Optimal user choice engineering in mobile crowdsensing with bounded rational users

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Mobile crowdsensing : context

Tasks spread in physical space

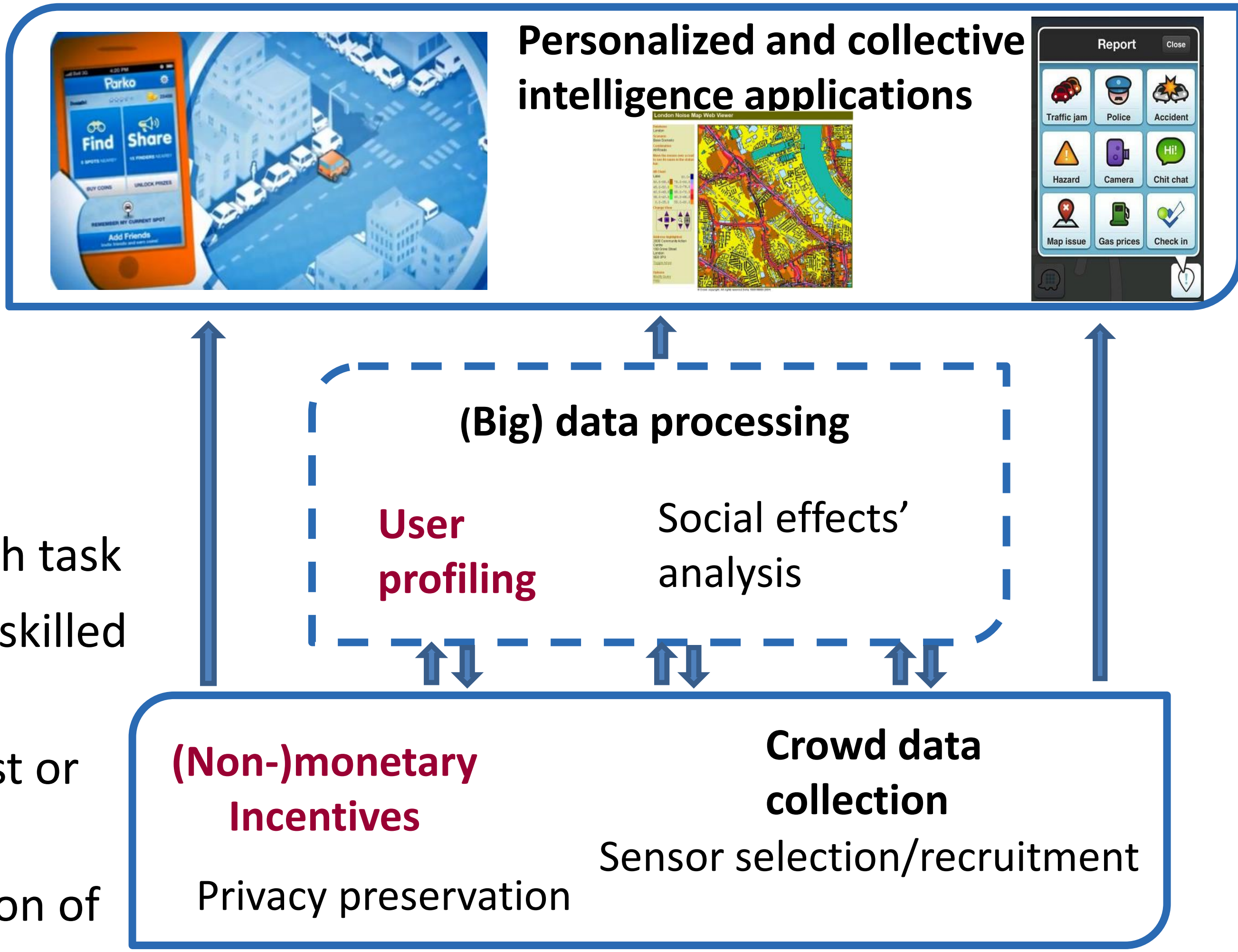
carried out through crowdsourced “**user**” contributions

+

Mobile crowdsensing : the multi-faceted role of the platform

- An MCS platform coordinates the process
  - Profiles users (preferences, interests, skills)
  - Manages tasks (issuing, advertisement)
  - Recruits users and incentivizes them

- Many problem variants, even more problem objectives
  - Task coverage → ensure several users for each task
  - Task quality → get users that are adequately skilled for the tasks
  - Campaign cost → minimize the aggregate cost or the max cost over all tasks
  - Sustainability → Ensure long term participation of users in the platform
  - …



Revisiting the user decision-making process

We depart from two main assumptions in literature

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Assumption 2 : Users are ~~*fully rational agents*~~ that optimize some utility function

$\Rightarrow$ **bounded rational** users, **satisficing** rather than optimizing

Bounded rationality and implications

→Homo sapiens ≠ Homo economicus

→Human decisions deviate from the **full rationality** norm and rather exhibit **bounded rationality** because of

- non-perfect information
- time pressure and computational complexity
- cognitive biases
  - “Think slow, think fast”, by D. Kahneman, 2011

Herbert Simon

Two questions come up:

1) Is this bounded rationality expressed in the mobile crowdsensing context?
2) How could some one capture bounded rationality and optimize the user-to-task matching (through engineering the user choices)?

