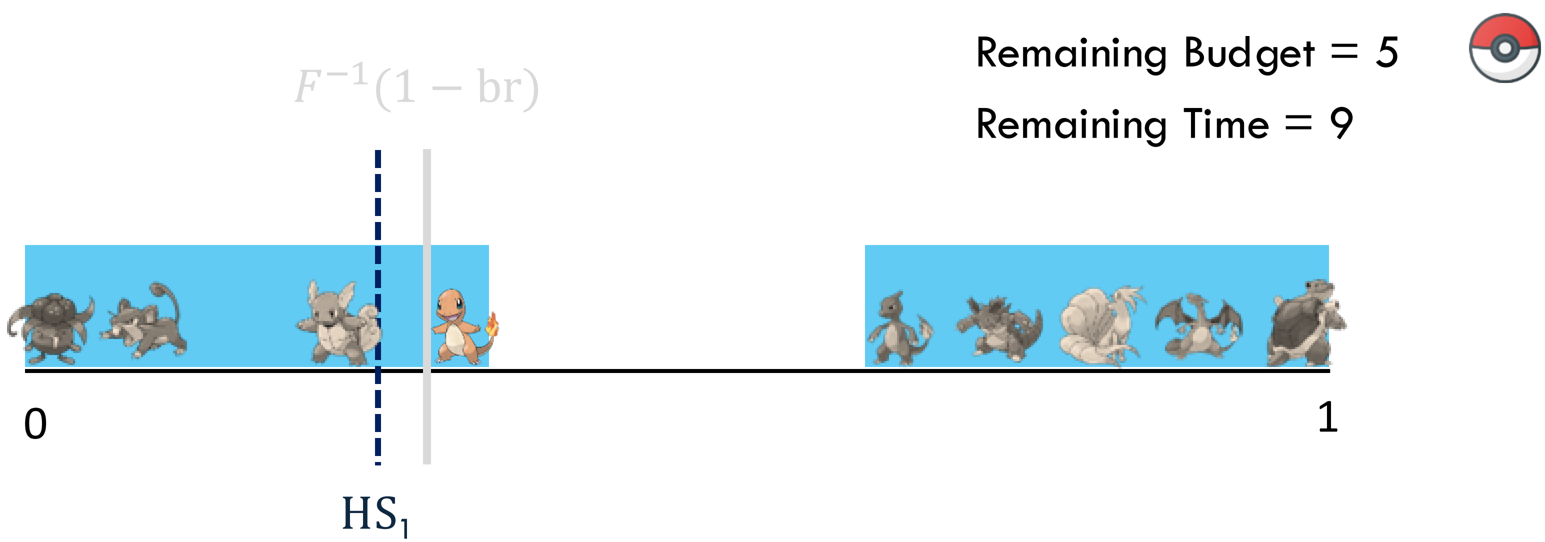

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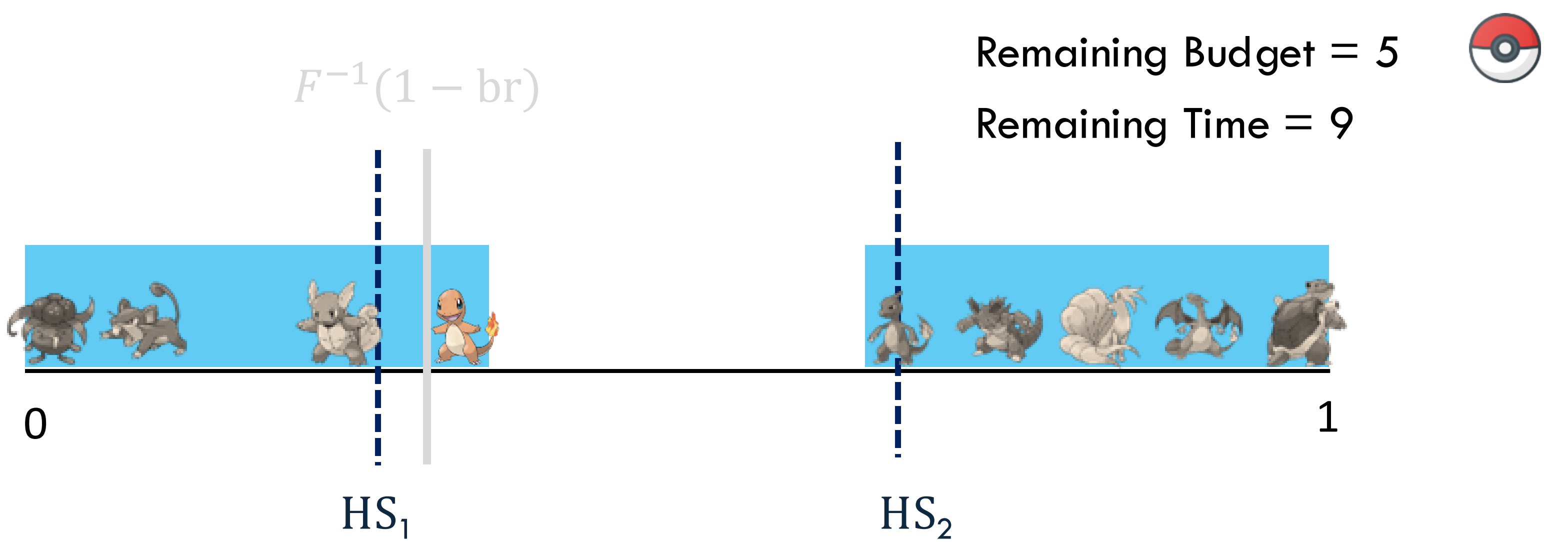

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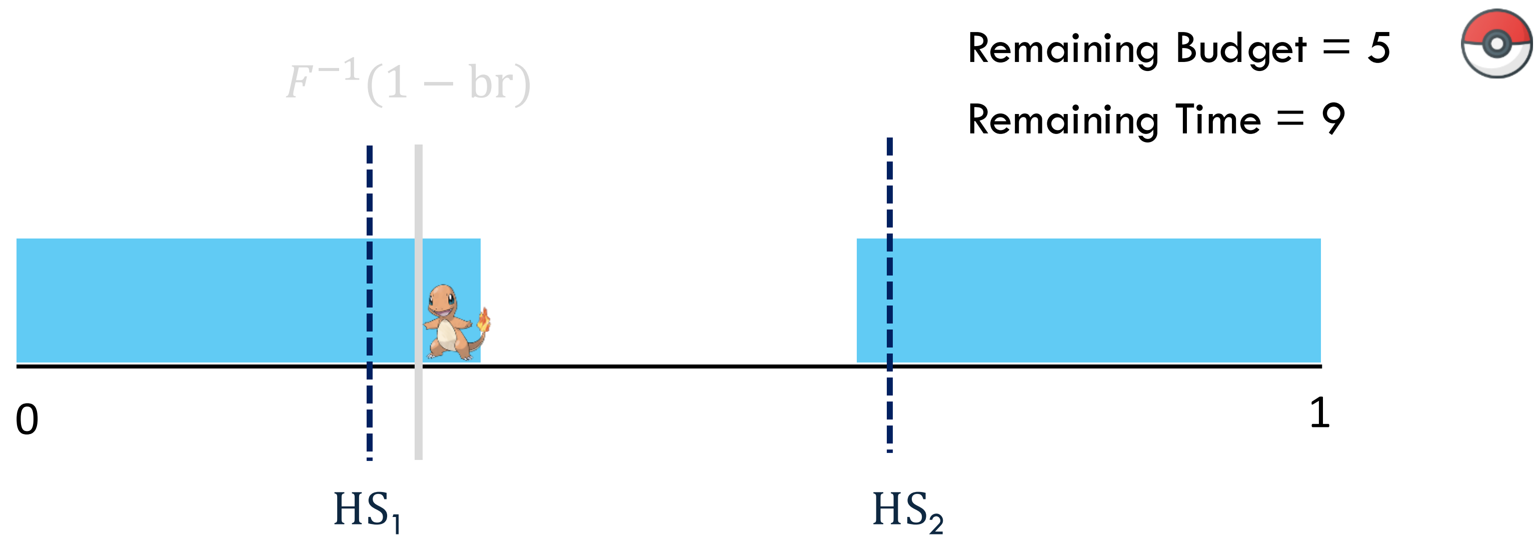
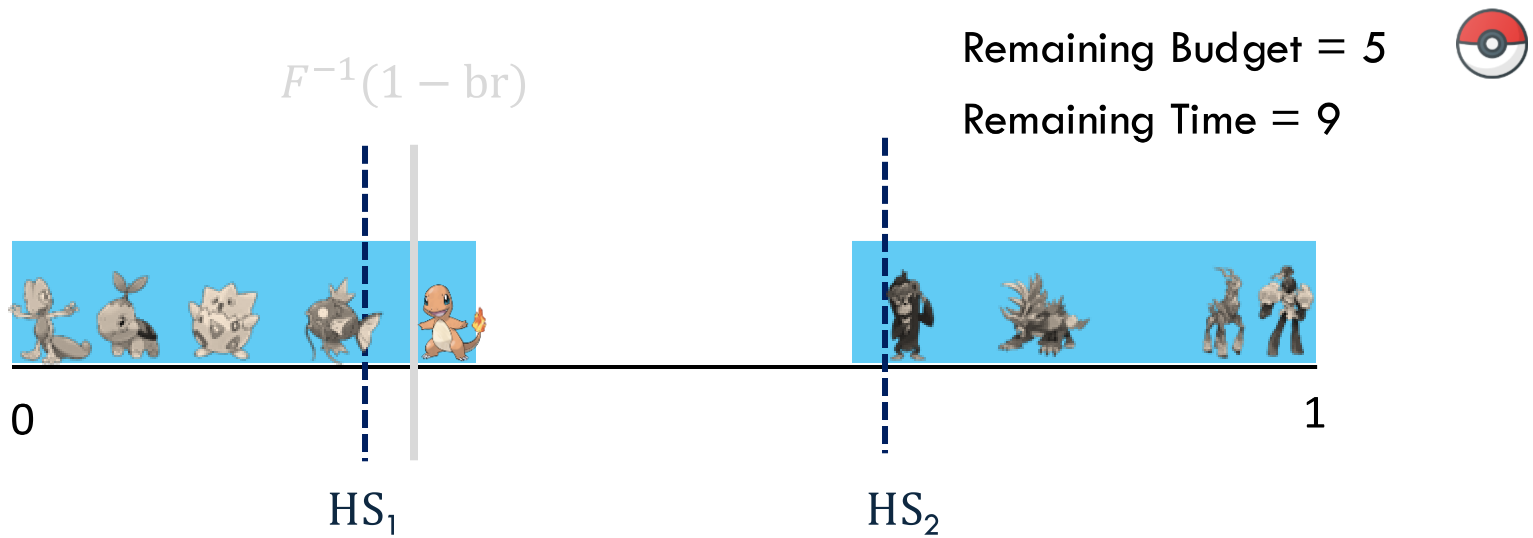


