Detecting and Tracking Ongoing Topics in Psychotherapeutic Conversations

Master Thesis
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Ilyas Chaoua,
04 February 2018
Abstract

Various elements associated with communication theories, emotions, and behaviors including semantic and pragmatic knowledge constitute psychotherapeutic conversations. Among the key aspects that need to explore this knowledge are the different topics driving the conversation. In this work, we propose a framework to detect and track topics in real-life psychotherapeutic conversations based on Partially Labeled Dirichlet Allocation. Topics detection summarizes the semantic themes in therapeutic conversations and predicts a specific topic for each talk-turn, converting, a sequence of talk to a distribution of ongoing topics. Topics tracking has the aims to explore the dynamics of how these topics propagate throughout the conversation and to offers insights into the underlying conversation logic and strategy. We present an alternative way to look at face-to-face conversations in conjunction with a new approach that combines topic models and transitions matrices to elicit valuable knowledge.

Keywords: Conversation Analysis, Psychotherapy, Topic modelling, Natural Language Processing, Computational linguistics
Contents

Abstract ..................................................... iii
Table of contents ........................................ v
List of Figures ............................................ vi
List of Tables ............................................. vii

1 Introduction ..................................... 1
   1.1 Project Overview ................................. 2
   1.2 Research questions ............................... 3
   1.3 Thesis outline ................................... 3

2 Related Work ..................................... 4

3 Topic Modelling .................................. 7
   3.1 Labeled Latent Dirichlet Allocation ............ 7
   3.2 Partially Labeled Latent Dirichlet Allocation .. 8

4 Data ................................................. 9
   4.1 Data sources ...................................... 9
   4.2 Meta-Data Preprocessing ........................... 10
   4.3 Text Preprocessing ................................ 12

5 Our Approach for TDT ......................... 13
   5.1 Detection of Topics ............................... 13
   5.2 Resulting Topics .................................. 14
   5.3 Tracking Topics ................................... 18

6 Evaluation ....................................... 21

7 Conclusion ....................................... 23
References
List of Figures

<table>
<thead>
<tr>
<th>Figure</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.1</td>
<td>An illustrative example of psychotherapeutic conversations</td>
<td>1</td>
</tr>
<tr>
<td>3.1</td>
<td>Bayesian graphical model for PLDA</td>
<td>8</td>
</tr>
<tr>
<td>4.1</td>
<td>The structure of a conversation in Input</td>
<td>9</td>
</tr>
<tr>
<td>4.2</td>
<td>The resulting 18 subjects (up) and 16 symptoms (bottom)</td>
<td>11</td>
</tr>
<tr>
<td>5.1</td>
<td>Example of the “per-document topic distribution” in each talk-turn over a conversation of the considered dataset</td>
<td>16</td>
</tr>
<tr>
<td>5.2</td>
<td>The difference matrix between $CP$ and $PC$.</td>
<td>20</td>
</tr>
<tr>
<td>1</td>
<td>Client to Counselor Topic changes</td>
<td>25</td>
</tr>
<tr>
<td>2</td>
<td>Counselor to Client Topic changes</td>
<td>26</td>
</tr>
</tbody>
</table>
List of Tables

5.1 An illustrative example of the three kinds of topics and their most likely associated terms. *Topic-5* shows an example of the discovered topic, *Parenting* presents an example of a known subject, and *Addiction* presents an example of a known symptom. . . . . . . . . . . . . . . . . 15

5.2 Examples of talk-turns and their associated topics after PLDA within different conversations. . . . . . . . . . . . . . . . . . . . . . . 17
Chapter 1

Introduction

This chapter gives a high-level overview of the project in general. The chapter begins with project overview including the scope of the project. This is followed by the problem statement and the corresponding research questions. Finally, the outline of this thesis is given.

