Interspeech 2018
2-6 September 2018, Hyderabad, India

Modeling Interpersonal Influence of Verbal Behavior in Couples Therapy Dyadic Interactions

Sandeep Nallan Chakravarthula[1], *Brian Baucom*[2], *Panayiotis Georgiou*[1]

[1]Dept. of Electrical Engineering, University of Southern California
[2]Dept. of Psychology, University of Utah

nallanch@usc.edu, brian.baucom@psych.utah.edu, georgiou@sipi.usc.edu

Abstract

Dyadic interactions among humans are marked by speakers continuously influencing and reacting to each other in terms of responses and behaviors, among others. Understanding how interpersonal dynamics affect behavior is important for successful treatment in psychotherapy domains. Traditional schemes that automatically identify behavior for this purpose have often looked at only the target speaker. In this work, we propose a text-based Markov model of how a target speaker's behavior is influenced by their own past behavior as well as their perception of their partner's behavior, based on lexical features. Apart from incorporating additional potentially useful information, our model can also control the degree to which the partner affects the target speaker. We evaluate our proposed model on the task of classifying Negative behavior in Couples Therapy and show that it is more accurate than the single-speaker model. Furthermore, we investigate the degree to which the optimal influence relates to how well a couple does on the long-term, via relating to relationship outcomes.

Index Terms: lexical n-grams, interaction dynamics, markov model, couples therapy, behavior prediction, relationship outcomes

1. Introduction

Conversations in social settings are often marked by each person expressing behaviors that are not only driven by their own internal state of mind but also affected by how the other person responds to them [1]. The nature of this phenomenon, referred to as interpersonal influence, can vary significantly, depending on the individual traits of the speakers as well as the relationship between them. Even for the same speaker, the type of influence might be different with different people, causing their behavior to change differently. For example, a person might respond positively when their friend compliments them but might respond in a lukewarm manner when a stranger compliments them. Therefore, creating models that explicitly incorporate influence can provide new understanding of the longer-term dyad dynamics along with better behavioral estimation.

Observational studies in psychotherapy domains involve interactions that are observed and assessed by human annotators on certain behaviors of interest. In Behavioral Signal Processing (BSP) [2, 3] we employ automated scoring of these interactions using speech and language analysis with machine learning to quantify these same behaviors. There are multiple methods of doing this, but one very successful technique has been through analysis of the spoken language of the rated speaker. Most work in this regard, however, either did not explicitly model the underlying states of the interlocutors [4, 5] or completely ignored the rated speaker's partner [6, 7]. These models lack explicit understanding of the interpersonal influence. While interlocutor influence models have been proposed in the past [8, 9], they assume direct interaction between the latent states of the speakers which is not applicable for our problem. Outside of BSP, mutual influence models have been proposed, such as [10] which predicts "attachment security" between mother and child based on their previous measures of security. However, these deal with fully observed processes which are different from the latent behavior we are interested in modeling.

Our proposed model, which we refer to as the influence model, is text-based and it describes how a speaker continuously perceives their partner's behavior based on their responses and how this perception, in addition to their own past behavior, affects their behavior over time. It also specifies parameters that determine the strength of the influence mechanisms. Thus, it provides a more complete understanding of how and why a person's behavior changes over time.

Additionally, we investigate if the interpersonal influence between the speakers of a couple during therapy relates to their relationship outcomes. It has been shown that interlocutor influence in couples dyadic interactions is important for relationship functioning [11], and therefore, outcomes. Empirical relations have also been found between outcomes and interaction-dependent measures such as vocal entrainment (through withdrawal behavior) [12] and dyadic prosodic features [13]. Therefore, we want to examine whether our model parameters, designed to describe the characteristics of dyadic interactions, can also provide information about outcomes.

