

# Health Forum Recommendation using an Interest Aware Topic Model

Kishaloy Halder  
School of Computing  
National University of Singapore  
kishaloy@comp.nus.edu.sg

Min-Yen Kan  
School of Computing  
National University of Singapore  
kanmy@comp.nus.edu.sg

Kazunari Sugiyama  
School of Computing  
National University of Singapore  
sugiyama@comp.nus.edu.sg

## ABSTRACT

We introduce a general, interest-aware topic model (IATM), in which known, higher-level interests on topics expressed by each user can be modeled. We then specialize the IATM for use in consumer health forum thread recommendation, by equating each user's self-reported medical conditions as interests, and topics as threads for recommendation. The IATM additionally models the implicit interests embodied by users' textual descriptions in their profiles. To further enhance the personalized nature of the recommendations, we introduce jointly normalized collaborative topic regression (JNCTR) which captures how users interact with the various symptoms belonging to the same clinical condition.

In our experiments with two real-world consumer health forums, our proposed model significantly outperforms competitive state-of-the-art baselines by over 10% in recall. Importantly, we show that our IATM-JNCTR pipeline also imbues the recommendation process with added transparency, allowing a recommendation system to justify its recommendation with respect to each user's interest in certain health conditions.

## KEYWORDS

Recommender Systems; Collaborative Filtering; Graphical Model; Topic Models

## 1 INTRODUCTION

People participate in online health forums in part to discuss their symptoms and clinical conditions with others. They post health related questions to learn from the experience of the community. The majority of users participate in online health communities with the goal of meeting a medical information need [10, 16, 18]. This is the problem we aim to address in this work. We acknowledge that patients also participate for emotional support and social reasons [3, 7, 35], but this is beyond the scope of this work.

Finding relevant information can be difficult, and recommendation systems can help bridge this gap by assisting users by suggesting appropriate discussion threads related to their condition- and symptom-specific interests.

We observe that the symptoms experienced by patients with different clinical conditions are often similar. However, the proper

**Table 1: A query ALS thread (left) and lexically similar but unrelated posts for Parkinson's Disease (right).**

ALS Threads	Parkinson's Disease Threads
does any one experience lower back pain after sitting a spell then standing up ? ...	... I have extreme pain in my lower back and hips. There are days it just hurts to walk ... I have been having back pain for 3 years and it gets continually worse. My lower back gets ...

treatment crucially depends on the underlying cause (*i.e.*, the clinical condition or disease). This leads to many lexically similar user queries that require different answers, as shown in Table 1. Many traditional approaches — such as topic models — struggle to identify the correct underlying condition, as they mainly use word co-occurrence to determine relevant answers.

We observe that context is a key factor to identify the appropriate latent conditions and symptoms. In this scenario, the key contextual evidence is the participation that a user manifests towards a specific medical condition, either by subscribing to a subforum related to a condition or by authoring a post in the forum inferrably related to a condition<sup>1</sup>. We believe that such context must be accounted for, in order to recommend relevant discussion threads in health forums. We introduce a two-stage approach that captures such context.

Our solution leverages the topic model framework to properly incorporate the contextual information. Our topic model — which we term the *interest-aware topic model* (IATM) — is a general model that encompasses both the evidence of each user's document and word interactions, but crucially also the user's self-reported (and thus observed) interests.

A key characteristic of the IATM is that even though it can model explicit user interests (*i.e.*, a patient is subscribed to a Parkinson's disease subforum), in the absence of such explicitly indicated interests, the IATM treats users' interests as a partially-observed random variable and attempts to infer the full and latent value. As users may not explicitly type themselves, yet actively participate, this is important to account for.

The IATM also natively models the side information of user profiles. User profiles are ubiquitous to many Web 2.0 sites, inclusive of health forums. In IATM, user profiles are treated as normal documents during the training process, used in determining the interests of the user. In our health forum recommendation scenario, user descriptions do give useful information about the user, which aids the recommendation process significantly, especially for users that have little interaction history — a form of cold start.

Permission to make digital or hard copies of part or all of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for third-party components of this work must be honored. For all other uses, contact the owner/author(s).

CIKM'17, November 6–10, 2017, Singapore.

© 2017 Copyright held by the owner/author(s). ISBN 978-1-4503-4918-5/17/11.  
DOI: <http://dx.doi.org/10.1145/XXXXXX.XXXXXX>

<sup>1</sup>In our scenario, we require actions that leave a traceable correlation with interest. This allows our framework to be applied even in cases where the recommendation is done by a third party (as done in our evaluation) and not necessarily done by the service provider.

In further analyses of our dataset, we note further modeling difficulties. Even when confined to a single condition, discussion on different symptoms also often appear similar due to commonly affected parts of the body. Consider the following posts:

(a) [about back pain] “I’ve had back pain for over a year now and it’s getting unmanageable — increasingly I can hardly put **weight** on my right **leg** ...”

(b) [about leg cramps] “Sometimes I get cramps in my **leg**. Only thing I have found that helps it is if I get up and put my body **weight** on it ...”

These posts have common words (bold ones) but are about different symptoms of Parkinson’s disease. Although the topic distributions in two posts (documents) are similar, each user’s preferences are clearly directed towards different particular topics. We observe similar distribution bias with users’ participation in clinical treatment discussions and other condition-specific topics.

To address this second, fine-grained disambiguation problem, we develop a novel graphical model, jointly normalized collaborative topic regression (JNCTR). JNCTR is a logical adaptation of the original collaborative topic regression (CTR) model [33], itself motivated to handle such divergences in each user’s interests in documents with similar topic distributions. JNCTR extends CTR by taking both the user–topic and thread–topic distributions coming from IATM as input, but additionally accounts for the user–thread interaction history in the form of ratings. This model allows us to understand the differences between symptoms that originate from a single condition. JNCTR updates both the user–topic and thread–topic distributions based on the past user–thread interactions. We compute thread recommendations for each user using the resultant user–topic and thread–topic distributions.

Online health forum users often use their own words and phrases to describe their experiences [12, 20]. Standard medical ontologies and thesauri (e.g., UMLS<sup>2</sup>) struggle to cover the medical terms found in user-generated medical content [9]. We believe that our specialized IATM+JNCTR model is the first attempt to understand how clinical conditions and their symptoms and treatments explain the interaction of users in a health forum. The contributions of our work are summarized as follows:

- We formalize the problem of interest-aware recommendation, of which health forum thread recommendation is a specific instantiation of *conditions-as-interests*. We investigate how to best utilize user participation in the forum, formulating this as an implicit feedback-based recommendation problem.
- We apply our framework to two real-world datasets obtained from PatientsLikeMe<sup>3</sup> and HealthBoards<sup>4</sup>, demonstrating significant improvement over state-of-the-art baselines.
- We extend our experiments to demonstrate how our proposed IATM+JNCTR model deals gracefully with both cold-start users and cold-start items. The model can explain a recommendation due to its modeling of latent variables. We further investigate how our model performs in recommendation justification by analyzing its recommendations to specific users.

## 2 RELATED WORK

The motivations behind user participation in consumer medical information discussion forums have been systematically studied by the medical informatics community in recent years [3, 14, 35], but to the best of our knowledge, such work has been limited to large-scale surveys of self-reported behavior, and the community has not seen much development of practical recommendation techniques for health forums as of current.

While acknowledging the varied societal and emotional support needs of users, we find value in addressing the primary information need for consumer health information. As such, our task falls into the guise of recommendation systems, an area which has seen much recent interest with the popularity of Web 2.0 systems that integrate users and items into Web applications. For brevity, we limit our discussion to relevant prior work in the areas of topic modeling, content-based and context-aware recommendations.

**Topic Models.** Topic models regard documents as mixtures of latent topics with certain distributional properties. For textual documents, several works have focused on modelling latent factors of the content using latent Dirichlet allocation (LDA) [4] and its variants [17, 26, 28]. For example, the author–topic model [28] learns the topic distribution of authors for a set of documents. On the other hand, labeled LDA relies on annotated tags to constrain the possible topics for each document [26].

