Analysis and modeling of the role of laughter in Motivational Interviewing based psychotherapy conversations

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Abstract

Motivational interviewing (MI) is a goal oriented psychotherapy involving natural conversation between a counselor and a client to instill motivation towards behavioral change in the client. Often during such an interaction, the counselor and client express themselves through nonverbal cues such as laughter. We analyze the role of laughters during MI sessions. Specifically, we perform a set of three studies to: (i) Investigate the distribution of utterances containing laughters in an MI session using Poisson process models, (ii) Analyze patterns in counselor and client behaviors with respect to laughter occurrences and (iii) Study the association of counselor utterances high in desirable behaviors such as empathy, acceptance and collaboration (referred to as *BrowniePoint* counselor utterances) with laughters. We quantify the impact of one persons laughter on the laughter rate of the other person. Our results show that the type of laughter (client/counselor stand alone laughter, shared laughter) can be associated with different patterns of counselor/client behaviors and depict unique relations with *BrowniePoint* utterances.

Index Terms: Laughter, Motivational interviewing (MI), Motivational Interviewing Skills Code (MISC), Poisson process

1. Introduction

Motivational interviewing (MI) is extensively used in treating addiction related problems and is defined as "a directive, client-centered counseling style for eliciting behavior change by helping clients to explore and resolve ambivalence" [1]. MI involves a dyadic conversation where a counselor helps the client to perceive both the benefit and harm (e.g. high/health loss) and aims to motivate a positive change. Such conversational interactions often incorporate nonverbal cues, including laughter, the topic of study here. Laughters are associated with several behavioral constructs such as emotional state [2], temperament [3], rapport [4] and empathy [5]. Several studies also identify different laughter categories (e.g. voiced vs unvoiced, initiating vs responding) and suggest differences in their functions [6, 7]. Understanding the role of laughters may provide a more complete picture of the efficacy of the psychotherapeutic interaction and can inform a more effective execution of the MI protocol. In this work, we perform several experiments to analyze the role of laughters during an MI session. We study the relation between counselor and client laughters and their association with an individual's behavior. Through these experiments we aim to both offer a means for objectively evaluating the efficacy of an MI session, and offer guidelines for its implementation by answering questions such as *"When is it appropriate to laugh ?"* and *"When do laughters relate to an empathetic response ?"*

Several previous studies have analyzed the role of laughters in human interaction. Glenn [8] explored the role of laughters during an interaction and analyzed the significance of events such as laughing together, the order of laughter and compared laughing at *vs.* laughing with in social interactions. Similar investigations on laughters in human interactions were made by Jefferson [9] and Herron [10]. Truong et al. [11, 12] found similarities in signal characteristics of overlapping laughters against stand alone laughters. They further investigated the relation between initiating and responding laughters and reported prosodic similarities [6]. Other studies have analyzed the relation between laughter and emotion [2, 13], engagement in interaction [14] and health conditions [15, 16]. In our previous work [17], we showed that laughters can help predict client behavior in MI settings. Our experiments also showed that laughters carry prosodic differences with respect to the client behavior. In this paper, we extend the investigation of laughters in the context of motivational interviewing through computational analysis and modeling. Through these methods, we study the mutual relationship between counselor and client laughters as well as their association with target participant behaviors such as empathic expression. We perform three sets of experiments to: (i) analyze and model the distribution of utterances containing laughters in MI sessions, (ii) identify behavioral patterns based on utterances containing laughters of different types and (iii) study the effect of laughter rates on collaborative (so called *BrowniePoint*) counselor utterances.

(i) Investigating the distribution of utterances containing laughters: We first model the occurrence of utterances containing laughters as a Poisson process (PP). We extend the model by taking into account the laughter events of the other interlocutor. The second model provides us a better predictive fit and suggests an increase in a person's laughter rate when the other interlocutor laughs.

(ii) Identifying behavioral patterns based on laughter types: To understand the dynamics of an MI therapy session, and to evaluate the efficacy, clinical researchers have developed the Motivational Interviewing Skills Code (MISC) manual [18]. This manual provides an annotation protocol to label each counselor utterance with a behavioral code (e.g. support, reflection) and the client utterances as "change talk" towards/away from a target behavior change like smoking and drugs use. For this paper, we also categorize utterances as carrying no laughter, stand alone client (/counselor) laughter or a client (/counselor) lead shared laughter. We conduct experiments to quantitatively identify behavioral code patterns specified by MISC in relation to the laughter categories.

