Newsfeed Screening for Behavioral Therapy to Social Network Mental Disorders

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ABSTRACT

While the popularity of social network applications continues to grow, increasing cases of social network mental disorders (SNMDs) are also noted. For behavioral therapy of SNMDs, an idea, similar to providing electronic cigarettes to addictive smokers, is to substitute highly-addictive newsfeeds with safer, less-addictive ones to those users. Nevertheless, this idea faces two major challenges: 1) how to measure the addictive degree of a newsfeed to an SNMD user, and 2) how to exploit the theories in Psychology to determine appropriate substitution of newsfeeds for the therapy. To address these issues, in this paper, we propose a learning framework, namely, SNMD-Aware Personalized Newsfeed Ranking (SAPER), that exploits features extracted from social network data to measure the addictive degree of a newsfeed. With the quantified addictive degrees of newsfeeds, we formulate a new optimization problem, namely, Multi-Efficacy Maximization with Interest Constraint (MEMIC), to maximize the efficacy of the behavioral therapy, without sacrificing the interests of users. Accordingly, we propose a randomized algorithm called Computing Budget Optimization for MEMIC with Newsfeed Differentiation (CBOM-ND). To validate our idea, we conduct a user study on 517 online social network users to evaluate the proposed SAPER framework. Moreover, we conduct experiments on large-scale datasets to evaluate the proposed CBOM-ND. The results show that our approach is promising for alleviating the symptoms of online social network users with potential SNMDs.

KEYWORDS

Social network, text mining, mental health

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1 INTRODUCTION

With the explosive growth in popularity of social networking and messaging apps, social media have become a part of many people’s daily lives. This trend inspires most research aiming to better understand social phenomena and behaviors of online users for new knowledge discovery and improvement of user experiences on these apps and services. In contrast, less research has been put forth on new “problems” arising due to the popularity of social network applications. Indeed, some Social Network Mental Disorders (SNMDs), such as Information Overload and Net Compulsion [32], have been recently noted. They are so serious that some countries, e.g., South Korea, is considering to regulate online games by law just like drugs and gambling.\textsuperscript{1} Moreover, a poll on Common Sense Media with 1, 240 participants shows that 52% teens think they’re addicted to their smartphones. Due to the epidemic scale of these phenomena, new terms such as Phubbing (Phone Snubbing) and Nomophobia (No Mobile Phone Phobia) have been created to describe those addictive to mobile social networking apps.

Detecting SNMD cases in early stages is crucial for the timely clinical intervention and treatment. Leading journals in mental health, such as American Journal of Psychiatry [7], have reported that the SNMDs may incur the excessive use, depression, social withdrawal, and a range of negative repercussions. In our previous work, we propose a machine learning framework that exploits features extracted from social network data to identify potential cases of SNMDs [25]. In this study, we take the next step to consider possible treatments of SNMD users via potential online behavioral therapy.

One practice in clinic intervention and treatment to treat SNMDs is total abstinence, i.e., prohibiting SNMD users from accessing online social networks (OSNs). However, a compulsive behavioral change may lead to the relapse [31], i.e., some patients may quickly revert to the excessive usage of social media after an abstinence period. Moreover, tension between patients and supervisors usually occur during clinic intervention and treatment, sometimes leading to tragedies.\textsuperscript{2} However, delay of the intervention may worsen SNMD symptoms into mental illness and thus seriously deteriorate the performance of treatments, especially for children. Thus, we propose to \textbf{incrementally alleviate the symptoms} of SNMD users.

\textsuperscript{1}\url{https://www.cnet.com/news/south-korean-government-to-debate-game-addiction-law/}
\textsuperscript{2}\url{http://www.dailymail.co.uk/news/article-2477401/}
of SNMDs while allowing the patients continue accessing OSNs. This approach is promising for the following reasons. 1) Direct observation. OSN activities (logs) of individual patients can be observed and analyzed to provide personalized treatment, accordingly to the severity of SNMD symptoms at the different time. 3) 2) Direct Treatment. Through the analysis of patient behaviors, direct treatment can be carried out by adjusting the OSN contents accessible to the users in order to reduce the addictions. To the best of our knowledge, this work is the first one studying how to alleviate the symptoms of SNMD users according to data mining techniques without sacrificing their interests.

Our idea, similar to providing electronic cigarettes to addictive smokers, is to substitute highly-addictive newsfeeds with safer, less-addictive ones to SNMD users. Nevertheless, this idea faces two major challenges. First, it’s difficult to automatically measure the addictive degrees of newsfeeds to a patient, which depends on the contents and the mental state of the user, in order to retain the current browsing behaviors of the user on OSN. Moreover, the personal preference and addiction of a user, both of which are internal states of the user, may not be correlated. For example, a patient may compulsively read articles posted by a potential competitor.

In contrast, clinical psychologists are only able to indirectly infer the severity of SNMD by inquiring the patients in clinics. In SAPER, we first extract several addictive factors (AFs) which are related to SNMD from newsfeeds by text mining and design a novel learning model to find personal addictive factors based on the findings of user behaviors and theories in Psychology. Note that model-based collaborative filtering (CF) techniques have been proposed to learn internal states (e.g., preferences) of users for recommendations. However, these techniques are not applicable to our problem because SNMD, unlike preference which may be inferred from historical feedbacks, is usually incurred from mental factors such as relapse and tolerance.

In SAPER, we first extract several addictive factors (AFs) which are related to SNMD according to research in Psychology on newsfeeds. Next, we further incorporate the social comparison theory [4] in Psychology to derive the addictive degrees. The theory states that an SNMD patient may generate malicious envy that leads to worsened SNMDs by reading positive newsfeeds from friends with similar profiles. Combining the effect into a factorization model, we capture the addictive degree by considering both explicit behaviors and mental factors. With extracted AFs and SNMD modelling, we design a learning framework to find personalized addictive factors of users from relatively sparse feedbacks in OSNs.

To address the second challenge, we develop a newsfeed screening system (NSS) that decides whether to show newsfeeds to an SNMD user based on the addictive degrees of newsfeeds. The design of NSS incorporates the social support theory. The goal of automatic newsfeed screening is to select the newsfeeds for patients by minimizing the maximum addiction degree of any patient in an OSN through sending p newsfeeds to each user, while avoiding sudden changes that may lead to relapse. At the core of our design is a new optimization problem, namely, Multi-Efficacy Maximization with Interest Constraint (MEMIC), which maximizes the efficacy of behavioral therapy without compromising the interests of users. We show that MEMIC is challenging and prove that it is NP-Complete.

To solve MEMIC, we propose a randomized algorithm called Computing Budget Optimization for MEMIC with Newsfeed Differentiation (CBOM-ND). We exploit the notion of Optimal Computing Budget Allocation (OCBA) [9], an efficient theoretical tool to solve challenging NP-Hard problems. The idea is to invest more computing budgets to search the combinations of top-p newsfeeds for users associated with many newsfeeds of high addictive degrees. The tradeoff between the solution quality and execution time can be effectively controlled by assigning different computing budgets. Thus, for each user, we randomly generate a few initial partial solutions and then iteratively select and add a newsfeed randomly with a different probability to the partial solution, until p newsfeeds are selected. We prove that the probability is optimally adjusted in each iteration, and the computing resources are optimally allocated to each user, according to the previous sampled addictive degrees of top-p newsfeeds for each user. We also provide a performance guarantee for CBOM-ND.

2 RELATED WORK

A recent line of studies in Psychology and Sociology report various mental factors related to social networks. Specifically, Sherman et al. study the power of the peer influence via “Like” in social media among adolescence with neural and behavioral responses [24]. Meanwhile, Woods et al. find that SNMDs frequently result in the bad sleeping, anxiety, low self-esteem, and depression [29]. Appel et al. show that the social comparison on Facebook leads to the depression [4]. However, most research only studies the negative effects of social media, instead of providing online treatments. In this paper, we exploit data mining techniques to provide online behavior therapy for SNMD based on theories in Psychology.

Statistical analysis on the prevalence and extent of mobile email addictions has been studied [27]. Althoff et al. analyze the counseling conversations related to mental health via natural language processing and develop a measurement of the correlation between linguistic aspects of conversations and outcomes [2]. Our research is unique as we exploit data mining and machine learning techniques to quantify the addictive degrees of newsfeeds based on...
Theories in Psychology. Moreover, we propose a new optimization problem to minimize the maximum addictive degrees of users while retaining the users’ interests for OSNs.