Modeling bounded rationality – three approaches*

- Optimization under constraints (as-if rationality) - Arrow, 2004
  - Boundedly rational procedures are in fact fully optimal procedures when ones takes into account the cost of computation in addition to the benefits and costs inherent in the problem as originally posed

- Cognitive illusions (deviations from optimization) - Kahneman, 2003
  - "Our research attempts to obtain a map of bounded rationality by exploring the systematic biases that separate the beliefs that people have and the choices they make from the optimal beliefs and choices assumed in rational-agent models"

- Homo heuristicus (ecological rationality) **-** Gigerenzer and Selten, 2001
  - Models of bounded rationality describe how a decision or judgement is reached (that is, the heuristical processes or proximal mechanisms) rather than merely the outcome of the decision, and they describe the class of environments, in which these heuristics will succeed or fail

* Reproduced from G. Gigerenzer's lecture @ 1st Herbert Simon Conference, available at youtube (Bounded Rationality updated)

Fast and frugal heuristics for decision/choice making

- Models for decision-making that
  - rely heavily on core human capacities
  - easy to understand, explain and apply
  - are simple to compute and use available information in non-exhaustive manner

- **Lexicographic heuristics :** an instance of fast and frugal heuristics
  - *decision alternatives* are described by a set of *decision attributes*
  - the decision attributes are inspected in order of decreasing importance; a choice is made when an attribute favors it over other choices
    - Fast and Frugal Trees (FFTs)
    - Deterministic Elimination by Aspects (DEBA)

In our case:

users $\leftrightarrow$ heuristic decision makers, decision alternatives $\leftrightarrow$ tasks,

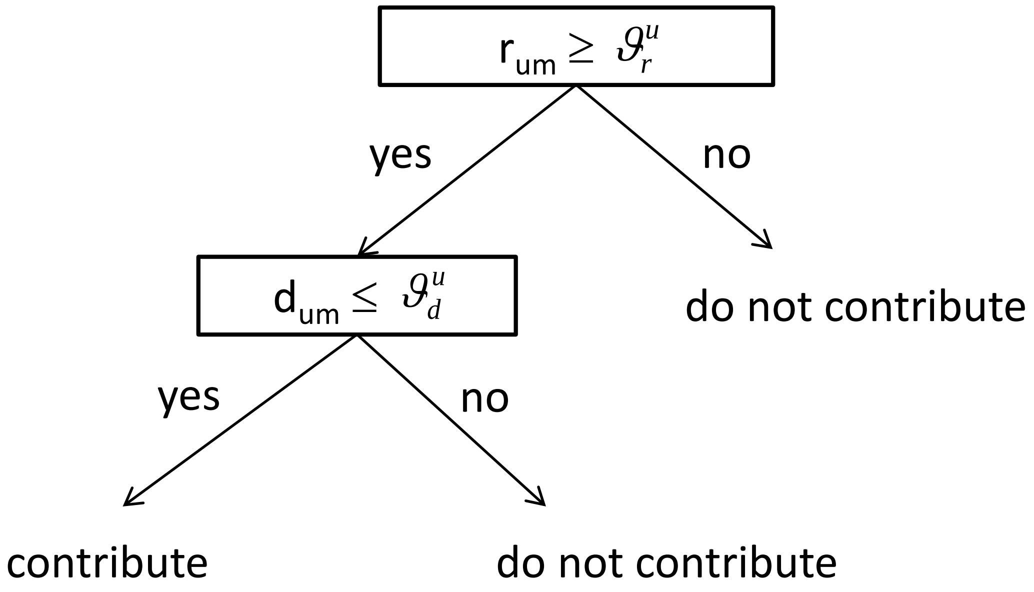
decision attributes $\leftrightarrow$ task features ranked in line with user preferences

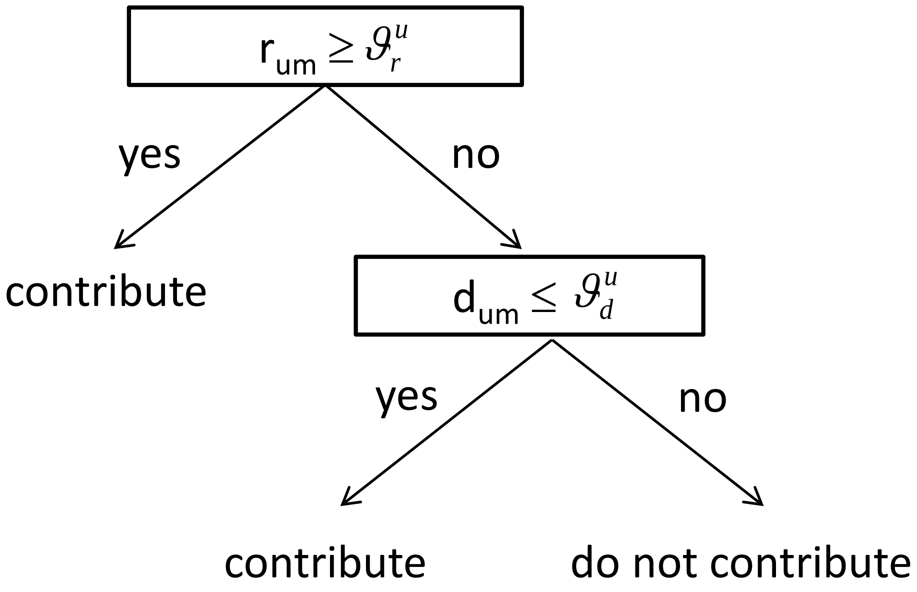
Fast-and-frugal trees as task assignment models in MCS