CwG via multiple simulations



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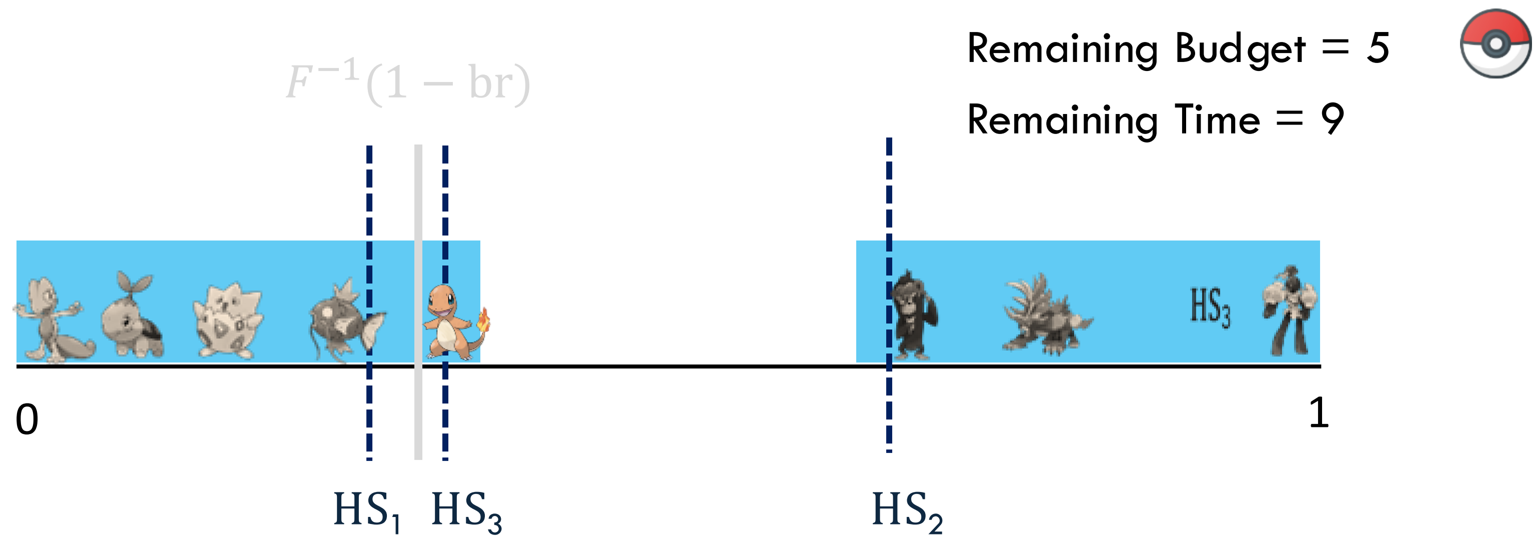
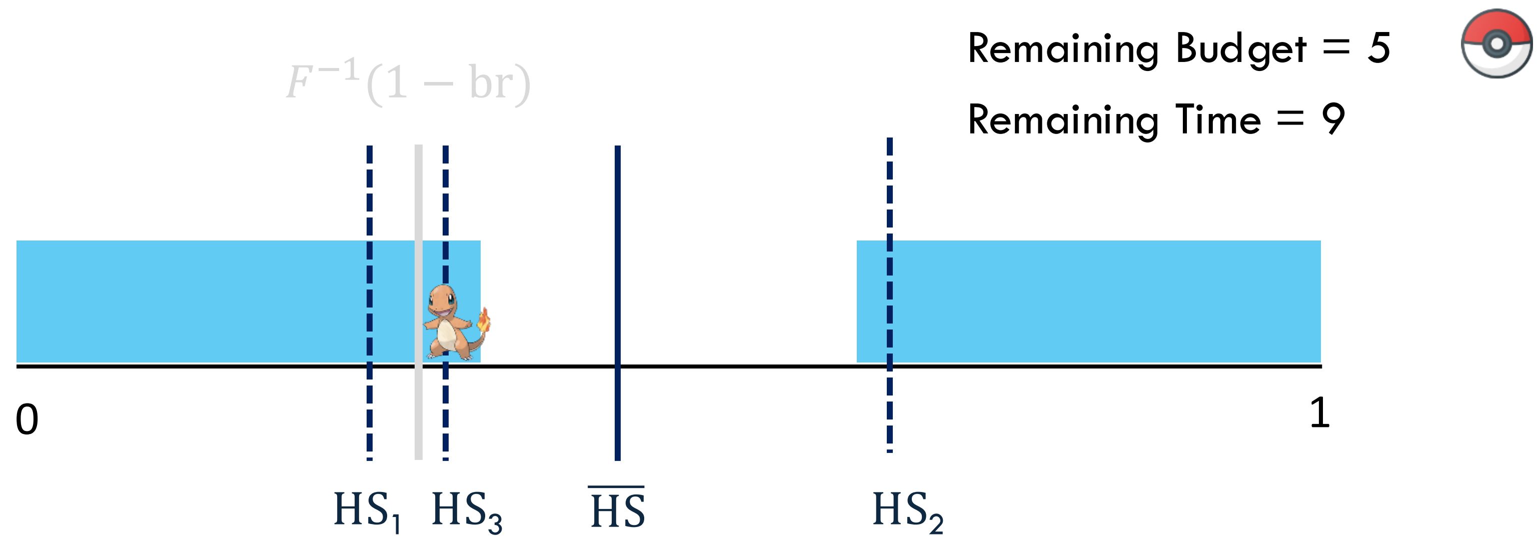
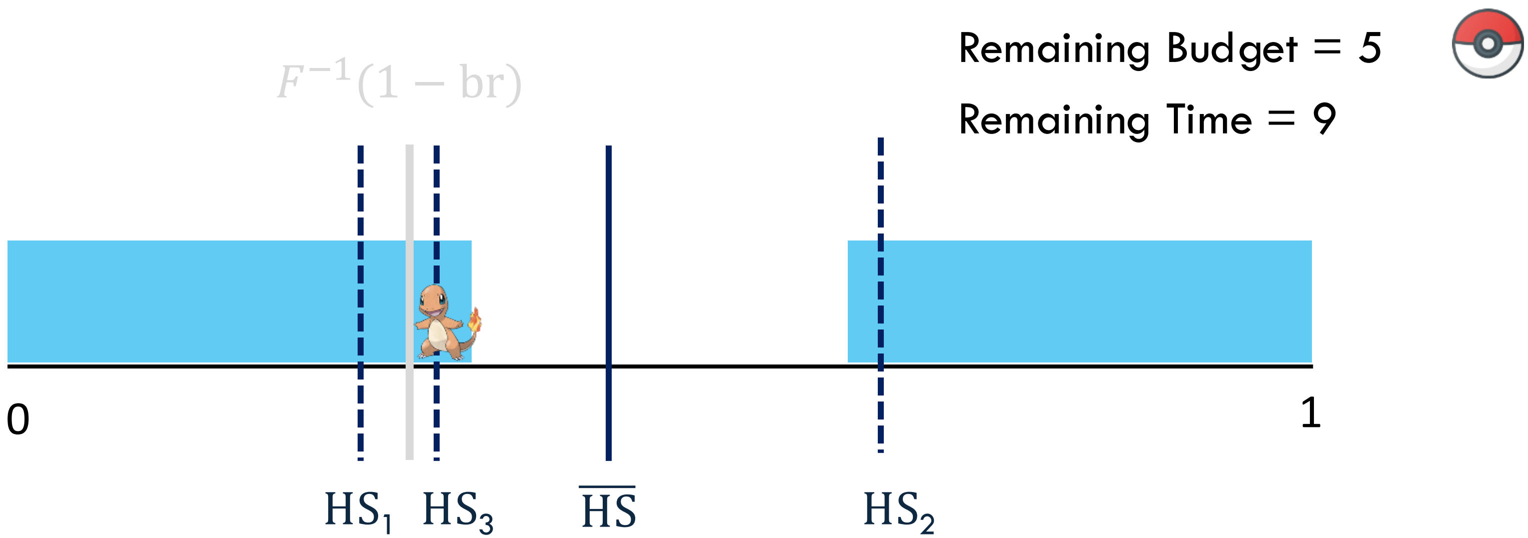