Handling text contents with numerical vectors has a long history of research. One simple approach is employing Vector Space Model with TFIDF weights. Moreover, latent semantic analysis and topic model, such as LDA [6], are designed to represent each latent topic as a numerical vector. However, the above approaches are not appropriate for the OSN contents due to the sparseness and shortness of feedbacks. On the other hand, previous research for recommender systems usually focuses on user preference. Collaborative Filtering [14] predicts user rating by Matrix Factorization, but it fails to handle implicit binary feedback. Although One-Class Collaborative Filtering (OCCF) models [21] can effectively address this issue, it ignores the huge contents, which is important for SNMD. Most importantly, these works are not designed to learn mental factors. Thus, we propose a hybrid learning framework to effectively address the above issues.

3 SNMD-AWARE PERSONALIZED NEWSFEED RANKING

In this section, we propose SNMD-Aware Personalized Newsfeed Ranking (SAPER) to derive the addictive degrees of users to newsfeeds for screening. Many latent factor models optimized for observed behaviors have been proposed for recommender systems according to user preferences. However, these techniques are not designed to quantify and analyze the addictive degree. For SNMD patients, psychological factors usually play more important roles to precisely capture implicit mental states. To achieve this goal, we first extract important AFs based on Psychology from reactions on previous newsfeeds and transfer them into numerical vectors as features. Based on the extracted features, we design a novel personalized newsfeed ranking framework to predict the addictive degree of a user on future newsfeeds.

3.1 Addictive Factors

To define the addictive degree, it is important to understand how human mental states are affected by the contents of newsfeeds to identify key factors of SNM addictions. In the following, we introduce several addictive factors (AFs) for our task based on Psychological research on OSNs. AFs play important roles to accurately model the SNMD of users.

3.1.1 Social-based Features. Social relationship is an important function of OSNs. Psychological research [26] manifests that different conditions of social relationships are closely related to social attractiveness. Many users obsessively interact with others on OSNs, and obsessive usage easily causes addiction [11]. The first related factor is Social importance. Although most people have many friends in OSNs, only some of them are considered as strong ties. OSN users, especially for those addictive to Cyber Relationship, usually pay more attention to the contents with higher social importance. Thus, we first analyze the frequency distribution of interactions for SNMD patients with different users and pages. Given a newsfeed one user sees, we regard the ratio of the observed interactions between the user and the newsfeed author to all the observed interactions of the user as social importance.

Research shows that loneliness is the primary reason for SNMD patients to excessively access OSNs [5]. Also, loneliness usually leads to the second factor, parasocial relationship [8], which is an asymmetric relationship between two people with one party caring more about the other, but the vice versa is not true. Therefore, for a newsfeed, the parasocial relationship can be measured by $|\text{a}_{\text{out}}|/|\text{a}_{\text{in}}|$ as a feature, where $|\text{a}_{\text{out}}|$ and $|\text{a}_{\text{in}}|$ denote the number of actions a user takes to the newsfeed author and the number of actions the author takes to the user, respectively. The parasocial relationship grows as the ratio increases.

3.1.2 Text-based Feature. In addition to social relationships, the content plays a crucial role in addictions. The first feature is text semantics. In Psychology, the effect of Echo Chamber and Filter Bubble states that people naturally fall into different groups according to their interests and opinions. People usually enjoy the sharing of the friends with similar opinions. Consequently, Filter Bubble is strongly related to Information Overload in OSNs [13]. Moreover, the social reinforcement in Internet meme [28] states that positive stimuli from social networks usually reinforce reactions. If someone prefers a topic and many friends also promote it, their connections are strengthened accordingly. Besides, mere exposure effect [33] also explains how people tend to develop preference or acceptance merely because they are familiar with things that provided in social media. For these factors, we exploit word embedding to extract the semantic and measure the degree of bursts to model the effect of Internet meme, for accurately capturing the semantic user feel.

Specifically, we exploit Word2Vec [19] to learn the embedding for the words. Two kinds of weights are used to model the semantic felt by users. First, for each word $w$, we calculate the degree of bursts $b_w$ for Internet meme. We regard $b_w$ as $f_{\text{short}}/f_{\text{long}}$, where $f_{\text{short}}$ and $f_{\text{long}}$ are the frequencies of a word $w$ in a short period and a longer period of time, respectively. The effect of internet meme is enhanced if a word suddenly becomes popular. Second, we take IDF as a weight to eliminate the effect of stop words. Finally, the text semantic is defined as follows. Formally, for a newsfeed $d = \{w_1, w_2, \ldots, w_{|d|}\}$ with $w_i$ as the $i$-th word in $d$, the semantic $s_d$ is:

$$s_d = \frac{1}{\sum_{i=1}^{|d|} \text{IDF}(w_i) \cdot b_{w_i} \cdot w_2 \text{c}(w_i)}$$

where $w_2 \text{c}(w_i)$ is the Word2Vec embedding, and $\text{IDF}(w_i)$ is the inverse-document frequency acquired from the corpus.

Most research in Psychology manifests that negative emotions, e.g., loneliness, are closely related to SNMDs [5]. Also, the emotions of OSN users are strongly affected by the emotions expressed form others’ newsfeeds. Therefore, we extract the second feature, text sentiment, as a proxy feature to quantify the addictive degrees of newsfeeds. Nevertheless, it is difficult to precisely quantify the addictive sentiment labels in massive OSNs. Therefore, we exploit the unsupervised lexicon-based method to identify the positive and negative polarity of newsfeeds. Based on the seed sentimental polarity, first identified by VADER [12] and NTUSD [16], the sentiment scores are propagated to other words according to similarity in the word embedding space. Moreover, related research on Facebook [30] suggests that long newsfeeds attract more attention, i.e.,
likes and comments. Therefore, we also adopt the text length of a newsfeed as a feature.

### 3.2 Personalized Newsfeed Ranking

Two challenges arise for identifying addictive newsfeeds from the above AFS. First, it is difficult to quantify the degree of SNMDs based only on observed behaviors because unseen mental factors are crucial in the formation of addictions. Second, it is difficult to appropriately optimize the learning model according to the Psychological observations previously discussed. In the following, we propose social comparison enhanced relation modelling and AF-based ranking optimization to address the above issues.

#### 3.2.1 Social Comparison Enhanced Relation Modelling

Our objective is to quantify addictive degree of a newsfeed for each user. Thus, modelling for relation between users and newsfeeds is necessary. One simple way is to employ the existing factorization approaches for user preferences based on the interactions between users and newsfeeds. The preference of user $u$ on newsfeed $i$ can be represented as $p_u \cdot q_i$, where $p_u$ and $q_i$ are factors of user $u$ and newsfeed item $i$. However, different from the preference, it is not sufficient to understand the mental state of SNMD with only user and item factorization, because those models are optimized for only observed behaviors. Therefore, we further incorporate the social comparison theory in Psychology in the model design to capture the mental states of users.

Research shows that users exposed to positive posts from others usually feel envy or depressed due to social comparison [4]. Many people are inclined to evaluate their own opinions and achievements with those in close friends, especially when the reference in comparison is not specific. The situation now becomes increasingly serious because status changes and updates between friends are easily accessible in OSNs. Two kinds of envy, benign envy and malicious envy, usually appear after comparison. Benign envy leads to a moving-up motivation to improve one’s own position. Malicious envy is triggered by the comparison among close friends with similar backgrounds and states. It leads to a pulling-down motivation and usually leads to SNMDs, e.g., information overload or net compulsion, because a person in this case usually feels pressured and tends to frequently check the updates of the corresponding friends. A teenager student in this case may seek online games or gambles as alternatives for acquiring the sense of accomplishments.

Therefore, for malicious envy, we first exploit emotional signal processing from sentiment analysis to identify positive newsfeeds and then calculate the profile similarity and relation familiarity between friends. Specifically, each user $i$ is associated with a profile vector $\phi_i$. An edge $e_{i, j} \in E$ between $v_i$ and $v_j$ is associated with a social tightness score $r_{i, j}$, and the similarity score between two users’ profiles $s(\phi_i, \phi_j)$ is ranged in $[0,1]$. Let $Pos_i$ denote the normalized positivity score, which is extracted previously, for each newsfeed $i$. Based on the above idea, we refine the factorization model as follows.

$$x_{ui} = \lambda (Pos_i \cdot r_{ui} \cdot s(\phi_u, \phi_u)) \cdot p_u \cdot q_i$$

(2)

where parameter $\lambda$ controls the effect of the social comparison.

