Real-time Topic Models for Crisis Counseling

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ABSTRACT

The proliferation of text-based crisis counseling platforms in recent months has opened an exciting opportunity for applied machine learning to **(1)** provide practical assistance for human counselors who provide emotional and practical support and **(2)** analyze counselor-caller interactions to build a landscape of the distribution of mental health issues experienced by callers on an unprecedented scale. We present ***Fathom***, a natural language interface powered by topic models to help crisis counselors on ***Crisis Text Line***, a new 911-like crisis hotline that takes calls via text messaging. We apply a mixed-initiative labeled LDA model to analyze counselor-caller conversations and use them to power real-time visualizations aimed at mitigating counselor cognitive load. We discuss *three* key aspects of crisis counseling and why topic models are suitable for mining this phenomenon. We propose new variants of topic models inspired by the practical constraints posed by their real-time deployment.

Categories and Subject Descriptors

I.2.7 [**Natural Language Processing**]: Discourse; H.5.3 [**Group and Organization Interfaces**]: Web-based Interfaces

General Terms

Machine Learning, Graphical Models, Psychotherapy

Keywords

Probabilistic Topic Models, User-Interface Design, Interactive Visualizations

1. INTRODUCTION

Research in psychology and psychiatry has shown that in a given calendar year, one in four Americans above the age of 18 suffer from a diagnosable mental health condition, with one in seventeen suffering from grave and virulent forms of these disorders [7]. While emergency hotlines like the 911 service in the United States are widely used during life threatening situations, their use for mental health disorders and emotional crises has found to be minimal at best [5]. Despite the existence of suicide hotlines, there is evidence that individuals in distress are more comfortable sharing sensitive information regarding their crises digitally via text than by voice [1]. Web-based and text-based chat support services have seen a proliferation in recent years [2], a phenomenon estimated to increase with the growing ownership of smart phones and the popularity of text-messaging [6].

In this paper, we describe a natural language interface powered by topic models to help ***counselors*** on a new 911-like, text-based adolescent crisis counseling platform called **Crisis Text Line**, where a ***caller*** communicates with a counselor using text messages rather than voice. The counselor uses a web application to communicate and manage their callers. We apply a mixed-initiative labeled LDA model to analyze counselor-caller conversations and use them to power real-time visualizations aimed at mitigating counselor cognitive load. We discuss *three* key aspects of crisis counseling and why topic models are suitable for mining this phenomenon. We propose new variants of topic models inspired by the practical constraints posed by their real-time deployment. The contribution of this work is two-fold, **(a)** an advanced natural language interface to help crisis counselors and **(b)** landscaping in-situ, the adolescent mental health distribution of the largest sample of self-selecting distressed teenagers in the United States.

2. WHY TOPIC MODELS?

Crisis counseling differs from traditional psychotherapy in its brevity and focus. A crisis counseling session usually spans less than an hour and focuses on helping the caller tide over the immediate crisis facing them. Given the asynchronous nature of the conversation, a counselor on CTL has multiple parallel text-based conversations with two or more callers at the same time. Three *key* responsibilities of the counselor for every conversation are as follows:

1. Risk assessment to discern if the caller is a grave threat to themselves or to others. Callers are categorized into high, medium and low risk buckets.

2. Elicitation of issues causing the crisis for the caller. Examples might include *job related issues* and *eating disorders*.

Actors & Conversations	
# Unique Counselors	214
# Conversations in total	8106
# Messages by counselors	469,849
# Messages by callers	412,050
Counselor Messages	
Total # of words	6,787,627
Mean # of words/message	14.44
Standard Deviation # words /message	6.99
Caller Messages	
Total # of words	4,363,010
Mean # of words/message	10.5885
Standard Deviation # words /message	4.5

Table 1: The CTL corpus. The counselor uses a web-app based chat interface to communicate via text messaging with a caller using a cell phone. This data was gathered over a span of six months since the launch of CTL.

3. Projection of empathy and formulation of an action plan to make the caller feel their plight is understood and their difficulties acknowledged; an action plan of simple steps to help the caller tide over their crisis.