(iii) Effect of laughter rates on BrowniePoint detection: Counselor utterances high in desirable therapeutic behavior such as empathy, acceptance, collaboration and/or evocation are marked as "*BrowniePoint*" utterances by MISC annotation. We investigate the relation between laughters rates and such counselor utterances. Our experiments suggest patterns such as shared laughters as being associated with a higher probability of *BrowniePoint* occurrences whereas stand alone counselor laughters lead to a lower likelihood for the same.

We finally discuss the implications of the three experiments for improving the efficacy of motivational interviewing. In the

Utterance	Couns. code	Change talk
Couns. - How is it going for you ?	Question	
Client - I am doing good and my parents are helping me		CL0
Client - I have been off since a month		CL+
Couns. - Thats a plus	Reflection :)	
Client - But sometimes I feel like going back (Laughs)		CL-

Table 1: An excerpt from an MI session with corresponding counselor behavioral codes and client change talk utterance codes. Counselor codes with a smiley ":)" represent a *BrowniePoint*.

Counselor behavior codes	
Advice (AD, 511)	Raise Concern (RC, 10)
Affirm (AF, 1.9k)	Filler (FI, 89)
Confront (CF, 4)	Reflect (RE, 11.3k)
Direct (DI, 6)	Reframe (RF, 11)
Emphasize control (EC, 146)	Support (SU, 641)
Facilitate (FA, 17.7k)	Structure (ST, 1.7k)
Giving information (GI, 17.8k)	Warn (WA, 8)
Question (QU, 9.2k)	
No. of counselor utterances with *BrowniePoint*s: 9.0k	

Client change talk utterance codes	
Positive valence (CL+, 5.1k)	No change talk in
Negative valence (CL-, 4.4k)	utterance (CL0, 49.3k)

Table 2: Statistics of counselor behavior codes and client change talk utterance codes over the 242 MI sessions. We show the short representation and count in brackets.

next section, we describe the database, and provide a detailed description of the three experiments in section 3.

2. Database

We use a set of 242 sessions from five MI clinical trials including HMCBI, ESPSB, ESP21, ARC and iCHAMP sessions [19–23]. An excerpt from one such trial is shown in Table 1. Each of these trials was structured to adhere to the MI protocol with the counselor addressing problems such as drug abuse and alcohol addiction with the client. Given the transcripts, between 1-3 annotators mark the utterance boundaries, counselor and client behavioral codes as per the MISC manual. Note that the laughter locations are available in the transcripts. As a majority of files are annotated by one annotator, we use annotations from a single annotator per file for our study. The annotator for files with multiple annotators is chosen randomly. Counselor utterances high in empathy, acceptance, collaboration and/or evocation are marked with a *BrowniePoint* (represented by a ":)"). The MISC manual suggests coding schemes termed as "content codes" and "change talk" codes for counselor and client behavior. A list of counselor behavior codes and client change talk is shown in Table 2 and a detailed description of the codes can be found in the MISC manual [18]. Client utterances reflecting a move towards(/away from) the desired direction from a target behavior change are termed as positive (/negative) "change talk" (e.g. decrease in drug use is a positive change talk). Such utterances are marked as CL+ (/CL-) in Table 1. Any other utterance without change talk is shown as CL0. Note that there are a few other MISC protocols, but we do not use them in this work due to incomplete annotation or a large majority of utterances ($> 90\%$) being assigned to a single code under that protocol.

3. Experiments

We perform three sets of experiments to investigate the characteristics of laughter distribution within MI sessions as well as their association with the counselor and client behavior. In the first experiment, we model the arrival of utterances containing laughters as a Poisson process. In the second experiment, we study the relation of counselor and client behavior to laughters. Finally, we investigate the relation of laughter with *BrowniePoint* assignment. The experiments are described in detail below.

3.1. Distribution of utterances containing laughter

We model the arrival of utterances consisting of client and counselor laughters using Poisson processes (PP). PPs have been widely used to model arrival times of event occurrences such as skin conductance responses [24], heartbeat intervals [25] and software failures [26]. Considering each utterance turn as one time unit, we hypothesize that the arrival times for counselor and client utterances with laughters follow an exponential distribution. PP is characterized by a rate parameter λ such that the expected number of utterances containing laughters per T utterances is given by $\lambda \times T$. We estimate λ using a Least Mean Square (LMS) [27] algorithm. We obtain the rate parameters separately for client and counselor utterances containing laughters. During LMS estimation, we use sections of MI sessions with 100 utterances each as instances of PP. In our first model, we assume that λ is a constant value which does not change over time and does not depend on other factors. Such a PP is termed as homogeneous PP (h-PP).

