Visualizations for Mental Health Topic Models

by

Ge (Jackie) Chen

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Abstract

Crisis Text Line supports many people with mental health issues through texting. Unfortunately, this support is limited by the number of counselors and the time each counselor volunteers, as well as the cognitive load needed to manage multiple conversations at once for long periods of time. We conducted a contextual inquiry with crisis counselors to find the specific problems in their workflow. In order to maximize the time and brainpower counselors spend helping clients, we believe topic modeling can provide summaries of conversation text to aid management. Four simple and familiar visualizations were developed to present the topic model data. Counselors can choose from varying levels of granularity: 1) a list of conversation topics, 2) a pie chart of topic percentages, 3) a line chart of topic trends throughout a conversation, and 4) a scatter plot of specific locations in the text where the topics were detected. Our hypothesis is that these visualizations will help counselors keep track of different conversations, provide clarifying details, and improve the quality of client support. Finally, the visualizations were evaluated through a user study with crisis counselors to determine their effectiveness against a control interface.

Thesis Supervisor: Henry A. Lieberman
Title: Principal Research Scientist

Acknowledgments

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Chapter 1

Introduction

Crisis Text Line (CTL) is an organization that provides counseling services to young people in crisis through texting. The goal of this thesis is to supply CTL counselors with assistive tools in order to offer their clients the best possible service. This section explains the motivation behind this research project, the problems we want to solve, the approaches to implement and evaluate, and the contributions made.

1.1 Motivations for Mental Health Visualizations

The main motivating factor for this thesis is to help people with mental health crises. Many people suffer from depression, suicidal thoughts, and emotional stress every day. Crisis Text Line provides an outlet for clients to discuss their issues and ask for support. However, there is a shortage of counselors compared to the number of people seeking aid. Each counselor may have to manage various conversations continuously for several hours. Counselors spend time on extraneous things such as reports. In addition to maximizing counseling time for clients, we want to assist counselors because crisis counselors tend to have a high attrition rate due to burnout and low morale. Many of these counselors are simply volunteers who undergo a short period of training. These constraints motivate us to maximize the amount of time and brainpower counselors spend on client support. Time is a critical factor in mental health situations because clients may be at risk of suicide or physical harm.

Fortunately, the unique thing about a texting hotline is that the use of written communication allows computer programs to analyze and extract meaningful data from the text. Topic modeling is a machine learning technique that discovers abstract topics occurring in a set of documents. It can be useful for summarizing large amounts of text. Counselors may benefit from summaries of their various conversations with clients, but topic modeling is a complex and advanced artificial intelligence concept. Therefore, we would like to provide counselors with an easy method of understanding the data through visualizations. Visualization is a powerful approach for presenting data that most people are familiar with.

1.2 Problem Definition

As mentioned in the motivation section, some main difficulties with Crisis Text Line are that there are not enough counselors to talk with all of the clients in crisis, the counselors are usually context switching between multiple different client texts at a time, they spend a nontrivial amount of time on other necessary tasks, and counselors may feel burned out. Since it is more difficult to control external factors such as the number of available counselors, we focus on tackling two specific problems:

1. Reduce the amount of time counselors spend not talking to clients.

2. Reduce the cognitive load of counselors so they feel less burned out.

1.3 Hypotheses

We believe a variety of topic model visualizations will offer assistance in solving the proposed problems. Using topic models, mental health conversations may be summarized by a combination of topics, such as job-related issues, family troubles, relationship difficulties, or self-injurious behavior, to name a few. Topic models also provide indexing information, which tells us where each specific topic can be found in the conversation text.

1.3.1 Context Switching

As the medium of texting usually involves gaps in response time during a conversation, counselors often switch context between talking to different clients. When a counselor returns to a previous conversation after a client response, he or she may have to spend time recalling what that particular conversation was about. However, if the counselor was given a visual summary of the conversation, with the option of quickly reading through chat details, less time may be spent recognizing the conversation topics. This approach can minimize both the time a counselor spends not talking to a client and the cognitive load that context switching has on the counselor.