Consider a user *u* that decides whether to contribute or not to a task (take or leave it)

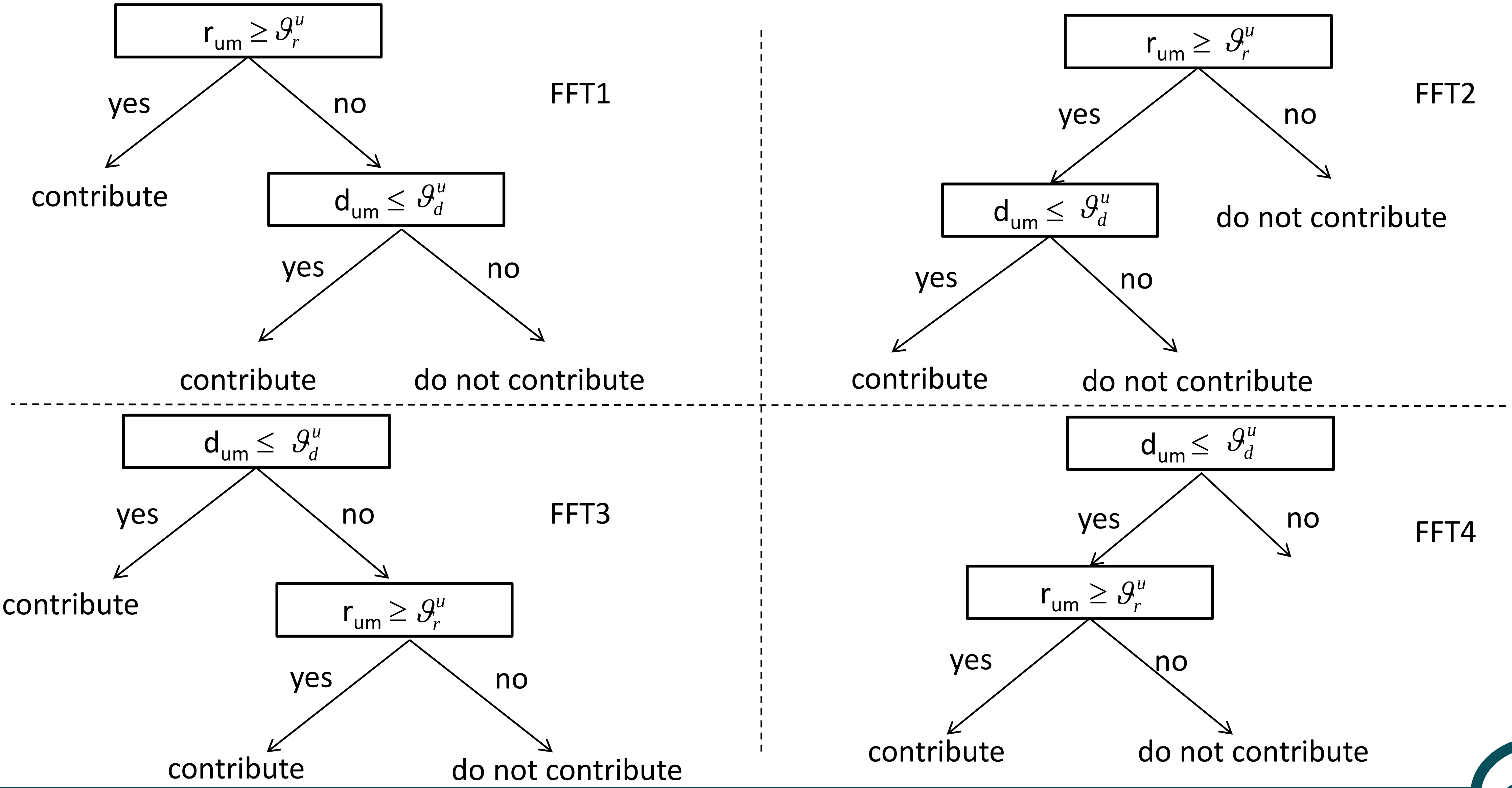
- each task *m* is related to a location l(m), hence a distance d_{um} from u, and presents a user-specific reward r_{um}
- the user may prioritize either one of the two decision attributes, d_{um} or r_{um} ; how good an attribute is depends on user-specific acceptability thresholds ϑ_d^u, ϑ_r^u