Figure 1.1: An illustrative example of psychotherapeutic conversations
1.1 Project Overview

 Therapeutic conversations methods such as Cognitive Behavior Therapy (CBT) refer to a range of therapies that can help treat mental health problems, emotional challenges, and some psychiatric disorders of patients by changing their ways of thinking and behave. Accordingly, these therapeutic methods create a new way of looking at severe psychological issues to help clients to move towards a solution and to gain a better understanding of themselves. The treatment is usually a face-to-face conversation where the counselor interacts directly with the client to understand his feelings, and what makes him feel, e.g., confident, anxious, or depressed. By adopting a set of techniques and conversational strategies coming from clinical practice, the counselor aims at solving behavioral and psychological problems of the client. As a result, the counselor and the client create a sequence of spoken sentences assigning a thematic topic’s structure to the whole therapeutic conversation. The theoretical and technological advances in several disciplines of linguistics, computer science, and healthcare have made possible the recent investigation of therapeutic conversation analysis as a growing field of research [13].

 Computational learning techniques have been leveraged to extract useful information from humans interactions through the identification and exploration of unusual patterns. Therefore, investigating and modeling the human-human dialogues may serve as a guide for the development of artificial human-machine dialogue systems [6]. Topic detection and tracking (TDT) has been the point of intensive studies since the beginning of natural language processing (NLP) [16] and artificial intelligence (AI) research. One aim of (TDT) [12] is identifying the appearance of new topics and following their reappearance and evaluation [2].

 To investigate how topics propagate during a therapeutic conversation and to characterize patient-therapist interactions, we employ Partially Labeled Latent Dirichlet Allocation (PLDA) [20] to 1729 transcribed conversations (each conversation is made up of several talk-turns) which we will describe further in Section 4. Firstly, we identify the most common topics in psychology corpus. Secondly, we assess the ability of trained PLDA to determine for each talk-turn a potential topic; then, within each conversation, we transform the flow of talk-turns to a sequence of potential topics. We evaluate the semi-supervised PLDA topic
model by computing the coherence over the most significant words for each topic. The reader notices that PLDA takes as input the conversations and detects significant words for each topic.

1.2 Research questions

Our goal is to find the quintessential patterns in therapeutic conversations and to understand the topic changes according to the dialogue strategy and topics propagation. To do that, we distinguish the topic changes driven by the counselor and the ones prompted by the client. Moreover, two topic transition matrices characterize the conversation and could lend to vital clues towards when the topics change during conversations and how they are propagated successively. We, therefore, ask ourselves the following research questions:

- **RQ1:** What topics are commonly discussed in therapeutic conversations?
- **RQ2:** How do topics propagate?
- **RQ3:** When and How topics change?

1.3 Thesis outline

The remainder of the paper is organized as follows:

In section 2, we will introduce related works of automatic topic detection and therapy dialogue analysis, that will help to establish the basis for the present work.

Next, within Section 3, we will explain two distinct kinds of topic modeling algorithms and specify their main differences.

Afterwards in Section 4, we will describe the data used for the experiment and the preprocessing steps.

Section 5 will show our approach regarding TDT by illustrating the results of the developed framework.

Lastly, Section 6 will discuss how to evaluate our model, while Section 7 will end the paper with conclusions and directions for future research.
Chapter 2

Related Work

Current trends in therapeutic conversations research focus on the digitalization of spoken interactions and the recommendation of the most appropriate treatments, i.e., what is referred to as digitally automated agents. Many computational methods such as NLP and Collaborative Problem-Solving (CBS) \cite{14} may be the potential tools to extract knowledge from consultation transcripts. This chapter shows and describes the efforts previously done in this area.

Authors in \cite{4} combined robust communication theory used in healthcare and a visualization text analytic technique called (Discursis), to analyze the conversational behavior in consultations. Discursis\footnote{http://www.discursis.com/} is a visual text analytic tool for analyzing human communication, that automatically builds an inherent language model from a given transcribed conversation and mines its conceptual content of each talk-turn, and creates a visual brief. The resultant report can identify communication patterns present during discussions, with appropriate results of engagement between interlocutors to understand the conversation structure.

During medical consultations, the classification of conversations suffers from critical weaknesses, including intensive labor requirements, time-consuming, and non-standardized annotating systems. To surmount these shortcomings, authors in \cite{15} built an automated annotating system employing Labeled LDA \cite{19} model to learn the relationships between a transcribed conversation and its associated annotations. Those anno-
tations refer to the subjects and patient symptoms discussed during the therapeutic conversations. The resulting system identifies automatically and restricts those annotations correctly in separate talk-turns within a given conversation.

