Improving Mobile Maternal and Child Health Care Programs: Collaborative Bandits for Time slot selection

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ABSTRACT

Maternal and child health is a global priority, reflected in the UN Sustainable Development Goal 3.1. Mobile health (mHealth) programs, using automated voice messages, are a vital tool for NGOs to disseminate health information in underserved communities. However, these programs face challenges: limited beneficiary phone access and unknown time preferences hinder timely outreach, leading to poor engagement. We address this by formulating the time preference inference problem as a multi-agent multi-armed bandit optimization problem, where beneficiaries are modeled as agents, and time slots as arms. We introduce a novel online collaborative filtering framework that infers preferred time slots by collaborating across beneficiaries to quickly identify their preferred time slots.

To highlight the scope and impact of this problem, we are working with Kilkari, the world's largest maternal and child mHealth program serving millions in India every week. Kilkari faces substantial reattempt costs to improve call answer rates. Through extensive experiments on real-world data obtained from Kilkari, we demonstrate that our collaborative bandit framework significantly outperforms both existing policies used by the NGO, and popular non-collaborative bandit algorithms (e.g., Upper Confidence Bound), both in terms of number of call retries, saving critical bandwidth that enables wider outreach, and by rapidly learning optimal time slots, improving beneficiary engagement and retention.

KEYWORDS

AI for Social Good, Maternal and Child Healthcare, Bandit Optimization, Collaboration, Matrix Completion

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1 INTRODUCTION

Maternal mortality is unacceptably high in several parts of the world. In 2020, an estimated 287,000 women died from preventable causes related to pregnancy and childbirth [30]. Consequently, the World Health Organization (WHO) has made improving maternal health one of its top priorities. As part of WHO's Sustainable Development Goals (SDGs), countries have committed to reducing the global maternal mortality ratio to less than 70 per 100,000 live births by 2030 and end preventable deaths of newborns and children under 5 years of age [31]. In line with this goal, several non-governmental organizations (NGOs) are leveraging mobile health programs extensively to disseminate critical health information [3, 17, 26, 28] economically due to the widespread availability of cellphones.

Kilkari is the largest maternal and child mHealth program in the world [3] which is implemented by the NGO ARMMAN in partnership with the Ministry of Health and Family Welfare of India, and currently has 3.2 million active users. Kilkari uses free pre-recorded voice calls to deliver vital preventive care information on maternal and infant health to pregnant women and new mothers. To ensure that beneficiaries listen to these messages in a timely manner, it is vital to reach out to them at the right time. The reality is, practical problems such as limited access to phones due to shared family phone for many women, working hours, house chore responsibilities significantly affect the likelihood of engagement at a given time slot [6]. And hence, sending these automated voice calls at an inconvenient/wrong time leads to poor listenership.

In fact, consistent low listenership of the calls can even lead to beneficiaries being dropped from the program. To address this, the NGO re-attempts sending voice messages multiple times in a week until the call is answered. Despite this listenership remains low with almost 50% of the economically weakest beneficiaries requiring more than 6 attempts on average [27] and on average 23% being unreachable despite multiple attempts [23]. [27] pointed out the positive impact of listening to Kilkari messages on health outcomes, particularly among the most marginalised who have the most to benefit from this program, and have the least access to resources. However, despite the known advantages of sustained high listenership, the scale of Kilkari's operations makes it difficult to gather individual time preferences, or demographic information that could help predict those preferences [34]. This makes the problem of identifying good time-slots even more challenging and critical to the efficacy of the program.

Randomized policies such as the one's currently deployed by Kilkari pick a time slot at random, and call the beneficiary. However, such policies tend to be sub-optimal as they do not adapt to beneficiary's preferences (see Section 4 for empirical evidence), and are a suboptimal use of the limited calling bandwidth [6]. To help NGOs overcome this challenge, we study the problem of time slot selection from the perspective of bandit optimization. To be precise, we formulate the problem as a multi-agent multi-armed bandit optimization problem where the beneficiaries are agents and time slots are arms. Every day, one arm of every agent gets pulled and we observe the feedback/reward corresponding to the arm. Our goal is to quickly identify good time slots of each beneficiary, which can be quantified using the following two metrics: (a) average number of retries before a successful pick-up, (b) time to learn these preferences. Numerous algorithms such as Upper Confidence Bound (UCB) [5], Thompson Sampling (TS) [1, 36], Successive Elimination [4] have been proposed to solve the problem in the single agent setting. While these algorithms are optimal for a single agent, they tend to be sub-optimal in the multi-agent setting where one can collaborate across similar agents to identify good arms much faster, which is critical to retain and engage beneficiaries with the program.

In this work, we consider collaborative bandit algorithms for solving the time slot selection problem. Our algorithms try to simultaneously identify similar agents and collaborate across them to learn their arm preferences. We would like to highlight that we do this without access to any features of the agent. This is achieved via a reduction of the collaborative bandit problem to low-rank matrix completion problem where one tries to reconstruct a matrix from a small subset of its entries [18, 22]. In this work, we propose two novel algorithms: Greedy Matrix Completion (MC), and Phased MC [19, 32]. In Greedy MC, we first collect exploratory data, then perform matrix completion with the collected data to estimate the arm preferences, and pull the best estimated arm for each agent in the rest of the rounds. One of the key novelties in Greedy MC, compared to existing works [19, 32], is that we bring in variance reduction techniques [8] into our algorithm which makes it robust to noise and improves its performance in practice. While Greedy MC is effective in practice, the random exploration it performs in early stages can hurt the user experience, which may lead to dropouts from the program. To address this, we introduce Phased MC, a novel bandit algorithm that operates in phases. Instead of having a lengthy random exploration phase at the beginning, it combines exploration and exploitation throughout the program duration. Within each phase, we use Boltzmann exploration based on the estimated reward matrix from previous phases [12]. At the end of every phase, we use robust matrix completion to revise the estimated reward matrix. In Section 2, we provide a more detailed comparison between our algorithms and existing collaborative bandit algorithms.

In Section 4, we evaluate our algorithms on an anonymized real-world dataset obtained from Kilkari, collected over a period of one year for $200k$ beneficiaries. The Kilkari program has 7 time slots in a day during which the calls can be placed. Moreover, calls are placed in a week at most 9 times until there is a pickup by the beneficiary. Considering each slot (irrespective of the day) as an arm, in our experiments, we demonstrate that the MC based bandit algorithms (Greedy MC and Phased MC) achieve a reduction of at least 27% in regret over non collaborative policies like UCB. Furthermore, our MC based algorithms obtain **>30%** reduction in average number of retries per week over random policy (that is in use by Kilkari) and **>8%** reduction over the non collaborative UCB policy, for **42%** of the beneficiaries. When we account for the weekend/weekday effect and increase our arm space to 14 (7 for weekends and 7 for weekdays), we get **>45%** reduction in the number of retries over random policy and **>25%** reduction over UCB policy for approximately **76%** of the users. *An optimistic estimate for the* 14 *time slots case shows that if one were to equalize the total number of calls to what the UCB policy would make, we could potentially onboard* ***56%*** *more beneficiaries (based on the plot in Fig. 2c).*

2 RELATED WORK

Maternal Healthcare. Restless Multi-Armed Bandits have been used for improving maternal healthcare by providing solutions for limited resource allocation particularly where NGO's serving underserved communities are operating with limited resources [26, 29, 37]. In contrast, this paper focuses on stochastic MABs for time slot planning.

Bandits. Multi-armed bandits (MAB) and other bandit optimization problems have been widely studied in recent decades. UCB [5], TS [1, 36], Phased Elimination [24, 35] are some of the most popular algorithms for regret minimization in MABs. Recent works have also studied best-arm identification in MABs and provided (near) optimal algorithms [2, 15, 20, 21].

Collaborative Bandits. Collaborative bandit optimization has recently gained significant attention due to its applicability in modern recommendation systems where millions of users interact with the system daily [9, 14, 16, 19, 32]. However, optimal algorithms for this problem are only known under certain special settings. [32] derived a regret optimal algorithm under the assumption that users can be grouped into a small number of latent clusters. [19] assumed the agents × arms reward matrix has rank 1 and derived an algorithm which achieves optimal regret. However, the assumptions made in both these works rarely hold in practice. [14] developed a heuristic, alternating linear bandits algorithm for low-rank reward matrices. However, this algorithm has poor performance in practice as the reward matrices in real-world are only *approximately* low-rank. One of key technical contributions of our work is to develop algorithms for collaborative bandits under *approximate* low-rank assumptions. Our Greedy MC algorithm is inspired by the greedy algorithm of [19]. The main novelty in Greedy MC comes from the variance reduction technique we introduce to make it robust to noise. Our Phased MC algorithm is inspired by the phased elimination algorithms of [19, 32]. But unlike the algorithms of [19, 32] which assume rank 1 reward matrix or cluster structure among agents, we work with a more general approximate low-rank assumption.

3 PROBLEM FORMULATION AND ALGORITHMS

Notation. We write $[m]$ to denote the set $\{1, 2, \ldots, m\}$. For a vector $\mathbf{v} \in \mathbb{R}^m$, $\mathbf{v}_i$ denotes the ith element; for any set $\mathcal{U} \subseteq [m]$, let $\mathbf{v}_{\mathcal{U}}$ denote the vector $\mathbf{v}$ restricted to the indices in $\mathcal{U}$. Similarly, for

$\mathbf{A} \in \mathbb{R}^{m \times n}$, $\mathbf{A}_{ij}, \mathbf{A}_i$ denotes the (i, j)-th element and the ith row of $\mathbf{A}$ respectively. For any set $\mathcal{U} \subseteq [m], \mathcal{V} \subseteq [n]$, $\mathbf{A}_{\mathcal{U},\mathcal{V}}$ denotes $\mathbf{A}$ restricted to the rows in $\mathcal{U}$ and columns in $\mathcal{V}$. Let $\|\mathbf{A}\|_\infty$ denote absolute value of the largest entry in matrix $\mathbf{A}$. $\text{Ber}(p)$ denotes the binary random variable that is 1 with probability p (0 with probability $1 - p$). $\mathbb{E}X$ denotes expectation of random variable X.

Problem Setting: We have M beneficiaries and N slots (distinct intervals of time during the day) where calls can be placed to each beneficiary. Furthermore, there are T rounds - each round corresponding to a day - at which the service provider can make calls to as many beneficiaries as possible. In Kilkari, we have $M \approx 10^6$, $N = 7$, and $T \approx 300$. Our goal is to design a sequential decision making algorithm $\mathcal{A}$ that recommends the service provider appropriate slots to call the beneficiaries. To do this, $\mathcal{A}$ relies on the data obtained via calls made until the previous day and aims to quickly find the preferred time slot for every beneficiary. We model the *unknown* preferences of the beneficiaries towards the distinct slots using the following two matrices:

(1) **Pick-up matrix.** We let $\mathbf{P} \in \mathbb{R}^{\mathsf{M} \times \mathsf{N}}$ denote the pick-up probabilities of beneficiaries. Here $\mathbf{P}_{ij}$ denotes the probability of beneficiary i picking-up a call at slot j.