CwG via multiple simulations

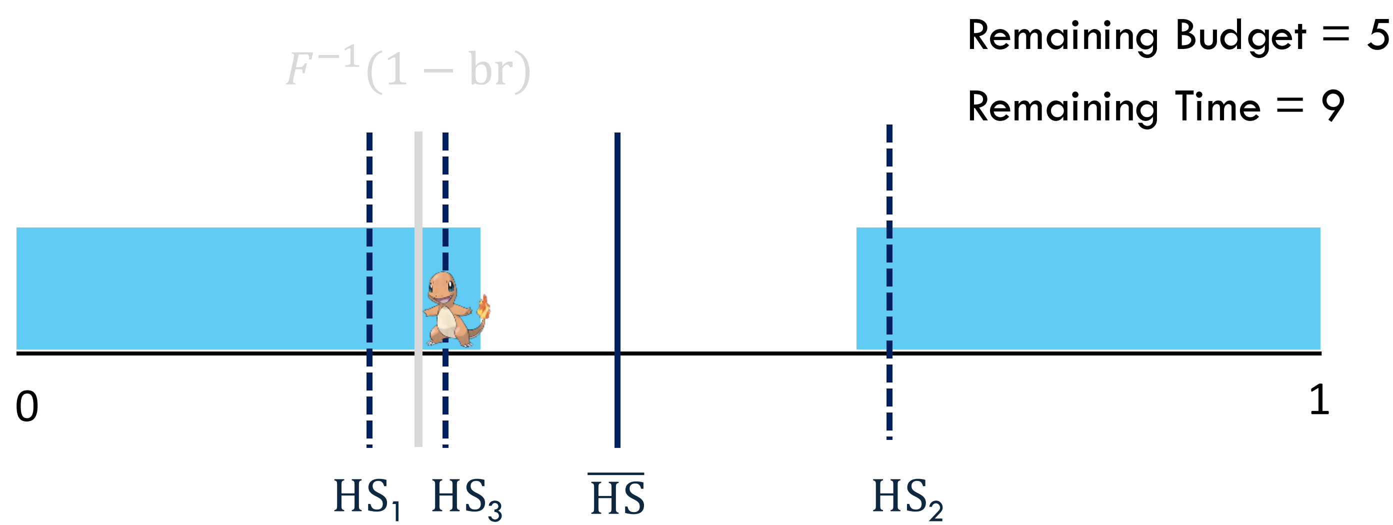


CwG via multiple simulations



Accept if the request type value is more than $\overline{\mathrm{HS}}$, else reject the request

CwG via multiple simulations



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Regret(RAMS) $= O(\log^2 T)$

CwG via multiple simulations

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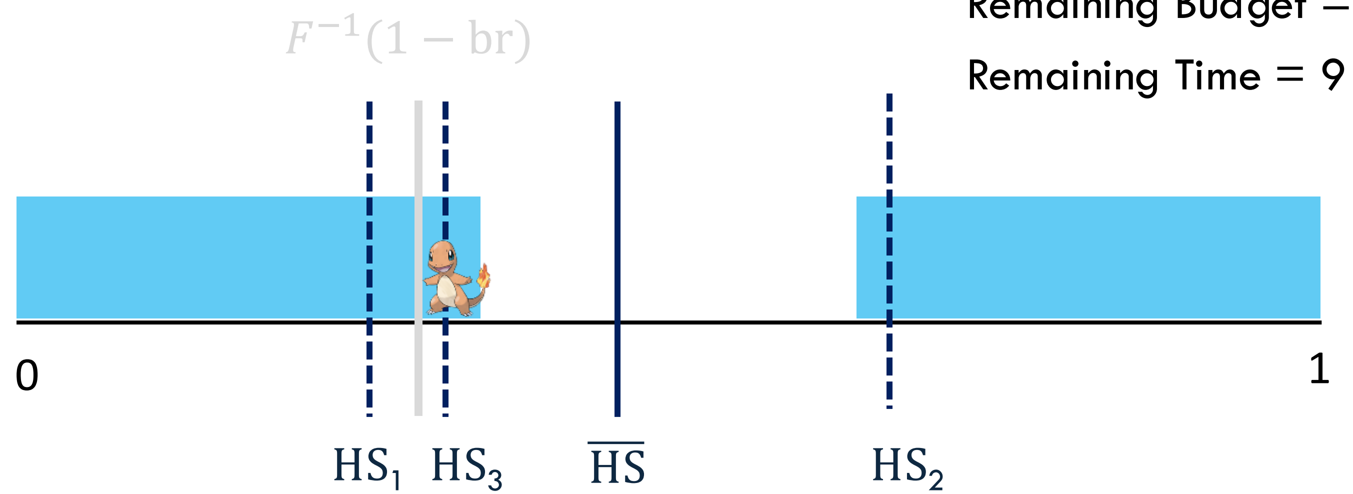
Remaining Time = 9



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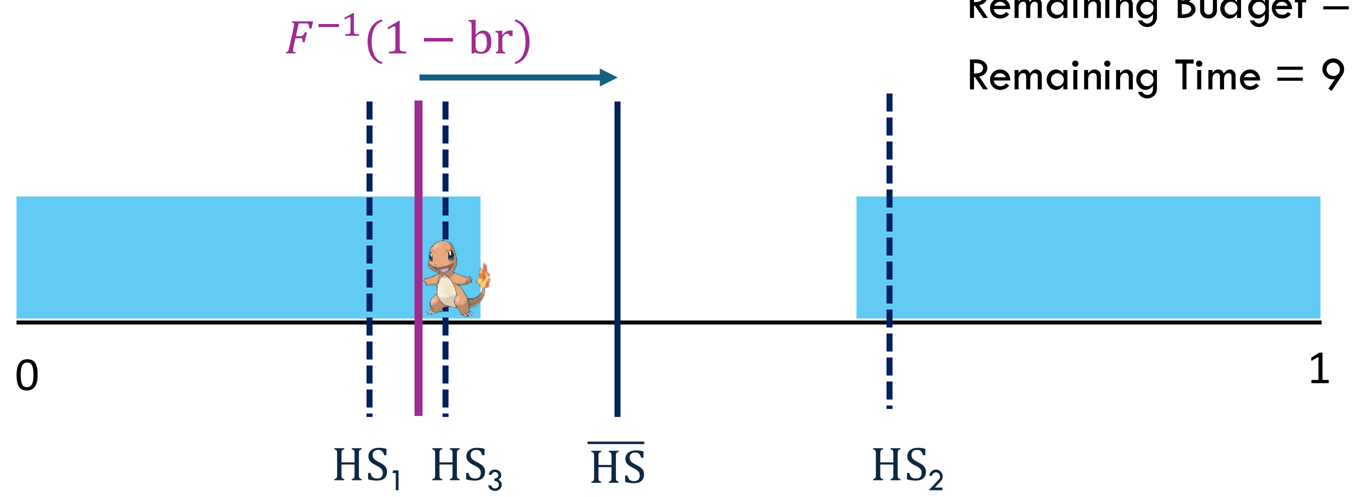
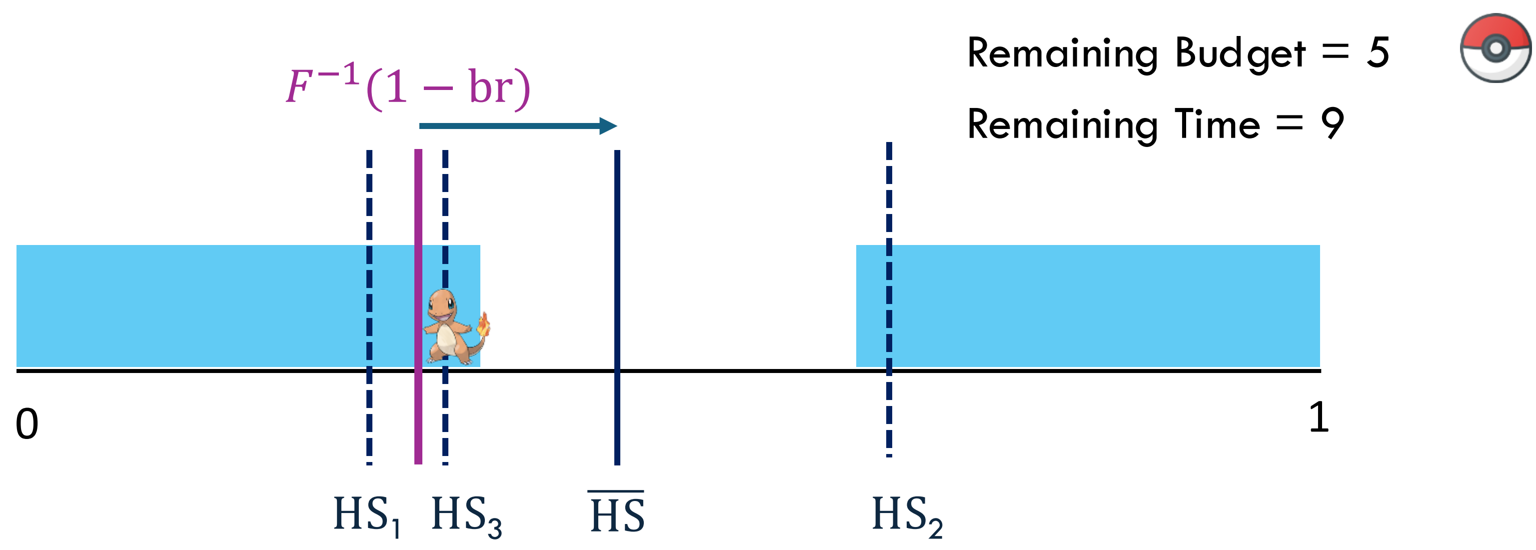


Accept if the request type value is more than $\overline{\mathrm{HS}}$, else reject the request