The order of these facets in a conversation was found to not be linear - callers varied in how quickly they opened up to counselors; risk assessment in many cases happened in multiple stages of the conversation, while multiple action plans were needed for callers facing a complex distribution of issues. Following are some of the reasons why topic models are well-suited to model this phenomemon:

(a) Capturing topic co-occurence and their proportions: A given conversation is always a distribution of issues, events, and high-level issues. For example, the utterance *"My dad always hits me"* has ***abuse*** as the issue, with ***hitting*** as the event and ***father*** as the entity in question. Futhermore there are multiple issues in every conversation. For example ***cutting*** and ***anxiety*** frequently co-occured together, as did ***job related issues***, ***health-care coverage loss*** and ***depression***. Several of the issues deemed relevant by prevention science psychologists that are worth extracting from a personal crisis account are complex and abstract notions such as *jealousy* and *feeling overwhelmed* which have a wide variation in verbiage. Recent work has shown that capturing related issues and issue proportion in such personal accounts outperform traditional discriminatory models such as gradient trees and support-vector machines, underlining the power and flexibility offered by topic models to model the latent structure of such a dialogue [4, 9].

(b) Large scale, fast annotation with experts in the training loop: The emic qualitiative approach [8], an established technique for deep analysis and annotation of a corpus, is very useful but expensive and time-consuming. In our work, we use emic coding on a random sample of 500 conversations to formulate an initial list of issues in the conversations. A labeled LDA model so trained against this labeled set was applied to the whole corpus to generate tentative labels for all the conversations. We adopted a mixed-initiative approach to training a final labeled latent Dirichlet allocation (L-LDA) model against this seeded labeled set, with prevention science experts providing refined labels, choosing topics they deemed most salient and assigning topic names after fitting the model.

Topics models are well suited to capture issue co-cooccurence and their proportion and also yield themselves rather elegantly to mixed-initiative training with experts in the loop. We describe these approaches in detail in related earlier work [4, 3]. Our approach of involving experts in the training loop to embed their judgment of the saliency of issues being modeled from the corpus assumes importance since the models being trained are meant for real-time live deployment.

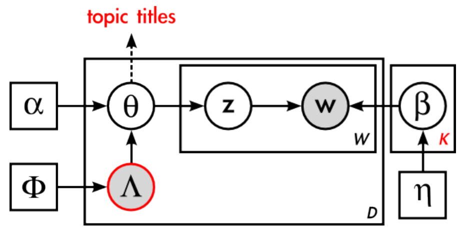

Figure 1: Human-in-the-loop labeled LDA. Experts assist with the parts shown in red: they provide labels for the training data, decide how many topics are needed, and assign topic names after fitting.

3. HELPING THE HELPERS: FATHOM

We now present Fathom, a prototype interface to help counselors. Fathom mimics the real Crisis Text Line (CTL) interface in its core functionality, with real-time conversations between a counselor using the interface and a caller using SMS text messaging. We created a demonstration of this system with fictitious data.[1]

We use topic models to help counselors assess the urgency and emotional content of each conversation. First, we trained a labeled LDA topic model on 412,050 CTL caller messages from 18,712 conversations initialed by 8,106 callers. Figure 2 shows examples of probabaility mass assigned to a caller's messages. Prevention Science psychologists made this a mixed-initiative process [4]; these experts provided labels for the training data, decided how many topics were needed, and assigned topic names after fitting.

Holding these topics fixed, we assign topic membership to each new message as it is recieved. The topic distribution can then be viewed in various ways for a given conversation, as shown in Figure 3.

These vizualizations are embedded in the full Fathom interface, shown in Figure 4. They allow the counselor to navigate conversation histories and get an immediate sense of the relevant issues when switching between conversations.

We evaluated the Fathom interface against a control that omitted the topic modeling. All seven participants had undergone training as crisis counselors; three of the participants were counselors on CTL. Through their answers to survey questions, the counselors indicated that the visualizations were useful for summarizing the conversations, and