Given a newsfeed from user $u'$ with a positive score $P_{i'}$ sent to user $i$, if the backgrounds of the two users are similar, i.e., $s(\phi_{u}, \phi_{u'}) = 1$, the newsfeed is expected to incur malicious envy. In contrast, benign envy is inclined to be generated if their backgrounds are quite different, i.e., $s(\phi_{u}, \phi_{u'}) = 0$. Later in Section 5, the experimental results manifest that the refined model is able to more accurately model the unobserved mental behaviors of users.

#### 3.2.2 AF-Based Ranking Optimization

How to optimize the model parameters based on Psychology factors is challenging. One possible way is assuming that users are more likely to get addicted to a newsfeed if they interact with it more often, and machine learning can be employed in this case. However, it does not consider Psychological factors explained previously to quantify addictions. Also, it is difficult to learn from only a few addictive clues hidden in massive newsfeeds to quantify SNMD because for a user, the number of interactions is usually smaller than the number of browsed articles. Logistic Regression and SVM are promising to learn the user factors with Psychological features. However, it suffers from label sparsity when observed interactions are limited in the whole data. By contrast, one-class collaborative filtering is more promising for sparse interactions. Nevertheless, the existing one-class collaborative filtering does not support Psychological features.

Therefore, in this paper, we propose AF-based ranking optimization to quantify the SNMD from extracted features based on Bayesian Personalized Ranking (BPR) [21], which is effective for the recommendation with implicit feedbacks. Different from previous research that learns latent factors from user and item sets, we aim to learn a transforming matrix for extracted AFS. The matrix can incorporate both the user latent factors, relation modelling, and the Psychological factors to effectively quantify the addictive degree. For a dataset $D = \{(u, i, j)|u \in U, i \in I_u, j \in I_u\}$, where $U$ and $I$ are the user and newsfeed sets, respectively, and $I_u$ is the newsfeed set that user $u$ likes, the goal is to maximize the probability of the observed behavior to infer implicit addictions by optimizing the model’s parameters. $\theta$ is the parameters of the model, and $x_{uij}$ is the pairwise error of triple $(u, i, j)$ according to [21]. Here the sigmoid function of the pairwise error is adopted to express the probability we want to optimize. Therefore, the optimization problem can be formulated as follows.

$$\text{argmin}_{\theta} \sum_{(u, i, j) \in D} - \ln(\sigma(x_{uij})) + \frac{\gamma \theta}{2}||\theta||^2$$

(3)

where $\sigma(\cdot)$ is the logistic function and $\gamma \theta$ is the regularization parameter. Stochastic gradient descent is employed to effectively learn the parameter. Specifically, $\theta$ is updated as follows.

$$\theta \leftarrow \theta - \eta \cdot (\sigma(-x_{uij})\delta x_{uij} / \delta \theta + \gamma \theta)$$

(4)

Following Equation (2), we combine our predictor into BPR and define the pairwise error as $x_{uij} - x_{uij}$. Although $p_i$ is a latent factor, $q_i$ needs to be modeled from the extracted AFS to accurately capture the mental disorder. Moreover, we exploit machine learning to select the crucial factor and consider the effective feature correlation. Therefore, we model $q_i$ as $(E \cdot v_i)$, where $E$ is the projection matrix to select the feature combination for the reduced space, and $v_i$ is the extracted feature of a newsfeed $i$. Based on the predictor, the objective is to learn the user personalized latent factor and appropriate projection matrix on AFS. Therefore, $\theta$ is required to be
optimized and represented by \( p_u \) and \( E \). We also exploit stochastic gradient descent to iteratively optimize Equation (3).

4 NEWSFEED SCREENING SYSTEM

Eqipped with addictive degrees, we develop a Newsfeed Screening System (NSS) to recommend suitable newsfeeds to SNMD patients according to the theory of social support in Psychology. Many recommendation schemes examine user preferences and thereby focus on the individual need. On the contrary, NSS considers not only the preference and addiction of an SNMD user but also the Psychological impacts incurred from potential feedbacks (e.g., Like and comments) of close friends. Therefore, the design of NSS is challenging due to the complicated interactions among friends. At the core of our design is a new optimization problem, namely, \( \text{Multi-Efficacy Maximization with Interest Constraint (MEMIC)} \). Given a social network \( G = (V, E) \) of \( n \) users, where each node \( v_i \in V \) denotes a user \( i \), the decision tensor is \( X \), where each element \( x_{i,j,k} \in X \) denotes a binary decision variable of the \( k \)-th newsfeed sent from user \( v_j \) to user \( v_i \). Let \( a(x_{i,j,k}) \) denote the addiction degree of the \( k \)-th newsfeed for user \( v_i \) sent from user \( v_j \) derived from Section 3.2. Let \( f_1(\cdot) \) denote the total addiction for \( v_i \) (explained later), and \( g_i(\cdot) \) represents the user interest of \( v_i \). The basic version of \( \text{MEMIC} \), i.e., without incorporating the theories in Psychology, is formulated as follows.

\[
\begin{align*}
\min_{1 \leq i \leq n} \max_{j \in V} (f_1(X)) \\
\text{s.t.} \quad & \sum_j \sum_k x_{i,j,k} = p_i, \\
& \sum_j \sum_k g_i(x_{i,j,k}) \geq \theta_i, \forall i.
\end{align*}
\]

where \( p \) is the number of newsfeeds assigned to each user, i.e., the top-\( p \) newsfeed recommendation. \( \theta_i \) is the threshold of interests, a shaping parameter to be set according to the successive approximation in behavioral shaping [20]. The goal is to avoid incurring a sudden change of many newsfeeds (the extreme case is total abstinence), because it usually leads to relapse (i.e., a user will quickly revert back) and thereby invalids the SNMD cure. It is required to lower \( \theta_i \) gradually [20]. The MinMax objective function is to lower the total addictive degree of all users by examining the worst case, i.e., the user \( v_j \) with the largest \( f_1(X) = \sum_j \sum_k x_{i,j,k} a_{i,j,k} \), the summation of the addiction degrees from all assigned newsfeeds. Note that the MinMax objective function examines not only one patient because the worst case may change during the minimization (i.e., the score of another patient exceeds the original worst case).\(^3\)

However, the above \( f_1(X) \) only considers the addictive degree of each newsfeed, without incorporating the theory of social support. Specifically, Psychology study shows that the recovery-oriented support can foster greater self-efficacy toward ongoing abstinence because recovering persons can acquire effective coping strategies from their peers [17]. The users move away from the addiction but have not developed a healthy relationship network are inclined to be addicted repeatedly. To address the above issue, we add a regularization terms as follows.

\[
\sum_j \sum_k x_{i,j,k} a_{i,j,k} = \lambda_1 \sum_j \sum_k r_{i,j} \text{SUP}(x_{i,j,k})
\]

where \( \lambda_1 \) is the parameter to control the extents of the social support. The second term, i.e., \( \text{SUP}(x_{i,j,k}) \) denotes the expected support that user \( i \) receives by sending her \( k \)-th newsfeed to user \( j \). \( \text{MEMIC} \) is unique because there is a tradeoff between social support and addictive degree. That is, although sending a user’s newsfeeds to others reduces her addictive degree due to the social support, it will increase other users’ addictive degrees at the same time.

Due to the above tradeoff, \( \text{MEMIC} \) is NP-Complete as proved in Appendix A.1.

One greedy approach to solving \( \text{MEMIC} \) is first sorting the addiction degree \( a_{i,j,k} \) of each user \( i \) and then selecting the newsfeeds that lead to the largest increment in the total addictive degree at each iteration, until the interest constraint of user \( i \), i.e., \( \theta_i \) is reached. However, this approach does not incorporate the theory in Psychology. Also, a greedy algorithm for an NP-Complete problem tends to be trapped in a locally optimal solution since 1) it constructs and iteratively improves only one partial solution, and 2) it only explores one possible direction to improve the current partial solution. Therefore, we propose a randomized algorithm, \( \text{CBOM-ND} \) (Computing Budget Optimization for \( \text{MEMIC} \) with Newsfeed Differentiation), to address the above two crucial factors. It iterates by randomly selecting \( p \) newsfeeds with different probabilities for each user to expand the partial solution toward multiple directions, while the probabilities are optimally derived according to the sampling results in previous iterations.