Say, she prioritizes the reward attribute





Possible “classes” of FFTs in decision-making



Formulating the user recruitment problem with FFTs

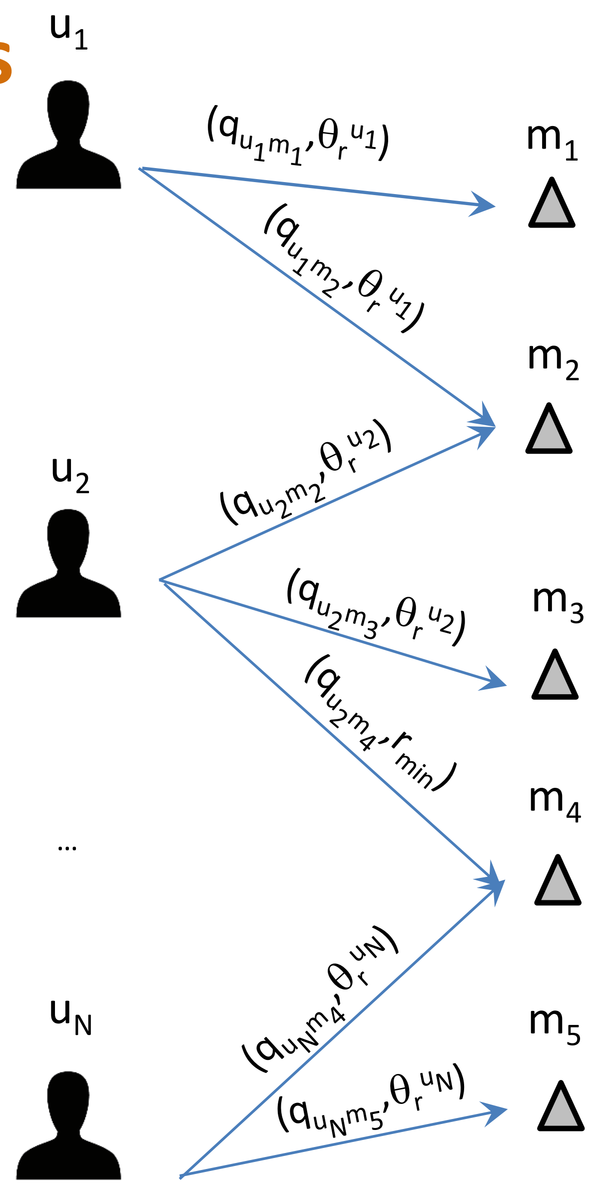
If U_i : set of users deciding according to FFT$_i$, the MCS platform provider can nudge a contribution from user u to task m offering rewards:

$$r_{um} \geq \begin{cases} \theta_u^r, u \in U_2 \cup U_4,\ d_{um} \leq \theta_u^d \\ \theta_u^r, u \in U_1 \cup U_3,\ d_{um} > \theta_u^d \\ r_{min}, u \in U_1 \cup U_3, d_{um} \leq \theta_u^d \end{cases} \qquad (1)$$

r_{min} : minimum default reward for a task contribution

with $x_{um} = 1$ if task m is assigned to user u after an offer according to (1), the problem faced by the MCS platform becomes

$$\begin{aligned} \max_{\mathbf{x}} \quad & \sum_{u \in \mathcal{U}} \sum_{t \in \mathcal{T}_u} q_{um(t)} x_{ut} \\ s.t. \quad & \sum_{u \in \mathcal{U}} \sum_{t \in \mathcal{T}_u : m(t) = m} r_{um(t)} x_{ut} \leq B_m \quad \forall m \in \mathcal{M} \\ & \sum_{t \in \mathcal{T}_u} x_{ut} = 1 \quad \forall u \in \mathcal{U} \qquad (P2) \\ & x_{ut} \in \{0,1\}, \quad u \in \mathcal{U}, t \in \mathcal{T}_u \end{aligned}$$



Discrete Elimination by Aspects (DEBA) for paired task offers

Task offers are made in pairs (m_1, m_2), task attributes are binary and users may be prioritizing either task distance or task reward.

For example, for a user u_1(u_2) that prioritizes distance (reward),

- an offer $r_{um1} \geq \theta_u^r$ for task m_1 at $d_{um1} \leq \theta_u^d$ would be written as [1 1] ([1 1])
- an offer $r_{um2} \leq \theta_u^r$ for task m_2 at $d_{um2} \leq \theta_u^d$ would be written as [1 0] ([0 1])
- another $r_{um3} \geq \theta_u^r$ for task m_3 at $d_{um3} \geq \theta_u^d$ as [0 1] ([1 0])

For user u_1 : $m_1 >_{DEBA} m_2, \quad m_1 >_{DEBA} m_3, \quad m_2 >_{DEBA} m_3,$

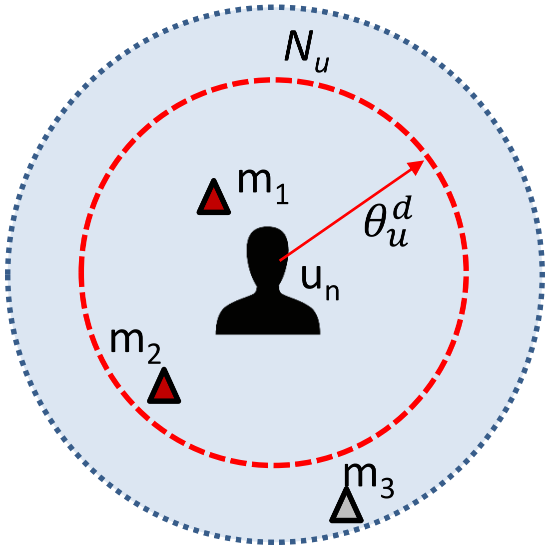
i.e., user u_1 would prefer m_1 over m_2 and m_3, and also m_2 over m_3