[1] http://stopdbully.media.mit.edu:4345/

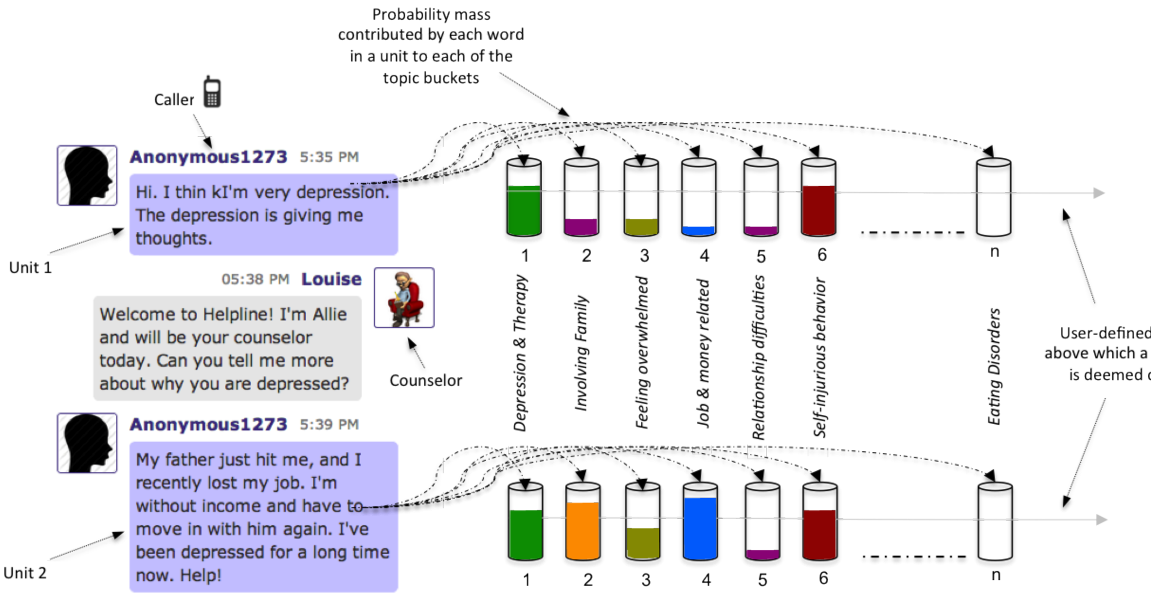

Figure 2: The relationship between example conversation text and the topic model. Words in the conversation each make a contribution to buckets representing topics. In the Fathom interface, a significance threshold is set by the counselor, allowing topic assignment below that threshold to be hidden.

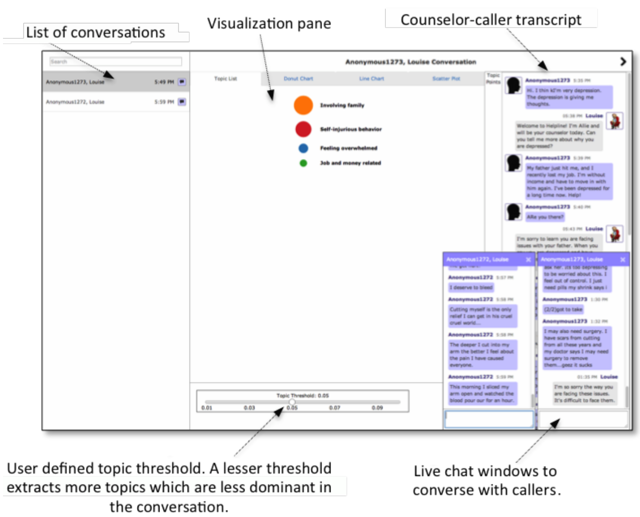

Figure 4: Fathom interface, showing a panel to navigate conversations on the left, a vizualization pane in the center, converstion history on the right, and live conversations with two callers in the lower right.

allowed them to spend less time taking notes and helped with repeat callers. Participants indicated that the scatter plot (lower right of Figure 3) was the most useful vizualization. While the visualizations helped a little with delevoping an action plan, we believe that we can still improve in this area. Participants were very positive about Fathom, but expressed a desire for even more functionality. Visualizing counselor notes along with conversation summaries, was a common feedback. It was also suggested that suicide risk be prominently displayed, nomatter how dominant it might be in a conversation.

4. ONGOING AND FUTURE WORK

We plan to include the 469,849 messages from 214 counselors in the Crisis Text Line (CTL) data set. These documents can be used to provide more detailed summaries, and also to recommend an action plan based on past situations and their corresponding actions.

Ideally, we would model the caller/counselor interactions more explicitly. This would give us a sense of the impact of a proposed action, and allow us to make real-time predictions in a caller's response to a draft of a counselor message before it is sent.