To effectively control the number of partial solutions and the number of explored directions, \( \text{CBOM-ND} \) exploits the theory of Optimal Computing Budget Allocation (OCBA) [9] to invest more computation resources (i.e., more explored directions) to the partial solutions with more potential to minimize the maximum addictive degree eventually. In other words, it allocates more computation budgets to cure the potential bottleneck nodes (i.e., severe patients), but the interests and addictive degrees of other patients are adequately handled. One advantage of \( \text{CBOM-ND} \) is that the tradeoff between the solution quality and execution time is controlled by assigning different \( T \), which denotes the number of randomly generated final solutions. Under a given \( T \), we prove later that \( \text{CBOM-ND} \) can optimally divide \( T \) into \( n \) parts for the \( n \) users to find the final solution. Moreover, we prove that \( \text{CBOM-ND} \) finds a solution with an approximation ratio. \( \text{CBOM-ND} \) has the following steps. (1) Selection and Evaluation of User. For each user, it first randomly generates a few final solutions as samples. It selects a newsfeed randomly and adds it to a partial solution, until \( p \) newsfeeds are selected. The addictive degree of each final solution is evaluated for the next phase to allocate different computational budgets to different users. (2) Budget Allocation: This phase derives the computational resources optimally allocated to each user according to the previously sampled addictive degree of each user.

Specifically, let \( J_i \) and \( J^*_i \) denote the random variables respectively representing the addictive degree sampled from a final solution expanded from node \( v_j \) and the minimal addictive degree

\(^3\)Another potential objective function is to minimize the total addictions of all users. However, it tends to induce the imbalanced addiction distribution amongst patients.

\(^4\)The setting of \( T \) will be study in Section 5.
expanded from node \( v_i \). To optimally allocate the computational budgets for each user, let the solution quality \( Q \) denote the maximum additive degree from all minimal sampled feasible results among all users, i.e., \( Q = \max \{ J_1^*, J_2^*, \ldots, J_n^* \} \). Since the minimal sampled result \( J_i^* \) of start node \( v_i \) is related to the number of final solutions \( N_i \) randomly generated from \( v_i \), the computational budget allocation problem is as follows.

\[
\min_{N_1, N_2, \ldots, N_n} Q,
\]

\[
s.t. \; N_1 + N_2 + \ldots + N_n = T.
\]

Because related research [9] and our user study (in Appendix A.2) indicate that the distribution of \( J_i \) in popular scenarios and OSNs is similar to the normal distribution. Therefore, in the following, we employ the normal distribution (with mean \( \mu_i \) and standard deviation of \( \sigma_i \)) to derive the theoretical results for \( J_i \). The probability density function and cumulative distribution function are as follows.

\[
p_{J_i}(x) = \frac{1}{\sigma_i \sqrt{2\pi}} e^{-\frac{(x-\mu_i)^2}{2\sigma_i^2}},
\]

\[
P_{J_i}(x) = \frac{1}{2}\left(1 + e^{-f\left(\frac{x-\mu_i}{\sigma_i}\right)}\right)
\]

The cumulative distribution function of minimal value \( J_i^* \) is \( P_{J_i}(x) = 1 - \left(1 - P_{J_i}(x)^{N_i}\right)^{N_i} \). As such, the probability density function is \( p_{J_i}(x) = N_i P_{J_i}(x)^{N_i-1} p_{J_i}(x) \). Let \( v_b \) denote the bottleneck node. The probability that \( J_i^* \) is greater than \( J_b^* \) is as follows.

\[
p(J_i^* - J_b^* \leq 0) = 1 - \int_{-\infty}^{\infty} p_{J_i}(x) P_{J_b}(x) dx
\]

\[
= 1 - \int_{-\infty}^{\infty} N_i p_{J_b}(x)^{N_i-1} p_{J_i}(x) \left(1 - \left(1 - P_{J_i}(x)^{N_i}\right)^{N_i}\right) dx.
\]

According to the above results, the second phase allocates the computing budgets to user \( i \) and \( b \) according to the ratio of \( p(J_i^* \leq J_b^*) \) in Equation 5. Specifically, Algorithm CBOM-ND is divided into \( r \) stages. In each stage, since the real values of \( v_b, \mu_i \), and \( \sigma_i \) are unknown during sampling, we approximate it according to the previous sampled results of each user. After allocating the computing budget to each user, each step is necessary to differentiate the probability for varied explored directions, i.e., selecting a newsfeed and adding it to the partial solution. CBOM-ND exploits the cross entropy method [23] based on importance sampling to adaptively assign a different probability to each newsfeed from the sampled results in previous stages. Specifically, let \( \bar{p}_{i,t} \) denote the newsfeed selection probability vector for user \( i \) in stage \( t \), i.e., \( \bar{p}_{i,t} = (p_{i,t,1,1}, p_{i,t,1,2}, \ldots, p_{i,t,1,k}, \ldots, p_{i,t,n,k}) \), where \( p_{i,t,j,k} \) is the probability of selecting the \( k \)-th of user \( j \) for user \( i \) in the \( t \)-th stage, and \( n \) is the number of newsfeeds from user \( n \). In the first stage, \( \bar{p}_{i,1} \) for each user \( i \) is initialized homogeneously for every newsfeed, i.e., \( \bar{p}_{i,1,j,k} = \frac{1}{n+1} \) if \( j \in G \), \( v_j \neq v_i \). In other words, the probability associated with every newsfeed is also the same. Afterward, CBOM-ND examines the top-\( p \) samples for each user \( i \) to generate \( \bar{p}_{i,2} \), so that the node probability will be differentiated according to sampled result in stage 1. A Bernoulli sample vector \( X_i \) defined as \( (X_i,q,1,\ldots,X_i,q,k,\ldots,X_i,q,n) \) is defined to be the \( q \)-th sample vector from user \( i \), where \( X_i,q,j,k \) is 1 if the \( k \)-th newsfeed of user \( j \) is selected in the \( q \)-th sample and 0 otherwise. Moreover, \( Y_{i,t} \) denotes the top-\( p \) sample quantile of the performances in the \( t \)-th stage of user \( i \), i.e., \( Y_{i,t} = W(P_{\gamma_{N_i}}) \). After collecting \( N_{i,t} \) samples \( X_{i,q,1}, X_{i,q,2}, \ldots, X_{i,q,q-1}, X_{i,q,q}, \ldots, X_{i,q,n} \) generated from \( P_{i,t} \) for user \( i \), CBOM-ND calculates the total additive degree of all the newsfeeds sent to user \( i \), \( S(X_{i,q},q) \). For each sample, it sorts them in the ascending order, \( S(t) \leq S(t+1) \), where \( y_{i,t} \) denotes the additive degree of the top-\( p \) performance sample, i.e., \( Y_{i,t} = S(P_{\gamma_{N_i}}) \). With those sampled results, the selection probability \( p_{i,t,j,k} \) of the \( k \)-th newsfeed of user \( j \) in the second stage is derived according to the following equation,

\[
p_{i,t+1,j,k} = \frac{\sum_{q=1}^{N_{i,t}} I(S(X_{i,q},q) \leq y_{i,t})X_{i,q,j,k}}{\sum_{q=1}^{N_{i,t}} I(S(X_{i,q},q) \leq y_{i,t})},
\]

where the indicator function \( I(S(X_{i,q},q) \leq y_{i,t}) \) is defined on the feasible solution space \( f \). \( I(S(X_{i,q},q) \leq y_{i,t}) = 1 \) if the total additive degree of sample \( X_i \) is smaller than a threshold \( y_{i,t} \).\( y_{i,t} \) and \( \sigma \).\( \sigma \) return.