Contributors in [17] examined the use of LDA [8] topic model as an automatic annotator tool, instead of the manual annotator, to explore topics and predict the therapy outcomes of the conversation. The authors assumed that the automated detection of topics does not aim at predicting the symptoms, but it can be used to predict some essential factors such as patient satisfaction and ratings of therapy quality. The examinations from both approaches show that identification and tracking of topics can give useful information for clinicians, enabling them to assist better the identification of patients who may afterward be at the peril of loss to the treatment. Analyzing human communication.

The authors in [3] converted transcribed conversations to time series by developing a discourse visualization system, a text analysis model and a set of quantitative metrics to identify significant features, understand the topic used by specific participants, and generate reports within a single conversation. The method can be used to observe the structure and patterns of interaction and notify about the dynamics, including the level of topic consistency between participants and the timing of state changes.

Contributors in [23] propose a conceptual dynamic latent Dirichlet allocation (CDLDA) model for TDT in conversational text content. Opposed to the traditional LDA model, which detects topics only through a bag-of-words technique, CDLDA considers essential information including speech acts, semantic concepts, and hypernym definitions in E-HowNet [11]. It extracts the dependencies between speech acts and topics. Hypernym information makes the topic structure more complete and extends the abundance of original words. Experimental results revealed that the proposed approach outperforms the conventional Dynamic Topic Models [7], LDA, and support vector machine models, to achieve excellent performance for TDT in conversations.

Authors in [11] present OntoLDA for the task of topic labeling utilizing an ontology-based topic model, along with a graph-based topic labeling method (i.e., the topic labeling method based on the ontological meaning of the concepts included in the discovered topics). The proposed ontology-based topic model improves the topic coherence in com-

[^1]: http://ckip.iis.sinica.edu.tw/taxonomy
parison to the standard LDA model by integrating ontological concepts with probabilistic topic models into a unified framework. The model describes each topic as a multinomial distribution of concepts, and each concept as a distribution over words. The results show the robustness of the proposed approach when applied to different kind of text collections.

Contributors in [9] show an approach to improve human-agent dialogues using automatic identification and tracking of dialog topics, including the resulting topic information into the agent’s existing system architecture via exploiting the basis of contextual knowledge provided by Wikipedia category system. The detection process is capable of identifying a topic without having an apriori knowledge of the domain underlying it. This process is done by mapping the several utterances to Wikipedia articles and specifying their shared Wikipedia categories as potential topics.
Chapter 3

Topic Modelling

*After having stated the thesis, and interpreted the related works, this chapter intends to present the required background knowledge on research techniques from the text-mining tools that allow processing of textual data.*

In machine learning and NLP, the topic model is a statistic algorithm which provides a probabilistic framework for discovering the latent semantic structures of an extensive text body, automatically organizing, understanding, searching, and summarizing vast electronic archives. Topic models recognize the hidden themes throughout a given collection and annotate the documents according to those themes. The “topic” estimates the hidden variable relations that link words in vocabulary and their occurrence in documents. A document is seen as a mixture of topics, while a topic is a mixture of words. The most used algorithm is Latent Dirichlet Allocation (LDA) [8].

3.1 Labeled Latent Dirichlet Allocation

Labeled LDA [19] is a supervised topic model of multi-labeled corpora. It improves upon LDA for tagged corpora by gracefully incorporating user supervision in the form of a one-to-one mapping between topics and labels. Like LDA, Labeled LDA model treats each document as a mixture of underlying topics and generates each word from one topic. Unlike LDA, Labeled LDA approaches incorporate supervision by merely constraining the topic model to use only those topics that correspond to
3.2 Partially Labeled Latent Dirichlet Allocation

PLDA [20] is a topic model incorporating label in an unsupervised way, which learns latent topic structure within the scope of observed, human-interpretable labels. It is an extension of LDA to incorporate labels, and of Labeled LDA to incorporate per-label latent topics. The model makes use of the unsupervised learning machinery of topic models to discover the hidden topics with each label, as well as unlabeled, corpus-wide latent topics. PLDA assumes that the document’s words are drawn from a document-specific mixture of latent topics, where each topic is represented as a distribution over words, and each document can use only those topics that are in a topic class associated with one or more of the document’s labels. This construction allows PLDA to discover large-scale patterns in language usage associated with each label.

