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# Human-Centered and Interactive: Expanding the Impact of Topic Models

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**Abstract**

Statistical topic modeling is a common tool for summarizing the themes in a document corpus. Due to the complexity of topic modeling algorithms, however, their results are not accessible to non-expert users. Recent work in *interactive topic modeling* looks to incorporate the user into the inference loop, for example, by allowing them to view a model then update it by specifying important words and words that should be ignored. However, the majority of interactive topic modeling work has been performed without fully understanding the needs of the end user and does not adequately consider challenges that arise in interactive machine learning. In this paper, we outline a subset of interactive machine learning design challenges with specific considerations for interactive topic modeling. For each challenge, we propose solutions based on prior work and our own preliminary findings and identify open questions to guide future work.

**Author Keywords**

Topic modeling, machine learning, mixed-initiative user interfaces, user studies.

**ACM Classification Keywords**

H.5.2. Information interfaces and presentation (e.g., HCI): User-centered design.

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#	Topic Words
1	mr ms back time home day people year years life family don man night told father didn mother left
2	mr police court case law judge justice lawyer yesterday ms federal lawyers department trial death investigation state man officials
3	game season team coach games players play year league football points giants bowl teams player field won back time
4	mr bush president house democrats senator republican senate democratic congress political white party Iraq campaign Clinton administration war committee
5	show mr television car million series ford corrections article news year fox cars radio executive ms viewers toyota nbc

Table 1: Five of the 20 topics of a model generated by LDA for 7,156 New York Times articles published in January, 2007. These topics, displayed as ordered lists of words, exemplify some common news themes, such as politics, sports, and crime.

## Introduction

A persistent problem in today’s data-rich society is how to support people in understanding the vast amount of text available about a particular subject or from a particular source. A financial analyst, for example, may want to glean public sentiment toward a company by quickly reviewing the top themes discussed about it in recent news articles. A useful tool in this case is *statistical topic modeling*, which is a method for automatically organizing a corpus into themes, or *topics* [1][2][3]. The resulting model is typically presented as a set of topics displayed as ordered lists of words and the set of documents associated to each topic.

Topic modeling supports overall understanding of the corpus—by exposing its topics to the user—and directed exploration of documents—by allowing users to ‘browse by topic’. *Latent Dirichlet Allocation* (LDA) [4] is a common statistical topic modeling algorithm that models each document as a distribution of topics and each topic as a distribution of words. LDA takes a “bag of words” approach, ignoring word order in the documents. As an example, Table 1 shows 5 of the 20 topics of a model generated from running LDA on 7,156 New York Times articles published in January, 2007. These topics cover news themes including crime (Topic 2), politics (Topic 4), and sports (Topic 3).

Topic modeling has traditionally been geared toward expert users. Configuring a topic modeling algorithm often requires an understanding of the underlying algorithm and corpus. Users must set not only the number of topics that should be discovered, but also control sometimes inscrutable parameters that dictate advanced concepts such as the per-document topic distribution and per-topic word distribution [5][6].

Even after the initial run, expert users typically perform a substantial amount of tuning as they notice unexpected issues, such as adding words to a global “stop words” list or running additional pre-processing to clean up the ingested documents [7]. For example, Topic 1 of Table 1 contain low-information words such as “ms” and “mr” that an expert user would likely add to the stop words list prior to re-running the algorithm. Also, due to the non-deterministic, unsupervised nature of topic modeling, even with the same initial configuration, each run of the algorithm may produce a model that looks completely different from the others [8].

*Interactive topic modeling* (ITM) allows a user to interactively refine the model as it is being generated and was proposed to make topic models more usable and accessible even to non-expert users [9]. Andrzejewski et al. [10] encode refinements as ‘must-link’ and ‘cannot-link’ relationships from domain experts. Our work [9] extends these to positive and negative correlations, allowing the user to specify words that are important to or should be ignored in a topic. Follow-up work has implemented other refinements such as merging and splitting of topics [11][12] as well as reassigning and removing documents from topics [13]. While these advances are promising, they have largely been driven by assertions of what a user may wish to do. Instead, explicit consideration of the needs of the end user is critical in the design phase of an effective system [14].

In this position paper, we outline several challenges from the interactive machine learning literature that need to be addressed for topic modeling to achieve the broad impact that it has the potential to make. We

examine each challenge in turn, proposing solutions based on prior work and our own preliminary findings and identifying open research questions. These challenges include the need for formative study of what non-expert users expect from ITM, faster (more interactive) model updates and user feedback, improved means of communicating complex model changes to the user across iterations, and mixed-initiative support to aid the refinement process.

### **Challenge 1: Reassessing User Expectations**

For topic models to be broadly accessible, non-expert users must be able to easily configure, modify, and adapt the models to their needs. This goal is a primary motivating factor for prior work in ITM, but earlier efforts have failed to properly anchor their approach in formative user studies with actual non-expert users [9][12][11][13]. Instead, early ITM interfaces were informed by the algorithm developers' assertions and predictions about what would be appropriate refinements; accordingly, the algorithms were designed to support these refinements. For example, our original ITM interface (Hu et al. [9]) included an option to add topic words to a global stop words list. Although this seems like a reasonable refinement for someone familiar with topic modeling, non-expert users are unlikely to know what a stop words list is or how adding a word to it will affect the topics and overall model.