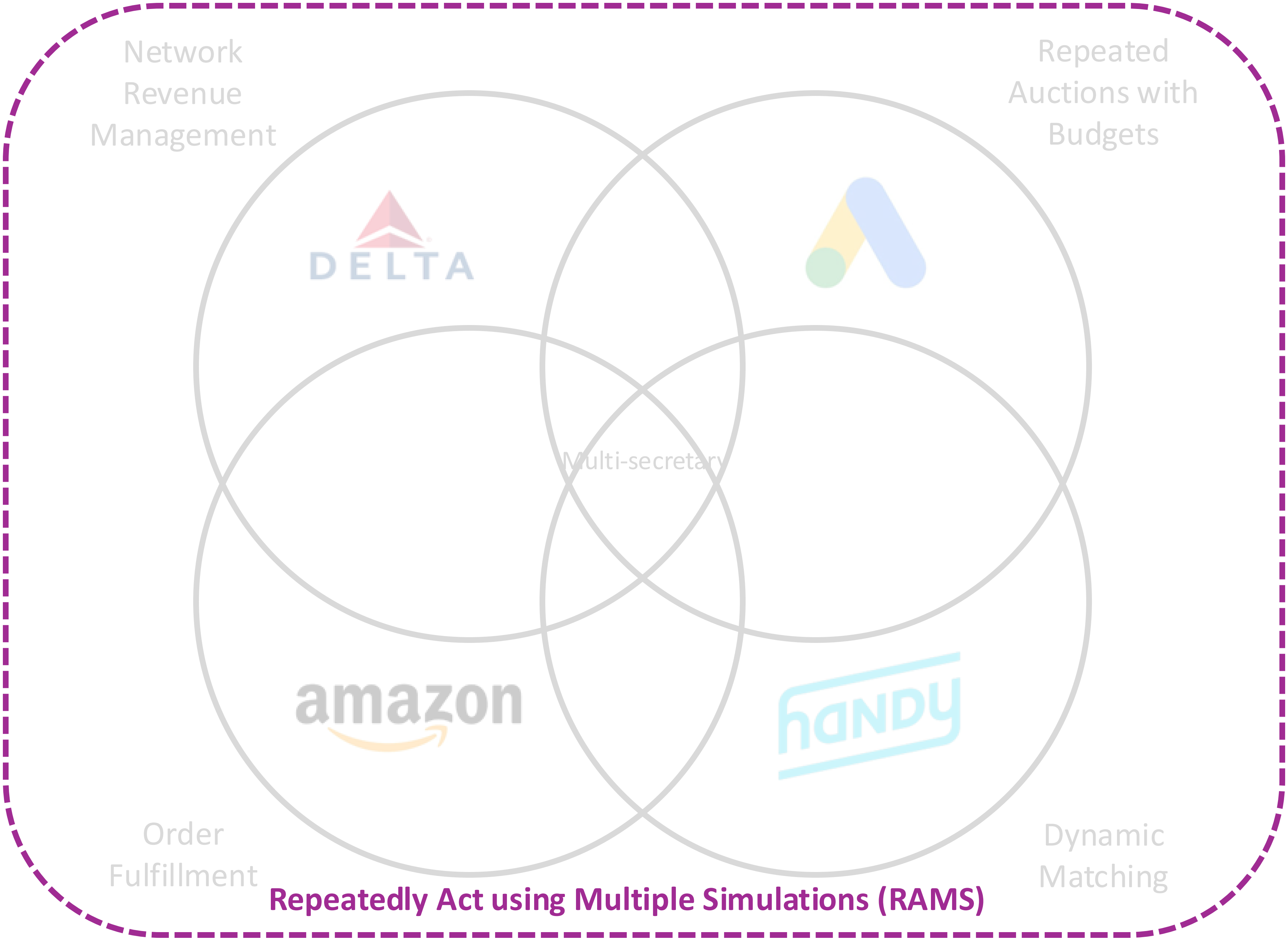
Conservativeness with respect to Gaps Principle
If the CE threshold $F^{-1}(1-\mathrm{br})$ is close to a gap, use the gap as the threshold. Otherwise continue using the CE threshold.

CwG via multiple simulations



Accept if the request type value is more than $\overline{\mathrm{HS}}$, else reject the request

Connections to "Dual Averaging"
The different HS thresholds are the shadow prices of the budget for different scenarios, the bid price is computed by averaging the HS thresholds


Network Revenue Management
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RAMS beyond multi-secretary

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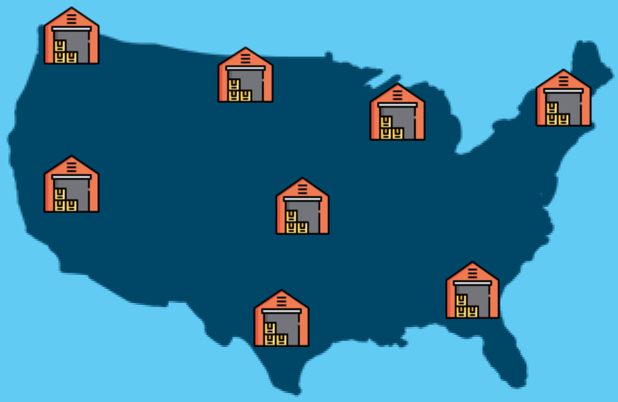
State (Budget) B_t and feasible set of actions A_t

RAMS beyond multi-secretary

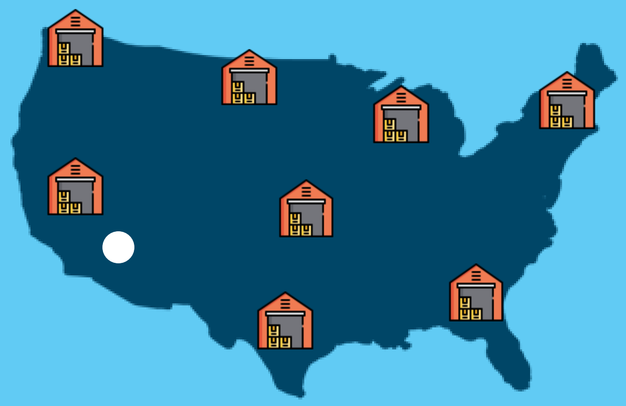
State (Budget) B_t and feasible set of actions A_t



RAMS beyond multi-secretary

State (Budget) B_t and feasible set of actions A_t

Request $\theta_t = (r_t, c_t)$ arrives at time t



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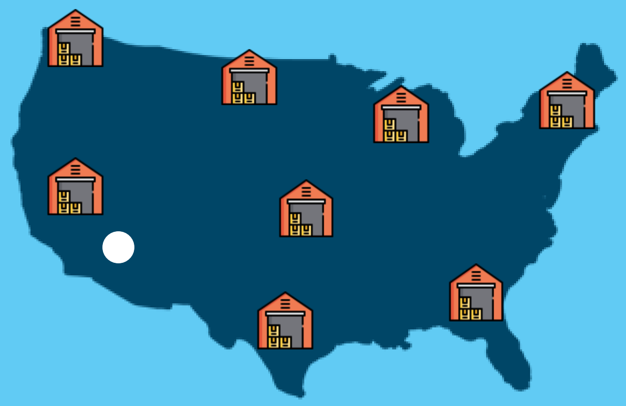
Simulate multiple request scenarios



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Request $\theta_t = (r_t, c_t)$ arrives at time t

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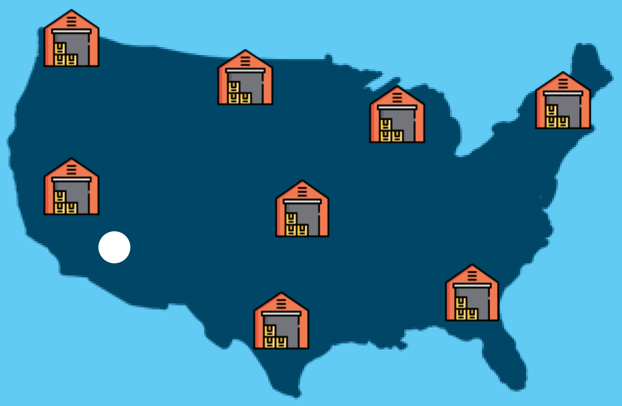
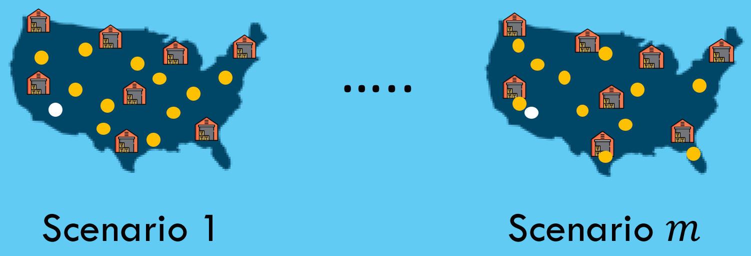
$\theta_t, \theta_{t+1}^{(1)}, \theta_{t+2}^{(1)}, \dots, \theta_T^{(1)}$ Scenario 1

$\theta_t, \theta_{t+1}^{(2)}, \theta_{t+2}^{(2)}, \dots, \theta_T^{(2)}$ Scenario 2

$\vdots$

$\theta_t, \theta_{t+1}^{(m)}, \theta_{t+2}^{(m)}, \dots, \theta_T^{(m)}$ Scenario m