While these models are useful on their own for modeling either users or items, they do not capture the dynamics between both. LDA can be used as a starting point for refinement to account these factors. Agarwal *et al.* [1] leveraged LDA-discovered latent topic distributions for matrix factorization-based collaborative filtering (CF). They report modest improvement over other methods — the reason being that often the topic distributions of different items look similar, even though they appeal to different sets of people. There also exists a set of focused topic models that cater to specific use cases [6, 36]. Chen *et al.* [6] proposed a Contextual Focused Topic Model, where they assume a word to be generated from either the author or the venue or the document characteristics – not from a joint combination of them, as in our case.

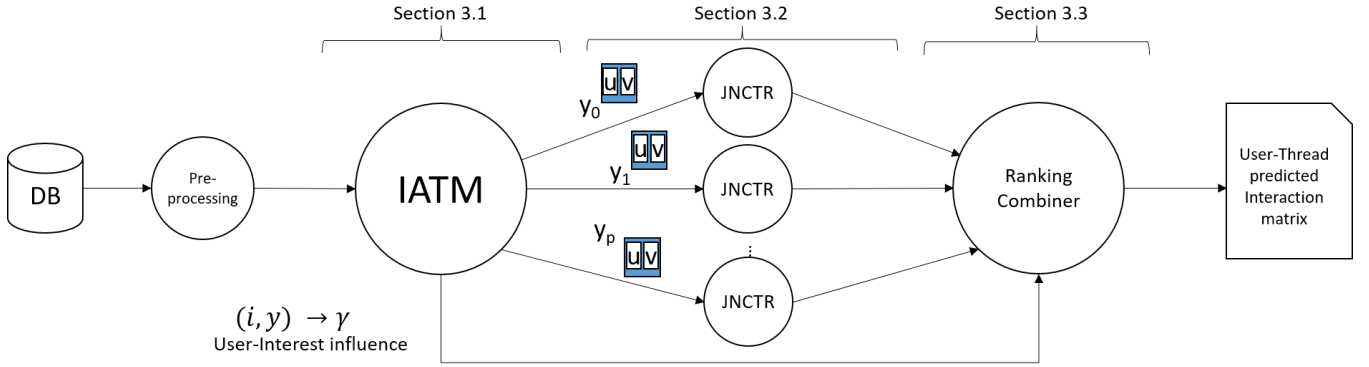
**Content-based and Context-aware Recommendation.** Certain content-based recommendation systems further account for information associated with content associated with users. Wang *et al.* [33] proposed collaborative topic regression (CTR) and showed the effectiveness of adjusting the LDA-discovered topic distributions by doing a regression from the observed user–item ratings in scholarly documents. In the same context, Charlin *et al.* [5] showed that the cold-start performance of a similar model can be improved if there is bootstrapping information available in the form of document content associated with users. Although it is possible to use a textual content agnostic off-the-shelf CF method to recommend articles to a user to comment on [31], considering associated textual content improves performance significantly in other platforms, e.g., news articles or blogs [2], demonstrating the efficacy of modeling such side information.

Along with the past user–item interaction history, *Context Aware Recommendation* methods consider the interaction contexts which can be equated to the medical conditions of a user in our scenario.

<sup>2</sup><https://www.nlm.nih.gov/research/umls/>

<sup>3</sup><http://www.patientslikeme.com>

<sup>4</sup><http://www.healthboards.com>



**Figure 1: The pipeline for our three-stage recommendation framework. IATM first provides user–topic and document–topic distributions for all the diseases, and then JNCTR further optimizes those distributions. Finally, the ranking combiner merges the ranked documents depending on the user–interest alignment estimated from the first stage.**

Tensor Factorization [11] and Factorization Machines [27] are two promising methods, primarily designed to predict ratings in an explicit feedback-based system. Nguyen *et al.* [19] demonstrate that such techniques can also be profitably applied in implicit feedback scenarios such as ours.

**Recommendation in Community Question Answering.** In community question answering system, some works address to recommend semantically related question threads that reflect different aspects of the user’s query and provide supplementary information. Wang *et al.* [34] recommend more relevant threads by extending a language model with the popularity of a question. Pedro and Karatzoglou [24] extend Learning to Rank to supervised LDA applied specifically to recommend relevant question threads. Zhou *et al.* [40] propose a translation model-based thread recommendation by incorporating answer information. In recent work, Omari *et al.* [22] and Palotti *et al.* [23] improve ranking of relevant discussion threads in health forums. However, they do not address recommendation that provides results relevant to each user’s interest.

While the previous work can handle recommendations in health forums, there is important evidence that needs to be modeled to achieve better recommendation accuracy [5, 15, 38]. In particular, in health forums, each user can often express explicit interests in different conditions. We note that the modeling of user profiles has largely been independently handled from the recommendation process itself. We propose a unified framework of both user profiles and user participation in a health forum. This leads to not only significant improvement over other state-of-the-art methods but also enhancement of transparency in the recommendation task.

### 3 METHODS

Our recommendation methodology takes full advantage of the different sources of evidence that influence recommendations of items in a generic context. It is a three-stage methodology comprising of: 1) a topic model (IATM), 2) topic regression (JNCTR), and 3) ranking combination, as shown in Figure 1. We first give a short overview of the first two key models, before describing how we instantiate them for the health forum recommendation task. We then describe the

three stages in technical detail, and finally discuss our instantiation of the model for health forum recommendation to create a condition-aware topic model.

**Method Overview.** Our proposed interest-aware topic model is a generic topic model that can be used in many recommendation scenarios involving users. Without loss of generality, IATM assumes that *users* interact with *documents* (or *items*, as referred to in the literature). The interactions generate some textual evidence that ties together users and documents — such as contributing a post within a larger, multi-user thread (document), commenting or authoring the entire document, such as one’s own user profile. Like the standard topic model, documents are modeled as mixtures of *topics*; however, a key distinction in IATM is that it assumes that topics are related to certain higher-level *interests* in a generative relationship. IATM captures explicit expressions of user *interests*, but crucially maintains the observations of these interests only as partially observed. This distinction allows the IATM to infer other interests of the user that are suggested by the contextual evidence of the user’s other interactions.

JNCTR advances this step further, taking in the output of IATM’s user–topic and document–topic distributions and further accounting for the user–document interactions. As IATM already accounts for interests, we can instantiate standard collaborative topic regression for each interest separately, and jointly normalize them to output refined user–topic and document–topic distributions. These are then fused to generate recommendations.

**Instantiating the Model for Health Forum Recommendations.** IATM+JNCTR can be applied to various Web 2.0 contexts — recommendation tasks such as ones for movies, products, and discussion forums. These contexts all have document–user interactions, where user interests are partially observed through forum subscriptions or folksonomy tags, among other means.

For clarity, we now instantiate IATM+JNCTR for the health forum thread recommendation problem. Under our scenario, users express their interests by subscribing to forums at health websites. Such forums are largely medical condition specific. As in the general case, we do not expect users to necessarily subscribe to all the condition-specific forums that are relevant to them; we believe that the subscriptions are partially observed.

Our recommendation system’s goal is to recommend relevant forum threads to users. Users can participate in forum threads by contributing posts, which forms the user–document interactions in our IATM+JNCTR framework. A user can report her clinical conditions as part of her user profile’s free text description (*e.g.*, “About Me.”). Such user documents are only used as evidence during training; to be clear, we do not recommend user profiles. Finally, individual threads on a particular condition discuss different symptoms and treatments in differing proportions. We assume that users are interested in certain symptoms that they experience, and treatments that they are undergoing.

Summarized, in our health forum thread recommendation scenario, we equate the following IATM terms with ones specific to our scenario: interest  $\rightarrow$  condition; topic  $\rightarrow$  (symptom, treatment); and document  $\rightarrow$  thread.