(2) **Engagement matrix.** We let $\mathbf{E} \in \mathbb{R}^{\mathsf{M} \times \mathsf{N}}$ denote the engagement probabilities of beneficiaries, where $\mathbf{E}_{ij}$ denotes the probability of beneficiary i picking-up and engaging with the call for at least 25% of the message duration at slot j.

In this work we assume that $\mathbf{P}, \mathbf{E}$ are approximately low-rank matrices. We note that this assumption typically holds in many domains; *e.g.,* movie preferences [7], genomics [10]. This assumption also holds in Kilkari, where we observed that $\mathbf{P}, \mathbf{E}$ are approximately rank 2 matrices (see Figure 11).

We model the problem of learning optimal time slots for beneficiaries as a multi-agent, multi-armed bandit optimization problem with M agents (beneficiaries), N arms (time-slots) and T rounds (days). For simplicity, we assume that at each round, the service provider has sufficient capacity to call all the agents. In practice, there can exist limitations on the number of beneficiaries that can be called at a certain time slot or on a certain day. As we show later in the paper, some of these constraints can be easily incorporated into our algorithms (Section 4.2).

Suppose, for beneficiary u at round t, algorithm $\mathcal{A}$ recommends the slot $\rho_u(t)$ for making the call and observes a noisy feedback - pick-up and engagement. The beneficiary u will pick-up the call with probability $\mathbf{P}_{u\rho_u(t)}$ and conditioned on the call being picked up, the beneficiary will engage with probability $\mathbf{E}_{u\rho_u(t)} \times [\mathbf{P}_{u\rho_u(t)}]^{-1}$. We will also define the functions $\pi_p : [\mathsf{M}] \to [\mathsf{N}]$ and $\pi_e : [\mathsf{M}] \to [\mathsf{N}]$ that takes as input a beneficiary and maps it to the slot with the highest pick-up probability and engagement probability respectively for the chosen beneficiary. Next, we define two notions of regret, namely $\text{Reg}_{\text{pick-up}}(\mathsf{T})$ and $\text{Reg}_{\text{engage}}(\mathsf{T})$:

$$\text{Reg}_{\text{pick-up}}(\mathsf{T}) = \sum_{u \in [\mathsf{M}]} \left(\mathsf{T}\mathbf{P}_{u\pi_p(u)} - \mathbb{E}_{\mathcal{A}} \sum_{t \in [\mathsf{T}]} \mathbf{P}_{u\rho_u(t)} \right) \quad (1)$$

$$\text{Reg}_{\text{engage}}(\mathsf{T}) = \sum_{u \in [\mathsf{M}]} \left(\mathsf{T}\mathbf{E}_{u\pi_e(u)} - \mathbb{E}_{\mathcal{A}} \sum_{t \in [\mathsf{T}]} \mathbf{R}_{u\rho_u(t)} \right). \quad (2)$$

Intuitively, $\text{Reg}_{\text{pick-up}}(\mathsf{T})/\mathsf{TM}$ measures how much the average call pick-up rate of an algorithm differs from the call pick-up rate of the best possible policy. Note that, even though we want to improve engagement more than call pick-up, it is much harder to do so because very few people engage with the calls, and consequently, the data on engagement is very limited. Nonetheless, in Section 4.1.2 we show that one could improve engagement rate by smartly combining the pick-up and engagement data.

3.1 Collaborative Algorithms

Our collaborative bandit algorithms rely on an offline low rank matrix completion oracle O. For an unknown matrix $\mathbf{Z} \in \mathbb{R}^{m \times n}$, O takes a subset of noisy observations of the matrix at positions Ω ($\{\mathbf{M}_{ij}\}_{(i,j) \in \Omega}$) as input, and returns an estimate $\widehat{\mathbf{Z}}$ of $\mathbf{Z}$. To implement this oracle, we minimize the following nuclear norm regularized objective [13]:

$$\text{minimize}_{\widehat{\mathbf{Z}}} \sum_{(i,j) \in \Omega} (\mathbf{M}_{ij} - \widehat{\mathbf{Z}}_{ij})^2 + \lambda \left\| \widehat{\mathbf{Z}} \right\|_\star . \quad (3)$$

Here $\lambda > 0$ is the regularization parameter and $\left\| \widehat{\mathbf{Z}} \right\|_\star$ denotes the nuclear norm of $\widehat{\mathbf{Z}}$. We note that this is a very popular technique for matrix completion, and comes with strong theoretical guarantees [13].

3.1.1 Greedy Matrix Completion (MC). In this section, we present our first algorithm, Greedy MC (Algorithm 1). The key idea here is to partition the T rounds into two phases - *exploration* phase spanning the first $\mathsf{T}_{\text{explore}}$ rounds and *exploitation* phase spanning the next $\mathsf{T} - \mathsf{T}_{\text{explore}}$ rounds. In the exploration phase, we randomly select a slot for each beneficiary and place a call in the chosen slot (Lines 2, 3 in Algorithm 1). We store the observed pick-ups and engagements of the beneficiaries in a matrix $\mathbf{M}$ (Line 4 in Algorithm 1). At the end of the exploration phase, we use the observed data $\mathbf{M}$ to estimate the unknown pick-up/engagement matrix. To do this, we propose a novel bagging-based use of the matrix completion oracle O (Algorithm 3) that we detail below. Subsequently, in the exploitation phase, we use the estimated matrix to find the most preferred time slot for each beneficiary and commit to that slot for the remaining $\mathsf{T} - \mathsf{T}_{\text{explore}}$ rounds (Lines 7-9 in Algorithm 1).

Robust Median Estimates using Bagging (Algorithm 3): Naively performing MC on the observed data ($\mathbf{M}$) to infer $\mathbf{P}$ (or $\mathbf{E}$) leads to estimates with high variance. To address this, we infer $\mathbf{P}$ (or $\mathbf{E}$) using multiple sub-samples of the data, and aggregate the estimates to produce a final estimate with reduced variance [8]. Specifically, for each beneficiary u, we consider K small groups of beneficiaries, i.e. $\mathcal{U}_1^u, \mathcal{U}_2^u \ldots \mathcal{U}_K^u$ where $u \in \mathcal{U}_i^u \subset [M]$ (each group contains u). These groups are chosen randomly such that $|\mathcal{U}_i^u| > N$. Suppose $\Omega \subset [M] \times [N]$ is the set of entries for which the pickup (or engagement) data is available in matrix $\mathbf{M}$. Note that $|\Omega|$ is typically much smaller than $\mathsf{N} \times \mathsf{M}$. For each group $\mathcal{U}_i^u$, we use the relevant data obtained from the exploration phase from matrix $\mathbf{M}$, i.e. $\tilde{\Omega}_i = \Omega \cap (\mathcal{U}_i^u \times [N])$ and apply the optimization routine in (3) with $\mathbf{M}_{\mathcal{U}_i^u,[N]}$. We obtain the completed sub-matrix $\widehat{\mathbf{Z}}_{\mathcal{U}_i^u,[N]}$ by using (3). Thus, for each beneficiary u, we obtain K estimates of it's pickup

Algorithm 1 Greedy MC Algorithm for maximizing engagement

Require: exploration rounds $\mathsf{T}_{\text{explore}}$.

Initialize $\Omega \leftarrow \emptyset,\ \mathbf{M} \in \mathbb{R}^{M \times N}$.
for $t = 1, 2, \ldots, \mathsf{T}_{\text{explore}}$ **do**
  For each u in $[\mathsf{M}]$, randomly sample a slot $\rho_u(t)$ and place a call. Let the indicator of engagement be $B_t(u)$
  If $(u, \rho_u(t)) \notin \Omega$, then $\Omega \leftarrow \Omega \cup (u, \rho_u(t)),\ \mathbf{M}(u, \rho_u(t)) \leftarrow B_t(u)$. If $(u, \rho_u(t)) \in \Omega$, then $\mathbf{M}(u, \rho_u(t)) \leftarrow \frac{B_t(u)}{t} + (1 - \frac{1}{t})\mathbf{M}(u, \rho_u(t))$
end for
For each beneficiary u in $[\mathsf{M}]$, estimate the engagement rates for all the slots, $\mathbf{E}_u \leftarrow$ MC_RME(u, M, Ω).
for each of remaining rounds **do**
  For each beneficiary u, choose the slot from vector $\mathbf{E}_u$ with highest estimated probability and make a call.
end for

Algorithm 2 Phased MC Algorithm for maximizing engagement

Require: Phase length Δ, temperature parameter β.

Initialize row stochastic matrix $\mathbf{Q} \in \mathbb{R}^{\mathsf{M} \times \mathsf{N}}$ with $\mathbf{Q}_{ij} = \mathsf{N}^{-1}$ for all $(i, j) \in [\mathsf{M}] \times [\mathsf{N}]$. Initialize $\Omega \leftarrow \emptyset,\ \mathbf{M} \in \mathbb{R}^{M \times N}$.
for phase $= 1, 2, \ldots, \lceil \mathsf{T}/\Delta \rceil$ **do**
  for $t = 1, 2, \ldots, \min(\Delta, \mathsf{T} - \text{phase} \cdot \Delta)$ **do**
    For each u in $[\mathsf{M}]$, sample a slot $\rho_u(t) \sim \mathbf{Q}_u$ and place a call. Let the indicator of engagement be $B_t(u)$.
    If $(u, \rho_u(t)) \notin \Omega$, then $\Omega \leftarrow \Omega \cup (u, \rho_u(t)),\ \mathbf{M}(u, \rho_u(t)) \leftarrow B_t(u)$. If $(u, \rho_u(t)) \in \Omega$, then $\mathbf{M}(u, \rho_u(t)) \leftarrow \frac{B_t(u)}{t} + (1 - \frac{1}{t})\mathbf{M}(u, \rho_u(t))$
  end for
  For each beneficiary u in $[\mathsf{M}]$, estimate the engagement rates for all the slots, $\mathbf{E}_u \leftarrow$ MC_RME(u, M, Ω).
  For each beneficiary $u \in [\mathsf{M}]$ and each slot $j \in [\mathsf{N}]$, update $\mathbf{Q}_{uj} \leftarrow \exp(\beta \mathbf{E}_{uj}) \Big(\sum_{j' \in [\mathsf{N}]} \exp(\beta \mathbf{E}_{uj'}) \Big)^{-1}$.
end for

Algorithm 3 Matrix Completion with Robust Median Estimates: MC_RME(u, M, Ω)

Require: User u, Observed Data $\mathbf{M} \in \mathbb{R}^{\mathsf{M} \times \mathsf{N}}$, set of observed entries Ω, Low Rank MC Oracle $\mathcal{O}$.

Construct K groups $\mathcal{U}_1^u, \mathcal{U}_2^u \ldots \mathcal{U}_K^u$ of $\mathsf{N}' > \mathsf{N}$ beneficiaries, each comprising u. In each group, the beneficiaries other than u are sampled uniformly at random without replacement.
For each group of beneficiaries $\mathcal{U}_i^u$, invoke the MC completion oracle $\mathcal{O}$, i.e. solving the optimization problem in (3), using $\tilde{\Omega}_i = \Omega \cap \mathcal{U}_i^u \times [N]$ and observed data $\mathbf{M}_{\mathcal{U}_i^u, [N]}$, to compute an estimate of $\widehat{\mathbf{Z}}^i_{\mathcal{U}_i^u, [\mathsf{N}]}$ (sub-matrix corresponding to rows in $\mathcal{U}_i^u$ and set of slots $[\mathsf{N}]$).
Construct final estimate of $\mathbf{E}_u$ by computing entry-wise median of the K estimates of row u, i.e. $\mathbf{E}_u = \text{Median}(\{\widehat{\mathbf{Z}}^i_{u,:}\}_{i=1}^K)$
Return $\mathbf{E}_u$

(or engagement) probabilities at each slot, and compute the entry-wise median of the K estimates and use it as the final estimate for that beneficiary. This procedure helps reduce the variance in our estimates, and makes it robust to outliers [11, 25, 33].