To more thoroughly assess user expectations for ITM, one thread of our current work focuses on understanding user needs and desires independent of how existing ITM algorithms work. We recently conducted a formative study on how users without prior knowledge of topic modeling understand, assess, and wish to refine topics. The study included a set of

interviews with ten users to elicit open-ended suggestions for the types of refinement operations users want when interacting with a topic model. Then, to quantitatively rank the suggested refinements by their use and subjective utility, we asked crowdsourced participants to use the refinements to improve individual topics.

Though this study is not yet published, preliminary results suggest that there are disconnects between current ITM implementations and user expectations. For example, none of the interviewed users specified 'must' or 'must-not' connections between words (as supported in [9]). Moreover, two of the top four identified refinements, "merge words" and "change word order", are not supported by existing ITM interfaces. These findings, though preliminary, demonstrate the importance of taking the user into account earlier in the algorithm design process. We expect to uncover implications for both user interface and algorithm design through this line of work.

### **Challenge 2: Combatting Algorithm Latency**

Algorithm latency is an important consideration in the design of any mixed-initiative interface, which must support rapid interaction cycles [14] to minimize attention loss [15] and reduce short-term memory load [16]. An effective ITM system must provide immediate feedback after each refinement specified by the user. Unfortunately, updating a topic model based on a user-specified refinement is not instantaneous. The inference time depends on the number of topics and size of the vocabulary. In our work [9], for example, updating the model took from 5 to 50 seconds, a non-trivial amount of time from the user's perspective. To provide an efficient and truly interactive experience that supports

exploration, experimentation, and undo actions by the user, this latency must be addressed.

We propose two parallel approaches. First, we need more efficient ITM algorithms. While prior ITM work has been guided by this concern [9], additional enhancements or a redesign is required to further reduce the model update time. One potential solution is to limit the extent to which changes propagate during the inference process, which would speed labeling time and have the added benefit that the model should appear more stable to the user across iterations (see Challenge 3). Second, if algorithmic improvements are insufficient, intermediate feedback should be provided. This feedback could range from superficially changing the user's view of the model while waiting for the ITM algorithm to run (e.g., adding a new word to the UI representation of a topic) to more abstract possibilities such as providing an estimate of the extent to which a proposed change will propagate throughout the model. Further study with end users is required to determine the optimal intermediate feedback approach.

### **Challenge 3: Communicating Model Changes**

User interface predictability is a design guideline for promoting user confidence and understanding [17]. Unfortunately, as others have discovered, interactive machine learning often violates this principle [14]. For ITM, in particular, small changes to the model can propagate in unexpected ways. To avoid frustrating or confusing the user, ITM interfaces must effectively communicate these changes and support comparison of the model before and after user refinement.

Existing topic visualization work supports efficient word-level comparison of topics using a matrix [18]

and topic-level comparison of models using a Sankey Diagram [19]. It is an open question how these can be adapted to visualize the complex model changes of ITM where words may be merged, replaced, documents added or removed.

### **Challenge 4: Actively Supporting the User**

Of equal importance to understanding how the user can best influence the system is to understand how the system can best influence the user [14]. For ITM, this influence could come in many forms. Here, we describe three possibilities: drawing the user's attention to problem topics, suggesting specific refinements, and increasing system transparency.

#### *Focusing the User*

Drawing the user's attention to areas of need is a common technique in mixed-initiative interfaces [20][21]. Naïvely asking users to refine all topics is at best intractable and at worst counterproductive (and nullifies the advantages of an unsupervised algorithm). The user's time and attention should be carefully directed to topics with the most *refinement potential*. A topic's coherence [22][23] is an automatic metric that represents how well the topic words belong together. Preliminary findings from our user study on topic refinement (described above) suggest that topics with topic coherence that is just above average may be a reasonable choice for maximizing refinement potential. We plan to conduct further user studies to verify this possibility.

#### *Suggesting Specific Refinements*

The set of possible refinements for ITM is infinite and considering all of them would be a daunting task for any user. The ITM system can facilitate ease of use by

suggesting appropriate refinements for particular topics. Further study is required to better understand this problem, but our initial ideas include suggesting that a user connect automatically discovered phrases or providing candidate words to add such as hypernyms, hyponyms, and synonyms of the original topic words. Also, the system can learn from how participants apply refinements, and how these refinements affect the model, to inform future suggestions.

#### *Increasing System Transparency*

Prior work [14] has suggested that system transparency is beneficial for reducing user mistakes [24], fostering trust [25], and fueling user motivation [26]. An effective ITM system should help the user to gauge refinement progress. One idea is to automatically measure a topic's coherence and present this information to the user after each iteration, supporting a historical view of how the model's quality has changed over time. An ancillary idea is to display the percentage of the model that has been *touched* by user refinements. We hypothesize that quantifying the refinements' impact on the model will motivate the user to continue using the system. Further work in this area should consider the trade-offs between transparency and overwhelming the user with algorithm details.

#### **Conclusion**

While existing work in interactive topic modeling shows promise for enhancing information seeking behavior [9] and user experience [12], prior interfaces were developed without first understanding the needs of the end user. Additionally, these interfaces do not account for many common challenges in interactive machine learning, including supporting rapid interaction cycles when dealing with slow model updates, explaining

system unpredictability or complex model changes, and considering how the system can actively support the user. Preliminary research by the authors and others may be applicable to handling these challenges, such as our formative user study of topic refinements and existing work in measuring topic quality. However, additional research is required in each case to work towards the end goal of an accessible interactive topic modeling system.

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