### 3.1 Interest-Aware Topic Model (IATM)

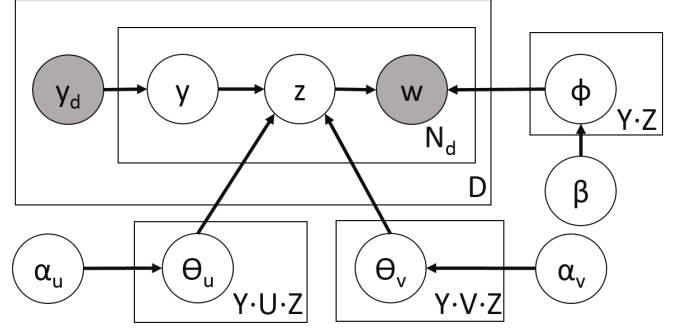
We use the standard plate notation for the graphical model as shown in Figure 2. There are  $U$  users and  $V$  item documents. Since each user has a user document (*i.e.*, a user profile), there are  $U$  user documents; hence we have altogether  $D = U + V$  documents.  $Y$  denotes the set of all possible interests. In Figure 2, an interest  $y$  is sampled from a uniform distribution from the set of interests  $y_d \subset Y$ , where  $y_d$  is the union of all interests reported by the users participating in document  $d$ . Each interest  $y$  has  $Z$  latent topics which denote the fine-grained sub-topics of an interest (*e.g.*, in our instantiated IATM for medical conditions, different symptoms, medications for a condition).

In the case of each word in a document, from an interest  $y$ , a latent topic  $z$  is sampled according to the topic distribution of the user  $\theta_u$ , as well as the topic distribution of the item  $\theta_v$ . The reason behind this is intuitive: when a user contributes to a document, the topic of the user’s words are dependent on the overall document topic, as well as the user’s own set of interests. However, in the case of a user document (*i.e.*, the user profile), the choice of topic is only dependent on the user’s own interests. A topic  $z$  is sampled only from the interest  $y$  and  $\theta_u$ , for such user documents.

A word  $w$  is sampled from  $z$  and the word–topic distribution  $\phi$ . We invoke blocked Gibbs sampling as the exact inference of the full posterior is intractable. The inference process is similar to the author–topic model [28]; but in IATM, the author of a document is observed. We have two sets of latent variables,  $z$  and  $y$ . We draw each  $(z, y)$  pair as a block, conditioned on all other variables:

$$P(z_x = h, y_x = k | w_x = m, z_{-x}, y_{-x}, w_{-x}, y_d) \propto (q_1 \frac{n_{hk}^i + \alpha_u}{\sum_z n_{zk}^i + Z\alpha_u} + q_2 \frac{n_{hk}^d + \alpha_v}{\sum_z n_{zk}^d + Z\alpha_v}) * \frac{n_{mh}^k + \beta}{\sum_w n_{wh}^k + W\beta}, \quad (1)$$

where  $z_x = h$  and  $y_x = k$  denotes that the  $x^{th}$  word in  $d^{th}$  document is assigned to topic  $h$  under interest  $k$ ,  $w_x = m$  represents that  $x^{th}$  word is the  $m^{th}$  word in the vocabulary,  $z_{-x}, y_{-x}$  represent all topic and interest assignments not including the  $x^{th}$  word,  $n_{hk}^i$  is the number of times topic  $h$  is assigned with interest  $k$  for user  $i$ , not including the instance under consideration, and  $W$  is the total number of unique words in the vocabulary. Similarly,  $n_{hk}^d$  represents the number of times topic  $h$  has appeared under interest  $k$  in the  $d^{th}$  document, and  $n_{mh}^k$  denotes the number of times the  $m^{th}$  word in the



**Figure 2: Plate notation for our interest-aware topic model (IATM).** We observe the document words as well as partially observe the interests that select the topics for the words in the document (gray nodes). Topics are dependent on the interest ( $y$ ), user ( $\theta_u$ ), and document ( $\theta_v$ ).

vocabulary has appeared in topic  $h$  under interest  $k$  — excluding the current instances in all the cases. The three factors in Equation (1) represent the random variables  $\theta_u$  (probability of topic given interest and user),  $\theta_v$  (probability of topic given interest and document), and  $\phi$  (probability of a word given interest and topic). The Dirichlet priors for these three distributions are  $\alpha_u$ ,  $\alpha_v$ , and  $\beta$ , respectively. We use a Dirichlet mixture of the two individual Dirichlet densities ( $\theta_u, \theta_v$ ) as the prior [25, 32]. We give equal weights to the mixture co-efficients (*i.e.*,  $q_1 = q_2 = 0.5$ ). We also learn the user–interest distribution  $\gamma$ . These distributions are estimated from the samples using the following equations:

$$\theta_u^{hik} = \frac{n_{hk}^i + \alpha_u}{\sum_z n_{zk}^i + Z\alpha_u}, \theta_v^{hdk} = \frac{n_{hk}^d + \alpha_v}{\sum_z n_{zk}^d + Z\alpha_v}, \quad (2)$$

$$\phi^{mhk} = \frac{n_{mh}^k + \beta}{\sum_w n_{wh}^k + W\beta}, \quad (3)$$

$$\gamma^{ik} = \frac{n_k^i}{\sum_y n_y^i}, \quad (4)$$

where  $n_k^i$  is the number of times interest  $k$  is sampled for user  $i$ .

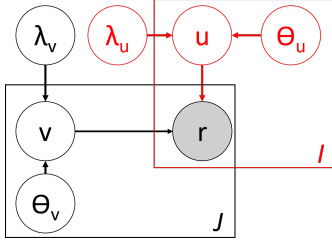
Once the distributions are learned, we create sub-spaces of the entire user–item interaction matrix based on each interest. The interaction matrix  $R^k$  for interest  $k$  is defined by:

$$r_{ij}^k = \begin{cases} 1 & \text{if } R_{ij} = 1, k \in Y_i \\ 0 & \text{otherwise,} \end{cases}$$

where  $Y_i$  is the set of interests for user  $i$ ,  $R_{ij} = 1$  if user  $i$  participated in item  $j$ ; 0 otherwise. Similarly, we define the user–, item–, and word–topic distributions for this sub-space as  $\theta_u^k, \theta_v^k$ , and  $\phi^k$ , respectively:

$$\theta_u^k = \theta_u\{k\}, \theta_v^k = \theta_v\{k\}, \phi^k = \phi\{k\}.$$

As an example, given the three threads in Table 1, IATM places the left one in the ALS sub-space, and the right ones inside the Parkinson’s disease sub-space.



**Figure 3: Plate notation for jointly normalized collaborative topic regression (JNCTR).** Components in black are from collaborative topic regression (CTR<sup>5</sup> [33]). Components in red are introduced for user modeling. Note that both plates for user and thread are form-identical.

### 3.2 Joint Normalized Collaborative Topic Regression (JNCTR)

We treat each of the resultant interest-specific user-item sub-spaces originating from IATM as a separate problem instance and optimize them individually using JNCTR, as shown in Figure 1.

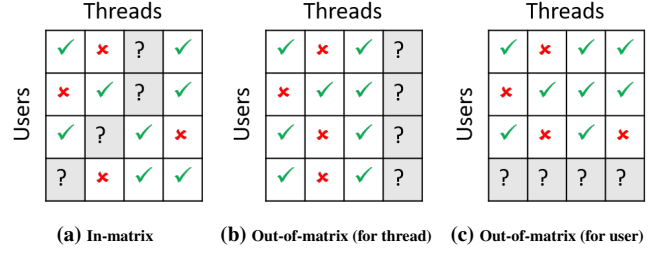
Figure 3 shows the plate model for each individual instance of JNCTR. Here, we use the notations  $\theta_u$ ,  $\theta_v$ ,  $\phi$ , and  $R$  without the interest-specific superscript  $k$ .  $I$  and  $J$  denote the set of users and documents within this sub-space, respectively. Note that we omit the plate for generation of words as we do not assume any particular generative process for them. As in CTR, we introduce a latent variable  $\epsilon_u^i$  that offsets the topic proportions  $\theta_u^i$  for  $i^{th}$  user when modeling the user’s ratings. JNCTR assumes that there are  $Z$  topics both in user content and document content  $\beta = \beta_{1:Z}$ . The generative process of JNCTR is defined in the following steps:

- (Step 1) For each user  $i$ , draw user latent offset  $\epsilon_u^i \sim \mathcal{N}(0, \lambda_u^{-1} \mathbb{I}_Z)$  and set the user latent vector as:  $u_i = \epsilon_u^i + \theta_u^i$ ,
- (Step 2) For each document  $j$ , draw document latent offset  $\epsilon_v^j \sim \mathcal{N}(0, \lambda_v^{-1} \mathbb{I}_Z)$  and set the document latent vector as:  $v_j = \epsilon_v^j + \theta_v^j$ ,
- (Step 3) For each user–document pair  $(i, j)$ , draw the rating as:  $r_{ij} \sim \mathcal{N}(u_i^T v_j, c_{ij}^{-1})$ ,

where  $\mathbb{I}_Z$  is  $Z$ -dimensional identity matrix,  $\lambda_u$  and  $\lambda_v$  are the regularization parameters,  $c_{ij}$  is the precision parameter for  $r_{ij}$ , a confidence parameter for rating  $r_{ij}$ , where larger values denote higher trustworthiness. This is important in the case of implicit feedback based systems like ours (note that  $r_{ij} = 0$  can mean either  $i^{th}$  user is not interested in it or the user is unaware of the document). We set  $c_{ij} = a$ , if  $r_{ij} = 1$ , otherwise we set it to  $b$ , where  $a$  and  $b$  are tuning parameters satisfying  $a > b > 0$ . We discuss parameter tuning in Section 4.