3.1.2 Phased Matrix Completion (Algorithm 2). Although the Greedy MC algorithm is conceptually quite simple, it has one main drawback: it needs a lengthy exploration phase in the beginning to get a good estimate of $\mathbf{P}, \mathbf{E}$ (see Figure 12). However, this can hurt the user experience, and can even drive beneficiaries away from the program, as slots are chosen randomly. To address this limitation, we propose an alternate algorithm called Phased Matrix Completion (MC) which reduces the initial exploration period.

The Phased MC algorithm partitions the T rounds into equally sized $\lceil \mathsf{T}/\Delta \rceil$ phases of length Δ (Lines 2, 3 in Algorithm 2). The first phase is similar to the exploration phase of Greedy MC; *i.e.,* in each round of this phase, for each beneficiary, a slot is chosen uniformly at random and a call is placed. At the end of each phase, we rely on the data collected so far ($\mathbf{M}$) to estimate $\mathbf{P}$ (or $\mathbf{E}$) by invoking the robust matrix completion subroutine (Algorithm 3). The key novelty in our algorithm is in the kind of exploration we perform in each phase. Within each phase, for each beneficiary, we sample slots with probability proportional to exponential of the estimated pick-up/engagement rate of the slot (modulo a scaling factor β). β provides a trade-off between exploration and exploitation, with larger values favouring exploitation and smaller values favouring exploration. This approach is also known as Boltzmann exploration, and has been recently studied in the context of classical multi-armed bandits [12]. We note that Δ in this algorithm is smaller than the exploration phase of Greedy MC. This helps us pick meaningful slots after the end of first phase itself (see Figures 13a, 13b). However, in contrast to Greedy MC, the Phased MC algorithm is computationally more intensive as it needs to compute $\lfloor \mathsf{T}/\Delta \rfloor$ estimates - one after each phase - of $\mathbf{P}, \mathbf{E}$ (see Appendix A).

4 EXPERIMENTS

Dataset: We obtained an anonymized call log dataset from our NGO partner ARMMAN. This data was collected over a period of one

year, and has $M = 200K$ beneficiaries, $N = 7$ time slots (across 8am to 8pm) at which the calls were made. Using this data, we first constructed "ground truth" matrices $\mathbf{P}, \mathbf{E}$ for simulation. Specifically, we estimated the pick-up (engagement) probability for each (beneficiary, slot) tuple as the ratio of number of times the beneficiary picked-up (engaged) to the number of calls placed in that slot. In all our experiments, we ensure that the algorithms don't have access to the matrices $\mathbf{P}, \mathbf{E}$. We use these matrices solely to simulate binary observations (pick-up, engagement). Finally, we note that the constructed matrices $\mathbf{P}, \mathbf{E}$ are completely filled (a small fraction of entries are missing in the ground truth matrix but they were imputed using ad-hoc techniques that are completely agnostic to the algorithm). As stated in the introduction, we use the following two metrics to compare various algorithms: (a) $\text{Reg}_{\text{pick-up}}(T)$, $\text{Reg}_{\text{engage}}(T)$ which measure the expected pick-up, engagement rates of an algorithm, and (b) number of retries before a successful call. The major takeaways from our experiments with the retries constraint (Section 4.2) that model the practical Kilikari set-up are the following:

- The MC based algorithmic framework (Greedy MC and Phased MC) obtain significant reduction in regret over the non-collaborative UCB policy (> 27%).
- Our MC based algorithms obtain a significant reduction in the number of average retries for 7 slots. The reduction over random policies and UCB policy is > 30% and > 9% respectively for several groups of beneficiaries.
- On extending our constrained setting to 14 time slots by taking into account, the weekday-weekend flag, the reduction in average retries for MC based algorithms become even more pronounced and goes up to > 45% over random and > 25% over UCB policies.

4.1 Online Collaborative Learning

In this section, we demonstrate the efficacy of collaborative bandit algorithms in identifying appropriate time-slots for beneficiaries. We first describe our experimental setting. We subsample $M = 1000$ beneficiaries uniformly at random from the $200K$ beneficiaries, and consider $T = 50$ rounds. At each round, for each of the M beneficiaries, a sequential algorithm chooses a time slot to call the beneficiary based on the data obtained in previous rounds. We simulate calls, pick-ups and engagements using the "ground truth" $\mathbf{P}, \mathbf{E}$ matrices as follows: the beneficiary u picks up the call made in the chosen time-slot $\rho_u(t)$ at round t with probability $\mathbf{P}_{u\rho_u(t)}$ and engages with probability $\mathbf{E}_{u\rho_u(t)}[\mathbf{P}_{u\rho_u(t)}]^{-1}$ conditioned on the pick-up. We compare the following algorithms: (a) UCB (Upper Confidence Bound) which treats each beneficiary independently[1], (b) Greedy Matrix Completion with T_{explore} set to 5, 10, and (c) Phased Matrix Completion with $\Delta = 5$. We repeat this experiment 15 times with different subset of beneficiaries. We used grid search to select the exploration hyper-parameter in UCB, T_{explore} in Greedy MC and Δ in Phased MC.

In addition to regret, for a more intuitive evaluation, we also compare the algorithms in terms of the average rank of the chosen time-slot at each round. Note that for each beneficiary, we only need to learn the right ranking of the available time-slots based on their preferences. Based on this observation, at each round, we will also consider the position (zero-indexed) of the time slot (position among time slots sorted in descending order of preference - pickup/engagement probability) chosen by the algorithm for a particular beneficiary and subsequently its average across all beneficiaries. For example, at the 10th round, an average position of 1.5 implies that the time slot chosen by the algorithm at the 10th round is roughly the 2.5^{th} best time slot for beneficiaries. Naturally, the average time slot position is expected to decrease with rounds.

[1]In the absence of user demographic features, UCB/TS are the best non-collaborative baselines that attempt to intelligently elicit preferred timeslot info from each user.

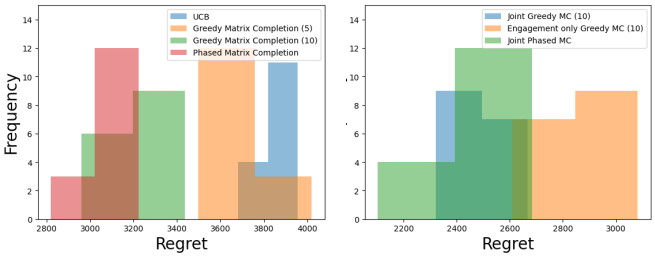


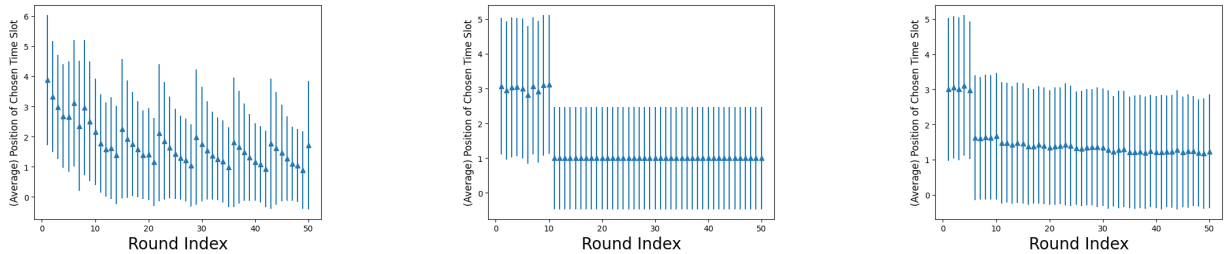
Table 1: (Left Figure) Histogram of regret $\text{Reg}_{\text{pick-up}}(T)$ (for $T = 50$ rounds) across 15 simulation runs of the 3 algorithms - 1) UCB 2) Greedy MC with 5, 10 exploration rounds 3) Phased MC. (Right Figure) Histogram of regret $\text{Reg}_{\text{engage}}(T)$ for the same setup - 1) Engagement data-only Greedy MC with 10 exploration rounds 2) Joint Greedy MC with 10 exploration rounds 3) Joint Phased MC. Note that the regret accrued by MC algorithms are significantly smaller than UCB.

4.1.1 Pick-up data. In this sub-section, we will focus on the pick-up matrix $\mathbf{P}$. Here, all the algorithms try to minimize the regret related to pick-ups $\text{Reg}_{\text{pick-up}}(T)$.

The left plot of Table 1 presents a histogram of regret of the three algorithms described above, across 15 simulation runs. It is clear from the figure that the Phased MC algorithm and the Greedy MC algorithm (with 10 exploration rounds) significantly outperform UCB (> 20% improvement in regret) and have the best performance overall. Finally, we note that the purely randomized policy that is currently implemented by the NGO has a regret more than 10000.

In order to understand intuitively the reason behind the improved performance of the MC algorithms, note that the top 3 eigenvalues of the gram matrix of $\mathbf{P}$ are $[182469.5, 24910.2, 7026.8]$. Clearly the first eigen-value is approximately 6 times the second one which in turn is approximately 3 times the third eigen-value. Thus, we can conclude that the pickup estimate matrix $\mathbf{P}$, despite being an incredibly tall matrix with 7 columns can be well approximated by a rank-2 matrix. This, in turn, implies that a significant amount of information is shared across the beneficiaries. This is the crucial structural prior exploited by MC algorithms. In contrast, UCB is implemented separately for each beneficiary and therefore cannot take advantage of the shared information across beneficiaries.

In Figure 1 we highlighted the average ranking (across beneficiaries) of the chosen time-slot by various algorithms. It is clear from the mean-variance plots that Greedy MC (with 10 exploration rounds) and Phased MC have significantly improved choice of slots as the learning progresses. We remark that there is a periodic structure in the choice of slots for the UCB algorithm - this stems from the algorithmic design itself where the constructed confidence interval is large enough for several beneficiaries who sequentially



(a) UCB **(b) Greedy MC with 10 exploration rounds** **(c) Phased MC**

Figure 1: (Pick-up) Figure shows the average rank/position of time-slot chosen, as a function of rounds. Each vertical bar represents the mean, variance of the rank. Note that the MC algorithms choose significantly better time-slots on average, as the algorithms progress.

go through all slots in a round-robin fashion. In the Greedy MC, in the initial exploration component, slots are chosen uniformly at random - thus the mean is close to 3. In the exploitation component, the greedy MC algorithm commits to a fixed time-slot for every beneficiary and therefore, vertical bars are identical across rounds in exploitation component. For Phased MC, note that the algorithm continues to improve its choice of slot gradually for all beneficiaries.