Figure 3.1: Bayesian graphical model for PLDA

Figure 3.1 shows an illustrative representation of PLDA. In the figure, each document’s words $\omega$ and labels $\Lambda$ are observed, with the per-doc label distribution $\psi$, per-doc-label topic distributions $\theta$, and per-topic word distributions $\Phi$ hidden variables. Because each document’s label-set $\lambda_d$ is observed, its sparse vector prior $\gamma$ is unused; included for completeness.
Chapter 4

Data

This chapter centers on the understanding and preprocessing of the transcribed conversations used in this research. Firstly, the structure of the data sets is presented, followed by the analysis and the preprocessing of meta-data and text with a particular focus on providing more results and figures. The reader notices that meta-data preprocessing has been executed for the two tasks we present in this paper (TDT) whereas text preprocessing has been run on topic detection only.

4.1 Data sources

<table>
<thead>
<tr>
<th>Example of a transcript</th>
<th>Annotations</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Role</strong></td>
<td><strong>Text</strong></td>
</tr>
<tr>
<td>Counselor</td>
<td>Will you be ok?</td>
</tr>
</tbody>
</table>
| Client | I am not good. | Subjects | Friendship, Medication ...
| Counselor | You were pretty high level of anxiety last time. | | |
| Client | I think it has to do with the trial therapy. | | |

Figure 4.1: The structure of a conversation in Input

This study used counseling and psychotherapy transcripts from a private dataset. This collection features a diverse set of clients, a wide range of topics, and various therapeutic approaches, making this an excellent resource for research. Hundreds of practicing counselors worldwide transcribed and rendered the conversations to adhere to the Amer-
ican Psychological Association\(^1\)(APA) Ethics Guidelines for use and anonymity. The transcripts expose the various kind of therapies by providing more than 2000 real-life and fully anonymized conversations. Each conversation includes meta-data information that consists of a table of topics discussed during the therapeutic conversation, school of psychotherapy and counselors-clients information represented by gender, age range, and sexual orientation.

For our purpose, we collected only one-to-one conversations which contained 1729 transcripts comprising a total of 340,455 talk turns, 75,732 unique terms, and more than 9 million words. Each transcript has on average 200 talk-turns and eight words by talk-turn. The table of topics from the meta-data conversation level contains two different kinds of information:

- **Subjects**: They are within the meta-data and organized into three hierarchical levels. The top level is the most general whereas the other two are more precise. As an example, one of our conversation included in its table of topics the word *Family* as a top level topic, *Family violence* as the associated second level and *Child abuse* as the third associated level. We counted 575 subjects in all the three hierarchies in our conversations data.

- **Symptoms**: there are 79 symptoms (e.g. *Depression, Anger, Fear*) not structured in any hierarchy and defined in the DSM-IV\(^2\) manual.

### 4.2 Meta-Data Preprocessing

The challenge was to reduce the number of items in the table of topics by grouping similar topics and to find their representative element. The following are the steps we performed to achieve this goal:

1. Eliminating all the subjects and symptoms that occurred less than 3% in our collection;

2. Grouping together all the subjects that had the same Wikipedia category\(^3\) without considering their position in the given hierarchical structure. Afterwards, we chose a name for the new subject

\(^{1}\)http://www.apa.org  
\(^{2}\)https://dsm.psychiatryonline.org  
\(^{3}\)https://en.wikipedia.org/wiki/Category:Main_topic_classifications
using the psychology topics table from APA. For example *Parent-child_relationship* and *Family* have been condensed in one new subject from APA known as *Parenting*.

3. Reducing the number of symptoms by using the DSM-IV manual with the expert support of a counselor. In particular, we grouped symptoms with high-level correlation into only one representative symptom. For example, *Sadness* and *Hopelessness* have been merged to the symptom: *Depression*.

![Figure 4.2: The resulting 18 subjects (up) and 16 symptoms (bottom)](image)

After applying the above steps to the initial 575 subjects and 79 symptoms of the considered dataset, we ended up with 18 subjects and 16 symptoms only. In Figure 4.2 the obtained resulting symptoms and subjects are reported. The original table of topics has been therefore updated with the new subjects and symptoms. We found out that the mentioned
preprocessing led to higher performances for the evaluation of the topic model.