**Learning the Parameters for JNCTR.** Given topic parameter  $\beta$ , computing the full posterior of  $u_i$ ,  $v_j$ ,  $\theta_u$ ,  $\theta_v$  is intractable. We now develop an EM-style algorithm to learn these parameters. Extending the posterior mentioned in [33], given  $\lambda_u$ ,  $\lambda_v$ , and  $\beta$ , the complete log likelihood  $\mathcal{L}$  of  $U$ ,  $V$ ,  $\theta_u^{1:I}$ ,  $\theta_v^{1:J}$ , and  $R$  is defined as follows:

<sup>5</sup>We omit the word plates, as CTR does not re-sample topics once  $\theta_v$  is obtained from the topic model as discussed in [33].



**Figure 4: Illustration of three prediction tasks for our thread recommendation system.** “✓,” “✗,” and “?” denote “like,” “dislike,” and “unknown,” respectively.

$$\begin{aligned} \mathcal{L} = & -\frac{\lambda_u}{2} \sum_i (u_i - \theta_{u^i})^T (u_i - \theta_{u^i}) - \frac{\lambda_v}{2} \sum_j (v_j - \theta_{v^j})^T (v_j - \theta_{v^j}) \\ & + \sum_i \sum_m \log(\sum_k \theta_{u^{ik}} \beta_{k, w_{im}}) + \sum_j \sum_n \log(\sum_k \theta_{v^{jk}} \beta_{k, w_{jn}}) \\ & - \sum_{i,j} \frac{c_{i,j}}{2} (r_{ij} - u_i^T v_j)^2. \quad (5) \end{aligned}$$

We optimize this likelihood function by coordinate ascent, optimizing the CF variables  $u_i$ ,  $v_j$  iteratively. To update  $u_i$  and  $v_j$ , we take the gradient of  $\mathcal{L}$  with respect to  $u_i$  and  $v_j$  and set it to zero. This yields:

$$u_i \leftarrow (VC_i V^T + \lambda_u I_K)^{-1} (VC_i R_i + \lambda_u \theta_u^i R_i), \quad (6)$$

$$v_j \leftarrow (UC_j U^T + \lambda_v I_K)^{-1} (UC_j R_j + \lambda_v \theta_v^j R_j), \quad (7)$$

where  $U = (u_i)_{i=1}^I$ ,  $V = (v_j)_{j=1}^J$ ,  $C_i$  is a diagonal matrix with  $c_{ij}$  ( $j = 1, \dots, J$ ) as its diagonal elements and  $R_i = (r_{ij})_{j=1}^J$  for user  $i$ .  $C_j$  and  $R_j$  are similarly defined for document  $j$ .

**Prediction.** Once the locally optimal parameters  $U^*$ ,  $V^*$ ,  $\theta_u^*$ ,  $\theta_v^*$  are learned, JNCTR can predict ratings. Given that  $D$  is the observed data, the prediction is estimated as:

$$\mathbb{E}[r_{ij}|D] \approx (\mathbb{E}[\theta_{u_i}|D] + \mathbb{E}[\epsilon_{u_i}|D])^T \cdot (\mathbb{E}[\theta_{v_j}|D] + \mathbb{E}[\epsilon_{v_j}|D]). \quad (8)$$

We characterize predictions as follows:

- (Fig. 4a) In-matrix prediction: All the users and threads have at least one interaction. We use the point estimate of  $\theta_u^i$ ,  $\theta_v^j$ ,  $\epsilon_u^i$ , and  $\epsilon_v^j$  to approximate the expectations:

$$r_{ij}^* \approx (\theta_u^{i*} + \epsilon_u^{i*})^T (\theta_v^{j*} + \epsilon_v^{j*}) = (u_i^*)^T v_j^*. \quad (9)$$

- (Fig. 4b) Out-of-matrix prediction (for thread): Some threads do not have interaction history; i.e.,

$$r_{ij}^* \approx (\theta_u^{i*} + \epsilon_u^{i*})^T (\theta_v^{j*}) = (u_i^*)^T \theta_v^{j*}. \quad (10)$$

- (Fig. 4c) Out-of-matrix prediction (for user): Some users do not have interaction history; i.e.,

$$r_{ij}^* \approx (\theta_u^{i*})^T (\theta_v^{j*} + \epsilon_v^{j*}) = (\theta_u^{i*})^T v_j^*, \quad (11)$$

substituting  $u_i$  and  $v_j$  from Steps 1 and 2 in the JNCTR generative process. We thus obtain a ranked list of interest-specific documents that is recommended to a user.

**Efficiency.** Note that in Figure 1, multiple instances of JNCTR are run, but each instance is run on a partition of the full matrix. The computational complexity of JNCTR is comparable to the original CTR algorithm; the number of updates in both are identical.

### 3.3 Fusing the Final Ranked List

Once we obtain the condition-specific optimized user- and item-topic distributions, we combine them into a single ranking using the  $\gamma$  distribution obtained by Equation (4). We explore three methods to fuse the individual, interest-specific lists:

**1. Proportional Selection.** For every interest that user  $i$  is interested in, we prepare a list of documents (in descending order of predicted score) that the user might find interesting. We select the top- $M$  threads from each condition sub-space according to user  $i$ 's  $\gamma$  distribution. For illustration, say John has a  $\gamma$  distribution of {Multiple Sclerosis : 0.8, Asthma : 0.2}. When recommending threads to John, 80% are chosen from the top threads in Multiple Sclerosis, and the remaining 20% would come from Asthma.

**2. Combined Score-Based Selection.** Here, we obtain a single ordered list of threads from their combined score for each user. First, we normalize scores in each interest sub-space between  $[0, 1]$ . For user  $i$ , the combined score of a thread  $j$  is defined as in Equation (12) which ranks the items in descending order of their total score:

$$R_{ij}^* = \sum_y \gamma^{iy} \times r_y^{ij}, (y \in Y_i). \quad (12)$$

**3. Maximum Split Preference-Based Selection.** This is similar to the binary preference based merging in [37]. For each user  $i$ , we only consider the condition with the highest preference  $\gamma$  score.

We note that although the proportional selection strategy makes the recommended list of threads more diverse in nature, the combination score-based selection obtains superior results on our datasets.

## 4 EXPERIMENTS

To answer important questions about our model, we consider specific experimental settings. We describe the main results of our study after detailing the datasets, evaluation metrics and baselines, respectively.

**Datasets.** We obtained two large real-world consumer health forum datasets to validate our model:

**PatientsLikeMe (PLM)**<sup>1</sup>: We crawled PLM in July 2015. Along with the threads, we also crawl user profile pages. User profile pages contain a text section called ‘About Me’. We concatenated this with a particular user’s past posts and consider for use as a user document, as described in Section 3. We also find a section called ‘Conditions’ — we use it during the first stage of our pipeline as described in Section 3. We filter out all the threads that belong to a category not specific to any condition, e.g., ‘Technical Help’, ‘Member Feedback Forum’, ‘Research Forum’. This anonymized dataset will be made public to aid others in replicating our results.