We also perform a similar set of experiments on the engagement data, where the goal is to minimize the engagement related regret $\mathsf{Reg}_{\mathsf{engage}}(\mathsf{T})$. We obtain similar trends as in the pickup setting - the relevant results are provided in Appendix D.1.

4.1.2 Combined Pick-up and Engagement data. Here, we aim to minimize the engagement related regret $\mathsf{Reg}_{\mathsf{engage}}(\mathsf{T})$. However, in contrast to experiments in Appendix D.1 where we relied solely on engagement data, here we try to exploit both pick-up and engagement data to improve $\mathsf{Reg}_{\mathsf{engage}}(\mathsf{T})$. While pick-up rate is only a noisy signal of engagement rate, it is a much denser signal than engagement. Consequently, we use it to augment the engagement data to improve the performance of MC algorithms. Intuitively, there can be several scenarios when the beneficiary had picked up but didn't engage (listened to less than 25%) due to several reasons (inconvenient time or call picked up by family member or lack of interest). In other words, even if the beneficiary picks up but does not engage, it might lead to some information about the engagement itself. The precise goal is to reduce $\mathsf{Reg}_{\mathsf{engage}}(\mathsf{T})$ by using pickup and engagement information jointly over just using engagement data. This is a challenging problem itself since it is non-trivial on how to model the interaction between pick-up and engagement.

Due to above reasons, extending baseline non-collaborative algorithms such as UCB to model interaction and pickups seems complicated - it would necessarily entail making a certain set of assumptions. However, the MC framework provides a very convenient and elegant solution - the main idea is to jointly estimate both pick-up and engagement matrices by combining all observations. More precisely, consider the ground truth matrix $\mathbf{R}$ to be a concatenation of the pickup and engagement matrices $\mathbf{P}, \mathbf{E}$ respectively - as usual, $\mathbf{R}$ is unknown to the algorithm. As before, in a single simulation run, we have $\mathsf{M} = 1000$ randomly sampled users. At each round, for each beneficiary, a slot is chosen to make a call - subsequently two binary observations are made corresponding to a pick-up and and engagement conditioned on a pick-up. Based on these noisy binary observations, we impute all missing entries of $\mathbf{R}$ jointly whenever we invoke the offline low rank MC algorithms. We compare the regret of the following algorithms: (a) Greedy MC algorithm with 10 exploration rounds that minimizes $\mathsf{Reg}_{\mathsf{engage}}(\mathsf{T})$ based solely on engagement data (b) Joint greedy MC algorithm with 10 exploration rounds, and (c) Joint phased MC algorithm. Note that (b), (c) perform MC on the joint pick-up and engagement data. The right figure of Table 1 presents the histogram of regret of various algorithms over 15 simulation runs. Notice that our Joint MC approaches achieve 10% improvement over the greedy MC algorithm which only relies on engagement data.

4.2 Handling Retry Constraints

In practice, the NGOs are usually faced with resource constraints and have an limit on the number of calls they can make to the beneficiaries. To make our algorithms deployable in practice, we now modify them to handle two such constraints that arise in the context of Kilkari: (a) at most 9 attempts can be made to reach a beneficiary via calls in each week (b) if a call is successful for a particular beneficiary, then no other attempts are made in that week to reach out to that beneficiary. In this setting, an important metric to evaluate our algorithms is to demonstrate improvement in the average retries needed before a successful call to the beneficiary. As a service provider, if the average retries is reduced, there is a significant increase in the capacity. This extra capacity can be used to place further calls to low-engagement beneficiaries, as well as potentially increase enrolments into the program which are currently limited due to the infrastructural constraints.

As before, in each run of the simulation, we sample $\mathsf{M} = 1000$ beneficiaries from the $200k$ beneficiaries uniformly at random and simulate calls, pick-ups and engagements. In this setting, we consider $\mathsf{T} = 270$ rounds - each week comprises of 9 rounds and thus, we simulate our experiment over 30 weeks of data. At each particular round in a week, we only simulate a call and pickup (or engagement) for those beneficiaries who have not picked up (or engaged) in any of the previous calls made in that week. Since we do not call every beneficiary in each round, we define a modified version of the usual regret $\mathsf{Reg}^{\mathsf{new}}_{\mathsf{pick\text{-}up}}(\mathsf{T}), \mathsf{Reg}^{\mathsf{new}}_{\mathsf{engage}}(\mathsf{T})$ for pick-up and engagement respectively. In these definitions, for each beneficiary, we only consider the rounds when calls are placed to them. More precisely, let $\mathcal{T}_u \subset [\mathsf{T}]$ be the set of rounds when calls are made to beneficiary u. We define the regret in this setting as

$$\mathsf{Reg}^{\mathsf{new}}_{\mathsf{pick\text{-}up}}(\mathsf{T}) = \sum_{u \in [\mathsf{M}]} \left(|\mathcal{T}_u| \, \mathbf{P}_{u\pi_p(u)} - \mathbb{E}_{\mathcal{A}} \sum_{t \in \mathcal{T}_u} \mathbf{P}_{u\rho_u(t)} \right)$$

$$\text{Reg}^{\text{new}}_{\text{engage}}(\mathsf{T}) = \sum_{u \in [\mathsf{M}]} \Big(|\mathcal{T}_u| \, \mathbf{E}_{u\pi_e(u)} - \mathbb{E}_{\mathcal{A}} \sum_{t \in \mathcal{T}_u} \mathbf{R}_{u\rho_u(t)} \Big).$$

With the above set-up, we again compare the regret and the average retries of the 3 aforementioned algorithm - (a) UCB (Upper Confidence Bound) implemented separately for each beneficiary (b) Greedy MC with exploration periods of 27, 45 rounds and (c) Phased MC with $\Delta = 27$. We implement our algorithms by simulating calls, pickups and engagement using the ground truth matrices related to pick-up (**P**), engagement (**E**) respectively.

4.2.1 Pickup Data: In this sub-section, we will again focus on the ground truth matrix **P** to simulate call pick-ups. For each beneficiary, we have the following template - 1) the 270 rounds are partitioned into 30 groups (representing weeks) of 9 rounds each 2) In each group of rounds, our designed algorithm chooses a slot to call the beneficiary until they have picked-up - pickups are simulated by entries of **P** as is usual 3) once the beneficiary picks up, no more calls are placed to that beneficiary in remaining rounds in that group 4) The algorithm restarts making calls in the subsequent week to the beneficiary.

Our simulation results (across 15 simulation runs) with pick-up data are summarized in Figures 2a, 2b and 2c. Figures 2a compares the regret for each simulation run across 15 runs. As in previous experiments, a random policy accrues a 10 times higher regret of more than 50000 in each simulation run. In Figure 2a, it is clear that there is a significant reduction in regret of more than 33% ($\text{Reg}^{\text{new}}_{\text{pick-up}}(\mathsf{T})$ for $\mathsf{T} = 270$) by the Greedy and Phased algorithms in MC framework over non-collaborative UCB algorithm. In turn, this also translates into a reduction of > 5% in the average number of call retries for pickup (average across users and rounds), for MC based algorithms over UCB. In Figures 2b and 2c, we dive deeper into the analysis of average retries.

Note that in our dataset, there are several beneficiaries who are low-pickup - in other words, no matter the slot that is recommended to these beneficiaries, they are unlikely to pickup and engage. For these beneficiaries, the choice of algorithm is almost irrelevant especially when there is a cap of 9 retries per week for each beneficiary (shown by red horizontal lines in the figures). To understand this better, we study the reduction in average retries of beneficiaries by stratifying them according to the maximum pick-up ground truth probabilities. We have 6 bins (partitioning the probability range) that comprise of the intervals $[0, 0.1]$, $[0.1, 0.2]$ and the interval $[0.2, 1]$ partitioned into 4 equal intervals. More precisely, the bin $[a, b]$ comprises all beneficiaries each of whom satisfies the following condition - the maximum probability of pick-up assigned to some slot for each of the aforementioned beneficiaries lies in the interval $[a, b]$. For each bin, we report 1) the average number of beneficiaries in that bin 2) average reduction in percentage of retries as compared to UCB policy 3) average reduction in percentage of retries as compared to a random policy - here the average is computed across all 15 simulation runs. The non-uniform splitting of bins is to highlight low pick-up users (bin $[0, 0.1]$) in particular - here the choice of algorithms is almost inconsequential as beneficiaries rarely pick-up. Yet, even for the aforementioned bin, greedy MC leads to a reduction of > 4% over random policy and > 1.5% over UCB.

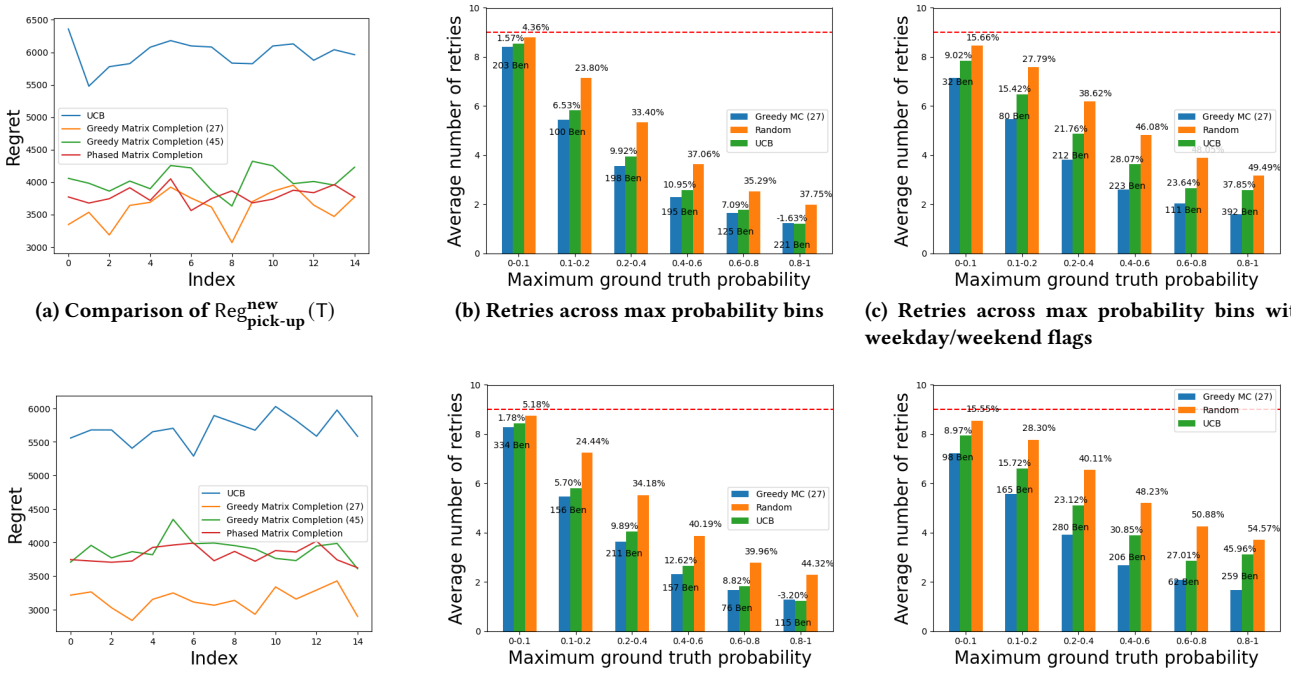
Clearly, in Figure 2b, the greedy MC with 27 exploration rounds leads to more significant reduction in average retries when the maximum ground truth pick-up probabilities is neither large nor small - we have 1) 14.49% and > 35% reduction in average retries over UCB and random policy respectively for the 195 beneficiaries (on average) that lie in the bin [0.4.0.6] 2) > 7% and > 35% reduction in average retries over UCB and random policy respectively for 332 beneficiaries (on average) in the two adjacent bins. This in particular highlights the efficacy of our algorithm. Note that for very low pickup beneficiaries and very high pick-up beneficiaries, UCB and Greedy MC have similar performance - however, in the latter case, there is a > 37% reduction in average retries.