2. Behavior Interaction Model

We first present our baseline model, proposed in [6], in Sec. 2.1 and then present our proposed influence model in Sec. 2.2

2.1. Likelihood-based Dynamic Behavior Model (LDBM)

The LDBM is a single-speaker model that characterizes a person expressing a certain *class* of behavior (ex: "High Anger" or "Low Anger") as a Hidden Markov Model (HMM)-based generative process. Specifically, in each turn, the target speaker occupies a latent behavior *state*, generates an utterance with some emission probability, either remains in the same state or moves to a different one with some transition probability, generates a new utterance and repeats this until the end of the interaction. The full behavior process is given by:

$$P(\boldsymbol{S_s}, \boldsymbol{U_s}) = P(\boldsymbol{S_s})P(\boldsymbol{U_s}|\boldsymbol{S_s}) \quad (1)$$

where $\mathbf{U}_s$ denotes the speaker's utterance sequence (ex:"No", "No", "I said no") and $\mathbf{S}_s$ denotes a speaker state sequence (ex:"Low Anger", "Low Anger", "High Anger"). Behavior classes in the LDBM share the same set of states but differ in their transition probabilities. For example, a "High Anger" speaker might tend to stay in a particular state and not change whereas a "Low Anger" speaker might frequently

10.21437/Interspeech.2018-1562

change states. The LDBM is the current best model in behavioral classification as it incorporates a more accurate model of time-varying behavior than then-existing methods. It does not however take the partner's effect into account.

2.2. Influence Model

As an extension, our proposed model introduces an additional latent "pseudo-state" that represents how the target speaker perceives their partner's behavior. Its purpose is to simulate the generation of the partner's utterance and affect the next state of the speaker. We do this to model the real-world scenario where a speaker does not know the state of mind of the partner they are interacting with [1] - the best they can do is to make an inference based on what they said. We call the partner's *perceived-by-target-speaker* state a pseudo-state to distinguish it from a state which represents the partner's internal state of mind. We use S_s to denote the state of the target speaker (whose behavior we are interested in identifying) and $\acute{S}_p$ to denote the pseudo-state of the partner (from whom we are obtaining supplementary information).

Furthermore, our influence model specifies parameters that control how much a speaker's behavior is influenced by their own past behavior versus their partner, motivated by the domain literature [14]. α and β respectively control how much the speaker's current utterance and partner explain their current behavior, relative to their previous state, which is always weighted by 1. Speakers who do not listen much to their partner and instead continually espouse only their point of view have $\beta \ll \alpha, 1$. In contrast, speakers that strongly react to what their partners say during discussions have $\beta \geqslant \alpha, 1$.

The behavior generation process is as follows: Before the ith speaking turn, the target speaker is in state S_s^{i-1} and, having observed the partner generate utterance U_p^{i-1}, has perceived them to be in pseudo-state $\acute{S}_p^{i-1}$. Then, in the ith speaking turn, based on S_s^{i-1} and $\acute{S}_p^{i-1}$, the speaker transitions to state S_s^i and generates U_s^i. As an illustration, Fig. 1 depicts this process over 3 turns of an interaction. It should be noted that while S_s^i depends on S_s^{i-1}, $\acute{S}_p^i$ does not depend on $\acute{S}_p^{i-1}$; it depends only on U_p^{i-1}.

For an interaction consisting of M speaking turns, the complete behavior generation process is given by:

$$
\begin{aligned}
&P(\boldsymbol{S_s}, \boldsymbol{\acute{S}_p}, \boldsymbol{U_s}, \boldsymbol{U_p}; \alpha, \beta) = \\
&\quad = P(\boldsymbol{S_s}, \boldsymbol{\acute{S}_p}; \beta) P(\boldsymbol{U_s}, \boldsymbol{U_p} | \boldsymbol{S_s}, \boldsymbol{\acute{S}_p}; \alpha, \beta) \\
&\quad = P(S_s^1) \cdot \prod_{j=2}^{M} P(S_s^j | S_s^{j-1}) \cdot \prod_{j=2}^{M-1} P(S_s^j | \acute{S}_p^{j-1})^{\beta} \\
&\qquad \cdot \prod_{j=1}^{M} P(U_s^j | S_s^j)^{\alpha} \cdot \prod_{j=1}^{M-1} P(U_p^j | \acute{S}_p^j)^{\beta}
\end{aligned}
\tag{2}
$$