**HealthBoards (HBD)**<sup>2</sup>: We use the publicly available HealthBoards dataset<sup>6</sup>. Unlike the PLM dataset, there is no ‘About Me’ section in HBD. We collate all the posts made by a user and treat them as the user document. As in PLM, we ignore generic categories of threads such as ‘Family’, ‘Support’, ‘Healthcare’, ‘General’.

We remove all stop words and select the top 8,000 words based on TF-IDF scores [29]. The TF-IDF computation was done only on

**Table 2: Statistics on our health forum datasets. ‘Avg P:T’ and ‘Avg C:U’ denote the average number of posts in a thread and conditions reported by a user, respectively.**

Dataset	# Users	# Threads	# Posts	Avg P:T	# Distinct Conditions	Avg C:U
PLM	3,385	51,172	182,019	3.6	1,115	4.82
HBD	127,903	155,863	716,744	4.6	235	4.01

the training data for all the experiments. Similar to other recommendation works, we remove users with few interactions; here, with less than three thread interactions. We summarize some statistics on our datasets and their user reported conditions in Table 2.

**Metrics.** Similar to [33], we do not rely on precision, as our ground truth is only implicit feedback. Samples with negative values could be threads that the user had not seen as well as those where the user explicitly did not interact with. As such, we use the following three metrics to assess recommendation quality:

**Recall@M** considers how many top- $M$  threads were actually interacted by the user (higher is better). The recall for the entire system can be summarized as the average recall value for all users.

**Mean Reciprocal Rank (MRR)** indicates where in the ranking the first relevant item is returned by the system, averaged over all users. This measures the ability of the system to return a relevant thread at the top of the ranking. Let  $r_i$  be the rank of the highest ranking relevant thread for a target user  $i$ , then MRR is just the reciprocal rank, averaged over all target users,  $N_U$ :

$$MRR = \frac{1}{N_U} \sum_{i=1}^{N_U} \frac{1}{r_i}.$$

**Normalized Discounted Cumulative Gain (nDCG)** is well suited for evaluation of recommendation system, as it rewards relevant items in the top ranked results more heavily than those ranked lower. nDCG is computed as:

$$nDCG_i = Z_i \sum_{j=1}^R \frac{2^{r(j)} - 1}{\log(1 + j)},$$

where  $Z_i$  is a normalization constant calculated so that a perfect ordering would obtain nDCG of 1; and each  $r(j)$  is an integer relevance level (for our case,  $r(j) = 1$  and  $r(j) = 0$  for relevant and irrelevant recommendations, respectively) of result returned at the rank  $j$  ( $j = 1, \dots, R$ ). Then,  $nDCG_i$  is averaged over all our target users. In this work, we use  $nDCG@R$  ( $R = 5, 10$ ) for evaluation where  $R$  is the number of top- $R$  threads recommended by our approaches.

**Baselines.** We compare our instantiated IATM+JNCTR with six baselines. Our complete model uses four signals overall: the user-thread interaction history, textual content of threads, user profiles, and the user-reported conditions. We chose baselines for their competitiveness, recency, and use of particular signals common to our model. Comparing among the various models can also be seen as assessing how important each form of evidence is in achieving quality recommendation. Table 3 summarizes how the baselines account for some subset of the evidence accounted for by our model.

<sup>6</sup><http://resources.mpi-inf.mpg.de/impact/peopleondrugs>



**Table 3: Signals considered by comparative methods.**

Method	User-Thread Interaction	User Docs	Thread Docs	User Reported Conditions
1. CF (NMF) [13]	✓			
2. AT [28]		✓	✓	
3. CTR [33]	✓		✓	
4. IATM		✓	✓	✓
5. CAR [27]	✓			✓
6. AT + JNCTR	✓	✓	✓	
7. IATM + JNCTR	✓	✓	✓	✓

1. **Collaborative Filtering (CF)**: We use non-negative matrix factorization-based (NMF) collaborative filtering [13] as one of comparative approaches.

2. The **Author-Topic Model (AT)** learns the author–topic distributions [28]. We estimate the thread–topic distributions from the learned word–topic distributions. These can be interpreted as the user and thread latent topic matrices for our task, respectively. We empirically set the hyperparameters  $\alpha = 0.1$ ,  $\beta = 0.01$ , and the number of iterations and latent topics to 2,000 and 50, respectively.

3. **Collaborative Topic Regression (CTR)** [33] is the basis for JNCTR, but without the individual interest- (condition-) specific instances, and with LDA (instead of IATM) as the input. We find that the parameter settings,  $b = 0.01$ ,  $\lambda_u = 0.01$ ,  $\lambda_v = 0.1$ , give the best results in our work.

4. **IATM alone** can also generate recommendations. Unlike the configuration described in Section 3.1, we consider the entire user- and thread-topic matrices obtained from IATM, and use them for the recommendation task. We empirically set the hyperparameters  $\beta=0.1$ , and  $\alpha_u=\alpha_v=5$ , and set the number of topics for each medical condition to 3 and the number of iterations to 2,000.

5. **Context Aware Recommendation (CAR)** uses Factorization Machines for the recommendation [27]. We use the libFM package (www.libfm.org). We create the test set following the sampling policy described in [19]. This models user-reported conditions as the context for each interaction.

6. **AT + JNCTR**: In this experiment, we replace the first stage of our pipeline with Author-Topic model (AT). This model directly contrasts with our full model to see the comparative difference when using IATM over AT.

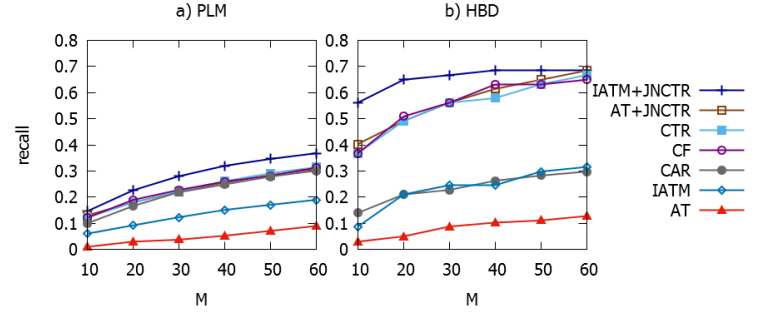
For our IATM+JNCTR model, we obtain the optimized matrices from the second stage of the pipeline and obtain the final prediction after combining the ratings as described in Section 3.3. We keep the optimal settings for IATM. For JNCTR, we empirically optimize the hyperparameters,  $\lambda_u = 0.01$ ,  $\lambda_v = 0.1$ , and  $b = 0.1$ , which are estimated from grid search.

**In-Matrix Setting:** We report results using 5-fold cross validation. For users that interact with 5+ threads, we split 80% of the threads to training, and assess how well the methods identify the remaining 20% test. Users with fewer than five interactions always appear in the training set. For these main results, we use a *warm-start* (i.e., in-matrix) setting, ensuring that each user or thread in the test set has been observed at least once in the training set.

**Temporal Setting:** Apart from the 5-fold cross validation, where a randomly selected 20% split is used as test, we also report results for a temporal experiment. In this setting, for each user, the last 20% of her interacted threads are kept for test. Similar to the in-matrix

**Table 4: MRR and nDCG scores obtained by in-matrix prediction. “\*” denotes the difference between the best baseline (“3. CTR”) and our methods (“6. AT+JNCTR”) and (“7. IATM+JNCTR”) is significant for  $p < 0.005$ .**

Method	PatientsLikeMe (PLM)			HealthBoards (HBD)		
	MRR	nDCG		MRR	nDCG	
		@5	@10		@5	@10
1. CF (NMF) [13]	0.171	0.071	0.091	0.179	0.180	0.194
2. AT [28]	0.051	0.019	0.025	0.023	0.033	0.036
3. CTR [33]	0.175	0.075	0.096	0.186	0.178	0.193
4. IATM	0.101	0.039	0.050	0.113	0.059	0.064
5. CAR [27]	0.151	0.065	0.084	0.092	0.081	0.087
6. AT+JNCTR	0.176	0.082	0.103	0.213*	0.221*	0.254*
7. IATM+JNCTR	0.183	0.083	0.107*	0.327*	0.329*	0.361*



**Figure 5: Recall scores at various  $M$  top ranks, across the a) PLM and b) HBD datasets.**

setting, we make sure that all the user and threads appear at least once in the training data.