Next, for Figure 2c, we consider a more complex setting with 14 time-slots (the 7 time slots considered previously along with weekday/weekend flag). With this granular definition of time slots, the beneficiaries have a significant amount of missing data. Out of approximately $200k$ beneficiaries in the actual data-set, we focused on $\approx 23k$ beneficiaries who had ground truth data for at least 10 slots out of the 14. For each of these $\approx 23k$ beneficiaries, we impute the missing data by simply taking the average of the available probabilities for the $\geq$ 10 slots of the concerned. Fig. 2c report average retries until pickup/engagement with retries constraint for 14 slots corresponding to 7 slots of the day combined with a weekday/weekend flag. We find upto > 45% benefit in retries over random policy and upto > 30% benefit in retries over UCB policy.

Finally, if we consider convergence within 0.15 of the true highest probability slot, Greedy MC converges for 93% beneficiaries after 27 rounds (by design), while UCB converges for 85.5% beneficiaries within 270 rounds (and 62% in 27 rounds), and fails to converge for 15.5% beneficiaries even after 270 rounds. This highlights the quick convergence of the algorithm for majority of the population enabling the NGO to act fast to avoid dropoffs from the program and boost engagement.

4.2.2 Engagement Data. We now focus on the ground truth matrix **E** to simulate call engagements. We have the same setting as in the pick-up case. In a particular simulation run, for each beneficiary among 1000 randomly sampled beneficiaries, 1) the $\mathsf{T} = 270$ rounds are partitioned into 30 groups of 9 rounds each 2) In each group of rounds, our designed algorithm chooses a slot to call the beneficiary until they have engaged - simulated by entries of **E** 3) once the beneficiary engages, the algorithm no longer places calls to that beneficiary in that week and restarts next week.

Our simulations with the engagement data are summarized in Figures 2d, 2e and 8b with analogous conclusions to the pickup setting. As before, we can conclude from the first figure that there is a significant reduction in regret (> 27%) accrued by MC algorithms over UCB. This, in turn, leads to a reduction in the number of average call retries for beneficiary engagement. This reduction is lower than that obtained for the pickup setting but it stems from the presence of a significantly larger fraction of low-engagement beneficiaries as compared to low pick-up beneficiaries. In Figure 2e, we stratify the users according to the maximum engagement probability for some slot. As before, we partition the range of engagement probabilities $[0, 1]$ into 6 disjoint intervals - $[0, 0.1]$, $[0.1, 0.2]$ and $[0.2, 1]$ split into 4 intervals. Notice that the reduction in average retries over the random policy is significantly large and is more than



(a) Comparison of $\text{Reg}^{\textbf{new}}_{\textbf{pick-up}}(\text{T})$

(b) Retries across max probability bins

(c) Retries across max probability bins with weekday/weekend flags

(d) Comparison of $\text{Reg}^{\textbf{new}}_{\textbf{engage}}(\text{T})$

(e) Retries across max-probability bins

(f) Retries across max probability bins with weekday/weekend flags

Figure 2: Our experiments with retries constraint on a weekly basis. The top row shows figures corresponding to our results for pick-up (bottom row for engagement) with the retries constraint. In the first column, we compare the regret for pick-up (engagement),i.e. $\text{Reg}^{\textbf{new}}_{\textbf{pick-up}}(\text{T})$ ($\text{Reg}^{\textbf{new}}_{\textbf{engage}}(\text{T})$), for $\text{T} = 270$ rounds across 15 simulation runs for 4 distinct algorithms. 1) UCB 2) Greedy MC with $27, 45$ exploration rounds 3) Phased MC. Clearly, the MC based algorithms lead to $> 27\%$ reduction in regret over non-collaborative algorithms. Figures in second column report reduction in average retries of MC based algorithms over baselines with beneficiaries slotted into bins. Bin $[a, b]$ has beneficiaries whose true max probability of pick-up (engagement) lies in $[a, b]$. Again the MC based algorithms show significant reduction in average retries over random policy ($> 30\%$ in some cases) and over UCB policy ($> 9\%$ in some cases). Fig. 2c and Fig. 2f report average retries until pickup/engagement with retries constraint for 14 slots corresponding to 7 slots of the day combined with a weekday/weekend flag. We find upto $> 45\%$ benefit in retries over random policy and upto $> 30\%$ benefit in retries over UCB policy.

40% for certain bins. Similarly, the reduction in average retries over UCB also goes to $> 12\%$ in certain bins. Again the objective of non-uniform splitting is to highlight the low-engagement beneficiaries. Figure 2e show that on average 33.4% of beneficiaries are extremely low engagement with maximum engagement probability for some slot to be between $0 - 0.1$. Even for these low-engagement beneficiaries, Greedy MC gets a $> 5\%$ and 1.78% reduction in average retries over random policy and UCB respectively. The improvement becomes more pronounced with higher-engagement users. Similar to the pick-up setting, on generalization our experiments to the case of 14 slots, the improvement in average retries again become significantly pronounced - these results are summarized in Fig. 2f.

Combined Pickup and Engagement data: We repeated the greedy version of our algorithms with the combined pick-up and engagement data to minimize the regret for engagement. However, in this setting, we find nominal gains on combining - over 15 simulation runs, the greedy algorithm on concatenated pickup and engagement data with 27 exploration rounds accrue average $\text{Reg}^{\text{new}}_{\text{engage}}(270)$ of 3072.69 while the greedy algorithm on sole engagement data with 27 exploration rounds accrue average $\text{Reg}^{\text{new}}_{\text{engage}}(270)$ of 3182.25.

5 CONCLUSION

We presented two methods inspired by collaborative bandits that exploit the low-rank structure of the problem to infer optimal time slots to boost listenership with the largest maternal mHealth program in the world. Additionally, we strengthen our models by combining pickup and engagement signals. We conducted multiple experiments with real-world data obtained from the NGO ARMMAN to show both the methods outperform the current baseline deployed by the NGO as well as a non collaborative approach (UCB). Particularly, for 7 time slot problem, the average number of retries needed to reach a person drastically reduces by 30% and 9% compared to random and UCB for 42% beneficiaries, and over 45% and 25% reduction for 14 time slots respectively (for 76% beneficiaries), saving critical bandwidth for the program to enable reaching out to more beneficiaries. For the 14 time slots case, we show that one can optimistically reach 56% more beneficiaries with our MC based approach when compared to UCB based non collaborative policies when resources for both are equalized. Additionally, the proposed methods converge to within 0.15 of the best time slot for 93% beneficiaries in 3 weeks, enabling the NGO to act fast and hence retain beneficiaries in the program as well as boost their engagement.

6 DATA USAGE AND ETHICS

The analysis presented in this paper falls into the category of secondary analysis of the anonymized dataset obtained from our NGO partner ARMMAN. There is no demographic or personally identifiable information available. We only use previously collected listenership trajectories of beneficiaries participating in the Kilkari program to train the predictive model and evaluate it's performance. All the data collected through the program is owned by the NGO and only the NGO is allowed to share data.

Bias and fairness. Prior studies on Kilkari [27] point out that exposure to Kilkari helps improve health behaviors among the most marginalised, and that the more marginalised population benefits from higher number of retries in Kilkari calls. While we don't have access to demographic data, we do hope for the proposed method to potentially help reduce such inequities by improving listenership of Kilkari messages particularly amongst low listeners.

Path to deployment. The proposed method is intended to be deployed at a national scale in India. With that goal in mind, the next step will involve a randomized control trial in one state in India to validate the true usefulness of the method in the field. With Kilkari being operational in 19 states in India, the model can then be deployed gradually across the different regions. Naturally a deployment at this scale and diversity of beneficiaries may reveal new challenges, such as regional differences in listenership patterns, bandwidth limitations. Most importantly, though, all of the steps will be done in close collaboration with our partner ARMMAN; with ARMMAN ultimately in charge of the actual deployment.

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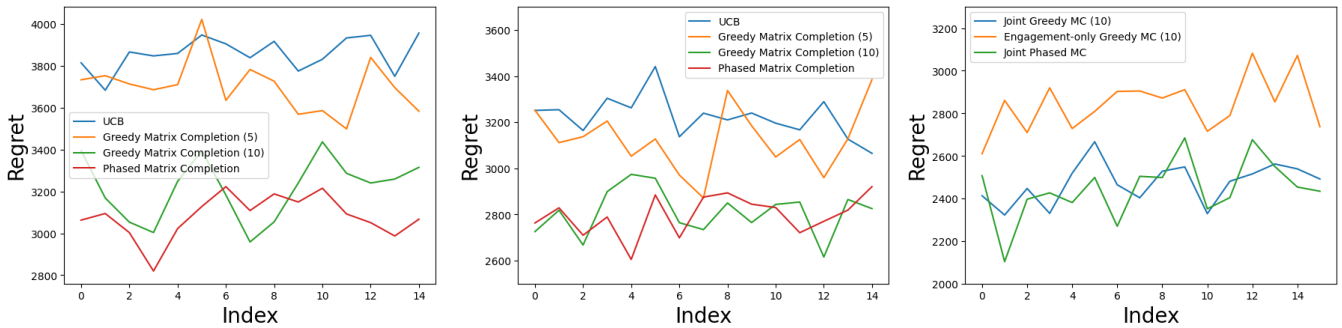


(a) Pickup Data **(b) Engagement Data** **(c) Joint Pickup and Engagement Data**

Figure 3: In first and second figure, we have compared the run-wise regret $\mathrm{Reg}_{\textbf{pick-up}}(T)$ and $\mathrm{Reg}_{\textbf{engage}}(T)$ (for $T = 50$ rounds) across 15 simulation runs of the 3 algorithms - 1) UCB 2) Greedy MC with 5, 10 exploration rounds 3) Phased MC. Here, the x-axis represents the index of the simulation run and y-axis represents the accrued regret. Note that the Phased MC and Greedy MC (with 10 exploration rounds) consistently outperform UCB. In the third figure, we have compared the Run-wise regret $\mathrm{Reg}_{\textbf{engage}}(T)$ (for $T = 50$ rounds) across 15 simulation runs of the 3 algorithms - 1) Engagement data-only Greedy MC with 10 exploration rounds 2) Joint Greedy MC with 10 exploration rounds 3) Joint Phased MC. Again, note that the joint MC algorithms consistently outperform engagement-only MC.