RAMS beyond multi-secretary

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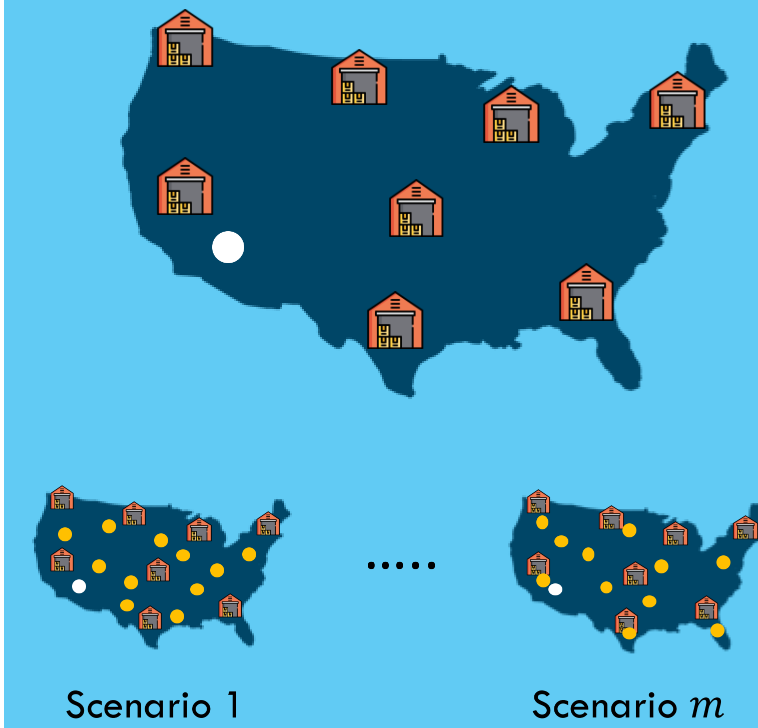
For each scenario k, compute the **compensation** for each action in A_t



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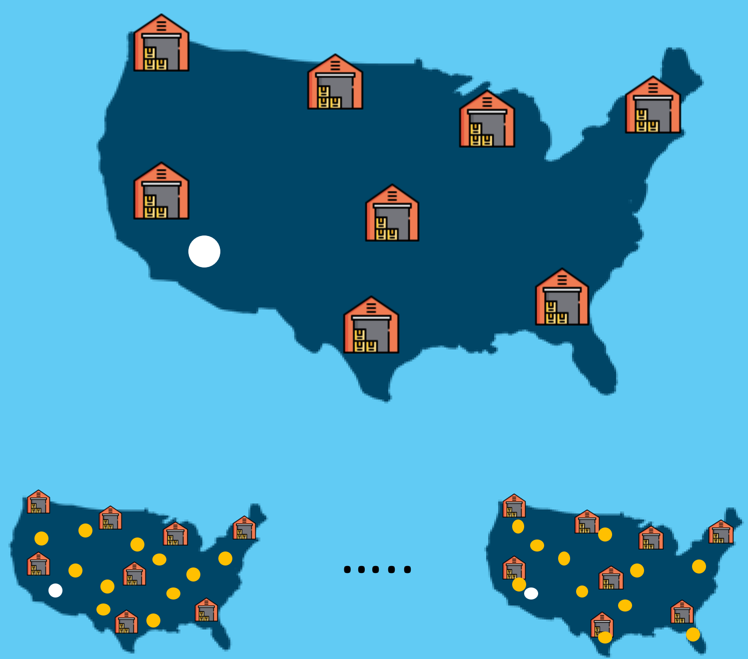

Scenario 1 ..... Scenario m

Compensation(scenario k, a) =
(Max total reward in scenario k) –
(Max total reward in scenario k if action a is taken at time t)

RAMS beyond multi-secretary

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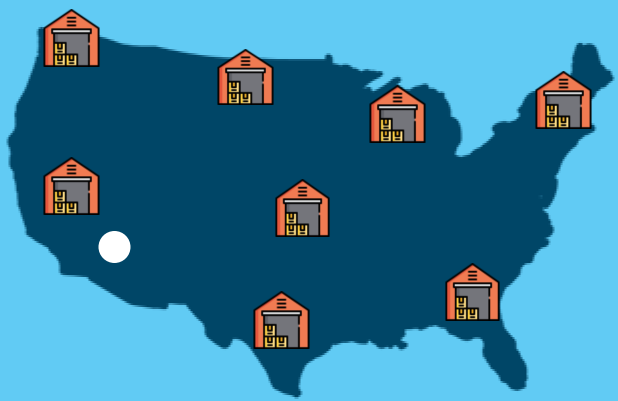
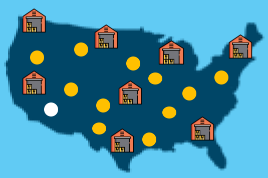
$\theta_t, \theta_{t+1}^{(m)}, \theta_{t+2}^{(m)}, \dots, \theta_T^{(m)}$ Scenario m

For each scenario k, compute the **compensation** for each action in A_t

Take the **action** with the **minimum compensation** averaged over m scenarios





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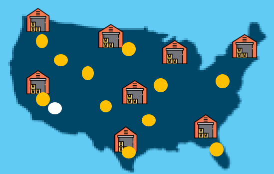

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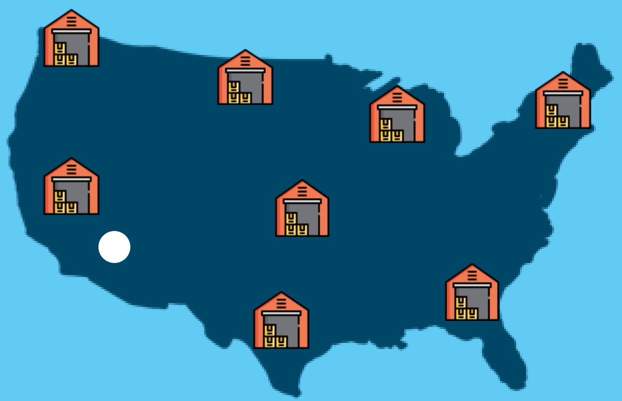
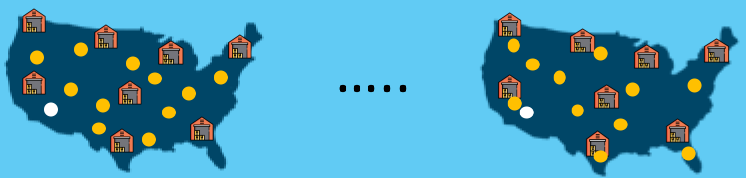
Take the **action** with the **minimum compensation** averaged over m scenarios

Repeat the process





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RAMS minimizes hindsight-based regret

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Informal Meta Theorem [RAMS inherits guarantees of near-optimal algos].

Given a dynamic resource allocation setting, if there exists an algorithm **ALG** satisfying certain technical conditions, then

Regret(RAMS) $\leq$ Regret Upper Bound of **ALG** + Sampling Error

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Proof of the Informal Meta Theorem.

$$\text{Regret(RAMS)} = \underbrace{\textstyle\sum_{t=1}^{T} \mathbb{E}\left[\mathrm{Comp}_t\left(a_t^{\mathrm{RAMS}}\right)\right]}_{\text{Compensated Coupling or Performance Diff. Lemma}} \underbrace{\leq}_{\text{RAMS chooses the action with the minimum compensation}} \textstyle\sum_{t=1}^{T} \mathbb{E}\left[\mathrm{Comp}_t\left(a_t^{\mathrm{ALG}}\right)\right]$$

RAMS is on-par with SOTA

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Corollary of the Meta Theorem.

Polynomial regret for multi-secretary problem under different type distributions **[this work]**

Bounded regret for Network Revenue Management and Online Matching for a **few types** [Vera and Banerjee '21]

Logarithmic regret for Network Revenue Management with many types and non-degeneracy assumps. [Bray '23]

Log-Squared regret for Network Revenue Management with many types and w/o non-degeneracy assumps. [Jiang et. al '22]

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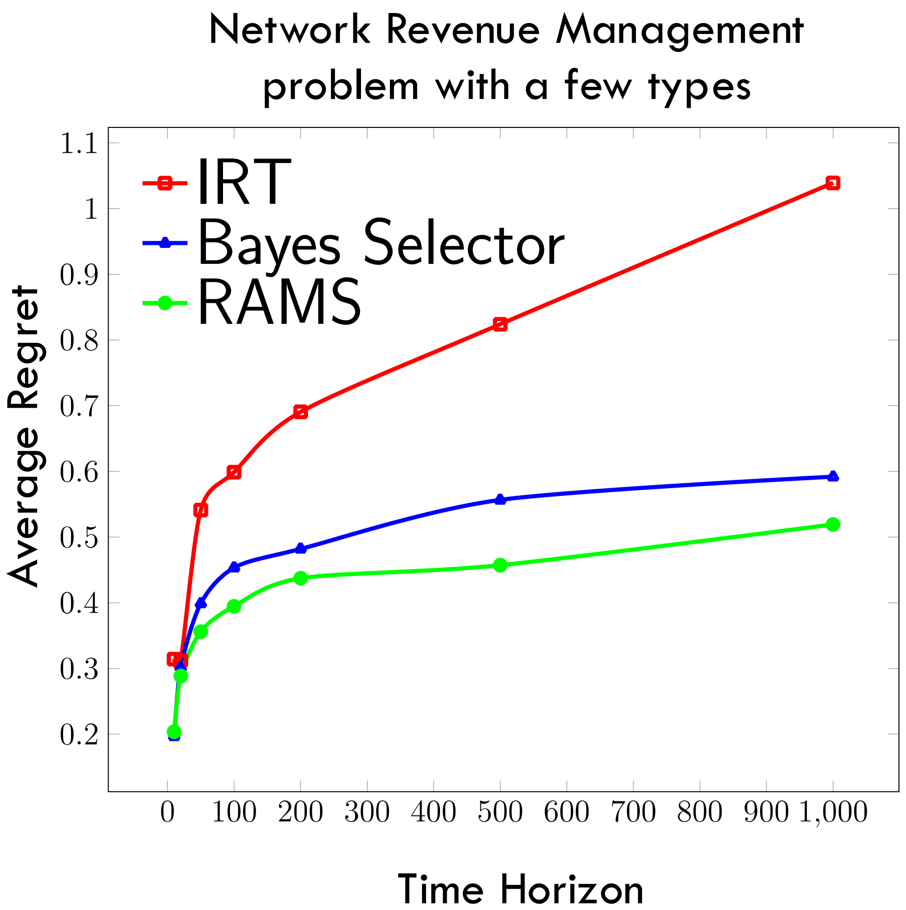
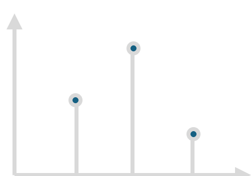


What is the interplay between the distribution of request types and achievable algorithmic performance?