1.3.2 Shift Changes

Counselors usually handle incoming client texts in shifts. A shift change may occur in the middle of conversations, in which case the leaving counselor gives the incoming counselor a brief summary of the talking points so he or she can take over. However, this summary is general and transient, and the incoming counselor would have to take time scanning through the existing conversation text for details. We suspect that a permanent visual summary computed using topic models would be more helpful for the incoming counselor. The visualizations can provide different levels of detail depending on what the counselor needs to know about the conversation history. Visual indexing can quickly point him or her to the parts of the conversation related to a certain topic. This technique minimizes the amount of time necessary to search through the text for details and potentially improves the quality of client service by better preparing the new counselor for the interaction.

1.3.3 Automated Reports

Certain crisis organizations require their counselors to complete reports on their conversations with clients. Although these reports may be helpful to some, they can be time-consuming to manually fill out. That time could be better spent interacting with clients. Given that we can use algorithms to analyze conversation text and extract information, we believe that this information can be used to automatically pre-populate reports. Another idea is to use visual summaries as a complementary form of a report.

1.3.4 Conversation Trends

As previously mentioned, counselors must keep track of multiple conversations at a time. These conversations may also contain gaps of time due to the use of texting. In order to aid the counselor's memory, we believe that displaying topic trends over time for each conversation could be useful. Showing trends, including where topics appear in the course of a conversation and how they accumulate, may potentially improve the quality of client service. A chart of topic trends could alert the counselor to important focus points. For example, if the topic of self-injurious behavior is on the rise, the counselor might want to react in a certain way to prevent escalation of injury. Conversation trends may also be useful for organization leaders to detect patterns that might be of use in supporting clients.

1.4 Contributions

Based on a topic model developed from a collection of real mental health conversations, I designed and implemented a website prototype for Crisis Text Line with four visualizations. These visualizations were designed based on four different levels of granularity, so the counselor can choose the amount of detail he or she wants.

The **Topic List** visualization lists the topics discovered in a conversation that are above a certain threshold. Topics are ordered from highest to lowest percentage detected in the conversation. This visualization is a quick, glance-able summary of the conversation topics.

The **Donut Chart** visualization adds a small level of detail by displaying the topic proportions in a pie chart variation to show the parts of the whole relationship. User interaction by hovering over the chart or the legend provides the topic percentages for quantitative information.

The **Line Chart** visualization reaches finer granularity by revealing topic proportions at the message level, where each client message in the conversation is analyzed for topics. A line exists for each topic above a certain threshold that shows the trend of that topic throughout the conversation timeline. There is also the option of viewing the accumulation of topic proportions across the conversation. When the user clicks on a topic, points are displayed to reveal the client messages in the conversation that contain the topic.

The **Scatter Plot** visualization is the deepest detail level, allowing the user to click on the topic instances that occur throughout the conversation. The conversation text then automatically scrolls to the appropriate message. The size of the scatter plot points represent the proportion of that topic in the corresponding message.

1.5 Thesis Outline

Chapter two presents related work, consisting of topic models, visualizations of topic models for other fields, and mental health topic modeling. The scope and limitations of the thesis is also included in this chapter.

Chapter three describes the contextual inquiry done with crisis counselors to analyze the needs of our users for a better design.

Chapter four discusses the design of the four visualizations contributed in this this thesis: a topic list, a donut chart, a multi-series line chart, and a scatter plot.

Chapter five explains how the system was implemented and lists the existing technologies that were used.

Chapter six evaluates the visualizations based on the user test results.

Chapter seven explores ideas for future work, some of which could not be completed due to time, resource, and technological constraints.

Finally, chapter eight discusses the main contributions presented in this thesis.

Chapter 2

Related Work and Scope

In this section, we first summarize relevant research presented in three categories: topic modeling, topic model visualizations, and mental health topic modeling. We then provide the scope and limitations of this thesis project.

2.1 Topic Modeling

Probabilistic topic models [1] are algorithms that aim to extract the main themes from a large collection of documents. These algorithms use statistics to analyze the words in each document's text and organize them into topics. Topic modeling can be used to aid summarization and information retrieval for various types of data without the need for humans to manually annotate a large amount of text.

The simplest topic model is *latent Dirichlet allocation* (LDA) [1]. LDA uses a statistical process to discover the topics in a corpus of documents. A *topic* is formally defined as a distribution over a fixed vocabulary. For example, a *genetics* topic should have the words *genetics* and *genes* with high probability. LDA consists of reverse-engineering an imaginary generative process. This process begins by taking a random distribution over topics. Each word for each document is then generated by randomly choosing a topic from the distribution over topics and randomly choosing a word from that topic's distribution over words. We refer to the topics, the per-document topic distributions, and the per-document per-word topic assignments as the topic structure. This generative process must be reverse-engineered because the words in the documents are observed, while the hidden topic structure that most likely generated the words must be inferred.