A COMPUTATIONAL COMPLEXITY OF PROPOSED ALGORITHMS

Both the proposed algorithms are very fast (with 10-20 minutes of run time on a laptop) and can easily scale to millions of beneficiaries. The key component in our algorithms is the low rank matrix completion (LR-MC) subroutine. While Greedy MC utilizes LR-MC once, Phased MC applies it $\lfloor T/\Delta \rfloor$ times. LR-MC is a well studied problem with very efficient algorithms known for matrices with billions of rows, columns; we can incorporate any of these algorithms as black-boxes into our technique. The other key component is the Boltzmann exploration, whose time complexity scales linearly with the number of timeslots (which is a small quantity).

B EXTENSIONS AND FUTURE WORK

Below we present some interesting avenues for future work:

(1) **Theoretical Analysis:** understanding the theoretical properties of our algorithm and deriving formal regret guarantees.
(2) **Exploration Strategy:** Investigating alternatives to Boltzmann exploration strategy that can potentially improve the performance of the algorithm.
(3) **Contextual Variants:** Exploring methods to incorporate contextual information, when available.

C UPPER CONFIDENCE BOUND (UCB) ALGORITHM

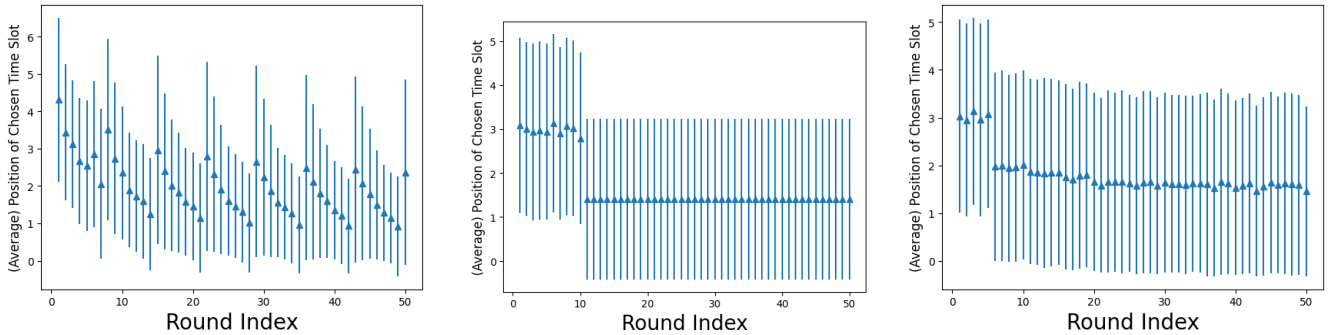
Here we discuss a strong baseline UCB for our problem setting that solve the online bandit optimization problem for each beneficiary separately. UCB is a folklore algorithm [5] for a single-agent bandit optimization problem that is known to obtain optimal regret guarantees. The algorithm computes the sample average of pickups/engagements for each beneficiary and a time slot along with a confidence interval for these estimates. At each round, for each beneficiary, UCB chooses the time slot with the highest upper confidence.

D ADDITIONAL EXPERIMENTS

D.1 Online Setting for Engagement data without Constraints

In this sub-section, similar to the setting in 4.1 for pickup data, we will focus on the ground truth matrix $\mathbf{E}$ related to call engagements. Here, the goal of the designed algorithm is to minimize the accrued cumulative regret related to engagements $\mathrm{Reg}_{\mathrm{engage}}(T)$. As discussed earlier, in each simulation run, we sample a subset of $M = 1000$ users with $N = 7$ slots (arms) and run our algorithms for 50 rounds.

In Figure 5, we have shown analogous histogram to Figure **??** with similar conclusions but for the engagement matrix $\mathbf{E}$ as ground truth. Again, this further validates the improved performance of matrix completion based algorithms. As before, random policies accrue an empirical regret of more than 8000 in all simulation runs. Intuitively the improved performance of MC algorithms stem again from the low rank structure - the top 3 eigenvalues of the gram matrix of $\mathbf{E}$ are $[90467.1, 17909.2, 4823.2]$. Hence $\mathbf{E}$ can be well-approximated by a rank-2 matrix - this is crucially exploited by MC algorithms that solve the bandit optimization problems jointly across beneficiaries. Note that in figures 4a,4b and 4c, we have also highlighted the average position (across beneficiaries) of the chosen time-slot for engagement. As in the pick-up setting, it is clear from the mean-variance plots that Greedy MC (with 10 exploration rounds) and Phased MC have improved choice of slots for purpose of engagement with increase in rounds.



(a) UCB **(b) Greedy MC with 10 exploration rounds** **(c) Phased MC**

Figure 4: (Engagement) At any round t, for each beneficiary the position of the chosen time-slot for engagement by an algorithm is computed - their mean, variance across beneficiaries is shown for the $\mathsf{T} = 50$ rounds. Note that the MC algorithms choose significantly better time-slots on average for engagement with progress in number of rounds.

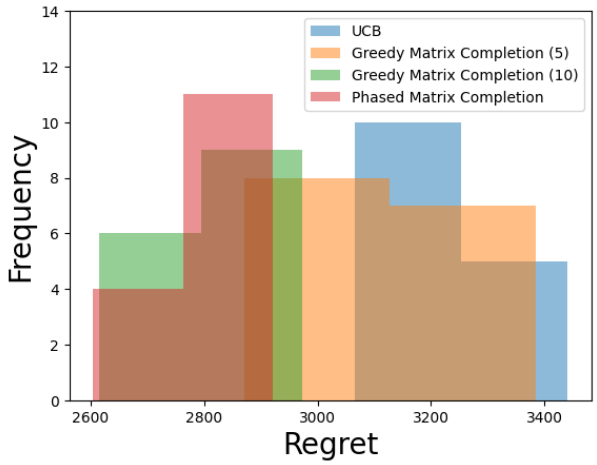
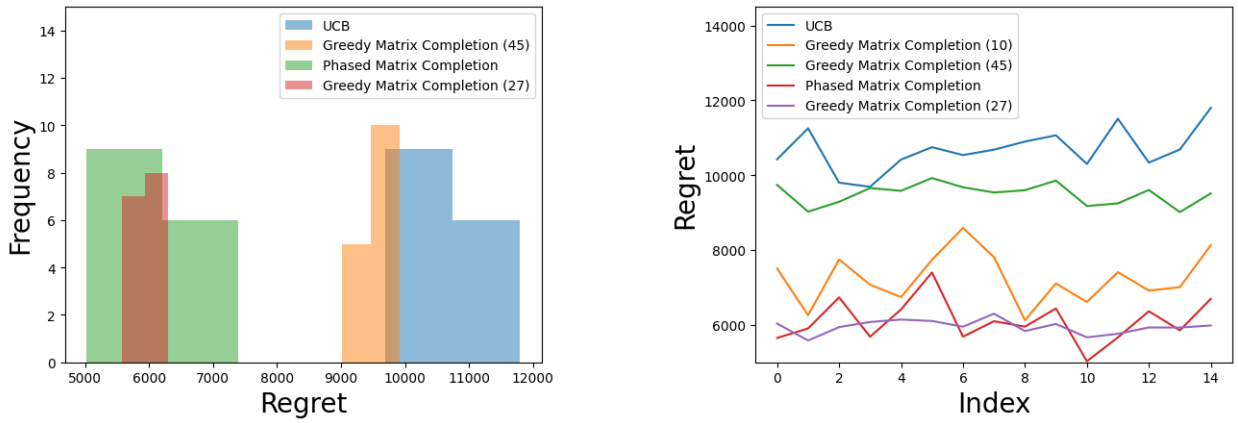


Figure 5: Histogram of regret $\mathrm{Reg}_{\mathbf{engage}}(\mathsf{T})$ (for $\mathsf{T} = 50$ rounds) across 15 simulation runs of the 3 algorithms - 1) UCB 2) Greedy MC with 5, 10 exploration rounds 3) Phased MC. Note that the regret accrued by MC algorithms are significantly smaller than UCB.

D.1.1 Run-wise comparison of regret from Section 4.1. In Figures 3a and 3b, we have also compared for each simulation run (over 15 runs) the regret that is accrued by the following algorithms: 1) UCB 2) Greedy MC with 5, 10 exploration rounds 3) Phased MC. In Figure 3c, we have also compared run-wise for 15 simulations the accrued regret for engagement when we jointly consider the concatenated pickup and engagement matrices versus just the engagement matrix as ground truth alone.

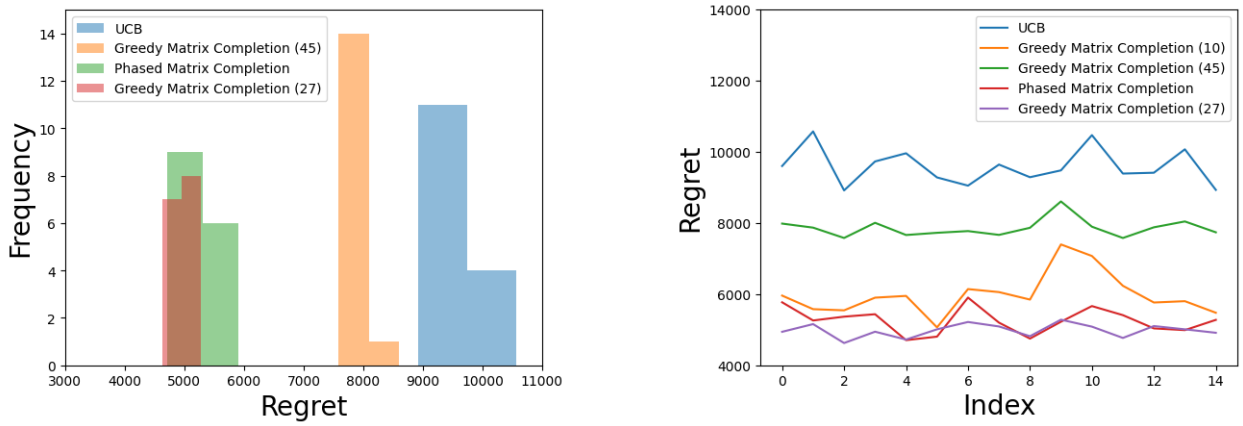
D.2 Unconstrained Setting with 270 rounds

In this setting, we will consider $\mathsf{T} = 270$ rounds without the retries constraint - this is in contrast to $\mathsf{T} = 50$ that we used to simulate our algorithms in Section 4.1. More precisely, in each run of the simulation, we sample $\mathsf{M} = 1000$ beneficiaries uniformly at random and simulate calls, pick-ups and engagements for $\mathsf{T} = 270$ rounds. At each round, for each of M beneficiaries, a sequential algorithm chooses a time slot to call the beneficiary based on past data obtained in previous rounds - the chosen time slot can be different for each beneficiary. Now we simulate the pick-up in the following way - the beneficiary u picks up the call made in the chosen time-slot $\rho_u(t)$ at round t with probability $\mathbf{P}_{u\rho_u(t)}$ and engages with probability $(\mathbf{E}_{u\rho_u(t)})(\mathbf{P}_{u\rho_u(t)})^{-1}$ conditioned on the pick-up. With the above set-up, we compare the empirical regret performance of several different algorithms - a) UCB (Upper Confidence Bound) implemented independently for each beneficiary b) Greedy Matrix Completion with exploration periods of 10, 27 and 45 rounds c) Phased Matrix Completion (Matrix Completion with Boltzmann Exploration). In this setting, from Figures 6a and 6b, it is clear that the Greedy MC algorithm (with 27 exploration rounds) and the Phased MC algorithm obtains a significant reduction of > 40% in regret ($\mathrm{Reg}_{\text{pick-up}}(\mathsf{T})$ for $\mathsf{T} = 270$ rounds) over UCB consistently. Therefore,



(a) Retries across max probability bins **(b) Retries across sparsity bins**

Figure 6: (Pickup for 270 rounds) In first figure, we compare the regret $\mathrm{Reg}_{\textbf{pick-up}}(\mathsf{T})$ corresponding to pickup for $\mathsf{T} = 270$ rounds and in the second figure, we compare the regret guarantees for every simulation run. From the experiments it is clear that Phased Matrix Completion and Greedy Matrix Completion (with 27 exploration rounds) does significantly better than UCB achieving a $> 40\%$ reduction in regret.