A few types are present

Bounded Regret



All types are present

Logarithmic Regret

Multi-secretary Problem

Entire spectrum of regret scalings are possible

β –clustered distributions

Can we design a **unified**, **simple** and **near-optimal** algorithms which works for all type distributions?

one policy to solve them all

Repeatedly **A**ct using **M**ultiple **S**imulations (**RAMS**)

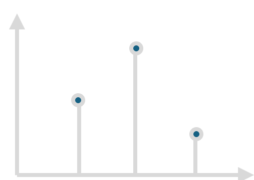
A few types are present

Bounded Regret

All types are present

Logarithmic Regret

Multi-secretary Problem



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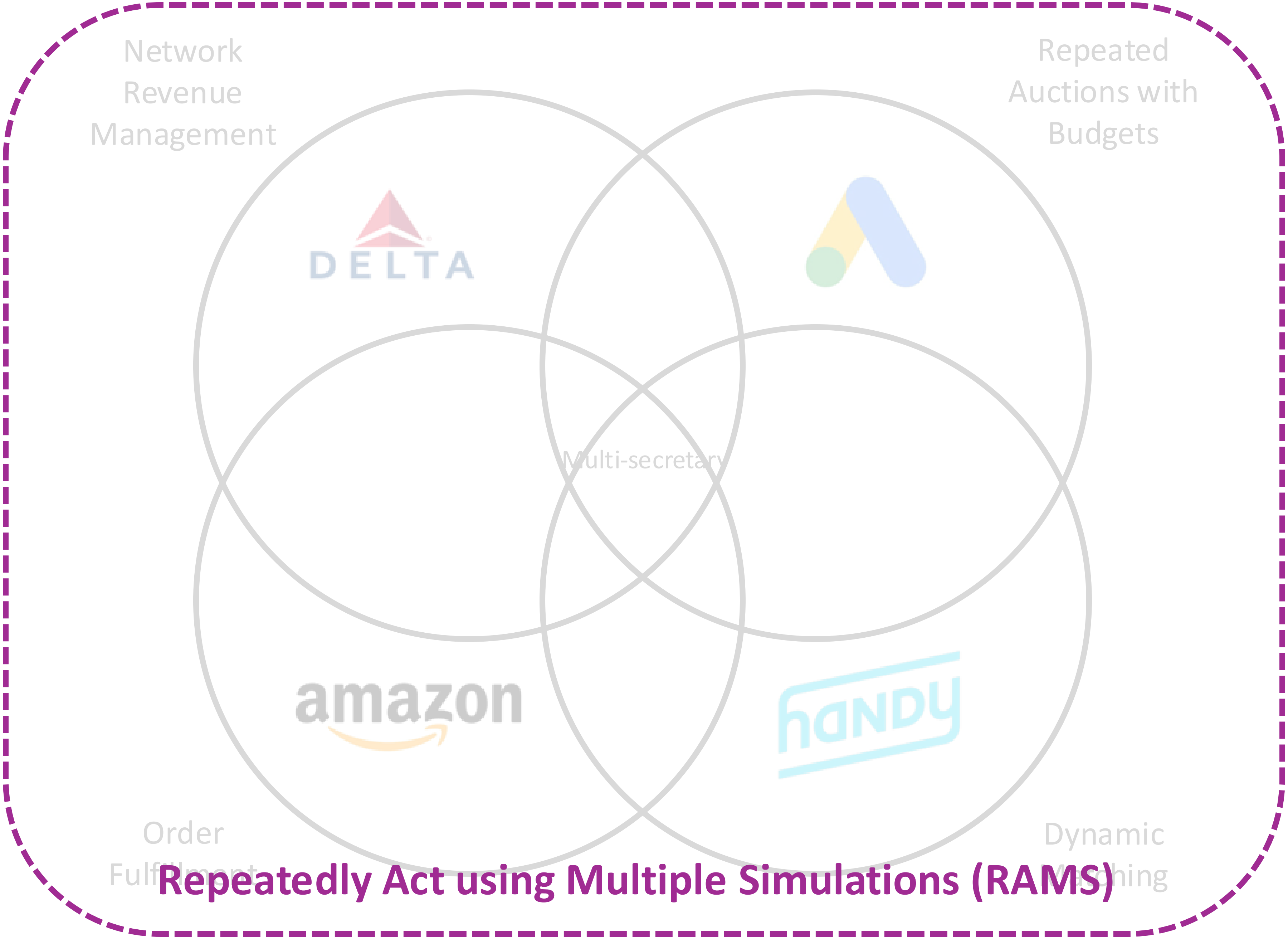
Network Revenue Management
Repeated Auctions with Budgets
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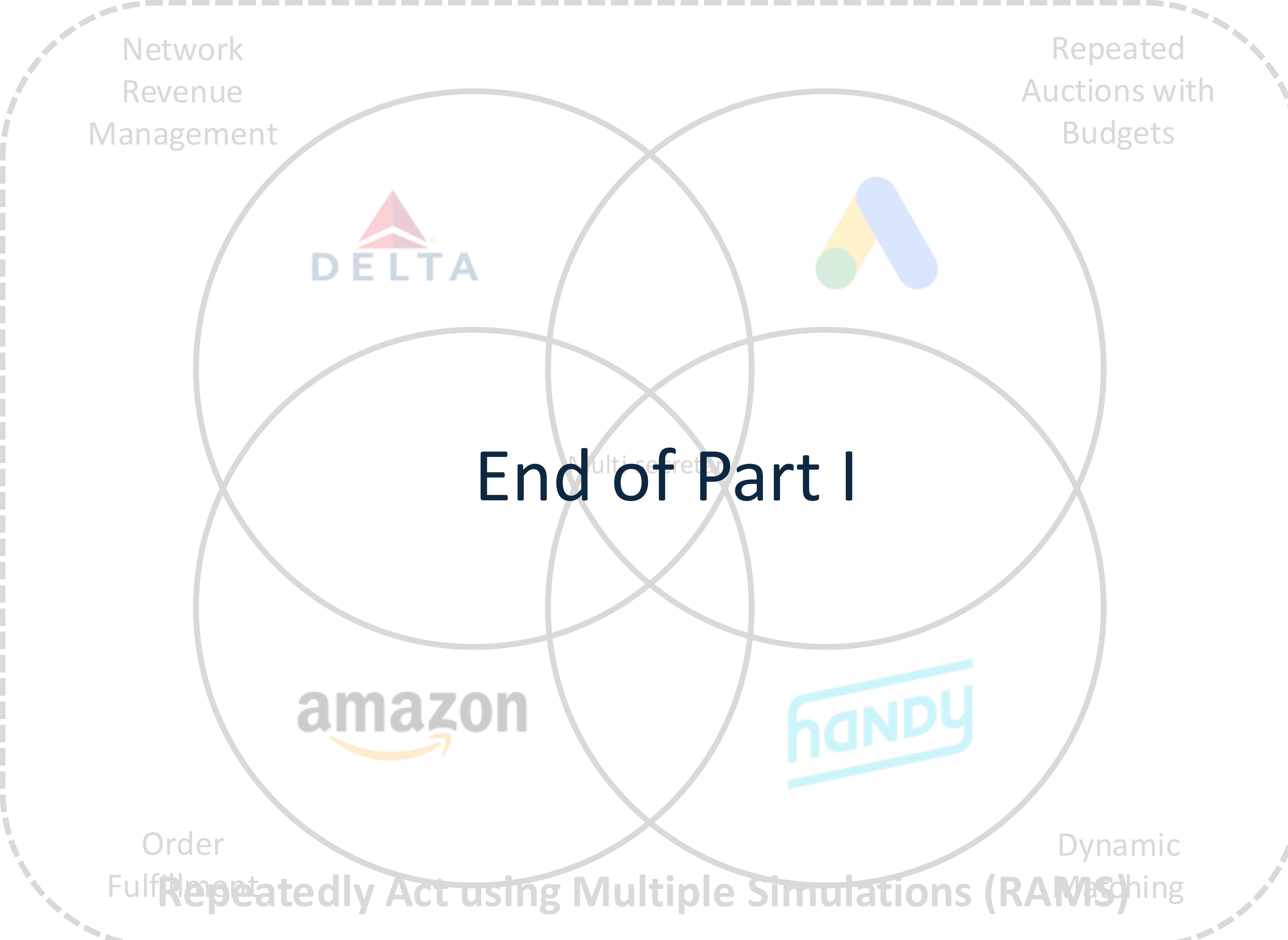
End of Part I


Network Revenue Management
Repeated Auctions with Budgets
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Dynamic Matching
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amazon
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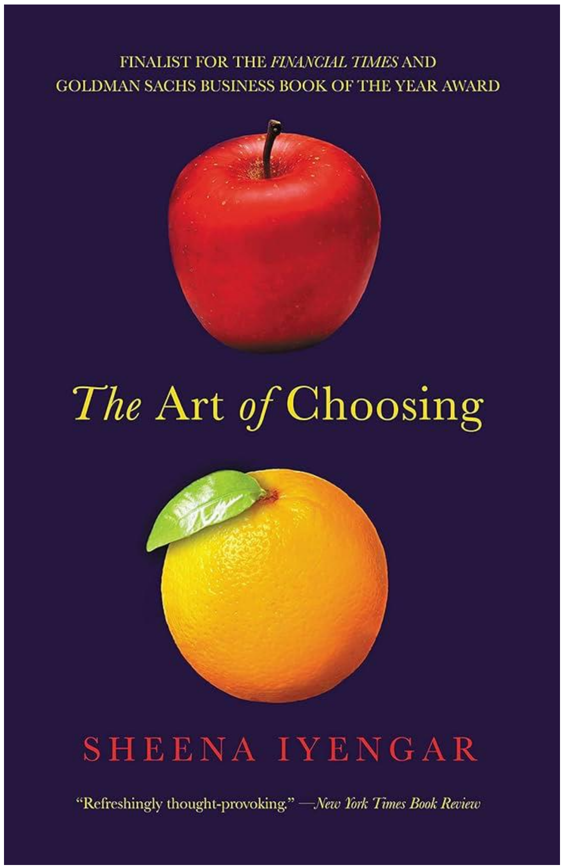
Repeatedly Act using Multiple Simulations (RAMS)