We will not go further into the specifics of topic modeling in terms of probability and statistics because this thesis is concentrated on visualization. The purpose of this overview is to familiarize the reader with the concept of topic modeling, focusing on how it is used to extract a set of topics from a document corpus and annotate documents with themes based on the document words.

2.2 Visualizing Topic Models

Topic model visualizations vary in design due to different goals and audiences. Many projects focus on visualizing relationships between documents instead of summarizing each document. Some were created for non-technical users to improve understanding, while others were made for technical users to evaluate a certain model. A few systems also aim to show topic changes over time.

2.2.1 Document Relationships

Numerous research projects revolve around visualizing documents to show similarities based on their latent topics. *Probabilistic Latent Semantic Visualization* (PLSV) [9] is a topic model approach to visualizing documents and topics as coordinate points in a visualization space. The distances between documents and topics are based on the topic distribution of a document. *Topic maps* [13] and *Exemplar-based Visualization* (EV) [4] provide similar graphs of a large collection of documents, with document points color-coded by their dominant topic. The Stanford Dissertation Browser [6] is also a notable visualization developed to evaluate word and topic similarities between the Ph.D. theses of different departments over time. The general purpose of these visualizations is to show documents with similar topics in clustered areas for a global overview of the corpus.

2.2.2 Thesis-Relevant Projects

Now we turn to a few systems that are more relevant to our research in terms of their goals, end-users, or visual design. We are focused on summarizing individual documents using topics, revealing topic trends of a document over time, and indexing topics within document text using simple visualizations for non-technical users. Our developed visualizations were inspired by different aspects of these projects.

The Wikipedia navigator [3] was specifically designed to summarize the corpus and show relationships between textual content and topics for non-technical users. Three straightforward visualizations were produced: an overview page that lists the set of topics associated with all documents, a topic page that displays associated words as well as related document and topic links, and a document page showing the content in addition to related document links and a pie chart of related topics. These visuals allow the user to be completely unaware of the underlying LDA topic models.

The interactive visual text analysis tool TIARA [12] summarizes a corpus over time using a stream graph with topic layers and distributed keywords. ThemeRiver [8] provides the same type of graph without keywords. The height of the topic layer areas illustrate the strength of each topic at a certain point in time. Although I personally find stream graphs difficult to comprehend, these visualizations show that area or line charts can be useful for expressing topic trends over time.

Finally, Termite [5] is a visual analysis tool for evaluating the quality of topic models. The main visualization of this tool is a term-topic matrix that can be described as a scatter plot of words for each topic, with the size of each point proportional to the word frequency for that topic. Clicking on a topic in this matrix shows its representative documents and a one-dimensional plot of where topical terms can be found within each document. These simple designs seem effective for visually indexing topics in each document.

2.3 Mental Health Topic Modeling

Very little research has been done related to the application of topic models to the mental health domain. The Software Agents Group at the MIT Media Lab first began branching into this area with their previous story-matching research and now our Crisis Text Line project. The topic models for both projects, developed by Karthik Dinakar, use similar approaches. We will first describe the previous project and then outline the topic model differences used for our CTL system.

2.3.1 Story Matching Project

The previous research revolved around an ethics website where teenagers share stories about their mental health issues [11]. Researchers aimed to mitigate the effects of cyberbullying by presenting teens with stories similar to their own. The approach uses LDA to discover themes within the stories [7]. First, LDA extracts topics, in the form of word clusters, and a distribution over the topics for each document. Each word cluster is then analyzed by a human and interpreted as a theme if possible. This process iterates with an increasing number of desired topics until a satisfactory collection of themes have been extracted. Each document has a distribution over the themes. Using the output of this process, *Reflective Interfaces* [10] displays stories with common themes in order to help the teenagers relate to each other.

2.3.2 Thesis Topic Model

The topic model algorithm used for the visualizations in this thesis is very similar to the story-matching approach with a few main differences. The documents are conversations between a client and a counselor, so only the words in the client messages are analyzed. After the algorithm is applied to a large set of sample conversations, the extracted topics and word distributions are used to analyze each client message in a conversation. Having the themes at the message level allows us to: 1) provide indexing information regarding where topics occur within a conversation and 2) dynamically apply the topic model to new messages. The topic model summary of a conversation is produced by normalizing the topic distributions for each client message.