For user u_2 : $m_1 >_{DEBA} m_2, \quad m_1 >_{DEBA} m_3, \quad m_3 >_{DEBA} m_2,$

i.e., user u_2 would prefer m_1 over m_2 and m_3, and also m_3 over m_2

Formulating the user recruitment problem with DEBA

Consider a user u_n who prioritizes rewards over distances and three tasks m_1, m_2, m_3 at distances $d_{um1} \leq \theta_u^d$, $d_{um2} \leq \theta_u^d$, and $d_{um3} \geq \theta_u^d$. The user can be directed towards



- task m_1 through
  - A paired offer for tasks (m_1, m_2) with $r_{um1} \geq \theta_u^r$ and $r_{um2} \leq \theta_u^r$
    - since $m_1 \equiv [1\ 1] >_{DEBA} [0\ 1] \equiv m_2$
  - A paired offer for tasks (m_1, m_3) with $r_{um1} \geq \theta_u^r$ and any r_{um3}
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- task m_2 through
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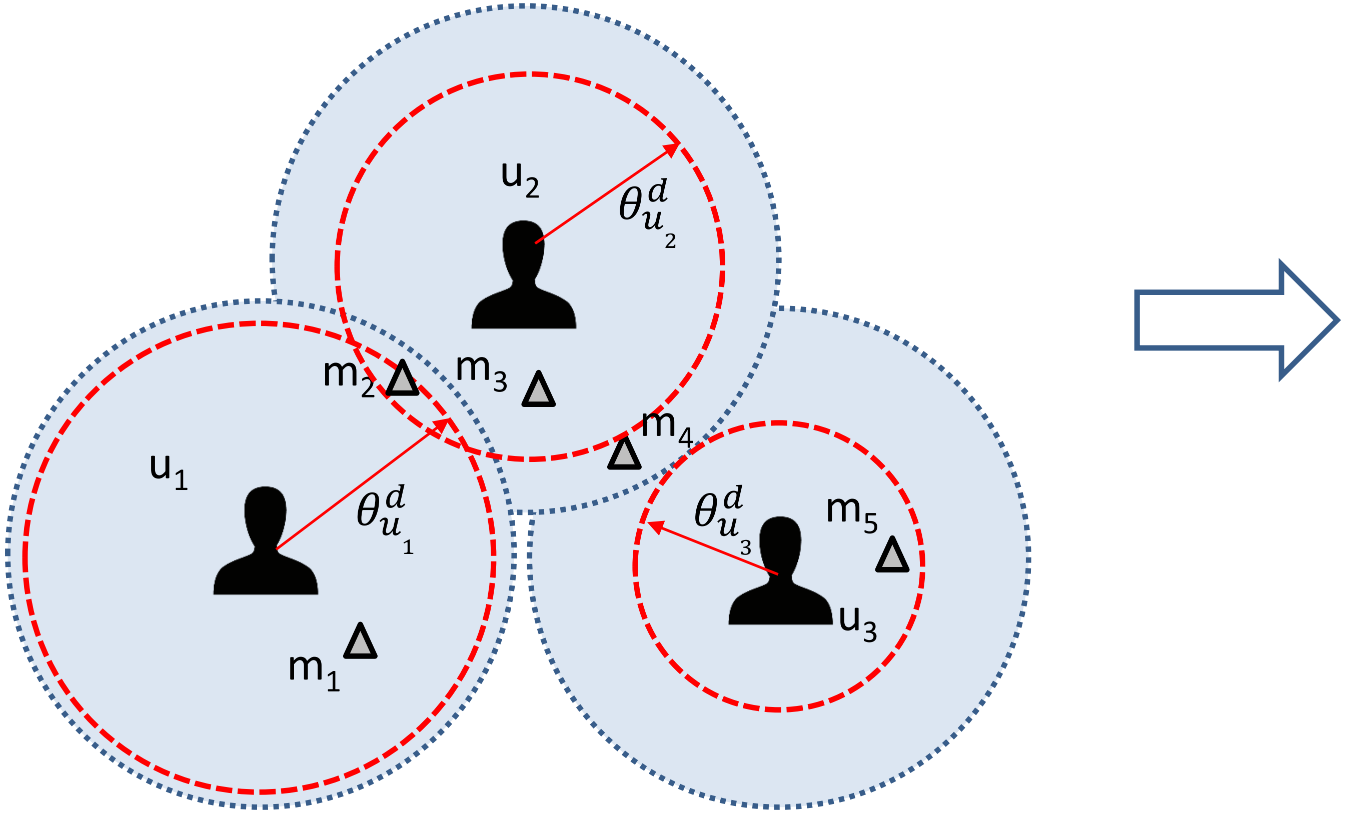
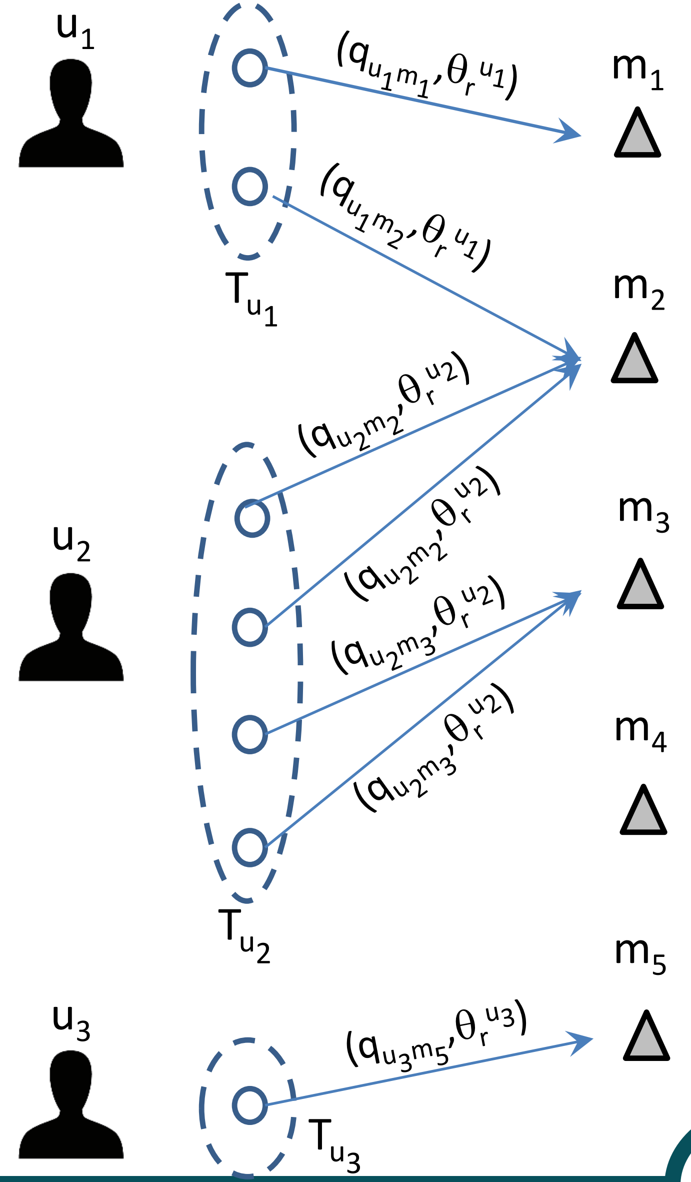
  - A paired offer for tasks (m_2, m_3) with $r_{um3} \geq \theta_u^r$ and $r_{um2} \leq \theta_u^r$
    - since $m_3 \equiv [1\ 0] >_{DEBA} [0\ 1] \equiv m_{12}$