where $\boldsymbol{U_s}$, $\boldsymbol{S_s}$, $\boldsymbol{U_p}$ and $\boldsymbol{\acute{S}_p}$ denote the speaker's utterance sequence, speaker state sequence, partner's utterance sequence and partner pseudo-state sequence respectively. $P(S_s^j | S_s^{j-1})$ and $P(S_s^j | \acute{S}_p^{j-1})$ are transition probabilities that denote how a speaker's previous state and their partner's previous pseudo-state are likely to affect the speaker's choice of next state. $P(U_s^j | S_s^j)$ is an emission probability describing the likelihood of the speaker saying U_s^j when occupying state S_s^j. $P(U_p^j | \acute{S}_p^j)$ describes the likelihood, according to the speaker, of the partner saying U_p^j in the perceived state $\acute{S}_p^j$. Since both emission probabilities deal with the speaker's perspective they

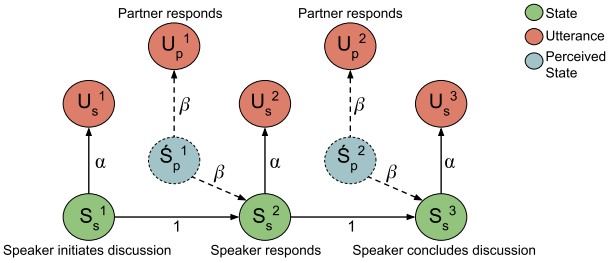


Figure 1: *Behavior generation process over 3 speaker turns in the Influence Model*

are obtained from the same model. The process of obtaining these probabilities is described in the training in Sec. 4.1.1.

3. Data

The Couples Therapy corpus [15] contains audio, video recordings and manual transcriptions of conversations between 134 real-life couples attending marital therapy. In each session, one person selected a topic that was discussed over 10 minutes with the spouse. At the end of the session, both speakers were rated separately on 33 "behavior codes" by multiple annotators based on the Couples Interaction [16] and Social Support [17] Rating Systems. Each behavior was rated on a Likert scale from 1, indicating absence, to 9, indicating strong presence. The average inter-annotator agreement, measured using Krippendorff's α, was 0.798.

A session-level rating was obtained for each speaker by averaging the annotator ratings. This process was repeated for the spouse, resulting in 2 sessions per couple at a time. The total number of sessions per couple varied between 2 and 6. Henceforth, for couples, we refer to the speaker whose behavior we want to classify as "rated speaker" and their partner as "spouse".

For classifying Negative behavior, we used the binarized dataset where sessions with ratings in the top 20 percentile i.e. High Negative are assigned the class label C_1 while those in the bottom 20 percentile i.e. Low Negative are assigned C_0. There are 280 sessions in total with 140 in each class. In each session, we formatted the interaction to enforce the rated speaker to begin the conversation as well as end it as illustrated in Fig. 1.

Each couple was also rated by the annotators at the 26-week or the 2-year time period on its recovery since starting therapy, referred to as "outcomes" [18]. They were rated as follows - 1 indicating deterioration in relationship, 2 indicating no change, 3 indicating measurably better improvement and 4 indicating recovery. We use 2-year outcome ratings for 79 couples belonging to the Top/Bottom 20 percentile classes. These are the ones we are interesting in analyzing and their demographics are shown in Table 1.

Outcome	Decline	No Change	Better	Recovery
Rating	1	2	3	4
No. Couples	18	9	18	34

Table 1: *Couples Therapy Outcome Demographics*

4. Experiments

In this section, we describe the classification experiment. We also describe in Sec. 4.2 how we can employ the optimized model parameters, α, β, as indicators of influence or inertia and

how these can be related to outcomes.