**Results.** Figure 5 shows the recall@ $M$  ( $M = 10, 20, \dots, 60$ ) for comparative methods for the in-matrix setting. In both datasets, the IATM+JNCTR pairing achieves the highest recall. CTR and CF give comparable performance, which is consistent with [33]. We observe that, in the HBD dataset, while the recall scores converge when  $M \geq 60$ , our IATM+JNCTR method outperforms the others with a significant margin for lower values of  $M$  (i.e., more important ranks). This indicates that our pipeline can highly rank relevant items in the recommendation list. This phenomena is also depicted in Table 4 where we present the MRR, nDCG@{5, 10} scores for all methods. The AT model alone works poorly in both datasets, indicating that only considering user and thread documents is insufficient. However, when paired with JNCTR (namely, AT+JNCTR), AT improves significantly, which factors in the user–item interaction. With IATM+JNCTR performing best, we conclude that considering the user documents and the user reported interests enhances the user–item interaction history for best recommendation accuracy. We perform a paired t-test to verify whether the obtained results are statistically significant or not. As shown in Table 4, we observe that in the HBD dataset our full IATM+JNCTR outperforms all the other baselines in both MRR and nDCG@{5, 10}. In PLM, our pipeline outperforms all others except CTR, and AT+JNCTR as they are statistically comparable in MRR.

Table 5 shows the recall@60, MRR, and nDCG@{5, 10} scores in the temporal setting experiment. We find a similar trend in recall scores at various top ranks compared to the in-matrix setting.

**Table 5: Recall@60, MRR, and nDCG@{5, 10} scores for temporal prediction. “\*” denotes the difference between the best baseline (“3. CTR”) and our methods (“6. AT+JNCTR”) and (“7. IATM+JNCTR”) is significant for  $p < 0.005$ .**

Method	PatientsLikeMe (PLM)				HealthBoards (HBD)			
	Recall@60	MRR	nDCG		Recall@60	MRR	nDCG	
			@5	@10			@5	@10
1. CF(NMF) [13]	0.261	0.105	0.067	0.080	0.483	0.166	0.136	0.160
2. AT [28]	0.092	0.043	0.014	0.018	0.114	0.021	0.027	0.032
3. CTR [28]	0.303	0.110	0.066	0.085	0.517	0.211	0.178	0.205
4. IATM	0.183	0.062	0.035	0.044	0.286	0.142	0.055	0.064
5. CAR [27]	0.287	0.087	0.056	0.072	0.348	0.183	0.132	0.152
6. AT+JNCTR	0.326	0.115	0.069	0.088	0.549*	0.256*	0.176	0.202
7. IATM+JNCTR	<b>0.363*</b>	<b>0.134*</b>	<b>0.073*</b>	<b>0.095*</b>	<b>0.674*</b>	<b>0.340*</b>	<b>0.289*</b>	<b>0.318*</b>

**Table 6: MRR and nDCG scores obtained by all relevant methods for out-of-matrix (thread) recommendation. “\*” denotes the difference between the best baseline (“3. CTR”) and our methods (“6. AT+JNCTR”) and (“7. IATM+JNCTR”) is significant for  $p < 0.005$ . (Note that CF and CAR do not work in this setting.)**

Method	PatientsLikeMe (PLM)			HealthBoards (HBD)		
	MRR	nDCG		MRR	nDCG	
		@5	@10		@5	@10
2. AT [28]	0.021	0.022	0.027	0.025	0.029	0.036
3. CTR [33]	0.112	0.058	0.074	0.131	0.098	0.114
4. IATM	0.086	0.057	0.073	0.094	0.068	0.081
6. AT+JNCTR	0.113	0.078*	0.101*	0.164*	0.146*	0.172*
7. IATM+JNCTR	<b>0.135*</b>	<b>0.085*</b>	<b>0.112*</b>	<b>0.221*</b>	<b>0.234*</b>	<b>0.263*</b>

We observe that IATM+JNCTR outperforms the others with statistical significance in this setting. Unlike the in-matrix setting, AT+JNCTR achieves statistically significant improvement only in the HBD dataset in MRR and recall@60 in this case. This indicates the robustness of our model in both the randomized 5-fold, and temporal settings.

## 5 DISCUSSION

Aside from the main in-matrix results, there are several important research questions that merit deeper investigation. We mentioned that the IATM+JNCTR pipeline handles cold start, due to the incorporation of prior knowledge. Our research questions (RQ) are:

- RQ1: How does it perform with cold-start *documents* (i.e., newly-introduced threads)?
- RQ2: What about cold-start *users* (i.e., newly-joined members)?
- RQ3: How well can the IATM+JNCTR pairing explain its recommendations?
- RQ4: How well does the IATM+JNCTR pairing capture users’ interests for specific symptoms and treatments?
- RQ5: Does it actually recover the users’ implicit interest in specific conditions?

In the following, we answer each of these research questions.

**RQ1: Out-of-matrix Thread Recommendation.** It is important for a newly-posted thread (usually some form of question) to receive quality answers. To simulate this, we partition all threads evenly among five folds. For each fold, we form a submatrix from the threads which are not within this fold and the corresponding users. We treat this submatrix as training data and learn user–topic and thread–topic distributions from the same. We ensure that none of the in-fold threads occurs in the training data. In the test phase, for all the in-fold threads, we consider the textual content of the query and

**Table 7: MRR and nDCG scores obtained by recommending threads to out-of-matrix users. “\*” denotes the difference between the best baseline (“4. IATM”) and our methods (“6. AT+JNCTR”) and (“7. IATM+JNCTR”) is significant for  $p < 0.005$ . (Note that CF, CAR, and CTR do not work in this setting.)**

Method	Recall@60	MRR	nDCG	
			@5	@10
2. AT [28]	0.062	0.101	0.015	0.020
4. IATM	0.109	0.199	0.036	0.045
6. AT + JNCTR	0.110	0.157	0.047*	0.059*
7. IATM+JNCTR	<b>0.146*</b>	<b>0.297*</b>	<b>0.062*</b>	<b>0.080*</b>

user profile (i.e., “About Me” text and user-reported conditions) of the user to estimate the topic distributions from the model learned during training. The task is to correctly predict the set of in-fold threads each user will actually interact with.

Table 6 shows the MRR and nDCG@{5, 10} obtained by the relevant comparative methods for this out-of-matrix thread recommendation task. IATM+JNCTR again achieves the best scores. In general, performance degrades compared to the in-matrix setting shown in Table 4, due to the harder nature of the task. It is interesting that prior evidence in the form of user profiles and the user-reported conditions significantly help, in the absence of observed user–item interactions. Examining the relative performance of IATM, CTR, and AT+JNCTR, we argue that the user-reported conditions further improve recommendation accuracy, compared against the evidence from user profiles.

**RQ2: Thread Recommendation for Out-of-matrix Users.** We consider the scenario when a new user joins the forum. The aim is to recommend relevant threads to her based on her user profile and reported condition. We simulate this by grouping all the users with “About Me” text, and at least one reported condition among five folds. For fair assessment in each fold, we ensure that no users in the test appear in the training sub-matrix. Other settings are similar to the previous case. Note that there is no user–thread interaction history for the users under test, rendering the CF, CAR, and CTR methods unable to do recommendation. We perform this experiment only on PLM, as HBD’s user profiles do not contain “About Me” text.

We present the relative performance of all the applicable methods in Table 7. Along with MRR, and nDCG@{5, 10}, we also show the recall@60 in this case. We find that the overall recall is lower (0.146) compared to that of in-matrix setting (0.368) – a similar trend is observed in case of nDCG as well. Interestingly, the MRR scores are improved. We analyzed the recommended threads and observed that our model was able to correctly guess the first relevant thread within the top 5 ranks for 60% of the test users. From the relative performances of IATM, and IATM+JNCTR across Tables 4 and 7, we argue that IATM plays an important role in the recommendation process in the absence of user–thread interaction history by effectively capturing the additional user-provided context.