Eq. (15) derives the newsfeed selection probability vector by fitting the distribution of the top-\( p \) performance samples. Intuitively, if node \( v_i \) is included in most top-\( p \) performance samples in \( t \)-th stage, \( p_{i,t+1,i} \) will approach 1 and then be selected in \( t+1 \)-th stage. Eq. (15) minimizes the Kullback-Leibler cross entropy (KL) distance [23] between newsfeed selection probability \( \bar{p}_{i,t} \) and the distribution of top-\( p \) performance samples, such that the performance of random samples in \( t+1 \) is guaranteed to be closest to the top-\( p \) performance samples in \( t \). Therefore, by picking the top-\( p \) performance samples to generate the solutions in the next stage, the performance is expected to be improved after multiple stages.

As \( v_b \), decided according to the samples in the previous stages, is actually the bottleneck user that generates the highest additive degrees. Due to the space constraint, we provide the theoretical results in Appendices A.3 and A.4. In summary, for MEMIC with parameter \( n, T \), where \( n \) is the number of users and \( T \) is the total computing budgets, the probability \( P_b \) that \( u_b \) is actually the bottleneck user that generates the highest additive degree is at least \( 1 - \frac{1}{n+1} \sum_{k=0}^{n-1} \left( \prod_{k=0}^{n-1} \frac{N_b}{N_b - k} \right) \), as proved in Appendix A.3. Moreover, for a MEMIC optimization problem with the \( r \)-stage computing budget allocation, the approximation ratio, i.e., the expectation of maximum additive degree \( E(Q) \) from the solution of CBOM-ND, is at most \( u_b - \sigma b \Phi^{-1} \left( \sum_{i=1}^{n} \sigma_i \right) \) (as proved in Appendix A.4). Finally, probability assignment scheme is optimal from the perspective of cross entropy (see Appendix A.5 for details).

5 EXPERIMENTAL RESULTS

In this section, we evaluate SAPER and CBOM-ND with three real datasets and a user study with 517 Facebook users.

5.1 Data Preparation and Evaluation Plan

We recruit 517 OSN users around the world via Amazon MTurk and RapidWorkers to model the correctness of SAPER and solution quality of CBOM-ND. The participants include 310 males and 207 females affiliating with universities, government offices, technology companies, art centers, banks, and businesses. Each user is first invited to install our Facebook crawler (for analysis of
newsfeeds) and Google Chrome extension (for screening the newsfeeds after analysis, as well as recording the browsing behaviors).\(^7\) They also periodically fill out questionnaires for SNMD detection (result serve as the ground truth) during the study [3, 32].\(^8\) The duration of the user study spans from 3 weeks to 8 weeks, depending on the efficacy on different people. In the experiment, we compare several approaches: 1) greedy approach (DGreedy) - sending top-\(p\) newsfeeds without considering the social support and social comparison, 2) aversive approach (AVS) - sending top-\(p\) newsfeeds with least addictive degrees, 3) the proposed NSS, and 4) abstinence approach (ABS) - prohibiting SNMD users from accessing OSNs on 5 weekdays but allowing them to use it in the weekends, and 5) normal approach (NORM) - sending the original newsfeeds. We randomly and evenly assign users to different approaches. The average number of newsfeeds \(p\) is set as 40 (by default) and the threshold is set as 75% of the previous threshold in every 7 days according to behavioral shaping [20]. We measure the SNMD scores from Psychological questionnaires\(^9\), average online frequency per day, and average duration per day with 3 severity impairment levels according to [31]: 1) none and mild (average online users, whose usage is normal or may be a bit too long at times, but are still under the control), 2) moderate (user who are experiencing occasional or frequent problems), and 3) severe (users who are experiencing significant problems in their life).

For large-scale experiments, three real datasets are included to evaluate the efficacy (objective function) and efficiency (running time). The sliding window is set as 3 days, i.e., considering the newsfeeds within three days for screening. We solve MEMIC for each sliding window and report the average results. The first dataset is Twitter [18] with 3M nodes and more than 50M tweets with timestamps. Each user on average has 14.8 friends and 14.9 followers. The second dataset is Instagram with 2K users, 9M tags, 1200M likes, and 41M comments [10]. The third dataset, Flicker\(^10\), with 1,846,198 nodes and 22,613,981 edges. Since there is no newsfeed content in the Instagram and Flicker datasets, we approximate the addictive degrees of newsfeeds according to the social-based features. Moreover, for MEMIC, we compare CBOM-ND with

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7 All materials can be found in https://arbor.ee.ntu.edu.tw/~hhshuai/NSS/.
8 IRB number of this project: AS-IRB-HS07-10609c.
9 Notice that SNMD scores are used for quantifying the severity of users, where addictive degrees are learnt by SAPER for newsfeeds.

10 http://socialnetworks.mpi-sws.org/data-imc2007.html.
deterministic greedy algorithm (DGreedy), randomized greedy algorithm (RGreedy).\footnote{For each user, DGreedy sorts all the addictive degrees of newsfeeds in the descending order and select newsfeeds until the summation reaches threshold $\theta$. After reaching the lower bound, DGreedy selects the newsfeeds with the least addictive degrees until $p$ newsfeeds are selected. On the other hand, RGreedy uses DGreedy as a basic solution, and iteratively exchanges the unselected newsfeeds and selected newsfeeds with the probability proportional to the decrement of the SNMD degree.} The default budget $T$ is set as 100 multiplying the network size with $r = 5$. Notice that CBOM-ND may not use all the budgets if the objective value converges. Note that RGreedy is computationally intensive and not scalable for large-scale OSNs (explained later). Therefore, we can only plot a few results of RGreedy in some figures. The default cross-entropy parameters $p$ and $w$ in CBOM-ND are 0.3 and 0.9, respectively, according to [23]. We also implement a parallel CBOM-ND to evaluate the gain with more CPU cores. The experiments are implemented in an HP DL580 server with 4 Intel Xeon E7-4870 2.4 GHz CPUs and 1 TB RAM.

5.2 User Study

Figure 1(a) presents the SNMD scores of severe users every week, where week 0 denotes the time the first questionnaire is taken (before the experiment starts). As the newsfeed screening lasts longer, the average SNMD score of severe users with NSS gradually decreases to moderate, showing NSS alleviates SNMD. In contrast, the SNMD scores of users with other approaches remain almost the same. All the users with ABS quit the experiments without filling the third questionnaire or are disqualified, which indicates that the sudden behavioral change is not suitable for severe users.\footnote{We actually provide rewards for users with ABS treatments to encourage them complete the study following the rule (i.e., accesses OSNs only in the weekends).} Previous study shows that the users with high SNMD scores lack of the delay of gratification, i.e., the ability to resist the temptation for an immediate reward and wait for a later reward [1]. Therefore, they usually decide to enjoy the instant pleasure of reading newsfeeds. Moreover, many users with AVS also quit the experiments since the newsfeeds with low SNMD scores are usually boring to them. Compared with NSS, NSS reduces addictive degrees but encourages social supports from friends to alleviate addictions.

Figures 1(b) and (c) analyze the average online frequency and durations per day, respectively. The online frequency of ABS users are much greater than the other treatments. It also exhibits the pattern of relapse, i.e., quickly reverting back to the excessive usage of OSNs after an abstinence period. Figure 1(b) shows that the online frequency for users with NSS in the second week also becomes greater than that in the first week. However, it becomes lower in the third week and more stable. Most importantly, the duration of users with NSS only slightly decreases, manifesting that NSS minimizes the addictive degrees but retains the users’ interests for OSNs. Therefore, NSS is not expected to harm the business of OSNs.

Figure 1(d) presents the SNMD scores of normal and moderate users in every week. Although the users with AVS do not quit the experiments, their SNMD scores increase to approach the severe level (80) at the fourth week, whereas the users of with NSS gradually decrease to mild level (30). Figures 1(b) and 1(c) further analyze the average online frequency and durations per day of moderate

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure2.png}
\caption{Experimental results on Twitter dataset.}
\end{figure}

users, respectively. The online frequency for users with AVS gradually decreases, while the duration increases 30% from the beginning due to the tolerance effects. In other words, AVS users feel less satisfied with the newsfeeds, but the time spent by an NSS user tends to increase because more newsfeeds are required to achieve the same satisfaction. For severe users and moderate severity users, the improvements of severe users with NSS is more significant, i.e., 18.3% to 15.9% within four weeks. Figures 1(g)-(i) compare the SNMD scores, average number of online frequency, and average duration per day of ABS, AVS, and NSS week-by-week for none and mild users. The average SNMD score of the users with ABS exceeds 50 in the fourth week, i.e., from mild level to moderate level. By contrast, NSS is still more effective than others for those users.