4.1. Behavior Classification

We use a nested leave-one-couple-out cross-validation scheme (N test * N-1 dev for each test) in order to account for the small number of samples and prevent over-fitting to the speaking styles or interaction topics of the test couple as well as to tune model parameters α and β. We evaluate our model against the LDBM with 1-grams, 2-grams and 3-grams to examine the effect of longer context. We also modify the LDBM process described in Eqn. 1 to allow scaling of the emission probabilities with the same α used in our model. This allows for a fairer comparison of the two models.

4.1.1. Training

The core training methodology is similar to that of the LDBM in our previous work [6]. We use two states S_0 and S_1 which are represented by statistical language models (LM) that we term language-to-behavior (L2B) models. In this case the L2B model is an n-gram LM as in [19, 6], trained using the SRILM toolkit [20]. These state LMs are used to score text to obtain emission probabilities $P(U_s^j|S_s^j)$ and $P(U_p^j|\acute{S}_p^j)$ in Eqn. 2. Both classes C_0 and C_1 use the same states but through different state transition probabilities. The state models, along with the transition probabilities, are trained using the Expectation Maximization (EM) algorithm [21].

In this first attempt at creating the influence model, our focus was on establishing its benefits. Thus, rather than risk overfitting through optimization, we decided to explore a range of α and β in logarithmic steps of 10 from 10^{-3} to 10^3, resulting in a search space of 49 points. The main idea is to get a general sense of the importance of the information streams. For example, α=1, β=1 implies that "the rated speaker is affected as much by their own past behavior as their spouse's".

The training procedure is as follows:

1. In a test fold, pick parameter configuration α, β
2. Initialize and iteratively train state models with α, β using the LDBM training described in [22]
3. Estimate state transition probabilities per class, classify dev couple sessions and repeat for all dev sessions
4. Pick best configuration α, β based on dev accuracy
5. Use this α, β, train class and state models to evaluate on the test session and repeat for all test folds

We avoided estimating transition probabilities at each iteration since they tended to skew towards not changing states as a result of the turns initially having the same label. For this experiment and evaluation we have 134 models, one for each test couple due to the n-fold nature of our evaluation. The training procedure for modified LDBM is similar with only α being optimized over the dev set. For baseline comparison, we also trained LDBM with fixed α=1. It should be noted that LDBM with α=1 is not the same as influence model with α=1,β=0 since their training data are different.

4.1.2. Testing and Evaluation

Given a session consisting of M rated speaker turns $\mathbf{U}_s$ and $M-1$ spouse turns $\mathbf{U}_p$, the goal is to classify the rated speaker as either C_0 or C_1. For each class, we get decoded state sequences, that best explain the observed utterances, along with its probability. The class that is most likely to have generated the utterances is then picked as the label of the rated speaker as denoted below:

$$C_i = \arg\max_{C_j} P(\boldsymbol{S_s^j}, \boldsymbol{\acute{S}_p^j} | \boldsymbol{U_s U_p}; \alpha, \beta) \quad (3)$$

$$= \arg\max_{C_j} P(\boldsymbol{S_s^j}, \boldsymbol{\acute{S}_p^j}, \boldsymbol{U_s}, \boldsymbol{U_p}; \alpha, \beta) \quad (4)$$

where $\boldsymbol{S_s^j}$ is the speaker state sequence decoded by model of C_j for $\boldsymbol{U_s}$, $\boldsymbol{\acute{S}_p^j}$ is the perceived partner state sequence decoded by model of C_j for $\boldsymbol{U_p}$, and α and β are the optimized parameters used to train final model

The joint probability in Eqn. 4 reduces to the conditionally independent probabilities in Eqn. 2. Using this scheme, we classify all test couples with their corresponding fold models trained in Sec. 4.1.1 and compute the classification accuracy. The same scheme is also used to test the LDBM and obtain its classification accuracy. The two models, along with the baseline, are then compared in Sec. 5.1.