Formulating the user recruitment problem with DEBA

- We come up again with a Generalized Assignment Problem
  - processors ↔ tasks, jobs ↔ offer tuples (rather than users)
  - additional multiple choice type constraints on groups of tuples





Evaluating the fast-and-frugal heuristics

Considered alternative approaches that decouple the task recommendation from the reward allocation problem, i.e., for single-task offers

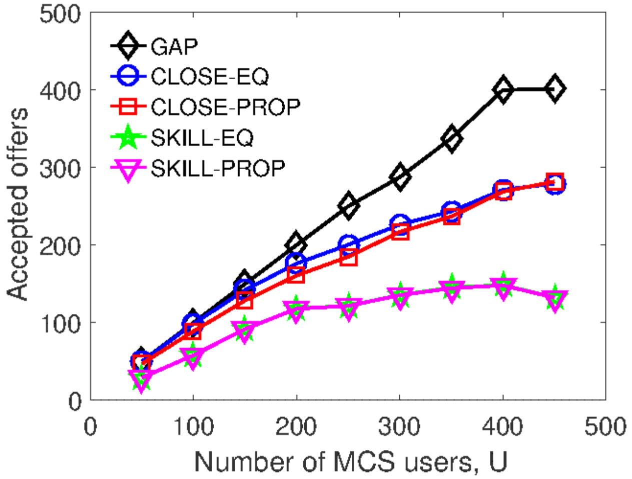
- Task recommendation
  - “make an offer to a user for the task that lies *closest* to him/her” or
  - “make an offer to a user for the task that (s)he is most *skilled* for
- Reward allocation
  - “split the task budget *equally* to users who get an offer”
  - “split the task budget to users who get an offer *in proportion to their skills*”

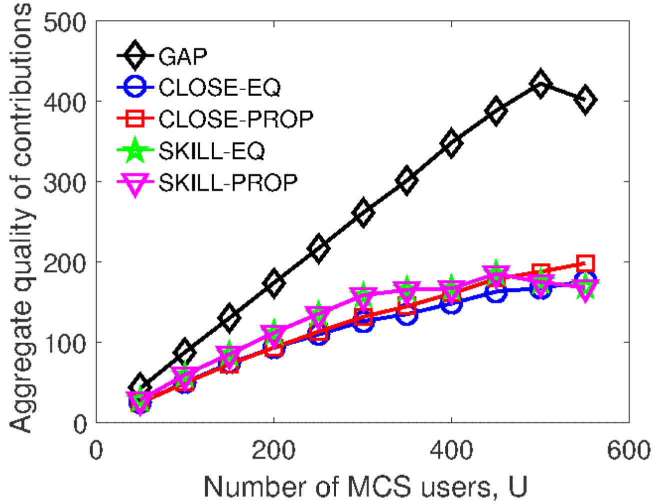
Legends - notation

Recommended task / Task budget split	Closest	User is most skilled for
Equally	CLOSE-EQ	SKILL-EQ
In proportion to user skills	CLOSE-PROP	SKILL-PROP