5.3 Performance Comparison and Sensitivity Analysis for CBOM-ND

Figure 2(a) presents the running time with different numbers of newsfeeds. RGreedy is computationally intensive since it is necessary to sum up the addictive degrees of newsfeeds many times during the exchange of a newsfeed (find the proportion of decrement). Therefore, RGreedy is unable to return a solution within even 12 hours when $p$ is greater than 20. In addition, the difference between CBOM-ND and RGreedy becomes more significant as $p$ grows. Figure 2(b) presents the objective value with different $p$, where $\rho = 0.3$, and $w = 0.9$. The results manifest that CBOM-ND outperforms DGreedy and RGreedy, especially for a large $p$. As $p$ becomes greater, CBOM-ND effectively uses the social support to reduce the addictive degrees of newsfeeds, whereas DGreedy doesn’t consider the interplay between the addictive degrees and
social support. On the other hand, RGreedy outperforms DGreedy since it has a chance to exchange the selected and unselected newsfeeds for jumping out of the local optimum.

In addition to the newsfeed sizes, Figure 2(c) compares the objective values of DGreedy, RGreedy, and CBOM-ND with different thresholds for $p = 20$. CBOM-ND consistently outperforms DGreedy and RGreedy with different thresholds, especially with a large threshold. Notice that if the threshold is set too small, the sudden change may incur the anxiety [20]. Therefore, the proposed CBOM-ND is suitable for behavioral shaping, i.e., CBOM-ND performs the best when the threshold is set as 75% of the previous threshold according to behavioral shaping. Figure 2(d) further presents the running time with different thresholds for $p = 20$. As the threshold increases, the running time of CBOM-ND slightly decreases since it is easier for CBOM-ND to allocate computing budgets to the bottleneck nodes and converge earlier when the difference of maximum summation of addictive degrees and other results becomes larger.

Figures 2(e) compares the objective values of two randomized approaches under different total computing budgets $T$. As $T$ increases, the objective value of CBOM-ND decreases faster than that of RGreedy because it can optimally allocate the computing resources. To evaluate the performance of CBOM-ND with multi-threaded processing, Figure 2(f) shows that the processing can be boosted to around 6.2 times with 8 threads. The acceleration ratio is slightly lower than 6 because the updates in different threads for exchanging the selected and unselected newsfeeds have to wait for each other, i.e., OpenMP forbids different threads to write at the same memory position at the same time. Therefore, it is expected that CBOM-ND with parallelization is promising for deploying as a streaming cloud service.

Similar observations are made on Instagram and Flickr datasets, while detailed experimental results can be found in Appendix B.

6 CONCLUSIONS

To the best of our knowledge, there is no real system or existing work based on data mining to alleviate the symptoms of SNMD users without sacrificing their interests. To fill this research gap, this paper formulates a new optimization problem called Multi-Efficacy Maximization with Interest Constraint (MEMIC) to maximize the efficacy of behavioral therapy without compromising the interests of users. We first propose SAPER for quantifying the addictive degree of newsfeeds. Afterward, we prove that MEMIC is NP-Complete and design a novel newsfeed screening system (NSS) based on a simple but effective randomized algorithm, namely CBOM-ND, with an approximation ratio. The user study demonstrates that NSS implemented on Facebook with Chrome extension indeed helps, especially for the users with severe SNMDs, while the duration remains the same. As such, this research result can be a key technology for OSNs. In the future, we plan to improve the treatment with content modification on newsfeeds to better catch and filter the causes of SNMDs.

$$S = \{3, 1, 1, 2, 2, 1\}$$

$$\sum_{j} \sum_{k} a_{u,j,k} x_{u,j,k} = 10$$

$$\sum_{p=1}^{\infty} \sum_{k} a_{u,j,k} x_{u,j,k} = 0$$

Figure 3: An illustrative example of the reduction from partition problem.

A THEORETICAL RESULTS

A.1 Hardness Results

In the following, we prove that MEMIC is NP-Complete.

Theorem A.1. MEMIC is NP-complete.

Proof. We prove that MEMIC is NP-Complete with the reduction from partition problem (PP) [15], which is NP-complete. Specifically, the partition problem is the task of deciding whether a given multiset $S$ of positive integers can be divided into two subsets $S_1$ and $S_2$ such that the sum of the numbers in $S_1$ equals the sum of the numbers in $S_2$. In other words, the purpose of the partition problem is to divide the numbers into two sets and to make the sums of these two sets equal. Without loss of generality, let $\Theta$ be 0 and $\lambda_1 = \tau_{i,j} = 1$. As such, given two users $u$ and $v$, we assume that the SNMD degree reduced for user $u$ is the SNMD degree increased for user $v$, i.e., $\tau_{u,v} = \sum_{x_{u,v,k}} a_{u,v,k} = \delta_{u,v,k}$. We first transform the original graph $G = (V, E)$ into a multidigraph $G'$, which is a directed graph permitted to have multiple edges, i.e., edges with the same source and target nodes. A multidigraph $G'$ is an ordered pair $G' = (V, A)$ where $V$ is a set of nodes and $A$ is a multiset of ordered pairs of vertices (called directed edges), which represent the newsfeeds of user $v$ can be sent to user $u$ for each instance of PP, we construct an instance for MEMIC by setting all the SNMD degree of newsfeeds to be 0 except for the newsfeeds that can be sent to $u$ (only user $u$ is addicted) and the newsfeeds of $u$ that can be sent to $v$. Moreover, user $u$ can only derive support from $v$. The minimum SNMD degree by selecting $p$ newsfeeds to user $u$ is equal to the sum of the support from $v$ ($\sum_{k} \sum_{\epsilon} \sum_{\tau} \sum_{x_{u,v,k}} a_{u,v,k}$). Let the support of each newsfeed map to each element in $S$, i.e., $\sum_{x_{u,v,k}} a_{u,v,k} = S(k)$, where $S(k)$ represents the $k$-th element in $S$. Moreover, we add $|S|$ edges with weights as $e = 0$. We first prove the sufficient condition. For each instance of PP with solution node sets $S_1$ and $S_2$, we let $x_{u,v,k} = 1$ for the corresponding element in $S_1$ and the size constraint $p = |S|$. If the total weight in $S_2$ is $\eta$, the MinMax function of MEMIC is also $\eta$. We then prove the necessary condition. For each instance of MEMIC with $X$, we select the corresponding elements for $S_1$, and weight in $S_2$ must be the same as the MinMax function of MEMIC. The theorem follows.

Figure 3 shows an example of the transformation. Partitioning the set $S$ into two subsets $S_1$ and $S_2$ such that the sum of the
numbers in $S_1$ equals the sum of the numbers in $S_2$ is equal to selecting the $p = |S|$ edges in $A$ such that the objective function $\min \{f_u, f_v\}$ can be optimized.

### A.2 Distribution of SNMD Degrees

Figure 4 shows the distribution of $J_i$, which is similar to the normal distribution. Therefore, in the following, we derive the theoretical results for $J_i$ following the normal distribution with mean $\mu_i$ and standard deviation of $\sigma_i$. Notice that the distribution of feasible solutions follows the truncated normal distribution. However, the random selection cannot guarantee that $g_i$ will be greater than $\theta_i$. Therefore, the minimal SNMD degree expanded from node $v_i$ still follows the normal distribution.