(a) Retries across max probability bins **(b) Retries across sparsity bins**

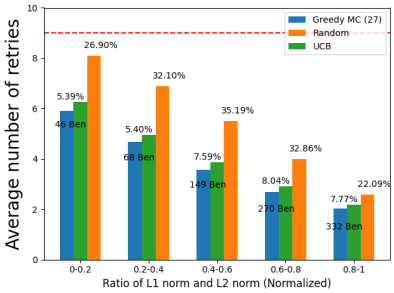
Figure 7: (Engagement data for 270 rounds) In first figure, we compare the regret $\mathrm{Reg}_{\textbf{engage}}(\mathsf{T})$ corresponding to engagement for $\mathsf{T} = 270$ rounds and in the second figure, we compare the regret guarantees for every simulation run. From the experiments it is clear that Phased Matrix Completion and Greedy Matrix Completion (with 27 exploration rounds) does significantly better than UCB achieving a $> 40\%$ reduction in regret.

we can conclude that the difference in regret between collaborative and non-collaborative algorithms increases with the increase in number of rounds - this is also corroborated by theoretical guarantees in similar collaborative bandits settings [32].

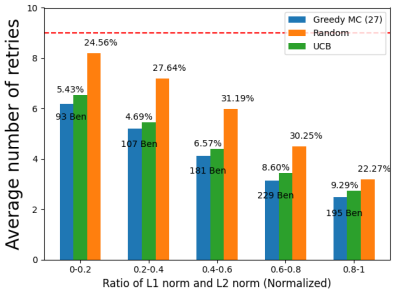
We also repeat the same set of experiments with $\mathsf{T} = 270$ rounds using the engagement dataset. Our results are summarized in the Figures 7a and 7b. As in the pickup case, we reached a similar set of conclusion - name the difference in regret ($\mathrm{Reg}_{\mathrm{engage}}(\mathsf{T})$) increases with increase in number of rounds.

D.3 Startification Based on Sparsity for 7 slots with Retries Constraint

In Figure 8a, we consider a different stratification of the beneficiaries based on the sparsity of their ground truth probability vectors. Sparsity of a vector $\mathbf{v} \in \mathbb{R}^d$ is often captured by $||\mathbf{v}||_1 / ||\mathbf{v}||_2$ (see [38]) - the ratio of the ℓ_1 and ℓ_2 norms of the vector $\mathbf{v}$. Note that the ratio is bounded from below by 1 and from above by $\sqrt{d}$. Intuitively, our goal is to understand the reduction in average retries separately for 1) users who have a significantly large preference for some particular slots - the ratio is close to 1 2) users who have similar-ish preferences for all slots - the ratio is close to $\sqrt{7}$. We partition the interval $[1, \sqrt{7}]$ mapped to $[0, 1]$ via appropriate scaling (for improved readability) into 5 bins of



(a) Retries across sparsity bins



(b) Retries across sparsity bins

Figure 8: (Setting with Retries Constraint for $T = 270$ rounds considered in Section 4.2). In this Figure, we stratify the beneficiaries into bins based on the sparsity level of ground truth probabilities captured by ratio of ℓ_1 and ℓ_2 norm. This ratio belongs to the interval $[1, \sqrt{7}]$ which, has been normalized to $[0, 1]$. Gains of MC based algorithms over UCB become more significant with denser ground truth probabilities. The horizontal red line shows hard thresholding at 9 retries.

equal length. [2] As before, the average reduction in retries over random policies are significantly pronounced - on the other hand, the gains over UCB become more significant as the ratio of ℓ_1 and ℓ_2 norm increase (the second case). This is because when all slots have similar preferences, they are easier to estimate for the low rank MC oracles via partial observations.

Finally, in Figure 8b, we stratify the users according to sparsity level captured by the ratio of ℓ_1, ℓ_2 norm of their ground truth engagement probability vector. As in the pick-up setting, the reduction in number of average retries becomes more pronounced as the ground truth probability vectors become denser. The intuition is that denser ground truth reveals more information via partial noisy observations.

D.4 Weekday Weekend Flag (14 time slots)

Recall that in Section 4.2, we modelled the following practical constraint in the real Kilikari set-up where calls are made on a weekly basis by the service provider a) at most 9 attempts can be made to reach a beneficiary via calls in each week b) if a call is successful for a particular beneficiary, then no other attempts are made in that week to reach out to that beneficiary. Therefore, as mentioned before in this setting, an important metric to evaluate our algorithms is by demonstrating the average retries (average across beneficiaries) in each week.

In contrast to Section 4.2, here we consider a more complex setting with 14 time-slots (the 7 time slots considered previously along with weekday/weekend flag). The difficulty here is that beneficiaries have a significant amount of missing data corresponding to slots in the ground truth call logs data that we collected - this is because many beneficiaries were not placed called at certain times in the data collection phase. Out of approximately $200k$ beneficiaries in the actual data-set, we focused on $\approx 23k$ beneficiaries who had ground truth data for at least 10 slots out of the 14. For each of these $\approx 23k$ beneficiaries, we impute the missing data by simply taking the average of the available probabilities for the ≥ 10 slots of the concerned beneficiary.

As in Section 4.2, we first consider the pickup data where the goal is to improve user pickup and subsequently reduce the average retries for placing calls so that the user picks up. In Figures 9a, 9b and 9c, our results are summarized in the analogous plots for this setting with 14 slots as in Figures 2a, 2b and 8a respectively. We stratify the beneficiaries in a similar manner (based on maximum ground truth probability and the ratio of ℓ_1, ℓ_2 norms) - the goal is again to highlight 1) beneficiaries with different rates of pickup 2) beneficiaries who are opinionated towards certain slots. Furthermore, note that in this setting, the reduction in average retries is very significant and goes above 50% for random policies and above 40% for UCB for certain beneficiaries based on our stratification.

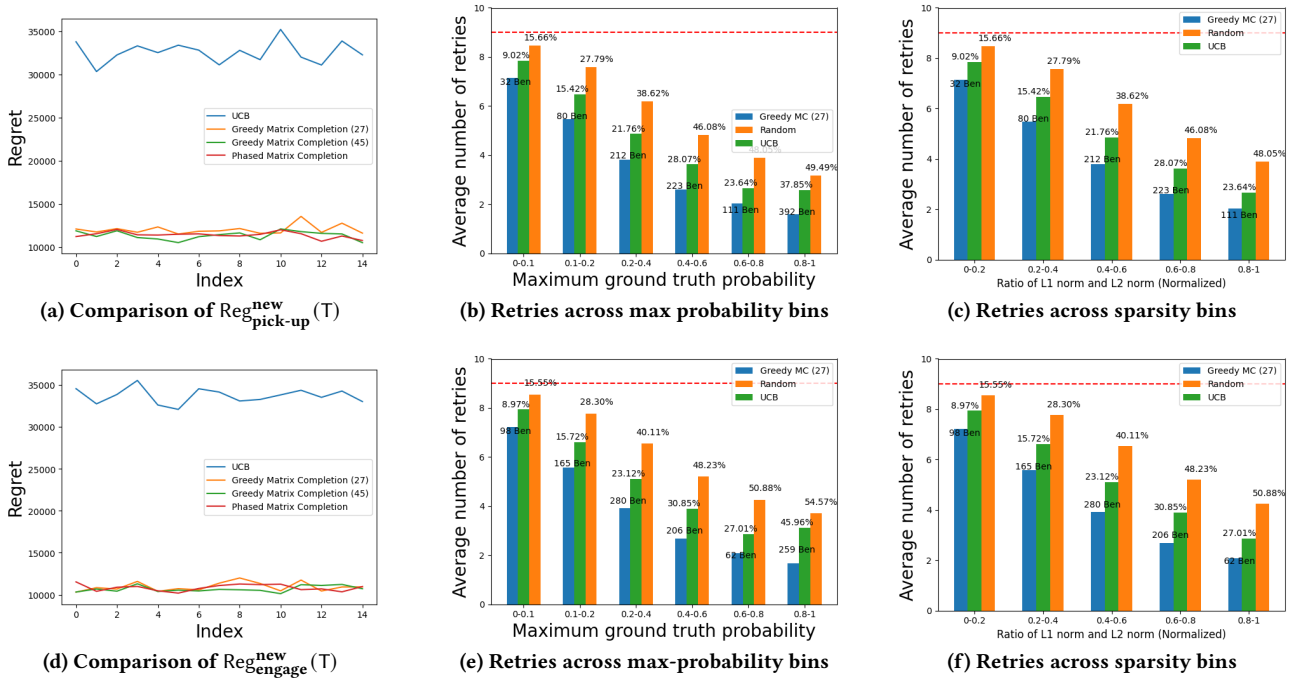
We then consider the engagement data in this setting where the goal is improve engagement of beneficiaries online - we consider the metrics of regret and average retries for successful user engagement. In Figures 9d, 9e and 9f, our results are summarized in the analogous plots for this setting with 14 slots as in Figures 2d, 2e and 8b respectively. Again, we obtain significantly high gains over both the random policy as well as the UCB algorithm.

D.5 Offline Matrix Completion for sparse fine-grained Pick-up data

In this setting we consider a more fine-grained version of the slots by taking the day of the week into account as well. Therefore we have $N = 49$ time slots corresponding to 7 days of the week and 7 time-slots in each day. However, it turns out that the ground truth matrix $\mathbf{P}$ (related to pick-ups) with $N = 49$ columns is extremely sparse with $< 25\%$ filled entries [3]. We consider a subset of $M = 1000$ randomly sampled beneficiaries. The lack of ground truth data makes evaluating an online algorithm infeasible - we have very sparse ground truth and so it is not possible to simulate pickups of a user called at a particular slot. Therefore, in this setting, the validation we can provide for our technique is via offline low rank matrix completion. Suppose we have the ground truth data - we split this data into train and held-out test data in the ratio of 4:1. Subsequently, using the training data, we run an off the shelf matrix completion algorithm to impute all the missing

[2] There are some ignored beneficiaries with zero ground truth pickup probabilities for all slots.