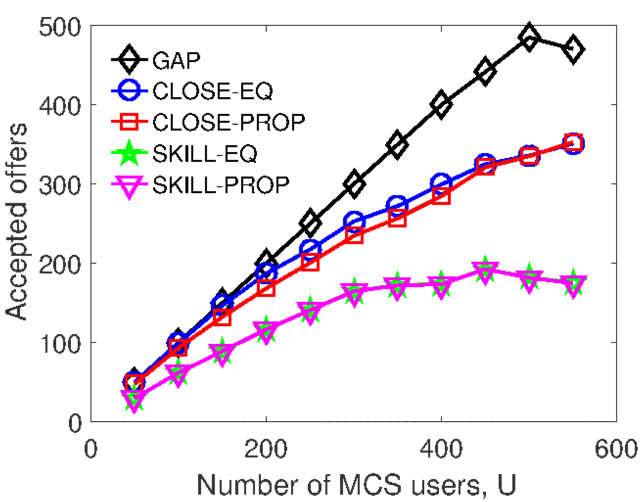
GAP : joint task recommendation and reward allocation

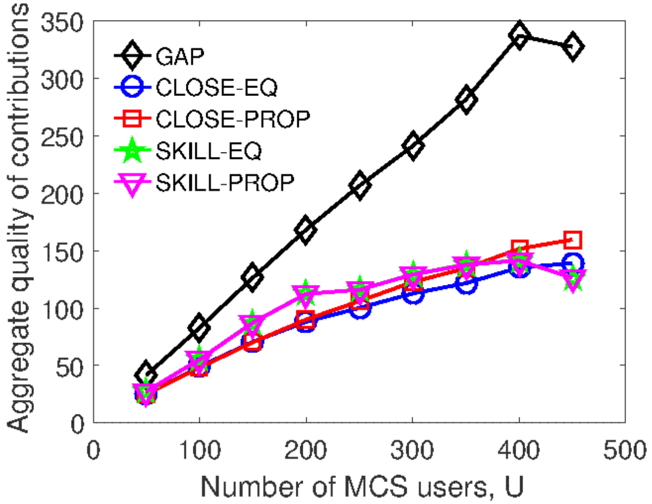
GAP *vs.* heuristic rules : general performance trends





500x500 square area, M=25, θ_u^d ~ unif [100,250], θ_u^r ~ unif [0.5,1.5]

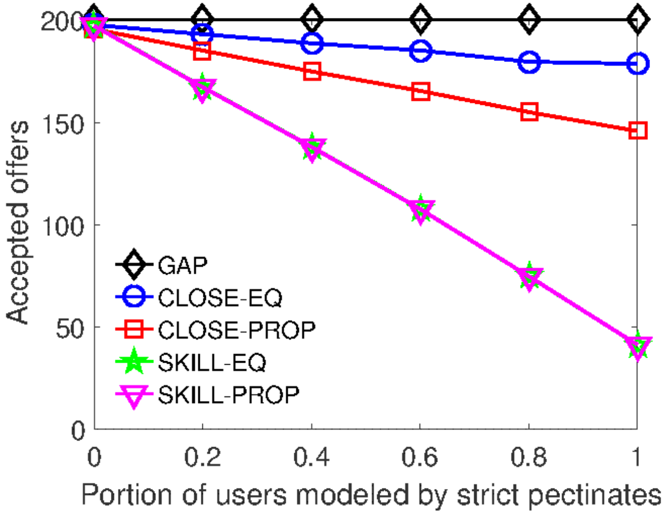


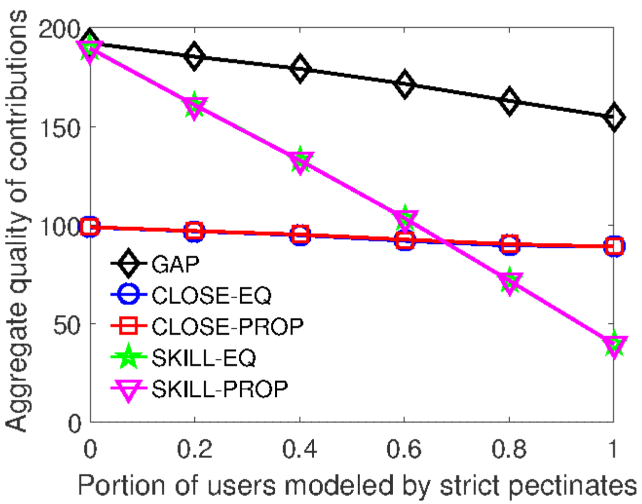


750x750 square area, M=20, θ_u^d ~ unif [100,350], θ_u^r ~ unif [0.5,1.5]

- GAP clearly outperforms the other two heuristics
  - manages better the task budgets and targets rewards to users
- The task recommendation rule weighs more than the reward allocation rule
  - *-EQ and *-PROP curves hardly differentiate
- The CLOSE-* rules attract more contributors
  - …but fail to capitalize this in terms of contribution quality