As laughing is sometimes a shared phenomenon [8], we hypothesize that we can improve an interlocutor's PP model given the laughter pattern of the other person. In a second model, we re-estimate the parameters of a non-homogeneous PP (nh-PP) with a modified rate parameter as shown in equation 1.

$$\lambda(t) = \lambda_0 + \lambda_1 \sum_{\substack{\tau \in \text{Set of laughter locations} \\ \text{from the other speaker}}} R_W(t-\tau) \quad (1)$$

$\lambda(t)$ is the rate parameter for t^{th} utterance. Note that in this case the rate parameter may vary across utterances unlike a constant rate for h-PP. τ represents the utterance indices containing the other interlocutor's laughter. $R_W(t-\tau)$ represents a unit rectangular function starting at utterance with index τ, lasting for W utterances. λ_0 is the portion of rate parameter which remains constant and an addition of λ_1 is made to the rate parameter for the next W utterances when the other interlocutor laughs. We estimate λ_0 and λ_1 using the LMS algorithm. W is tuned for the best log likelihood.

Table 3 shows the rate parameter values and a plot showing $\lambda(t)$ for utterances in a synthetic session is shown in Figure 1. The rate parameter for h-PP is constant over the session. However an increase in nh-PP rate ($\lambda(t)$) is observed for a person when the other interlocutor laughs. We also perform a residual analysis with Kolmogorov-Smirnov (KS) goodness of fit test [28] to compare the empirical Cumulative Distribution Function (CDF) of laughter arrival times and CDF obtained through h-PP and nh-PP modeling. The KS statistics are also shown in Table 3. Notice the improvement in KS statistic using nh-PP over h-PP.

The rate parameter values suggest a higher rate for client laughters than counselor laughters. As seen in the Figure 1, the rate parameter λ for h-PP is slightly higher than λ_0 for

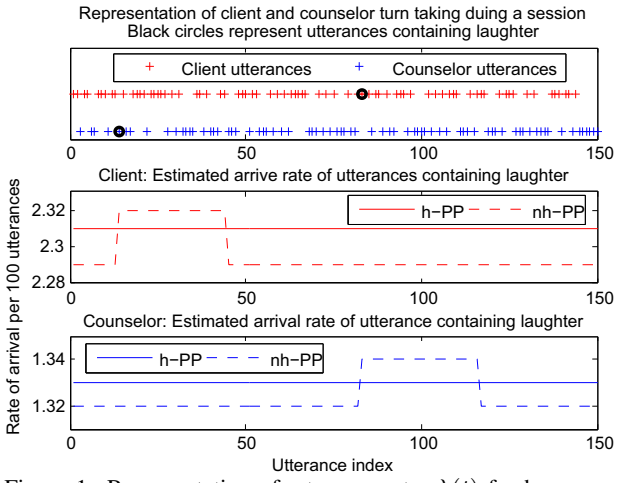

Figure 1: Representation of rate parameter $\lambda(t)$ for homogeneous (h-PP) and non-homogeneous PP (nh-PP). Notice the increase in nh-PP laughter rate for a person when the other person laughs.

Speaker	Homogeneous PP		Non-homogeneous PP	
	Rate parameter (λ)	KS statistic	Rate parameters (λ_0, λ_1, W)	KS statistic
Client	2.31	0.057	(2.29,.03,30)	0.051
Couns.	1.33	0.094	(1.32,.02,33)	0.086

Table 3: Arrival rate of utterances with laughter (per 100 utterances) as estimated using h-PP and nh-PP. All KS statistics of fit are significant at 0.1% level. Also notice improvement in KS statistic when modeling using nh-PP over h-PP.

nh-pp. However λ_1 accounts for a slight transient increase in both counselor and client laughter rates when the other person laughs. This increase in rate lasts for about thirty utterances for both the participants. The KS statistics provide an evidence that utterances with laughters can be modeled using a PP. Coupling in laughter behavior has been hypothesized by several previous works [8], and in this section we quantify the effect of one person's laughter on the other by using PP model. Next, we identify patterns in counselor and client behavior with laughter occurrences.