Part II

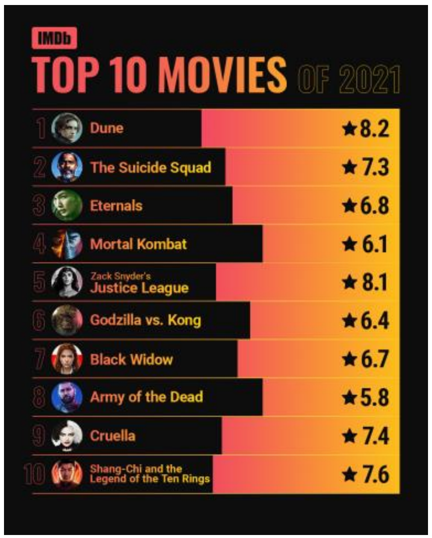
The Impact of Rankings and Personalized Recommendations in Marketplaces

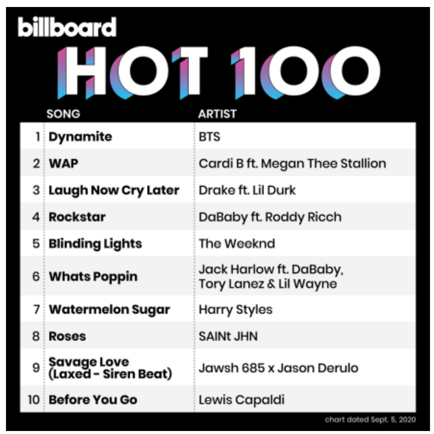
People have ill-formed preferences



"Majority of Americans would pursue a different degree, institution or major if given a chance to do it all over again"

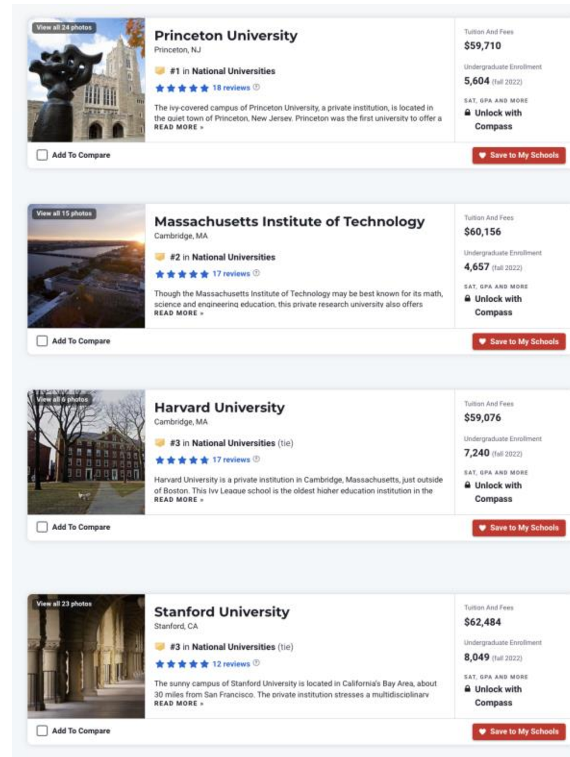
Rankings offer a plausible solution to aid decision-making




billboard HOT 100

	SONG	ARTIST
1	Dynamite	BTS
2	WAP	Cardi B ft. Megan Thee Stallion
3	Laugh Now Cry Later	Drake ft. Lil Durk
4	Rockstar	DaBaby ft. Roddy Ricch
5	Blinding Lights	The Weeknd
6	Whats Poppin	Jack Harlow ft. DaBaby, Tory Lanez & Lil Wayne
7	Watermelon Sugar	Harry Styles
8	Roses	SAINt JHN
9	Savage Love (Laxed - Siren Beat)	Jawsh 685 x Jason Derulo
10	Before You Go	Lewis Capaldi

chart dated Sept. 5, 2020

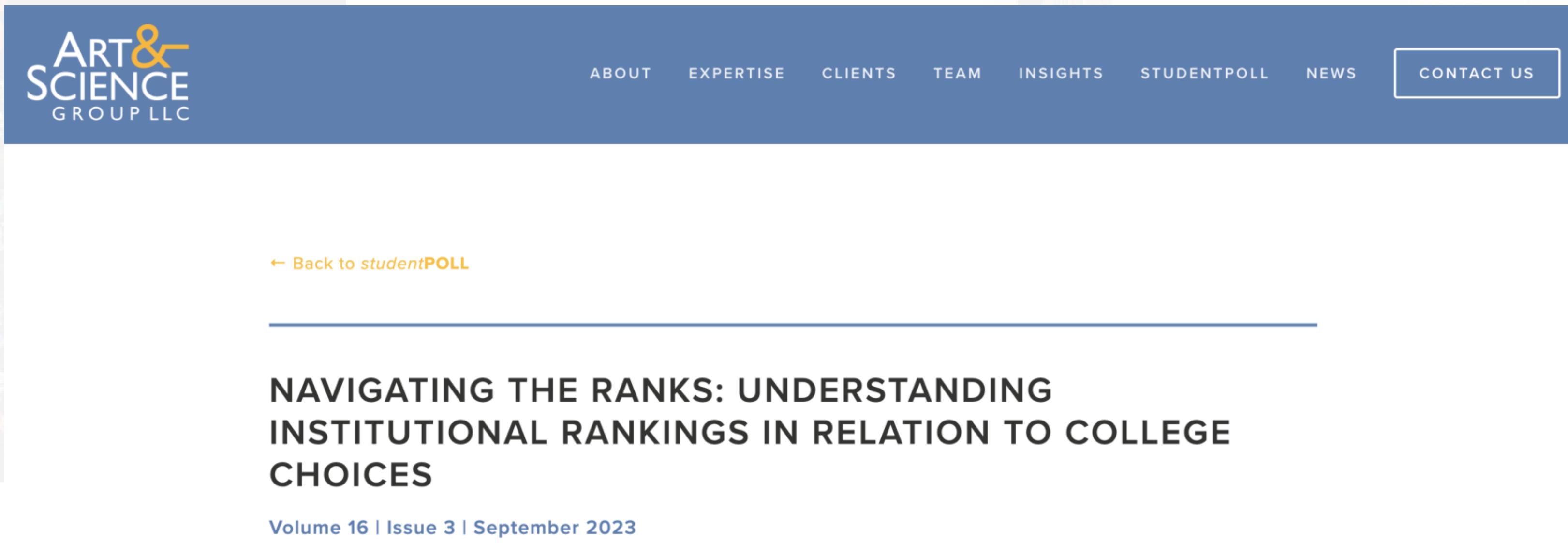


IMDb

NATIONAL INSTITUTIONAL RANKING FRAMEWORK

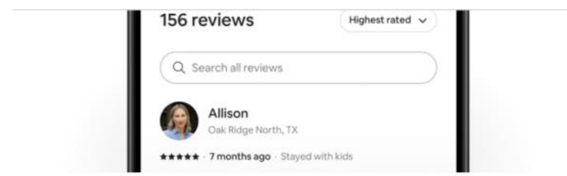
QS WORLD UNIVERSITY RANKINGS

Rankings offer a plausible solution to aid decision-making



58% of high school seniors actively considered college rankings in their decision-making process

Rankings are not personalized to individual tastes



See the rating distribution

A new overall rating chart shows you a breakdown of a home's 1 to 5 star reviews.

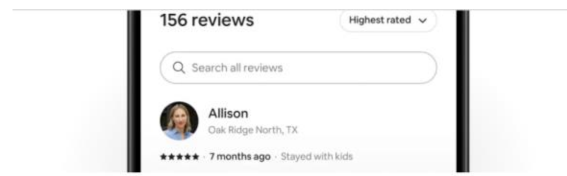
Sort by recency and rating

Now you can sort reviews to read the latest and greatest from prior guests.

Find relevant reviews

New details, like type of trip or length of stay, make it simple to pick out relevant reviews.

Significant work on personalized recos in uncapacitated settings



See the rating distribution

A new overall rating chart shows you a breakdown of a home's 1 to 5 star reviews.

