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# Mobile App User Choice Engineering using Behavioral Science models

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## Setting

- When interacting with mobile apps, users need to make a choice out of a set of alternatives offered by the app
- Goal: Nudge users towards decisions that are best for them and for the app platform**
- Examples:

Application domain	Instance	Platform optimization objective
Mobile crowdsensing	App assigns crowdsensing tasks to users	Maximize quality of fulfilled tasks
Smart Energy apps	App issues energy-saving recommendations	Maximize amount of energy savings
Mobile advertising	App displays ads or offer coupons to users	Maximize revenue through user response to ads

## Challenges

- How to model user choice-making**
- Users do not decide rationally, have to make a choice quickly while interacting with mobile app
- How to Incorporate choices in platform optimization objective**
- Need to appropriately engineer user incentives

## Idea

- Model user choice-making through concepts from Behavioral Science
  - class of Fast-and-Frugal-Tree (FFT) Lexicographic heuristics
- Use incentives as one of the **features** that determine **user choice** (to a different extent for different users) and **allocate** them so as to achieve platform optimization objective

## Model

- Set of features  $\mathcal{F}$  that determine user choices
- $\mathcal{F} = \{\text{distance (effort) to do a task (d), incentive (p)}\}$
- Mobile app issues pairs of recommendations (choices) to each user  $u$
- Example message e.g. in a mobile crowdsensing app

Choice A: "Go to place A at distance  $d_A$  to do a task for payment  $p_A$ " OR

Choice B: "Go to place B at distance  $d_B$  to do a task for payment  $p_B$ "

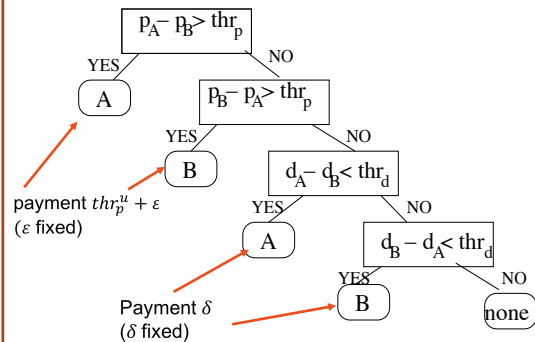
## Deterministic user decision model

- A certain **order** in which to consider features of alternative choices A, B offered (e.g. first p then d - or vice versa)
- If choice A (B) is "clearly better" than the other, B (A) w.r.t. 1<sup>st</sup> feature in order, select A (B);
- Else consider 2<sup>nd</sup> feature
- If choice A (B) is "clearly better" than the other, B (A) w.r.t. 2<sup>nd</sup> feature in order, select A (B);
- If no choice is "clearly better than the other, select none of the choices
- Thresholds**  $thr_p^u, thr_d^u$  determine when a choice is "clearly better" than the other in terms of a feature (p or d)

## User model training

- Find feature order for each user
- Compute decision thresholds for each user

Users prioritizing payment (p) over distance (d) decide according to tree below



Users prioritizing distance (d) over payment (p) decide according to a tree that first considers distance, then payment

## Problem Statement

Given:

- set of  $N$  users  $\mathcal{U}$ , each modeled by a decision tree
- set of tasks  $\mathcal{C}$
- set of available pairs of choices  $\mathcal{P} \subseteq \mathcal{C} \times \mathcal{C}$  for assignment
- limited budget  $b_i$  for each task  $i$
- a quality index  $q_i^u$  for user  $u$  and task  $i$

**Allocate pairs of choices and payments to users so as to maximize total expected quality of fulfilled tasks** (here: allocate 1 pair of choices)

## Decision variables for each user $u$

- Choice pair  $(i, j)$  offer variable  $y_{(i,j)}^u \in \{0,1\}$
- Variables  $z_i^u \in \{0,1\}$ ; determine whether to make a choice  $i$  "clearly better" than the other
- Even for fixed variables  $z$ , problem is Generalized Assignment Problem (GAP); NP-Hard

## Numerical Results

- Synthetic dataset; performance metric: total quality
- Heuristics for budget and task assignment

	Recommend doest task	Recommend task to most skilled user
Split task budget equally	CLOSE-EQ	SKILL-EQ
Split task budget in proportion to user skills	CLOSE-PROP	SKILL-PROP

	GAP	CLOSE-EQ	CLOSE-PROP	SKILL-EQ	SKILL-PROP
$N=200, b_i \sim \mathcal{U}[10, 20]$	172.67 ± 2.2	85.03 ± 7.3	88.24 ± 6.5	100.26 ± 6.37	111.64 ± 4.17
$N=100, b_i \sim \mathcal{U}[10, 20]$	87 ± 1.55	47.9 ± 3.18	47.39 ± 2.76	59.47 ± 3.07	59.93 ± 2.97
$N=200, b_i \sim \mathcal{U}[15, 25]$	172.65 ± 2.36	93.05 ± 5.51	93.59 ± 4.91	110.27 ± 4.67	112.22 ± 4.42

## Future work

- Many applications where **user choices can be engineered through user-app interaction**
- Recommender systems, online social networks, social media, online advertising, ...
- Enhanced choice and user decision models
- Testing with real data

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