Prior to modeling the interaction sequentially, we can model the conversation generally as two parallel topic models: the first is similar to the labeled LDA on caller messages, which we have already described. The second topic model would be labeled LDA performed on counselor messages, but instead of the labels being psychological issues, they would be actions.

We can imagine that the per-message topic distributions are drawn from conversation-level topics. Additionally, these higher-level topics can impact the per-message topics of the partner topic model through interaction matrix A, which describes how much counselor action topics reveal about caller issue topics and vice versa. This relationship is shown as a graphical model in Figure 5. One possible generative process for this paradigm could be as follows.

$$\theta \sim \mathrm{Dir}((\phi^* * A) \times \theta^* \times N)$$

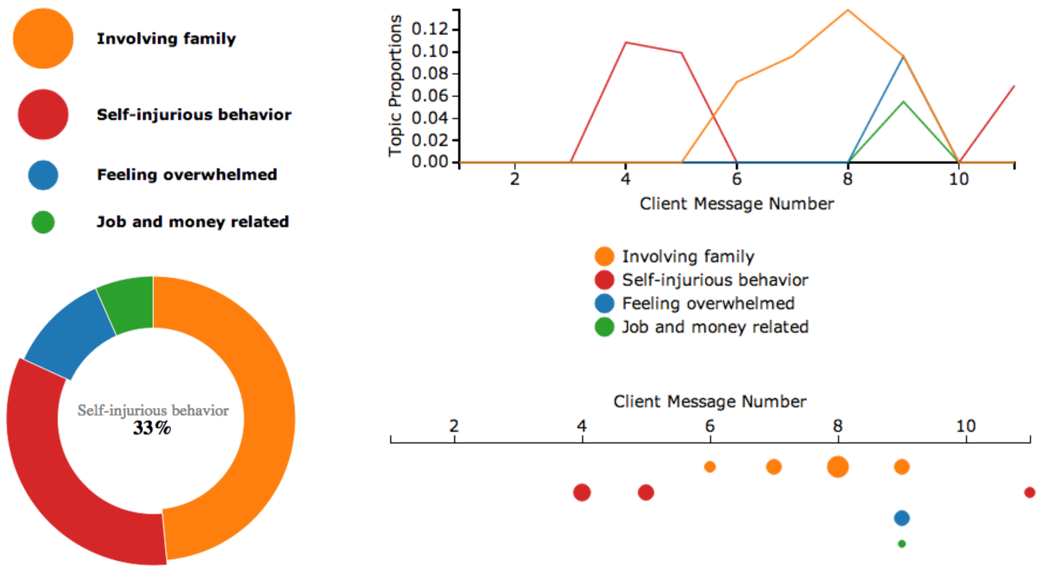

Figure 3: Four visualizations of conversation topics, three of which are interactive. On the left are two ways of viewing the conversation as a whole. On the right are ways to see how conversation changes over time; interacting with these visualizations allows the counselor to navigate the conversation history.

$$\phi \sim \mathrm{Dir}((A * \theta^*) \times \phi^* \times M)$$

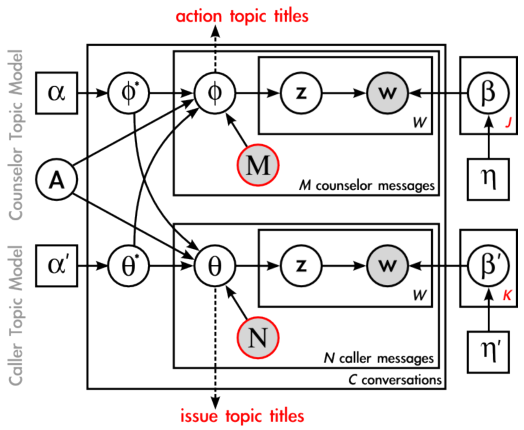

Figure 5: Dual labeled topic models for counselor and caller messages within a conversation. Matrix A reveals the connections between the two topic models in terms of conversation interactions.

In addition to these interaction dynamics, it may be interesting to expore dynamic topics in a long-running live system, as well as the issues surrounding an evolving vocabulary.

We think it may be worthwhile to model risk separately, possibly as a function both counselor and caller topics. We may be able to achieve a good model for risk using current issue labels, but it might require expert assigned labels specific to risk, or an expert-generated issue-risk matrix.

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