4.3 Text Preprocessing

The text preprocessing step we performed had a noticeable influence on the NLP pipeline completion[22]. One of the components we employed is the tokenizer which transforms texts into a sequence of tokens. However, different steps can be further used in practice (e.g., cleaning, filtering, etc.) We removed all the punctuations, stop words, numbers, words that frequently appeared in the text with less content information (e.g., ”mm-hmm”) and words that occurred in less than five documents. We used unigram part-of-speech tagger [13] to identify the types of words in each talk turn.

As a best practice in PLDA, we also threw out all the 100 most common words in all talk turns and kept only the nouns, verbs, adjectives, and adverbs. We kept each talk turn that contained more than one word, and we retained the only words that have more than three characters. The steps of stemming and lemmatization have been neglected because they modified the forms of words changing the common base body of the corpus which may influence the evaluation of the topic model. For the text preprocessing step we employed the NLTK platform[4]. The resulting corpus consisted of 2,849,457 tokens (14,274 unique) and a total of 268,478 talk turns.

Chapter 5

Our Approach for TDT

This chapter presents our approach for automatic TDT method in therapeutic conversations, which, represents a new approach to recognize and evoke the linguistic semantics in counselor-client dialogues.

5.1 Detection of Topics

The first part of our study was to look at the topics commonly discussed in therapeutic conversations as well as their propagation over talks. Accordingly, we approached the question of detecting topics through the use of PLDA, which was implemented by using the Stanford Topic Modeling Toolbox\(^1\) (TMT). The model requires the definition of parameters such as the number of hidden topics to discover, the hyperparameters $\alpha$ and $\eta$ (see Figure 3.1), and a vast amount of short text as input for training purpose. To enlarge the number of corpora, we defined each talk-turn as a document, and we associated each document (talk-turn) with the corresponding topics from the table of topics of the corresponding transcript because PLDA is useful in general only when each document has more than one label associated to it. As a result, we obtained a broader set of documents with higher word co-occurrences. More in detail, we needed to specify how many new topics (different from those in the table of topics) the model will discover.

Experimentally this number was set to 20. As a further input we fed the PLDA with the list of 34 topics, we set experimentally to 0.01 the values of $\alpha$ and $\eta$, and we provided the 268,478 talk turns we obtained after the preprocessing step. Moreover, we used the CVB0 algorithm

\(^1\)https://nlp.stanford.edu/software/tmt/tmt-0.4/
with an overall number of iterations equal to 150. After training the model, we obtained a list of topics and the associated learned words as shown in Table 5.1. Moreover, another output we obtained was the “per-document topic distribution” for each talk turn. An example is illustrated in Figure 5.1 where the five topics with the highest likelihood in a conversation are depicted (i.e. Stress and Job; Suicide and Death; Sexuality; Depression; Fear), each with the corresponding talk-turns.

5.2 Resulting Topics

Here it is explained how each talk-turn was linked to a certain topic. PLDA, after computing, returns as an output each topic and the associated terms. Based on the terms in each document (talk-turn), we can then determine how likely each document was associated with a topic.

Table 5.1 shows a completion of the terms learned from the trained PLDA topic model. There we list the top ten terms for each topic. In the first column, the reader can see the discovered topic and its associated words whereas the second and third columns indicate two of the 34 topics already known and their related words. The terms on the same topic tend to be similar, particularly for subjects and symptoms. For example, Parenting carries the member of the family, such as mom, mother, dad, etc.. Moreover, Addiction includes the terms close to alcohol and drugs (drinking, smoke, etc.). On the other hand, the domain of the discovered topics has inherent interpretations and contain words that are not covered by the annotations in psychotherapy corpus. For example, the Topic-5 includes similar terms, but their meaning (work) is far from any annotations in APA. For this reason, for the tracking step, we only used the 34 elements present in our table of topics.
Besides the 54 topics (34 known and 20 discovered by PLDA) and their relevant terms, we aimed to know the likelihood of each topic in each talk-turn. As such, another output of the PLDA topic model consisted in the partition of the documents into a set of 54 topic proportions, called per-document topic distributions, where each talk-turn was represented as a combination of topics with different proportions. As already explained earlier, Figure 5.1 shows an example of the potential ongoing topics in each talk-turn within a therapeutic conversation from the dataset.