3.2. Identifying behavioral patterns based on laughter type

In an MI setting, client and counselor laughters may occur under specific behavioral backdrops. Moreover, occurrence of shared laughters may provide information regarding the behavioral state of the interlocutors. In this experiment we identify patterns in utterances containing laughters of different types with respect to the counselor and client MISC codes. Initially, we categorize utterances consisting of laughters as being stand alone or shared. Utterances with shared laughters are the ones which are followed by other person's laughter at least within the next utterance. On the other hand, utterances with stand alone laughters are not surrounded by any other utterance containing laughter. We assign each utterance in an MI session to one of the five utterance categories as listed below along with their counts in the database:
(a) Utterance with no laughter **(NL)**: $\sim$ 117k
(b) Utterance with a *stand alone* client laughter (**SA-Cl**): $\sim$2.5k
(c) Utterance with a *stand alone* counselor laughter (**SA-Co**): $\sim$1.5k
(d) Utterance with a client-lead *shared laughter* (**Sh-Cl**): 227

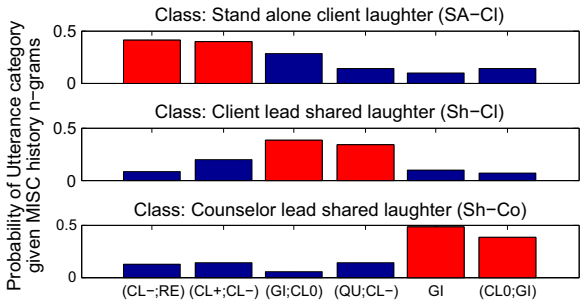

Figure 2: Probability of utterance classes given MISC history. Bars in red represent the top two n-grams associated with highest probability outcome for an utterance category.

Recall for each utterance category					UAR
NL	SA-Cl	SA-Co	Sh-Cl	Sh-Co	
14.9	31.9	17.5	35.2	51.1	30.1

Table 4: Recalls on classifying utterance class based on the MISC annotation history. Note that whereas the UAR is above chance prediction (20%), the predictions for NL and SA-Co are below chance levels ($< 20\%$).

(e) Utterance with counselor-lead *shared laughter* (**Sh-Co**): 149

From the empirical counts, we observe that a higher Sh-Co to SA-Co count ratio (149:1470) than that for Sh-Cl to SA-Cl classes (227:2530). This implies a shared laughter is more likely to be triggered after the counselor laughs. In order to further understand the relation between behavioral codes and laughter occurrences, we train a model to identify the utterance category based on the MISC annotation history. We aim to capture the patterns in interlocutor behavior and the utterance categories using this model. We train a maximum entropy classifier to predict the utterance category using unigrams and bigrams computed on MISC code history as features. For instance, we predict the utterance category of last client utterance in Table 1 based on n-grams computed on the MISC history of CL-, RE, CL+, CL0, QU (please refer to Table 2 for the expansion of each acronym). We perform a leave one session out cross validation for evaluation. For an equal class weighting during training, we downsample the instances from majority classes to contain same number instances as the least represented class.

We report the class recalls in Table 4 along with unweighted average recall (UAR). During training, the window of n-gram history taken into account is tuned by performing an inner cross validation on the training set. A significantly higher UAR over chance value of 20% (binomial proportions test, p-value $< 5\%$) suggests that there exist patterns in behavioral codes with respect to the kind of laughter. However, we observe that class recalls for NL and SA-Co are below chance levels. While this may be an artifact of heavily downsampling the class instances, we nevertheless fail to capture the relation between NL and SA-Co utterances and the MISC annotations. Highest class recalls are observed for classes with shared laughter. This suggests that shared laughters may occur under more structured behavioral circumstances when compared to NL/SA-Co utterances.

We further analyze these relations between n-grams of MISC annotations and the five classes. Figure 2 shows the probability of utterance class given an n-gram as output by a maximum entropy model trained on the entire data. Values are shown only for SA-Cl/ Sh-Cl/ Sh-Co classes as our model failed to capture patterns in behavioral codes for NL/ SA-Co. We list the n-grams associated with highest outcome probabilities for SA-

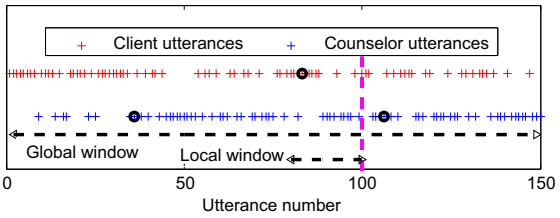

Figure 3: Sample extraction of laughter count features for utterance # 100 in a session with 150 utterances. In the local window, there is just one SA-Cl laughter. Globally, there are two SA-Co and one SA-Cl. Therefore the local laughter count is 1 for SA-Cl and global laughters rates are 150 utterances/SA-Cl and 75 utterances/SA-Co.

Cl/ Sh-Cl/ Sh-Co. In the x-axis of Figure 2, a value (CL-,RE) implies a bigram of CL- being followed by RE. GI is a unigram representation. Top two n-grams associated with highest probability outcome for SA-Cl (plotted with a red bar) show that such an utterance is likely to happen around the client change talk utterance with a negative change. Thus SA-Cl laughter type associates with an undesired event with client moving away from targeted behavior change. Shared laughters are most likely to happen in a context of the counselor giving information (GI). Bigrams involving combination of GI and CL0 occur as top two for both of the classes involving shared laughter.