**RQ3: Transparency of Recommended Threads.** While CF-based recommendation algorithms work well in terms of prediction accuracy, their latent factors make it difficult to justify the recommendation to the user [8, 39]. User participation (measured through metrics like clickthrough rate) alleviates this difficulty if items are recommended to a user with semantic explanation. Our



**Table 8: Recommended threads for sample users. The explaining condition chosen by IATM+JNCTR is bolded.**

Recommended Thread	Candidate Conditions
I have known I have lupus for a .. getting red dots over my face..Any tips..?	<b>1. Systemic Lupus Erythematosus</b> 2. Spinal Stenosis
I have degenerative spine, spinal stenosis, severe scoliosis...	<b>1. Spinal Stenosis</b> 2. Systemic Lupus Erythematosus
Are there more people with ALS who don't get colds anymore?	<b>1. ALS</b> 2. Dysautonomia
anybody stop rytary and go back to stalevo or another med?	<b>1. Parkinson's Disease</b> 2. Vitamin B12 Deficiency

IATM+JNCTR adds transparency by providing users with the context when recommending a thread. We learn the user-condition distribution ( $\gamma$ ) in the first phase of our model. It is used downstream to combine recommended threads from different condition-specific sub-spaces. While presenting the combined list of threads to the user, the recommendation system can disclose which sub-space a particular thread belongs to. When a thread exists in multiple sub-spaces, we can select condition  $c = \text{argmax}_c \gamma_{ic}$  and present it as the context recommending it to a user  $i$ , as “recommended due to your interests in  $c$ ”. Table 8 presents sample threads recommended by our pipeline. Note that it can identify the context (*i.e.*, the condition) for recommending the threads.

#### RQ4: Significance of Discovered Symptoms and Treatments.

A challenge in achieving quality recommendation is to appropriately learn the topics even when overlapping words appear among several conditions. Our IATM+JNCTR leverages the user-reported conditions and learns the appropriate word distribution. Table 9 shows the top words discovered by our model for several conditions. Note that, while there are few common words across conditions, — *ALS*, *Epilepsy*, and *Multiple Sclerosis* all list *brain* among top keywords — our method is able to distinguish among these conditions.

It is important to analyze the condition-specific topics learned by our approach. Since different users express various levels of interest towards particular aspects (symptoms or treatments) of a condition, it is necessary to capture these aspects to achieve quality recommendation. Table 10 presents some condition-specific topics discovered by our pipeline. From simple observation, one can see correspondences for *Diabetes*, Topic 0 lists affected body parts and associated difficulties, Topic 1 discusses diets, and Topic 2 relates to human physiology — having words such as *blood*, *insulin*. In the scenario where a user has *Diabetes* and is interested in managing the condition through her diet, our model can recommend threads that would match her interests at this topical level.

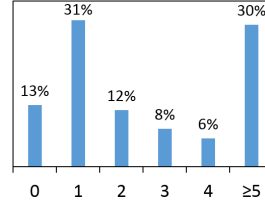
In the case of serious terminal diseases, such as *cancer*, psychological and spiritual words, such as *god* and *luck*, appear in the top words as topics. Consider the following posts by cancer patients:

“Would like to connect with anyone who has ovarian cancer...truly think faith plays a major part in healing and also a positive outlook...I wouldn't wish this disease on anyone”  
 “I will pray for you...I'm here for you to reach out to if you need support”.

Users with similar conditions often participate in health forums for such emotional support, rather than informational need [21, 30, 35]. Our model can capture this phenomenon as a topic for certain conditions.

**Table 9: Example of the top words for certain medical conditions learned by our IATM+JNCTR model.**

Eye & Vision	ALS	Parkinson's Disease	Diabetes	Cancer	Epilepsy	Multiple Sclerosis
eye	als	neurologist	carb	cancer	seizure	copaxone
vision	reflexes	pd	sugar	chemo	seizures	lesions
drops	muscle	nervous	insulin	radiation	keppra	mri
cataracts	amyotrophic	tremors	glucose	cells	hope	immune
red	nervous	scan	levels	kidney	meds	brain
reduce	irregular	shaking	eat	scan	brain	help
laser	brain	facial	diet	prayers	care	celebrex
ophthalmologist	feel	control	exercise	god	pain	scoliosis
omeprazole	weight	tissue	test	luck	alcohol	breathing



(a)

# held-out conditions	Perfect recall
1	0.64
2	0.45
3	0.39

(b)

**Figure 6: (a) Distribution of user reported medical conditions in PLM. About 13% users report 0 condition. (b) Unreported conditions recovered by the IATM. Perfect recall denotes to the fraction of cases where it can recover all the held-out conditions.**

**RQ5: Predicting Implicit Conditions.** In IATM, recall that we sample both interest (condition) and topic (symptom or treatment) for each word as described in Section 3.1. As a result, along with word- and thread-topic distribution, the model also learns the user-condition distribution  $\gamma$ . Although it is used later on for recommendation in our pipeline, it can also serve to predict implicit conditions. For an example culled from our dataset, a user reports *Multiple Sclerosis* as a condition he is afflicted with in his profile. However, from all of the posts that he interacts with, our model estimates the  $\gamma$  distribution to be {*Multiple Sclerosis* : 0.8, *Asthma* : 0.2}. In this case, the unreported, implicit condition “*Asthma*” is predicted by our model. We argue that this is a desirable nature of our model. In the PatientsLikeMe dataset, we found 430 users (13% of all users) do not report any condition, as shown in Figure 6a.

To quantitatively evaluate the capability of our model to predict the missing condition, in a separate experiment, we omit 1 to 3 conditions for each user for 1/5 of the users during training. We train our model and obtain the  $\gamma$  distribution for all users. We then evaluate how many cases our model can recover all of the missing conditions, *i.e.*, whether it achieves perfect recall. Figure 6b reports our findings, indicating that our model can correctly predict single missing conditions in over 60% of cases. Unsurprisingly, performance degrades as the number of missing condition increases, but gradually, for three missing conditions, it can yield perfect recall in 39% cases.

## 6 CONCLUSION

We have systematically investigated how to best utilize each user’s participation in online health forums to recommend relevant threads. Our IATM-JNCTR model leverages the user-reported clinical conditions to distinguish lexically similar yet different threads, additionally accounting for each user’s specific, latent preferences for particular treatments and symptoms. In experiments spanning both warm- and cold-start scenarios involving both users and threads,

**Table 10: Example of condition-specific topics (i.e., symptoms and treatments) discovered by our IATM+JNCTR model.**

Diabetes			Parkinson's Disease			ALS			Multiple Sclerosis			Cancer		
Topic 0	Topic 1	Topic 2	Topic 0	Topic 1	Topic 2	Topic 0	Topic 1	Topic 2	Topic 0	Topic 1	Topic 2	Topic 0	Topic 1	Topic 2
legs	carbs	blood	neurologist	feel	shaking	leg	pain	disc	brain	warm	instruction	cancer	treatment	prayer
shake	sugar	insulin		help	cold	heart	feel	cervical	feeling	burning	breathing	lump	chemo	god
feet	eat	high	mri	hope	tension	muscles	issues	spine	painful	lesions	remembering	lymph	radiation	afraid
walking	diet	glucose	disorders	people	dizziness	body	help	brain	walker	harder	recall	growth	stage	doctor

our framework demonstrated significant improvements over the current state-of-the-art methods. Deeper analysis reveals that IATM-JNCTR's modeling of latent conditions and user profiles are key to its competitive performance.

As our framework is general and language independent, we believe that it could be useful in other domains, including community question answering and scholarly paper recommendation. We hope the research community will apply our model to other scenarios to validate its modeling capabilities.