In the x-axis of the figure are reported the different talk-turns of the conversation, whereas in the y-axis are reported the different topics. The figure shows the topics with the highest likelihood (five in our example). Each of them comprehends a set of talk-turns (e.g., Sexuality is discussed within the talk-turns 15, 16 and 17). Table 5.2 reports some examples of talk-turns of the client and their associated representing topics, with the corresponding probabilities, produced by our PLDA-based method. These acquired topics provide a new approach to explore spoken therapeutic conversations to derive useful insights to be used for therapy selection.

<table>
<thead>
<tr>
<th>Associated Words</th>
<th>Weight</th>
<th>Associated Words</th>
<th>Weight</th>
<th>Associated Words</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>pay</td>
<td>1125.386</td>
<td>mom</td>
<td>1354.692</td>
<td>drinking</td>
<td>120.9583</td>
</tr>
<tr>
<td>month</td>
<td>957.7061</td>
<td>mother</td>
<td>1190.696</td>
<td>drugs</td>
<td>78.25677</td>
</tr>
<tr>
<td>working</td>
<td>809.5385</td>
<td>dad</td>
<td>1103.559</td>
<td>alcohol</td>
<td>60.09412</td>
</tr>
<tr>
<td>end</td>
<td>799.9208</td>
<td>family</td>
<td>996.8899</td>
<td>drug</td>
<td>59.39509</td>
</tr>
<tr>
<td>help</td>
<td>649.7758</td>
<td>brother</td>
<td>786.8062</td>
<td>stoned</td>
<td>47.30778</td>
</tr>
<tr>
<td>giving</td>
<td>516.6524</td>
<td>parents</td>
<td>745.5274</td>
<td>smoking</td>
<td>44.19726</td>
</tr>
<tr>
<td>months</td>
<td>502.375</td>
<td>father</td>
<td>689.4923</td>
<td>marijuana</td>
<td>41.16274</td>
</tr>
<tr>
<td>year</td>
<td>463.4732</td>
<td>sister</td>
<td>490.4897</td>
<td>girlfriend</td>
<td>37.31469</td>
</tr>
<tr>
<td>paid</td>
<td>421.3631</td>
<td>kids</td>
<td>376.6678</td>
<td>smoke</td>
<td>36.22964</td>
</tr>
<tr>
<td>paying</td>
<td>416.7115</td>
<td>children</td>
<td>313.5798</td>
<td>uptight</td>
<td>35.90694</td>
</tr>
</tbody>
</table>

Table 5.1: An illustrative example of the three kinds of topics and their most likely associated terms. Topic-5 shows an example of the discovered topic, Parenting presents an example of a known subject, and Addiction presents an example of a known symptom.
Figure 5.1: Example of the "per-document topic distribution" in each talk-turn over a conversation of the considered dataset.
I came into it late, and it was a story about a father and daughter. And it was very much about feelings and...this was a man whose only family was his daughter and...had reappeared in her life and all that. And I remember thinking "Oh I bet Dad’s not watching this at all." Or...is not enjoying it because I don’t think ever of my family could feel ever be shared. Not with mom and me but even there I mean there were layers of...constraint. Etc.

No. I don’t know-maybe I do like it underneath it all. You know it keeps coming back to this climaxing - that I think I would enjoy intercourse if I could climax. And that seems to be you know know-maybe know keeps coming climaxing think to enjoy intercourse climax seems to know.

It’s a kind of close friendship I guess of being able to just talk to them about anything or to not talk to them about anything. I mean just to sort of be able to be with them and have them understand how your feeling if you happen to be feeling any way at all or do enjoy things with you. Etc.

Right. These feelings. That you know beginning to wonder if you know. You know I’m going to be this unhappy in marriage. To feel this lonely in the marriage. I don’t want to be alone you know. In fact, I have all of the responsibility but none of the advantages. I want just to know have some of the advantages of being alone. And it feels pretty screwed up.

Like sometimes when I’m thinking about sex or just getting away from everything including the person I’m talking to, and I don’t feel like I can say that to a person right to his face.

I never get really happy about anything very rarely, and at the same time, I never get really depressed about anything. I just don’t let myself you know. And I was consciously sitting there trying to get - I mean after I started getting depressed I decided to relax and get just as depressed as I could get because Meg says that often helps.

It’s craving the marijuana. It’s craving the alcohol. It’s craving you know whatever it is.