3.3. Detecting *BrowniePoints* based on laughters

Utterances marked with *BrowniePoints* reflect high degree of empathy, acceptance and/or collaboration by the counselor towards the client. Such utterances are desired in an MI session as they indicate enhanced understanding between the participants. In our third experiment, we investigate the relation of laughters with utterances marked with a *BrowniePoint*. We initially develop a baseline model to detect utterances with *BrowniePoints* and evaluate the effect of accounting for laughters during detection. Specifically, we evaluate the effect of accounting for a *global laughter rate* as well as *local laughter count* in detecting *BrowniePoints*. We describe these models below.

3.3.1. Baseline model for BrowniePoint detection

The entire dataset consists of approximately 9k counselor utterances marked with a *BrowniePoint*. We train a model to predict if a counselor utterance is a *BrowniePoint* based on its lexical content. For instance, in Table 1, the model predicts if the second counselor utterance is a *BrowniePoint* utterance based on the contents of the phrase "Thats a plus". For *BrowniePoint* prediction, we train a maximum entropy classifier trained on n-grams extracted from counselor utterances. The model is trained to classify *BrowniePoint* vs other utterances and is trained on a downsampled set with equal number of *BrowniePoint* and regular utterances for class balance. Given the *BrowniePoint* utterances have a relatively rare occurrence, we use Area Under Curve (AUC) of the receiver operating characteristics curve as our metric. We evaluate the baseline model by performing a leave one session out cross validation.

3.3.2. BrowniePoint detection with laughter features

We use two sets of laughter features to evaluate the effect of laughters on *BrowniePoint* detection. These features reflect an overall laughter rate during the MI session (global laughter rate) and an immediate history of laughter occurrences (local laughter count). We describe them below.

Global laughter rate: This feature accounts for the global rate of utterances containing laughters during an MI session. In a session, we again assign utterances with laughters as containing a stand alone client laughter (SACl), stand alone counselor laughter (SACo), client lead shared laughter (ShCl) or counselor lead shared laughter (ShCo) (same assignment criteria as in Section 3.2). We then define a global laughter rate for each utterance category as the average number of utterances between two utterances from that category. A synthetic example for extraction of this feature is shown in Figure 3. Note that this feature will be the same for all utterances from a given session, but will vary across sessions.

Local laughter count: This feature yields the utterance type count over the immediate history of an utterance. We again use the four categories of utterances as in global feature computation. Given a window of past utterances categories for an utterance at hand, we count the occurrences of the SACl, SACo, ShCl and ShCo utterances. Please refer to Figure 3 for a sample extraction.

We recompute the AUC values after appending baseline n-gram features with (a) global laughter rate only (b) local laughter count only and (c) both global rate and local laughter count. We use same downsampling and training strategy as in the baseline model. The window length for local laughter count is tuned by inner cross validation on the training set. We list the baseline results and results with laughter features in Table 5.

Features	Baseline	+ global rate	+ local count	All features
	82.6	83.1	84.4	84.9

Table 5: AUC for *BrowniePoint* detection based on baseline and laughter derived features.

Results show that both the global and local features improve the *BrowniePoint* detection. This suggests that occurrences of counselor utterances showing a high empathetic response, acceptance and collaboration is related not only to the immediate laughter context but overall laughing frequency during the MI session. The results reflect a stronger association of *BrowniePoints* with laughters in the immediate context than the global rate. This finding suggests that empathetic response of counselors correlate with the laughter behavior, apart from the lexical content of utterances.

4. Conclusion

Laughters are reflective of emotions, rapport and internal mental state of a person. We performed several experiments to analyze laughter in MI-based psychotherapy settings. We model the joint occurrence of laughters of the counselor and client as Poisson process and observe that a person's rate of laughter increases when the other interlocutor laughs. We also observe that certain counselor and client behaviors are associated with stand alone client laughters and the shared laughters. Finally, our predictive experiments suggest that the global and local laughter features are positively related to *BrowniePoint* occurrences. We interpret these findings and derive patterns which can be useful for improving the efficacy of MI protocol including in training counselors.

Similar studies on laughter and other non-verbal cues can be conducted on other domains involving multi-party interactions. Our study needs to be extended to analysis of other aspects related to laughter such as prosody, lexical context and emotion. Laughter is one of the possible non-verbal vocalizations that may include sighs, cries, grunts and such. Investigations that include such broader inventory into the analysis can reveal further insights into the overall role of non-verbal vocal cues in psychotherapy interactions.

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