## REFERENCES

- [1] D. Agarwal and B.-C. Chen. fLDA: Matrix Factorization through Latent Dirichlet Allocation. In *Proc. of WSDM '10*, pages 91–100, 2010.
- [2] T. Bansal, M. Das, and C. Bhattacharyya. Content Driven User Profiling for Comment-Worthy Recommendations of News and Blog Articles. In *Proc. of RecSys '15*, pages 195–202, 2015.
- [3] A. Batenburg and E. Das. Emotional Coping Differences Among Breast cancer Patients from an Online Support Group: A Cross-Sectional Study. *Journal of Medical Internet Research (JMIR)*, 16(2):e28, 2014.
- [4] D. M. Blei, A. Y. Ng, and M. I. Jordan. Latent Dirichlet Allocation. *Journal of Machine Learning Research (JMLR)*, 3:993–1022, 2003.
- [5] L. Charlin, R. S. Zemel, and H. Larochelle. Leveraging User Libraries to Bootstrap Collaborative Filtering. In *Proc. of KDD '14*, pages 173–182, 2014.
- [6] X. Chen, M. Zhou, and L. Carin. The Contextual Focused Topic Model. In *Proc. of KDD '12*, pages 96–104, 2012.
- [7] K. Halder, L. Poddar, and M.-Y. Kan. Modeling Temporal Progression of Emotional Status in Mental Health Forum: a Recurrent Neural Net Approach. In *Proc. of WASSA, EMNLP '17*, 2017.
- [8] X. He, T. Chen, M.-Y. Kan, and X. Chen. TriRank: Review-aware Explainable Recommendation by Modeling Aspects. In *Proc. of CIKM '15*, pages 1661–1670, 2015.
- [9] Z. He, M. S. Park, and Z. Chen. UMLS-Based Analysis of Medical Terminology Coverage for Tags in Diabetes-Related Blogs. *ICConference 2016 Proceedings*, 2016.
- [10] S. Kanthawala, A. Vermeesch, B. Given, and J. Huh. Answers to Health Questions: Internet Search Results Versus Online Health Community Responses. *Journal of Medical Internet Research (JMIR)*, 18(4):e95, 2016.
- [11] A. Karatzoglou, X. Amatriain, L. Baltrunas, and N. Oliver. Multiverse Recommendation: N-dimensional Tensor Factorization for Context-aware Collaborative Filtering. In *Proc. of RecSys '10*, pages 79–86, 2010.
- [12] S. Kim. An Exploratory Study of User-centered Indexing of Published Biomedical Images. *Journal of the Medical Library Association (JMLA)*, 101(1):73–76, 2013.
- [13] D. D. Lee and H. S. Seung. Algorithms for Non-negative Matrix Factorization. In *Proc. of NIPS '01*, pages 556–562, 2001.
- [14] J. Li, Y.-L. Theng, and S. Foo. Predictors of Online Health Information Seeking Behavior: Changes between 2002 and 2012. *Health Informatics Journal*, 22(4):804–814, 2016.
- [15] J. Lin, K. Sugiyama, M.-Y. Kan, and T.-S. Chua. Addressing Cold-Start in App Recommendation: Latent User Models Constructed from Twitter Followers. In *Proc. of SIGIR '13*, pages 283–292, 2013.
- [16] R. Magnezi, D. Grosberg, I. Novikov, A. Ziv, M. Shani, and L. S. Freedman. Characteristics of Patients Seeking Health Information Online via Social Health Networks versus General Internet Sites: A Comparative Study. *Informatics for Health and Social Care*, 40(2):125–138, 2015.
- [17] J. D. McAuliffe and D. M. Blei. Supervised Topic Models. In *Proc. of NIPS '07*, pages 121–128, 2008.
- [18] A. Meier, J. E. Lyons, G. Frydman, M. Forlenza, and K. B. Rimer. How Cancer Survivors Provide Support on Cancer-Related Internet Mailing Lists. *Journal of Medical Internet Research (JMIR)*, 9(2):e12, 2007.
- [19] T. V. Nguyen, A. Karatzoglou, and L. Baltrunas. Gaussian Process Factorization Machines for Context-aware Recommendations. In *Proc. of SIGIR '14*, pages 63–72, 2014.
- [20] L. Nie, Y.-L. Zhao, M. Akbari, J. Shen, and T.-S. Chua. Bridging the Vocabulary Gap between Health Seekers and Healthcare Knowledge. *IEEE Transactions on Knowledge and Data Engineering (TKDE)*, 27(2):396–409, 2015.
- [21] H. J. Oh, C. Lauckner, J. Boehmer, R. Fewins-Bliss, and K. Li. Facebooking for Health: An Examination into the Solicitation and Effects of Health-Related Social Support on Social Networking Sites. *Computers in Human Behavior*, 29(5):2072–2080, 2013.
- [22] A. Omari, D. Carmel, O. Rokhlenko, and I. Szpektor. Novelty based Ranking of Human Answers for Community Questions. In *Proc. of SIGIR '16*, pages 215–224, 2016.
- [23] J. Palotti, L. Goeuriot, G. Zuccon, and A. Hanbury. Ranking Health Web Pages with Relevance and Understandability. In *Proc. of SIGIR '16*, pages 965–968, 2016.
- [24] J. S. Pedro and A. Karatzoglou. Question Recommendation for Collaborative Question Answering Systems with RankSLDA. In *Proc. of RecSys '14*, pages 193–200, 2014.
- [25] L. Poddar, W. Hsu, and M. L. Lee. Author aware Aspect Topic Sentiment Model to Retrieve Supporting Opinions from Reviews. In *Proc. of EMNLP '17*, 2017.
- [26] D. Ramage, D. Hall, R. Nallapati, and C. D. Manning. Labeled LDA: A Supervised Topic Model for Credit Attribution in Multi-labeled Corpora. In *Proc. of EMNLP '09*, pages 248–256, 2009.
- [27] S. Rendle. Factorization Machines with libFM. *ACM Transactions on Intelligent Systems and Technology (TIST)*, 3(3):Article No. 57, 2012.
- [28] M. Rosen-Zvi, T. Griffiths, M. Steyvers, and P. Smyth. The Author-Topic Model for Authors and Documents. In *Proc. of UAI '04*, pages 487–494, 2004.
- [29] G. Salton and M. J. McGill. *Introduction to Modern Information Retrieval*. McGraw-Hill, 1983.
- [30] L. Schnitzler, S. K. Smith, H. L. Shepherd, J. Shaw, S. Dong, D. M. Carpenter, F. Nguyen, and H. M. Dhillon. Communication During Radiation Therapy Education Sessions: The Role of Medical Jargon and Emotional Support in Clarifying Patient Confusion. *Patient Education and Counseling*, 100(1):112–120, 2017.
- [31] E. Shmueli, A. Kagan, Y. Koren, and R. Lempel. Care to Comment?: Recommendations for Commenting on News Stories. In *Proc. of WWW 2012*, pages 429–438, 2012.
- [32] M. D. Smucker, D. Kulp, and J. Allan. Dirichlet Mixtures for Query Estimation in Information Retrieval. Technical Report IR-445, Center for Intelligent Information Retrieval, University of Massachusetts, Amherst, 2005.
- [33] C. Wang and D. M. Blei. Collaborative Topic Modeling for Recommending Scientific Articles. In *Proc. of KDD '11*, pages 448–456, 2011.
- [34] J. Wang, X. Hu, Z. Li, W. Chao, and B. Hu. Learning to Recommend Questions Based on Public Interest. In *Proc. of CIKM '11*, pages 2029–2032, 2011.
- [35] Y.-C. Wang, R. Kraut, and J. M. Levine. To Stay or Leave?: The Relationship of Emotional and Informational Support to Commitment in Online Health Support Groups. In *Proc. of CSCW '12*, pages 833–842, 2012.
- [36] S. Williamson, C. Wang, K. A. Heller, and D. M. Blei. The IBP Compound Dirichlet Process and its Application to Focused Topic Modeling. In *Proc. of ICML '10*, pages 1151–1158, 2010.
- [37] B. Xu, J. Bu, C. Chen, and D. Cai. An Exploration of Improving Collaborative Recommender Systems via User-Item Subgroups. In *Proc. of WWW '12*, pages 21–30, 2012.
- [38] M. Zhang, J. Tang, X. Zhang, and X. Xue. Addressing Cold Start in Recommender Systems: A Semi-supervised Co-training Algorithm. In *Proc. of SIGIR '14*, pages 73–82, 2014.
- [39] Y. Zhang, G. Lai, M. Zhang, Y. Zhang, Y. Liu, and S. Ma. Explicit Factor Models for Explainable Recommendation based on Phrase-level Sentiment Analysis. In *Proc. of SIGIR '14*, pages 83–92, 2014.
- [40] T. C. Zhou, M. R.-T. Lyu, I. King, and J. Lou. Learning to Suggest Questions in Social Media. *Knowledge and Information Systems (KAIS)*, 43(2):389–416, 2015.