All right sure. What effect does the medications we have you on now which is predominantly Lamictal and we have you on some Trazodone at night for sleep and I understand that’s a catch 22 type of medication.

<table>
<thead>
<tr>
<th>Talk-turns</th>
<th>Associated topic</th>
</tr>
</thead>
<tbody>
<tr>
<td>I came into it late, and it was a story about a father and daughter. And it was very much about feelings and...this was a man whose only family was his daughter and...had reappeared in her life and all that. And I remember thinking &quot;Oh I bet Dad’s not watching this at all.&quot; Or...is not enjoying it because I don’t think ever of my family could feel ever be shared. Not with mom and me but even there I mean there were layers of...constraint. Etc.</td>
<td>Parenting, 40%</td>
</tr>
<tr>
<td>No. I don’t know-maybe I do like it underneath it all. You know it keeps coming back to this climaxing - that I think I would enjoy intercourse if I could climax. And that seems to be you know know-maybe know keeps coming climaxing think to enjoy intercourse climax seems to know.</td>
<td>Sexual Dysfunction, 92%</td>
</tr>
<tr>
<td>It’s a kind of close friendship I guess of being able to just talk to them about anything or to not talk to them about anything. I mean just to sort of be able to be with them and have them understand how your feeling if you happen to be feeling any way at all or do enjoy things with you. Etc.</td>
<td>Friendship, 46%</td>
</tr>
<tr>
<td>Right. These feelings. That you know beginning to wonder if you know. You know I’m going to be this unhappy in marriage. To feel this lonely in the marriage. I don’t want to be alone you know. In fact, I have all of the responsibility but none of the advantages. I want just to know have some of the advantages of being alone. And it feels pretty screwed up.</td>
<td>Spousal Relationship, 42%</td>
</tr>
<tr>
<td>Like sometimes when I’m thinking about sex or just getting away from everything including the person I’m talking to, and I don’t feel like I can say that to a person right to his face.</td>
<td>Sexuality, 82%</td>
</tr>
<tr>
<td>I never get really happy about anything very rarely, and at the same time, I never get really depressed about anything. I just don’t let myself you know. And I was consciously sitting there trying to get - I mean after I started getting depressed I decided to relax and get just as depressed as I could get because Meg says that often helps.</td>
<td>Depression, 46%</td>
</tr>
<tr>
<td>It’s craving the marijuana. It’s craving the alcohol. It’s craving you know whatever it is.</td>
<td>Addiction(s), 99%</td>
</tr>
<tr>
<td>All right sure. What effect does the medications we have you on now which is predominantly Lamictal and we have you on some Trazodone at night for sleep and I understand that’s a catch 22 type of medication.</td>
<td>Medication, 76%</td>
</tr>
</tbody>
</table>

Table 5.2: Examples of talk-turns and their associated topics after PLDA within different conversations.
5.3 Tracking Topics

The second part of our work consisted of understanding how the known topics from our table propagate, are localized and change for each talker in conversations. We already used PLDA to identify a potential topic for each talk-turn from the table of topics converting the face-to-face conversation to a sequence of topics for each speaker. For the tracking topics task we added a new topic annotated as *Meaningless talk* which we associated to talk-turns that provide poor semantics contents or language, or non-verbal communication (e.g., ”Yahh!!”, Mm-hmm”). We built two topics transitions matrices (TTMs) to understand how the topics change from one talk-turn to another on.

Topics changes have tended to be seen as a dynamic mechanism that frequently occurs inside a conversation where speakers move from one topic to another and can be contested by either speaker. We recognize three kinds of changes:

1. Counselor keeps talking about the same topic of the client from the previous talk-turn;
2. Counselor moves to a new topic after the talk-turn of the client;
3. Client moves to a new topic after the talk-turn of the counselor.

More in detail we constructed client-to-counselor TTM $CP_k$ that describes all the topics changes within the conversation $k$. In particular, $CP_k[i,j]$ is the number of times that topic $i$ changes into $j$ in the conversation $k$. We merged the $CP_k$ matrices together by summing up corresponding elements obtaining our final matrix $CP$. Similarly, we built a counselor-to-client matrix $PC$ by using the topics-change defined earlier by switching counselor and client.