GAP vs. heuristic rules : the impact of user mix





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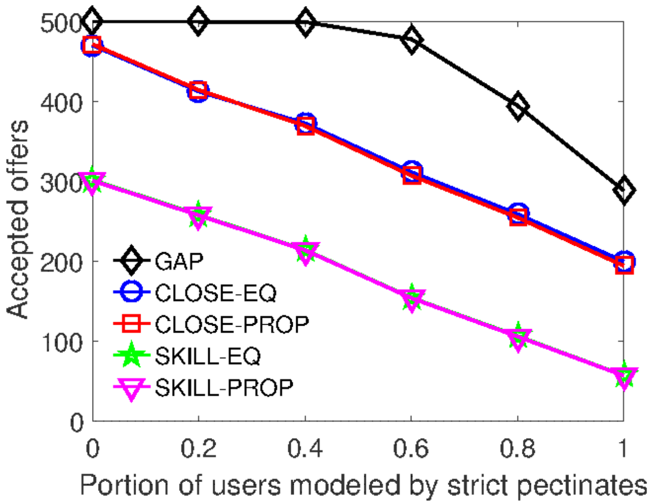

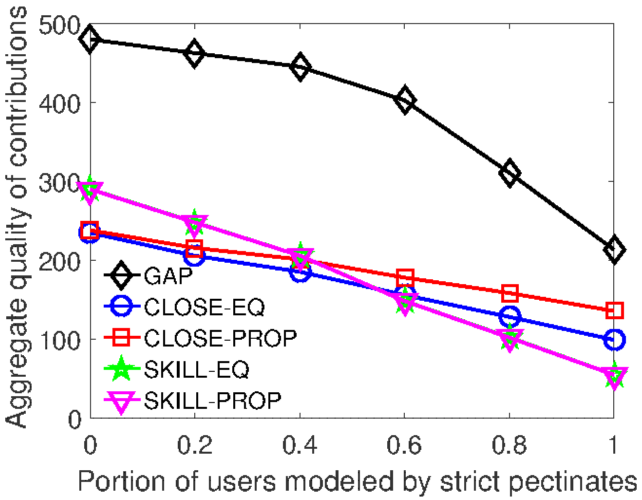

500x500 square area, M=25, θ_u^d ~ unif [100,500], θ_u^r ~ unif [0.5,1.5], U = 500

- For 200 users, GAP can mobilize all users and get good contributions
  - budgets get exhausted for more users as strict pectinate users grow
- The CLOSE-* rules are consistently attracting more contributions
  - in particular, under equal budget sharing
- The SKILL-* rules are much more vulnerable to the mix of users
  - Outperform (lose to) CLOSE-* rules at low (high) numbers of strict pectinate users

Concluding and the way forward

- There is a bulk of work in behavioral sciences (cognitive psychology, behavioural economics) about human decision making and its bounded rationality

- We tried to explore its implications in mobile crowdsensing (MCS) settings
  - Identified models of decision-making heuristics capturing bounded rationality properties
  - **Made the bold hypothesis** that these are activated in MCS context
  - Formulated optimization problems for the user recruitment (in our case: task recommendation) and reward allocation task in MCS

- The hypothesis has to be tested → infer the activation of heuristics
  - Need real datasets of the right context (user responses to task recommendations) for this purpose
  - Ideas/pointers are welcome !

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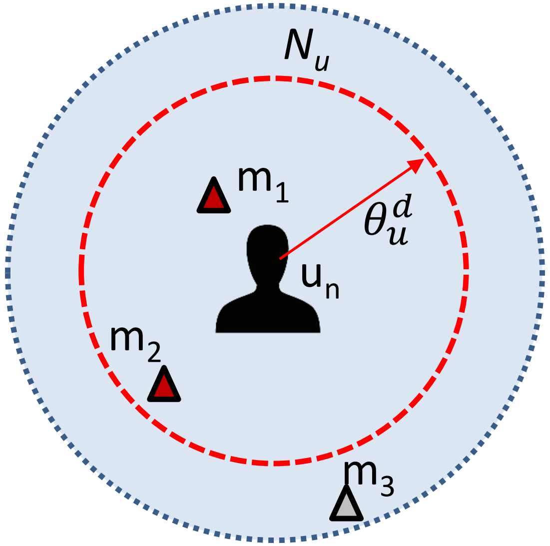

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  - A paired offer for tasks (m_1, m_3) with $r_{um2} \geq \theta_u^r$ and any r_{um3}

- task m_3 $\rightarrow$ no way!

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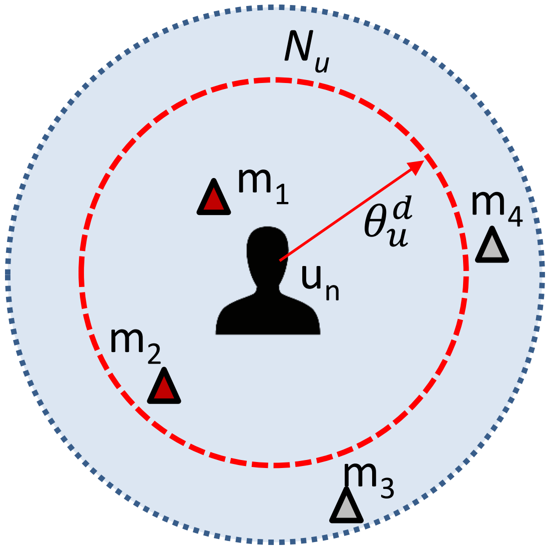

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