2.4 Scope and Limitations

We will now give an assessment of the scope and limitations of this thesis project. First, the goal of this research is to provide a prototype for a Crisis Text Line website that makes use of topic model visualizations. It is designed on a development server and is not deployment-ready. The CTL developers may use the system design and implementation as guidelines or inspiration for future work. We do not have the time or resources to fully test and deploy this system to real users due to thesis deadlines and lack of additional developers.

We are also focused on crisis hotlines that use texting because we are mainly limited to conducting contextual inquiries and tests with the Crisis Text Line organization and the Boston Samaritans, which is a local hotline that uses texting. Some of the problems we are trying to solve, such as context switching and cognitive recall, are also unique to texting due to the longer and more frequent gaps in conversation.

In this thesis, the evaluation of the visualizations is emphasized rather than topic model accuracy. These are two different aspects of the group project, so we are concentrating our efforts on visualization effectiveness. We realize that the topic model may be improved with counselor feedback, such as having counselors interpret themes from the word distributions, merging topics they find to be too similar, or allowing them to indicate confusing topic assignments.

Finally, we have additional ideas that may improve the quality of counseling but choose not to implement them at the moment due to constraints on time and external resources. For example, topic-specific resources may be provided to counselors as they are having an ongoing conversation. Resources could be specialized hotline numbers or training documents on how to deal with a specific situation, as determined by counseling experts. Exploring this avenue would require controlled testing on whether this addition is distracting or helpful and gathering resources for predetermined topics.

Chapter 3

Contextual Inquiry

This chapter covers a contextual inquiry [14] on mental health counselors working at a crisis hotline organization. We spoke with three Boston Samaritans counselors for two hours each on three different days. It is important to gain background and perform analysis of users by observing and interviewing them in their natural environment. User-centered design allows an interface to focus on solving specific needs.

3.1 Counselor Workflow

Counselors talk with clients using a chat-based web application on the Crisis Text Line platform. Clients access the hotline using SMS text messaging and are placed in a waiting queue if a counselor is not available at the moment. Counselors handle two or more conversations at a time because the incoming texts are asynchronous and sometimes sporadic. The observed workflow is described as follows:

1. **Accept client:** Each time the system receives an incoming text from a new client, an alert is sounded and the client is placed in the queue. Counselors select a client from the queue when they are ready to take on another conversation by maintaining a balance of new and repeat clients. If a fellow counselor has become overloaded because they are managing more than three clients at once or one of the conversations has increased in severity, one of the conversations

can be *warm-transferred*. This simply means that a new counselor takes over the conversation while it is still ongoing. To get up to speed, the new counselor can read conversation notes taken by the original counselor or consult with them if necessary.

2. **Examine profile:** If the client is a repeat caller, the counselor can refer to a client profile consisting of previous counselor notes and a transcript of the three most recent conversations. Otherwise if the client is new, the counselor fills out the profile by asking them questions. Even with prior information to gain context, counselors are trained not to let the client know that they have access to that information because each conversation should be treated separately. We observed that it was time-consuming to read notes on previous conversations and even more time-consuming to read full transcripts.

3. **Provide counseling:** Counselors are trained to handle clients following this three-step system:

   (a) ***Risk assessment:*** Determine the amount of risk involved in a client's situation. High risk might be if the client is in physical danger or may potentially hurt someone. A client that mostly wants someone to talk with in order to reduce stress might be lower risk.

   (b) ***Issues and emotional state:*** Learn what the main issues are and how the client feels about them. Issues can range from job-related worries to relationship problems.

   (c) ***Action plan:*** Develop a concrete plan with the client that may help them deal with their pressing crisis or general problems. For example, if the main issue is a lack of financial means, one plan might be an outline of steps to take to apply for jobs.

4. **Take notes:** For each conversation, counselors take notes to cover the significant aspects of the interaction based on the three-step system. Some counselors take notes while the conversation is ongoing, and others take notes at the end.

Our observations determined that roughly more than one third of the counselor's time was spent taking notes.