[3] The analogous matrix for engagement is even more sparse with very few non-zero entries. Hence we conduct the experiment only with pick-up estimates



(a) Comparison of $\mathrm{Reg}^{\mathbf{new}}_{\mathbf{pick\text{-}up}}(\mathrm{T})$ **(b) Retries across max probability bins** **(c) Retries across sparsity bins**

(d) Comparison of $\mathrm{Reg}^{\mathbf{new}}_{\mathbf{engage}}(\mathrm{T})$ **(e) Retries across max-probability bins** **(f) Retries across sparsity bins**

Figure 9: Our experiments with retries constraint for 14 slots corresponding to 7 slots of the day combined with weekday/weekend flag. The top (bottom) row shows figures corresponding to our results for pick-up (engagement) with the retries constraint. In the first column, we compare the accrued regret for pick-up (engagement) namely $\mathrm{Reg}^{\mathbf{new}}_{\mathbf{pick\text{-}up}}(\mathrm{T})$ ($\mathrm{Reg}^{\mathbf{new}}_{\mathbf{engage}}(\mathrm{T})$ for engagement) for $\mathrm{T} = 270$ rounds across 15 simulation runs for 4 distinct algorithms 1) UCB 2) Greedy MC with 27, 45 exploration rounds 3) Phased MC. Clearly, the MC based algorithms lead to $> 27\%$ reduction in regret over non-collaborative UCB-based algorithm. In the second column, we compare the reduction in average retries of MC based algorithms over UCB and random policy after stratifying the beneficiaries into bins - each bin $[a, b]$ corresponds to beneficiaries with maximum probability of slot pick-up (engagement) lies in $[a, b]$. Again the MC based algorithms gain significant reduction in average retries over random policy ($> 50\%$ in some cases) and over UCB policy ($> 40\%$ in some cases). In the third column, we stratify the beneficiaries into bins in a different manner based on the sparsity level of ground truth probability vectors captured by ratio of ℓ_1 and ℓ_2 norm. This ratio belongs to the interval $[1, \sqrt{7}]$ which, for readability has been mapped to $[0, 1]$ by appropriate normalization. Note that the gains of MC based algorithms over UCB become more significant with denser ground truth probabilities. The horizontal red line shows hard thresholding at 9 retries.

entries. We evaluate the matrix completion algorithm by their performance on the held out test data. The hypothesis is that if the offline matrix completion algorithm is doing well on the held out test data, it will have good performance on completely unobserved entries as well.

Evaluation Metric. - For each data-point p in the held-out test data, suppose the corresponding estimated value is $\widehat{p}$. A very popular measure of computing the statistical distance between two distributions is the KL divergence [4]. For two Bernoulli distributions with parameters p, q, we have that

$$\mathrm{KL}(p||q) = p \log \frac{p}{q} + (1-p) \log \left(\frac{1-p}{1-q} \right)$$

In that case, we compute $\mathrm{KL}(p||\widehat{p})$ for all data-points in the held-out test data and report its histogram in Figure 10. Note that the average KL divergence is 0.25 and Figure 10 clearly shows a peak at zero with an exponentially decaying tail. Thus the offline low rank matrix completion algorithm is able to predict the held-out test data decently well from a very small number of observed entries in the ground truth matrix.

[4]Note that KL divergence is strictly not a distance measure as it is not symmetric in its arguments

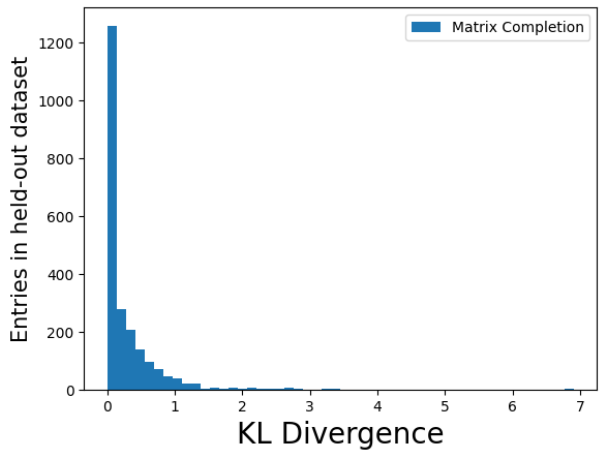


Figure 10: Histogram of the KL divergence accrued by Offline MC algorithm for the held out test data-set obtained by masking 20% of observed entries in a sparse ground truth matrix.

E FURTHER EXPERIMENTAL DETAILS

Note that all our experiments have been done on Google Colab Pro+ with 12.7GB RAM and 225.8GB Disk Memory. Below, we mention the choice of hyper-parameters in each of our experiments:

Experiments in Section 4.1. In all experiments for the unconstrained setting, we ran UCB algorithm for a particular slot s and beneficiary tuple b with a confidence interval of $\sqrt{\frac{2\log\delta^{-1}}{n_{s,b}}}$ where $\delta = 0.99$ and $n_{s,b}$ is the number of times calls were placed in slot s for beneficiary b. For the Greedy MC algorithm with $\mathsf{T} = 50$, we used the low rank matrix completion oracle with a nuclear norm regularizer $\lambda = 10$. The same value of regularizer was also used for the Phased MC algorithm. Furthermore, for the phased MC algorithm, Δ (phase length) was set to be 5. The same parameters were also used for both Greedy and Phased MC when invoked for concatenated Pickup and Engagement Matrices.

Experiments for Unconstrained Setting with 270 *rounds.* In all experiments for the unconstrained setting, we ran UCB algorithm for a particular slot s and beneficiary tuple b with a confidence interval of $\sqrt{\frac{2\log\delta^{-1}}{n_{s,b}}}$ where $\delta = 0.99$ and $n_{s,b}$ is the number of times calls were placed in slot s for beneficiary b. For the Greedy MC algorithm with $\mathsf{T} = 270$, we used the low rank matrix completion oracle with a nuclear norm regularizer $\lambda = 2$. Furthermore, for the phased MC algorithm, Δ (phase length) was set to be 10. Finally, recall that in the Phased MC algorithm, the low rank matrix completion oracle is invoked in every phase (27 phases in all) - in the ith phase, the value of the nuclear norm regularizer that was used was $2 - (i-1) * (2/27)$.

Experiments in Section 4.2. In all experiments for the constrained setting, we ran UCB algorithm for a particular slot s and beneficiary tuple b with a confidence interval of $\sqrt{\frac{2\log\delta^{-1}}{n_{s,b}}}$ where $\delta = 0.99$ and $n_{s,b}$ is the number of times calls were placed in slot s for beneficiary b. For the Greedy MC algorithm with $\mathsf{T} = 270$, we used the low rank matrix completion oracle with a nuclear norm regularizer $\lambda = 2$. Furthermore, for the phased MC algorithm, Δ (phase length) was set to be 27. Finally, recall that in the Phased MC algorithm, the low rank matrix completion oracle is invoked in every phase (10 phases in all) - in the ith phase, the value of the nuclear norm regularizer that was used was $2 - (i-1) * 0.2$. The same hyper-parameters were also used for the experiments with 14 time slots (7 slots along with weekday/weekend flag) incorporating the retries constraints.

F ADDITIONAL PLOTS

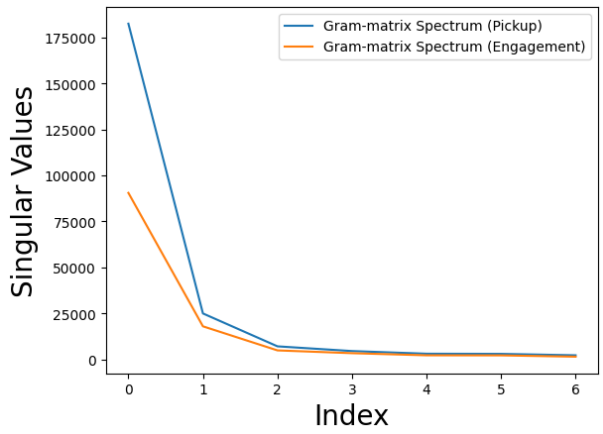


Figure 11: Spectrum of singular of the gram matrix of ground truth matrices P, E corresponding to pickup and engagement respectively.

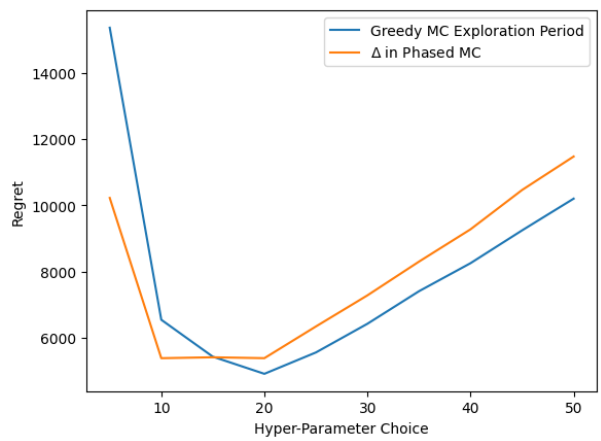
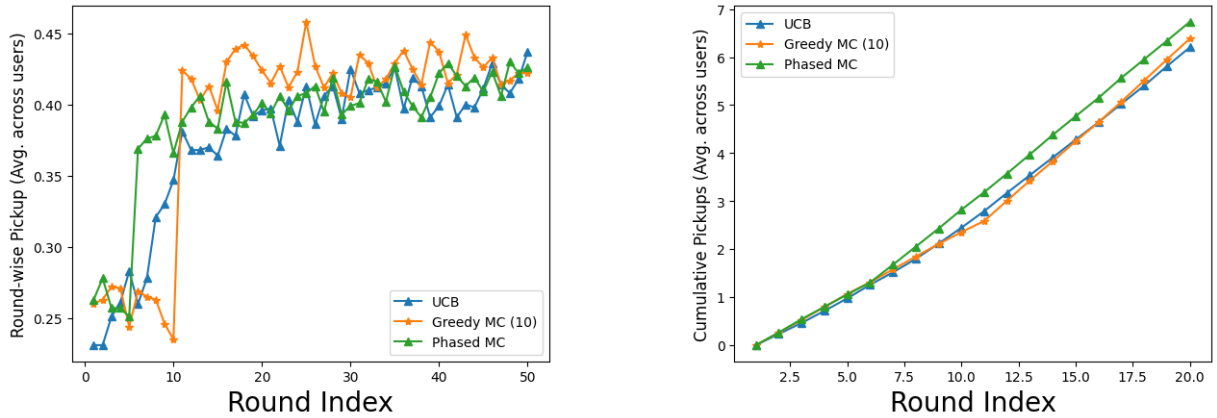


Figure 12: Experiment for comparison of regret for varying exploration parameter in greedy MC vs phase length Δ in Phased MC with $T = 270$ rounds. This experiment is for a randomly sampled set of $M = 1000$ beneficiaries. Note that Greedy MC obtains the smallest regret at 20 exploration rounds while Phased MC obtains a comparable regret at phase length 10 itself.



(a) Retries across max probability bins

(b) Retries across sparsity bins

Figure 13: (Unconstrained Setting for $T = 50$ rounds considered in Section 4.1). Here we compare the actual simulated pick-ups that are obtained by the different algorithms. Note that Phased MC has a sharp increase in actual pickups after 5 rounds itself and the pickup rate continues to increase. This is also observed in the second figure - the cumulative pickups is significantly larger for Phased MC. On the other hand, Greedy MC has the sharp rise in pick-up after the exploration component of 10 rounds. Finally, note that UCB has a continuously increasing pickup rate but it is inferior to the MC algorithms.