The difference between the two matrices is illustrated in the Figure 5.2, which, shows the engagement patterns between counselors and clients, providing a new way to describe one-to-one conversations. There are three possibilities, as depicted in the figure, depending on whether the resulting value is lower than -10 (black), between -10 and +10 (gray) and greater than 10 (white). The diagonal of the matrix in Figure 5.2 gives an idea about the first type of topics changes which correspond to the “resistance level” on the same topic; it has 17 gray values which proves the fact that the speakers like continuing to talk on the same topic. It also has twelve black values and six white values. The former means that the counselor switches topics twice as the client does because he
tries investigating other correlated symptoms or subjects that would lead
to a mental disease. The other values of the matrix describe the second
and third type of topic changes; the number of white and black values
are approximately equal, which means that the conversations, in gen-
eral, are discussed without perceived tactics. Nevertheless, some rows
and columns are mostly negative or positive, like Parenting, and indicate
the use of some strategies. The counselor often switches the topic if the
previous one was Mania, Medication or Client-Counselor Relations. In-
stead, he frequently starts a new topic if the client’s talk restrains less se-
monic contents (Meaningless Talk). Contrary, the client often switches
topics if the previous topic was related to Parenting, Friendship, Sexual
dysfunction, Crying, or Stress-and-Work. Conclusively, TTM guides to
a bright understanding of how and when topics are changing by giving
important insights to the counselor for CBT.
Figure 5.2: The difference matrix between CP and PC.
Chapter 6

Evaluation

*In this chapter, we present the results of evaluating our model of detecting topics. The principal focus lies in defining the most useful way of assessing the topic models qualitatively.*

It is not usually easy to evaluate the performance of a topic model. In most cases, the created topics have to be evaluated manually by humans, and everyone may express a different opinion on which word is the most similar to another. More in detail, the most common quantitative way to assess a probabilistic model is to measure the log-likelihood of a held-out test set. A slight variation of this probability is called perplexity. Although, the authors in [10] have shown that, surprisingly, perplexity and human judgment are often not correlated, and may infer less semantically meaningful topics.

A potential solution to this problem is topic coherences; it is a typical way to assess qualitatively topic models by examining the most likely words in each topic. For such a purpose, we employed Palmetto[^1] a tool to compute topic coherence of a given word set and suggested six different methods. One is C_V[^21], which uses word co-occurrences from the English Wikipedia, and has been proven to correlate with human ratings. C_V is based on a sliding window, a one-set segmentation of the top words and an indirect confirmation measure that uses normalized pointwise mutual information. The one-set segmentation calculates the cosine similarity between every top word vector and the sum of all top word vectors.

[^1]: http://aksw.org/Projects/Palmetto.html
The coherence is the arithmetic mean of these similarities. In this work, we evaluate our PLDA topic model for topic detection using C_V coherence. In particular, we give in input the top five terms (according to the weight of PLDA shown in Table 5.1) for each of the 34 topics. The output consists of a coherence value for each topic whose average is 50%.
Chapter 7

Conclusion

This chapter exhibits the general conclusions of how our research attempted to tie in with detecting and tracking ongoing topics in psychotherapeutic conversations.

Constituting a crucial aspect of analyzing and modeling counselor-client conversations, the automatic TDT in a psychotherapeutic conversation poses a significant challenge. We implemented a topic detector which efficiently understands better therapeutic discussions in consultations. We exploited PLDA and the state-of-art of NLP techniques and topic coherence evaluation system. Furthermore, we performed TTM to capture the dynamics of each ongoing topic in the conversations understanding how much each interlocutor is affected in the conversation and when he/she prefers switching topics. Knowing how topics change and their propagation can affect the discussion can be used by counselors to drive the conversation and adjust his/her statements to detect client’s state and feelings during the therapeutic conversation. These aspects of interaction are critical for all mental health specialists as they are involved in patient’s health concerns. We conclude that PLDA and TTM contribute to conversational speech analyses and communication theory, which could have an impact on several applications in psychotherapy.
1 Topic Transitions Matrices for the counselor to client changes and vise-versa in all conversation:
Figure 1: Client to Counselor Topic changes
Bibliography


[16] A. Gelbukh. Natural language processing. In Fifth International Conference on Hybrid Intelligent Systems (HIS’05), pages 1 pp.–.