5. **Complete report:** At the end of each conversation, the counselor must fill out a separate report using a static template. The template has high-level categories of client problems and counselor responses. Completing the report was also time-consuming.

6. **Monitor queue:** Each counselor must keep an eye on the queue in addition to maintaining their own conversations. This is done because clients in the queue could be having a high-risk crisis, and therefore minimizing their wait time is important.

Based on our observations of the typical counselor workflow, we concluded that there were many time-consuming tasks that reduced client-counselor interaction time. Taking over a *warm-transferred* conversation requires reading prior notes or additional consultation. Counselors also read previous conversation notes or transcripts to gain context for a repeat caller. Taking the notes manually and filling out the end report took up a substantial amount of time as well.

3.2 Interview Results

In addition to observing the counselors as they managed conversations, contextual inquiry also involves interviewing them to gather their opinions. The three counselors we interviewed all discussed similar aspects that they wanted to change, which agreed with our observations:

1. Taking detailed notes while handling multiple conversations in parallel was time-consuming.

2. For repeat clients, reading through previous conversation notes and transcripts was very helpful but also labor-intensive.

3. The conversation reports were determined to be both time-consuming and not useful. None of the three counselors even read previous reports, only taking the time with notes and transcripts. They explained that the report was too simple and rigid to be able to capture the complexity of most client problems.

Our takeaway from the contextual inquiry was that we need to design our interface to solve or mitigate the problem of manual note-taking and reading. We believe that using topic modeling to automatically read and extract information from conversation transcripts will reduce or complement note-taking, while visualizing the extracted information will be a faster alternative to reading written text.

Chapter 4

Visualization Design

Based on the results of the contextual inquiry, we designed four topic model visualizations. These visualizations provide different levels of detail so that counselors can choose the amount of data they see. This design allows the visualizations to be useful but not unnecessarily overwhelming.

4.1 Visual Summary

The goal of the first two visualizations is to summarize a conversation at a high level. The topic model data presented is the topics and their proportions that make up the entire conversation text. For example, one data point might be that the topic *Rejection* constitutes *50 percent* of the client's side of the conversation. These visualizations are designed for the user to absorb the data with a quick glance.

4.1.1 Topic List

The first visualization, shown in Figure **??**, is simply a list of the topic names with a colored circle next to each name. For each topic's circle, the color corresponds to the topic and the size corresponds to that topic's proportion of the conversation text. Topics are ordered by highest proportion first, and only the topics with proportions over a certain threshold are shown.

A list format was chosen because the focus of this visualization is the topics. We omit any numbers that emerged from the topic modeling, but the topic names still need to be ordered to be most useful. Counselors may only care to see the most dominant topics, and performing a short linear scan of an ordered list allows them to stop when they please.

The accompanying circles are the visual representations of the topics. They stay consistent throughout all of the visualizations. Each topic is associated with a color, and the size of each circle is generally proportional to the percentage of the topic it represents. These circles allow us to convey the topic model proportions visually instead of using numbers, which may ease the cognitive load of the visualizations.

We believe the topic list will be useful to counselors when they need a fast reminder or context. In the case of context switching between parallel conversations with time gaps, the counselors have already read the conversation text but may need a reference for recall to jump back into a conversation. For a repeat client, a list of their main previous issues may be enough context to begin a counseling session.

4.1.2 Donut Chart

The second visualization, shown in Figure **??**, is a donut chart that displays the topic proportions as parts of a whole conversation. The included legend is a mini-version of the topic list, so users are aware that the topics are presented in order. The slices of the donut are color-coded with our system of topic-color matchings. Mousing over a slice of the chart or a topic in the legend pops that slice out and replaces the center text with the topic name and percentage, as shown in Figure **??**.

We chose to design a donut chart because pie charts and donuts charts are a familiar graphic for displaying proportions. This visualization adds to the topic list by placing some more focus on the proportions in addition to the topic names. Counselors have access to the specific topic percentage numbers through mouse interaction, but they are hidden by default to reduce cognitive load.

The donut chart has use cases similar to the topic list, mentioned in the previous section. We designed both in order to evaluate which one counselors find to be more helpful for a visual summary.