### A.3 Computing Budget Optimization

**Theorem A.2.** For MEMIC with parameter $(n, T)$, where $n$ is the number of users and $T$ is the total computational budgets, the probability $P_b$ that $v_b$, selected according to the previous stages is actually the bottleneck user that generates the highest SNMD degree is at least

$$1 - \frac{1}{n-1} \sum_{k=0}^{N_b} (-1)^k C_k^N \frac{N_b}{k + N_b}.$$

**Proof.** According to the Bonferroni inequality, $p(\bigcap_{i=1}^m \{Y_i < 0\}) \geq 1 - \sum_{i=1}^m [1 - p(Y_i < 0)]$. In our case, $Y_i$ is replaced by $J_i^* - J_b^*$ to acquire a lower bound for the probability that $v_b$ is actually the bottleneck. Therefore,

$$P_b = p(\bigcap_{i=1, i \neq b}^n (J_i^* - J_b^* \leq 0)) \geq 1 - \sum_{i=1, i \neq b}^n [1 - p(J_i^* - J_b^* \leq 0)]$$

$$= 1 - \sum_{i=1, i \neq b}^n p(J_b^* \leq J_i^*)$$

Although $p(J_b^* \leq J_i^*)$ has no closed-form, we further simplify the equation by considering the worst case, i.e., the distribution of all nodes are independent and identically distributed ($J_i = J_b$) and normalized (ranged in $[-1, 1]$).

$$p(J_b^* \leq J_i^*)$$

$$= 1 - \int_{-\infty}^{-1} N_b P_b(x)^N \phi(x)(1 - [1 - \phi(x)]^{N_i}) \, dx$$

$$= 1 - N_b \int_0^1 (\Phi(x))^N \phi(x)(1 - [1 - \Phi(x)]^{N_i}) \, dx$$

Letting $t = \Phi(x)$ and using binomial theorem, we have

$$p(J_b^* \leq J_i^*)$$

$$= 1 - N_b \int_0^1 t^{N_b-1}(1 - (1-t)^{N_i}) \, dt$$

$$= 1 - N_b \int_0^1 (t^{N_b-1} - t^{N_b-1})(1)^{N_i} \, dt$$

$$= 1 - N_b \int_0^1 (t^{N_b-1} - t^{N_b-1}) \sum_{k=0}^{N_b} (-1)^k C_k^N \, dt$$

$$= 1 - N_b \left( \frac{1}{N_b} t^{N_b} - \sum_{k=0}^{N_b} (-1)^k C_k^N \frac{1}{k + N_b} \right)$$

$$= \sum_{k=0}^{N_b} (-1)^k C_k^N \frac{N_b}{k + N_b}.$$

Therefore,

$$P_b = 1 - \sum_{i=1, i \neq b}^n p(J_b^* \leq J_i^*)$$

$$\geq 1 - \frac{1}{n-1} \sum_{k=0}^{N_b} (-1)^k C_k^N \frac{N_b}{k + N_b}.$$

The theorem follows. \hfill \qed

### A.4 Approximation Ratio

Given a total budget $T$, the following theorem derives an upper bound of the solution obtained by CBOM-ND.

**Theorem A.3.** For a MEMIC optimization problem with $r$-stage computational budget allocation, the expectation of maximum SNMD degree $E[Q]$ from the solution of CBOM-ND is at most $u_b = \sigma_b \Phi^{-1}(\frac{N_b - \alpha}{N_b - 2\alpha + 1}) + \sum_{i=1}^n \sigma_i$, where $N_b$ after $r$ stages is $\frac{4r(m-1)}{4n}T$.

**Proof.** We first derive the upper bound of $E[Q]$ with the inequality given by Aven, i.e.,

$$E[Q] = E[\max_{1 \leq i \leq n} J_i^*] \leq \max_{1 \leq i \leq n} E[J_i^*] + \sqrt{\frac{n - 1}{n} \sum_{i=1}^n V ar(J_i^*)}. \quad (7)$$

According to the approximation in [22], $E[J_i^*] \approx u_b = \sigma_b \Phi^{-1}(\frac{N_b - \alpha}{N_b - 2\alpha + 1})$, where $\alpha = 0.375$. Moreover, $V ar(J_i^*) \geq V ar(J_i^*)$. Therefore, we have

$$E[Q] \leq u_b = \sigma_b \Phi^{-1}(\frac{N_b - \alpha}{N_b - 2\alpha + 1}) + \sum_{i=1}^n \sigma_i. \quad (8)$$

If the computational budget allocation is $r$-stages with $T \gg n$, $N_b$ is $\frac{T}{n} + \frac{1}{2} \frac{4(m-1)}{4n}T$, which is $\frac{4r(m-1)}{4n}T$. \hfill \qed

### A.5 Newsfeed Differentiation

In the following, we prove that the probability assignment with the cross-entropy method [23] in Eq. (15) is optimal. The idea of
cross-entropy method originates from importance sampling\textsuperscript{13}, i.e., by changing the distribution of sampling on different neighbors such that the neighbors having the potential to lower the addictive degree are able to be identified and included. Therefore, we first derive the probability of a random sample according to the sampling results in previous stages. After this, we introduce importance sampling and derive the newsfeed selection probability vector in the MEMIC problem to replace the original sampling vector such that the Kullback-Leibler cross entropy (KL) distance between the sampling vector and the optimal importance sampling vector is minimized. Intuitively, a small KL distance ensures that two distributions are very close and implies that the newsfeed selection probability vector is optimal because the KL distance between the newsfeed selection probability vector in CBOM-ND and optimal newsfeed selection probability vector is minimized.

More specifically, let $\chi$ denote the feasible solution space, and $X$ is a feasible solution in $\chi$, i.e., $X \in \chi$. MEMIC chooses a set of newsfeeds $X^*$ to find the maximum addictive degree $y^*$,

$$S(X^*) = y^* = \max_{X \in \chi} S(X).$$

To derive the probability that the addictive degree of a random sample $X$ is less than a value $y$, i.e., $S(X) \leq y$, it is necessary to generate many samples given that it uniformly selects a newsfeed at random. CBOM-ND leverages the notion of importance sampling to change the distribution of sampling on different newsfeeds. In the following, we first derive the optimal distribution of sampling. First, for the initial partial solution with a user, let $f(X; \overrightarrow{p})$ denote the probability density function of generating a sample $X$ according a real-valued vector $\overrightarrow{p}$, and $f(\cdot; \overrightarrow{p})$ is a family of probability density functions on $\chi$, i.e.,

$$f(\cdot; \overrightarrow{p}) = \{f(X; \overrightarrow{p}) | X \in \chi\}.$$  

A random sample $X(\overrightarrow{p})$ for $\overrightarrow{p} = \{p_{1.1}, \ldots, p_{1.k}, \ldots, p_{n.1}, \ldots, p_{n.k}\}$ is generated with probability $f(X(\overrightarrow{p}); \overrightarrow{p})$, where $p_{j.k}$ denotes the probability of selecting the $k$-th newsfeed of user $j$. The probability $P_p(y)$ that the addictive degree of $X(\overrightarrow{p})$ is less than the threshold $y$ is

$$P_p(y) = \sum_{X \in \chi} I\left(S(X(\overrightarrow{p})) \leq y\right) f(X(\overrightarrow{p}); \overrightarrow{p}).$$

However, the above equation is impractical and inefficient for a large solution space, because it is necessary to scan the whole solution space $\chi$ and sum up the probability $f(X(\overrightarrow{p}); \overrightarrow{p})$ of every sample $X$ with $S(X(\overrightarrow{p})) \leq y$. To more efficiently address this issue, a direct way to derive the estimator $\widehat{P}_p(y)$ of $P_p(y)$ is by employing a crude Monte-Carlo simulation and drawing $N$ random samples $X_1(\overrightarrow{p}), \ldots, X_N(\overrightarrow{p})$ by $f(\cdot; \overrightarrow{p})$ to find $\widehat{P}_p(y)$,

$$\widehat{P}_p(y) = \frac{1}{N} \sum_{i=1}^N I\left(S(X_i(\overrightarrow{p})) \leq y\right).$$

However, the crude Monte-Carlo simulation poses a serious problem when $\{S(X(\overrightarrow{p})) \geq y\}$ is a rare event since rare events are difficult to be sampled, and thus a large sample number $N$ is necessary to estimate $P_p(y)$ correctly.