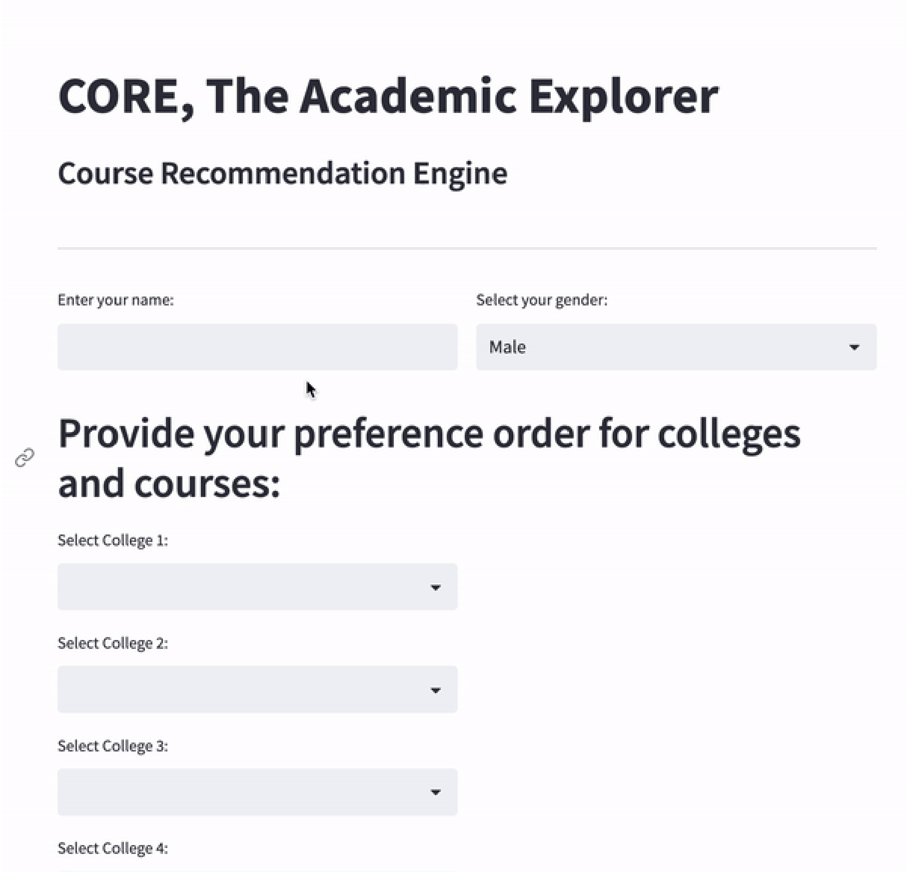
Sort by recency and rating

Now you can sort reviews to read the latest and greatest from prior guests.

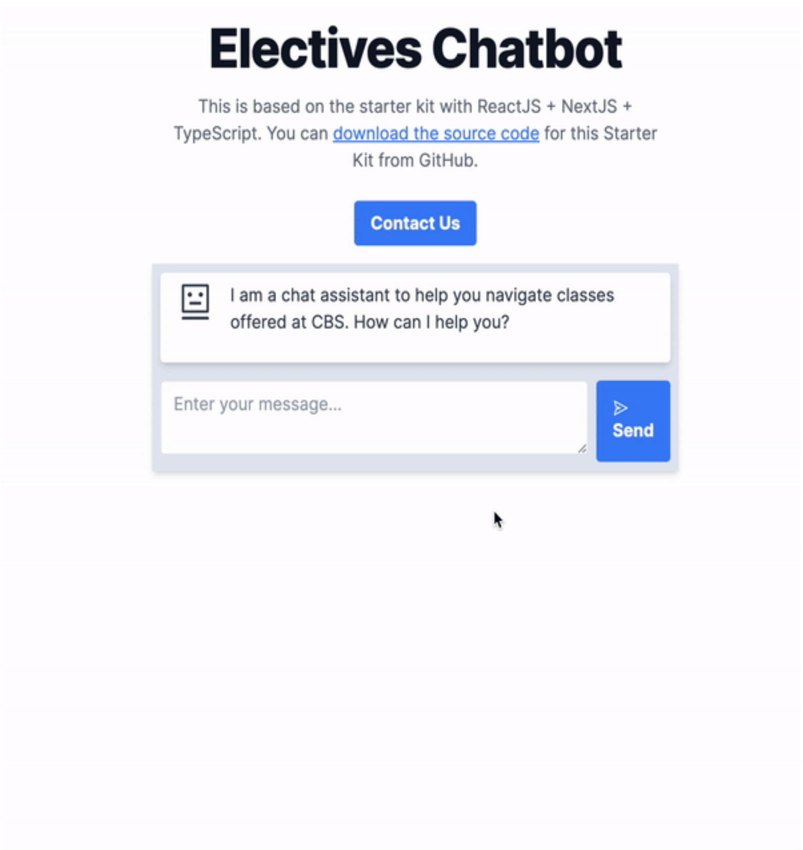
Find relevant reviews

New details, like type of trip or length of stay, make it simple to pick out relevant reviews.

My vision for the future



Recommender Systems for College Recommendations



Chatbots for Course Recommendations

Research Questions

What are the implications of providing personalized recommendations in marketplaces with capacity constraints?

How does this contrast with marketplaces with no capacity constraints?

In a Nutshell

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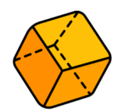
Model

n individuals 

n items 

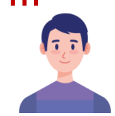
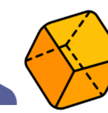
$u($  ,  $) = \rho \times$  $+ (1-\rho) \times$ 

Common term

Depends only on 

Known through publicly available rankings

Private term

Depends on both  

Apriori unknown, can be known using personalized recos

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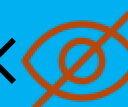
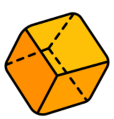
$u($  ,  $) = \rho \times$  $+ (1 - \rho) \times$ 

Uncapacitated supply setting

 =  

Many-to-One matching

Individuals simply choose the item they want to consume

Capacitated supply setting

 = 

One-to-One matching

Individuals are matched by centralized clearinghouse using some matching mechanism

Model

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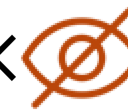
$u($  ,  $) = \rho \times$  $+ (1 - \rho) \times$ 

Uncapacitated supply setting

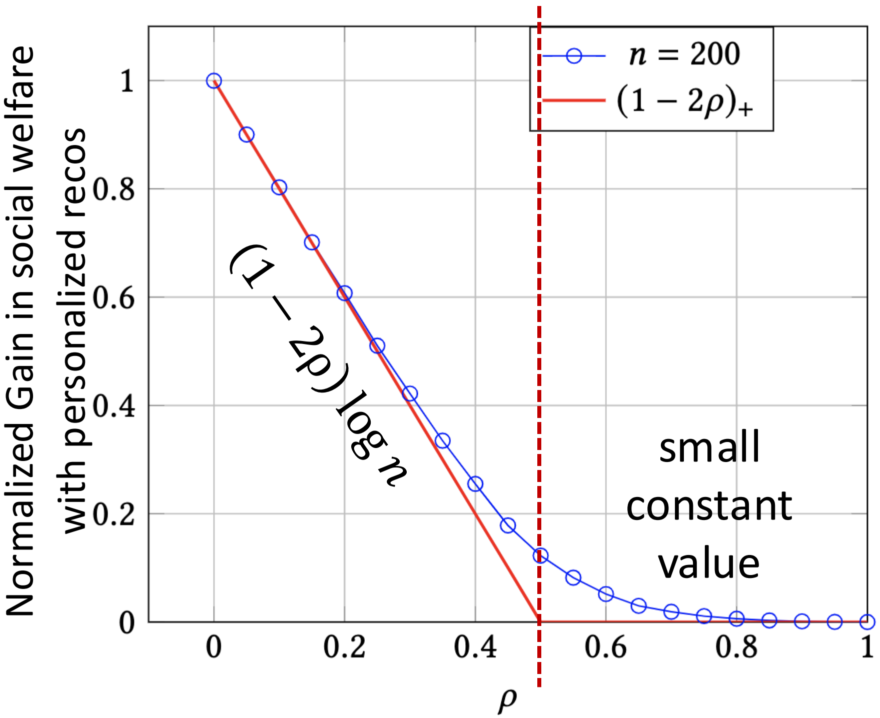
Capacitated supply setting

We care about the social welfare which is the average (across the n individuals) utility obtained by the individuals

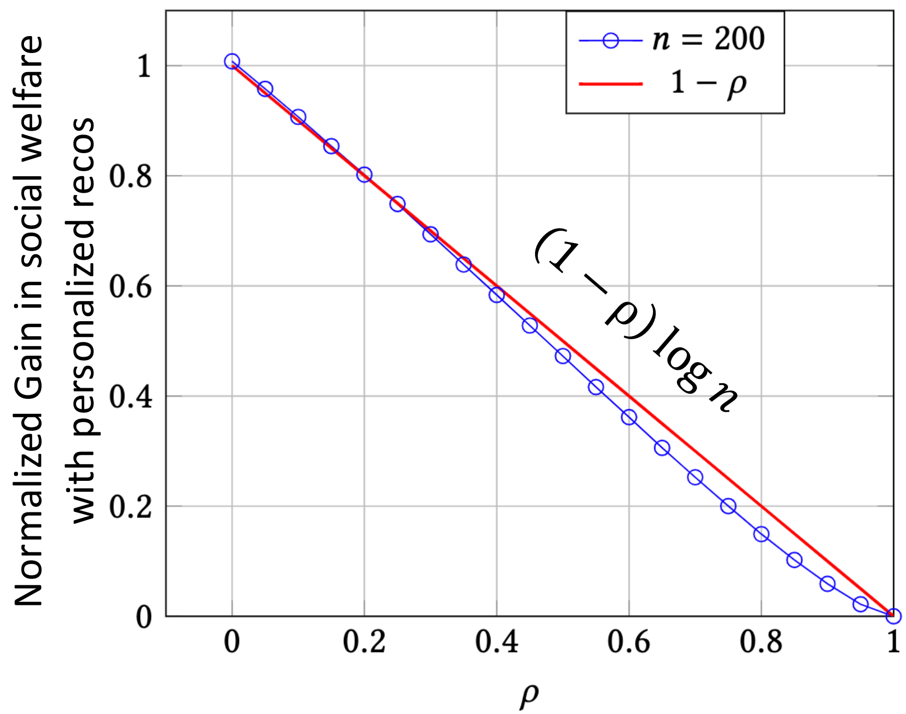
Results

Common term is Exponentially distributed with rate 1
Private idiosyncratic term is Exponentially distributed with rate 1

Uncapacitated Supply Setting



Capacitated Supply Setting



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- Design a simple and near-optimal policy called Repeatedly Act using Multiple Simulations **(RAMS)**

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So long and **Thanks** for all the fish