4.2 Visual Indexing

The topic model data for the next two visualizations dive into more detail. A distinct set of topics and proportions is given for each client message in the conversation, rather than one set for the entire conversation. This data allows us to provide information about where topics are detected within a conversation. We refer to showing this information in a visual way as *visual indexing* of a conversation. Specifically, selecting a topic will take the user to the messages visually tagged with that topic in the conversation transcript. This functionality may be able to greatly reduce the amount of time a counselor takes to find and read only relevant parts of a transcript. Especially for a warm transfer or repeat client, the counselor may only want to read the transcript for information on a specific issue. Automatic visual indexing also represents a form of note-taking, marking down the important messages so that counselors do not have to spend time or energy on it.

4.2.1 Line Chart

The line chart visualization in Figure **??** shows topic trends along the timeline of a conversation. Each topic is displayed as a separate line in this multi-series line chart, again color-coded by topic. Client message numbers are on the x-axis, and a topic's distribution for each message is on the y-axis. The user can also click the **Show Topic Accumulation** button to show the cumulative topic distribution on the y-axis instead, shown in Figure **??**. When the user hovers over a topic in the legend, the area under that topic line is filled to emphasize the topic.

Multi-series line charts are a typical graph for showing multiple trends over time. Streamgraphs are used for similar purposes, but trends can be difficult to comprehend for individual data series. The focus of this visualization is the changes in topic proportions over time. As outlined in the introduction, we believe topic trends may help with recall in the situation of context switching with time gaps. Trends may also alert the counselor to topics on the rise, such as *self-injurious behavior*, that would compel a certain course of action. Cumulative distributions can be useful for exhibiting the dominant topics in the conversation encountered so far.

The visual indexing visualizations have an additional interactive aspect. When a topic is clicked, as in Figure **??**, colored circles appear in the **Topic Points** column next to the conversation transcript, and the transcript automatically scrolls to the first circle. These topic circles act as message tags for visual indexing. Counselors can use these tags to quickly find the specific messages related to a certain topic. Only one topic is displayed at a time to reduce cognitive load.

4.2.2 Scatter Plot

Figure **??** shows the scatter plot visualization. Similar to the line chart, topics are displayed over time. The x-axis has client message numbers, while the y-axis has topic names. Each data point in the scatter plot is consistent with our design for a topic circle: its color corresponds to the topic and its size corresponds to that topic's proportions. Hovering over a data point or topic name reveals a row border for easy visual alignment.

This design is tailored to visual indexing. We move away from the line chart's emphasis on topic proportion numbers and concentrate on the existence of a topic in a message. For counselors searching for any relevant details in the text, proportions may not matter much. Clicking on any point in the plot will automatically scroll the conversation transcript to the corresponding tagged message, not just the first one tagged. This visualization is even more optimized for fast navigation than simply showing topic points, which the user would still have to scroll through. Counselors could save a lot of time and energy skimming transcripts without missing relevant details using this tool.

Like the summary visualizations, the two visual indexing designs have similar purposes and use the same topic model data. We developed both to evaluate which one counselors would find more useful, or whether there were aspects of both that are helpful.

Chapter 5

System Implementation

The product of this thesis is a prototype website for counselors with topic model visualizations in addition to the core Crisis Text Line functionality. In this chapter, we describe each aspect and the variety of technologies used to assist in development.

5.1 Front-End Website

The front-end was built for the Chrome browser using HTML, CSS, and JavaScript with the help of jQuery, the JavaScript library, and Bootstrap, a front-end framework for web projects. It has not been tested with other browsers because this project is only a prototype, and the CTL framework mostly uses Chrome as well. Figure **??** shows a complete view of the webpage. On the left is a searchable, scrollable list of conversations, and on the right is the conversation view. The conversation view has a title header on top with previous and next arrows for navigating between conversations, tabs for the four visualizations on the left, and the conversation transcript on the right.

The list of conversations also acts as a chat list, as shown in Figure **??**. Clicking on the chat icon for a conversation will open a typical chat box. The title in the chat box header is a link to the view for that conversation. Chat boxes can be minimized or closed by clicking on the header. Typing text into the text area and hitting the Enter key will send a message as the counselor for the corresponding conversation.

The website was designed from scratch following good user interface practices such as efficiency, learnability, and consistency. Navigation between conversations is efficient with search functionality, previous/next arrows, and links in the chat box headers. Typical elements such as the scrolling list and chat boxes have behavior that is consistent with external applications. The interface is simple in terms of layout and color with no extraneous elements.