Based on the above observations, CBOM-ND attempts to find the distribution $f(X(\overrightarrow{p}); \overrightarrow{p})$ based on another importance sampling pdf $f(X(\overrightarrow{p}); \overrightarrow{p})$ to reduce the required sample number. In finer detail, let $X_i(\overrightarrow{p}_g)$ denote the $i$-th random sample generated by $f(X(\overrightarrow{p}_g); \overrightarrow{p}_g)$. CBOM-ND first creates random samples $X_1(\overrightarrow{p}_g), \ldots, X_N(\overrightarrow{p}_g)$ generated by $\overrightarrow{p}_g$ on $\chi$ and then estimates $\widehat{P}_p(y)$ according to the likelihood ratio (LR) estimator

$$\widehat{P}_p(y) = \frac{1}{N} \sum_{i=1}^N I\left(S(X_i(\overrightarrow{p}_g)) \leq y\right) f(X_i(\overrightarrow{p}_g); \overrightarrow{p}_g).$$

Notice that the above equation holds when $N$ is infinite, but in most cases $N$ only needs to be sufficiently large in practical implementation. Now the question becomes how to derive $\overrightarrow{p}_g$ for importance sampling pdf $f(X(\overrightarrow{p}_g); \overrightarrow{p}_g)$ to reduce the number of samples. The optimal importance sampling pdf $f^*(X(\overrightarrow{p}_g); \overrightarrow{p}_g)$ to correctly estimate $P_p(y)$ thus becomes

$$f^*(X(\overrightarrow{p}_g); \overrightarrow{p}_g) = \frac{I\left(S(X_i(\overrightarrow{p}_g)) \leq y\right)}{P_p(y)} f(X_i(\overrightarrow{p}_g); \overrightarrow{p}_g).$$

In other words, by substituting $f(X_i(\overrightarrow{p}_g); \overrightarrow{p}_g)$ with $f^*(X(\overrightarrow{p}_g); \overrightarrow{p}_g)$ in Eq. (9), $\widehat{P}_p(y) = \frac{1}{N} \sum_{i=1}^N P_p(y)$ holds, implying that only 1 sample is required to estimate the correct $P_p(y)$, i.e., $N = 1$. However, it is difficult to find the optimal $f^*(X(\overrightarrow{p}_g); \overrightarrow{p}_g)$ since it depends on $P_p(y)$, which is unknown a priori and is therefore not practical for MEMIC.

Based on the above observations, CBOM-ND optimally finds $\overrightarrow{p}_g$ and the importance sampling pdf $f(X(\overrightarrow{p}_g); \overrightarrow{p}_g)$ to minimize the Kullback-Leibler cross entropy (KL) distance between $f(X(\overrightarrow{p}_g); \overrightarrow{p}_g)$ and optimal importance sampling pdf $f^*(X(\overrightarrow{p}_g); \overrightarrow{p}_g)$, where the KL distance measures two densities $f^*$ and $f$ as

$$D(f^*, f) = \sum_{X \in \chi} f^*(X) \ln f^*(X) - \sum_{X \in \chi} f(X) \ln f(X).$$

The first term in the above equation is related to $f^*$ and is fixed, and minimizing $D(f^*, f)$ is equivalent to maximizing the second term, i.e., $\sum_{X \in \chi} f^*(X) \ln f(X)$. It is worth noting that the importance sampling pdf $f(X(\overrightarrow{p}_g); \overrightarrow{p}_g)$ is referenced to a vector $\overrightarrow{p}_g$. Thus, after substituting $f^*(X(\overrightarrow{p}_g); \overrightarrow{p}_g)$ in Eq. (10) into the Eq. (11), the reference vector $\overrightarrow{p}_g$ of importance sampling pdf $f(X(\overrightarrow{p}_g); \overrightarrow{p}_g)$ that maximizes the second term of Eq. (11) is the optimal reference vector $\overrightarrow{p}_g$ with the minimum KL distance, $\overrightarrow{p}_g$ is derived as follows:

$$\arg \max_{\overrightarrow{p}_g} \sum_{X \in \chi} I\left(S(X(\overrightarrow{p}_g)) \leq y\right) f(X(\overrightarrow{p}_g); \overrightarrow{p}_g) \frac{P_p(y)}{\ln f(X(\overrightarrow{p}_g); \overrightarrow{p}_g)}.$$  

\textsuperscript{13}Importance sampling is used to estimate the properties of a target distribution by using the observations from a different distribution. By changing the distribution, the ‘important’ values can be effectively extracted and emphasized by sampling more frequently to reduce the sample variance.
Since $P(y|\gamma)$ is not related to $P(y)$, Eq. (13) is equivalent to
\[
\arg\max_{P(y)} \mathbb{E}_{P(x)} \{ f(X(p(y); y) \} \nln f(X(p(y); y).
\]

Because it is computationally intensive to generate and compare every feasible $P(y)$, we estimate $\mathbb{E}_{P(x)} \{ f(X(p(y); y) \}$ by drawing $N$ samples as
\[
\arg\max_{P(y)} \frac{1}{N} \sum_{i=1}^{N} I(S(X(p(y)) \leq y) \ln f(X_i(p(y), y) = \frac{1}{N} \sum_{j=1}^{N} h_j(1 - p_j)^{1-x_{i,j}}.
\]

Specifically, we first assume each user only has one newsfeed to simplify the deviation. Therefore, for each user, CBOM-ND first generates random samples $X_1, \ldots, X_N$, where $X_i$ is the $i$-th sample and is a Bernoulli vector generated by a newsfeed selection probability vector $P_{i}(y)$, i.e., $X_i = (x_{i,1}, \ldots, x_{i,j}, \ldots, x_{i,n}) \sim \text{Ber}(P(y)_i)$, where $P(y)_i = \{ p_1, \ldots, p_j, \ldots, p_n \}$ and $p_j$ denotes the probability of selecting the newsfeed of user $j$. Consequently, the pdf $f(X_i(p(y); y)$ is
\[
f(X_i(p(y); y) = \prod_{j=1}^{N} p_j^{x_{i,j}} (1 - p_j)^{1-x_{i,j}}.
\]

To find the optimal reference vector $P^*$ with Eq. (13), we first calculate the first derivative w.r.t. $p_j$,
\[
\frac{\partial}{\partial p_j} \ln f(X_i(p(y); y) = \frac{\partial}{\partial p_j} \ln p_j^{x_{i,j}} (1 - p_j)^{1-x_{i,j}}.
\]

Since $x_{i,j}$ can be either 0 or 1, Eq. (14) is simplified to
\[
\frac{\partial}{\partial p_j} \ln f(X_i(p(y); y) = \frac{1}{1 - p_j} (x_{i,j} - p_j).
\]

The optimal reference vector $P^*$ is obtained by setting the first derivative of Eq. (13) to zero.
\[
\frac{\partial}{\partial p_j} \sum_{i=1}^{N} I(S(X_i) \leq y) \ln f(X_i(p(y); y) = \frac{1}{1 - p_j} \sum_{i=1}^{N} I(S(X_i) \leq y) (x_{i,j} - p_j) = 0.
\]

Finally, the optimal $p_j$ assigned to each node $v_j$ is
\[
p_j = \frac{\sum_{i=1}^{N} I(S(X_i) \leq y) x_{i,j}}{\sum_{i=1}^{N} I(S(X_i) \leq y)}.
\]

Therefore, it is easy to extend to newsfeed selection probability the $k$-th newsfeed of user $j$, i.e.,
\[
P_i,t+1,j,k = \frac{\sum_{q=1}^{N} I(S(X_q) \leq y_{q,i}) x_{i,j} k}{\sum_{q=1}^{N} I(S(X_q) \leq y_{q,i})}.
\]

B SUPPLEMENTARY EXPERIMENTAL RESULTS ON FLICKR AND INSTAGRAM DATASETS

In the following, we further show the results on Flickr and Instagram datasets with $T$ as 100 multiplying the network size and threshold $\theta$ as 0.75. Figure 5(a) presents the running time with different numbers of newsfeeds on the Flickr dataset. RGreedy is still computationally intensive since it is necessary to sum up the addictive degrees of newsfeeds many times during the exchange of a newsfeed to find the proportion of decrement. Therefore, RGreedy is unable to return a solution within even 12 hours when $p$ is greater than 20. Figure 5(b) presents the objective value with different $p$, where $p = 0.3$, and $w = 0.9$. CBOM-ND outperforms DGreedy and RGreedy by at least 11%. On the other hand, RGreedy outperforms DGreedy since it has a chance to exchange the selected and unselected newsfeeds for jumping out of the local optimum. Figure 5(c) presents the running time with different numbers of newsfeeds on the Instagram dataset. Notice that the number of newsfeeds (photos) is set as 2, 4, 6, 8, and 10 since there are much fewer photos on the Instagram dataset. If $p$ is greater than 20, the results of different approaches becomes similar since every user is sent with all the photos to satisfy the newsfeed size constraint. The trend of running time is the same, while CBOM-ND outperforms DGreedy and RGreedy by 6.5% and 14.7% in terms of objective values when $p = 2$.

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