5.2 Back-End Server and Database

The back-end uses Flask, a framework for Python web development, and the data is stored in a mySQL database. Flask runs a simple development server with an easy API for handling requests, which made it suitable for our prototype development. The website is served using a single url, with additional communication between the front-end and back-end done through AJAX calls with Flask routing. A Python class was created to interact with mySQL and process the data going into and out of the database.

5.3 Topic Model Data

Karthik Dinakar developed the topic model for our conversation summaries using a labeled mixed-initiative latent dirichlet allocation (L-LDA) approach. The model was trained using a dataset of 881,901 messages between counselors and clients from CTL. With this computational model, he wrote a function that takes a message as input and outputs the topics and proportions associated with the words in that message. We run this function on all client messages in the database, as well as any new messages, and store the output in an additional column in the database.

The visual indexing visualizations use the topic model data directly in the output format described, with a set of topics and proportions for each message. Topics may be filtered out if the corresponding proportions are below a given threshold. For the visual summary visualizations, we combine the data from all client messages in a given conversation by normalizing the proportions for each topic across the messages.

5.4 Visualizations

With the topic model data in the formats described above, the four designed visualizations were developed using D3, a JavaScript library for creating SVG visualizations based on data [2]. D3 is a great framework for this thesis because the visualizations are built around the data as input. As the topic model data changes between conversations or with new messages, no additional code needs to be written. The framework also has many examples online, as well as tools for updating the graphics with smooth transitions.

The topic list visualization was programmed based on D3 examples of a legend. Similarly, the donut chart, multi-series line chart, and scatter plot all have example code to follow to learn the framework. With new topic model data, the summary visualizations are completely redrawn. The indexing visualizations transition the axes and points as new messages are received, since they are time-based. All visualizations update dynamically in real-time, so they can be used for ongoing conversations.

For visual indexing, the line chart and scatter plot also perform AJAX calls. The first time a topic is selected for a conversation, the front-end sends the HTML positions of the client messages in the transcript to the server, and the server retrieves the message tags for the **Topic Points** column. Only the tags for the selected topic are shown; the other tags are in the HTML document but hidden.

The last aspect of the D3 work is the **Topic Threshold** slider. This slider allows the user to change the threshold for filtering topics based on proportions. Increasing the threshold shows fewer topics. Changes are updated for all visualizations in real-time.

5.5 Texting Integration

Finally, Twilio was used to simulate the CTL functionality of clients sending text messages that are received by counselors in chat form. Twilio has a global text messaging API that allows web applications to send and receive SMS messages. Integrating text messages required some nontrivial changes to our front-end and back-end.

When a text message is received as a request by the server, the server needs to communicate this information to the front-end client. There are a number of ways to do this, such as adding web sockets, using server-side events, long-polling, or trying additional frameworks. We chose to implement long-polling to minimize the use and integration of extraneous technologies. The idea of long-polling is basically to keep an open connection between the server and client until the server has information to send to the client. We implement this by having the client make a request to the server as soon as it loads. When this request is received by the server, the server checks if there is new information to send to the client. If there is a new text message with updated topic model data, the server completes the request and the client immediately polls the server again when it receives the response. Otherwise if there is no new data, the server sleeps for a second and checks for new information again in a continuous loop.

By default, Flask is not compatible with long-polling because the development server handles only one request at a time. To be able to serve the website, perform long-polling, and receive text messages through Twilio simultaneously, we chose to make the Flask application multi-threaded instead of switching to a deployment framework that handles multiple requests at once. The mySQL database access points then required locking to be thread-safe.

Besides these additions, the rest of the changes were expected. When a text message is received, the database must be checked to see whether the text is for an old or new conversation. New conversations must be added to the conversation list. If the chat box for the conversation is already open, the messages must be updated. Otherwise the chat box must open automatically. If the view for this conversation is shown, the visualizations must be updated. Finally, any message added through the web interface by the counselor must be sent to the client's phone number using Twilio.

Chapter 6

Project Evaluation

Chapter 7

Future Work

7.1 Currently Possible Features

7.2 Additional Resources

7.3 Advanced Topic Models

Chapter 8

Conclusion

Appendix A

Tables

Table A.1: Armadillos

Armadillos	are
our	friends

Appendix B

Figures

Figure B-1: Armadillo slaying lawyer.

Figure B-2: Armadillo eradicating national debt.

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