4.2. Mapping Parameters to Outcomes

We investigated whether our model parameters contain information about couples outcomes using the following procedure: For an outcome rating, select couples with this rating. Select a couple and obtain its average dev classification accuracy over all test folds for each parameter configuration α, β. Pick the parameter configuration with the highest accuracy and add 1 count to its bin; equal fractional counts if there are multiple configurations. Repeat for all couples and normalize the counts to get a 2-D histogram. Since the weights corresponding to the speaker's state and the partner's effect are 1 and β respectively, convert 2-D histogram into a 1-D histogram with new axis $\gamma = log10(1/\beta)$ and repeat for all outcomes. The results of this analysis are discussed in Sec. 5.2.

5. Results & Discussion

5.1. Behavior Classification Results

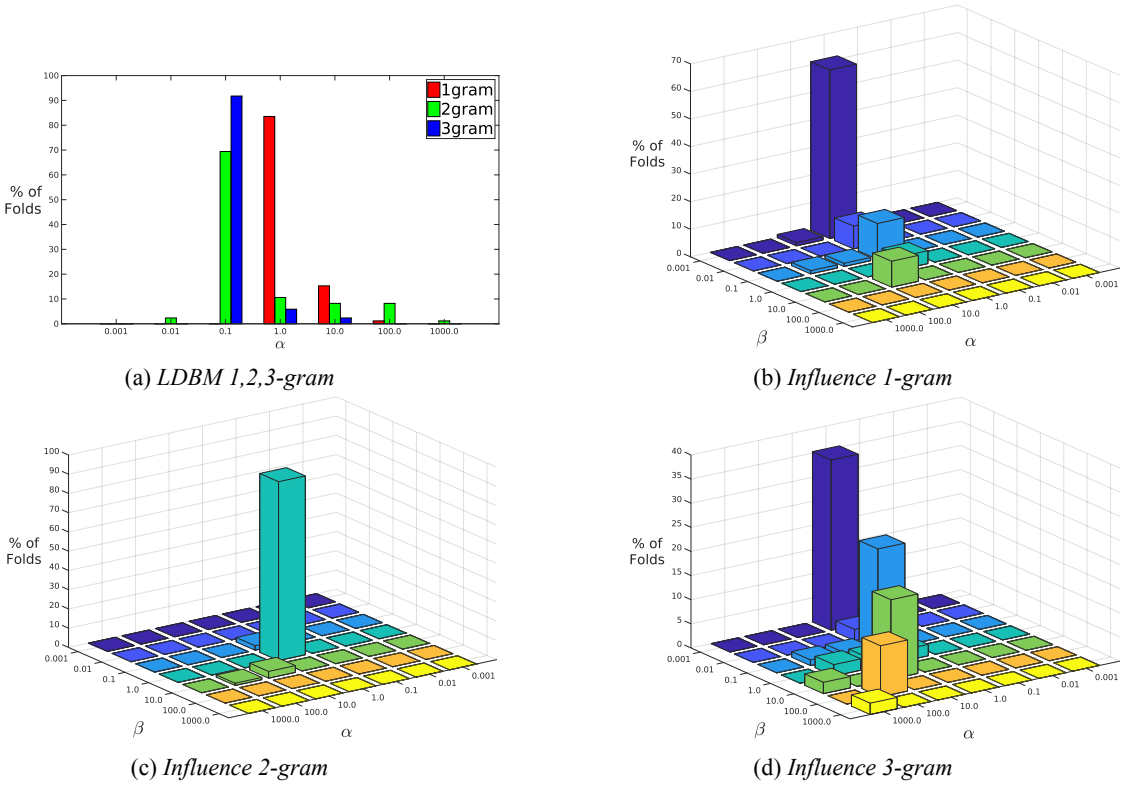
The test results comparison betwen the baseline LDBM (α=1), LDBM and influence model is shown in Table. 2.

Model	LDBM (α=1)	LDBM	Influence Model
1-gram	84.64	82.86	**85.00**
2-gram	86.78	86.43	**88.93**
3-gram	85.71	87.86	**88.21**

Table 2: *Comparison of Test Classification Accuracy % with best performing model indicated in* ***bold***

We see that our proposed model improves upon the existing one and the baseline in every context scenario. This indicates that the partner's responses do provide supplementary information about why the speaker behaves in a certain way. We also see that while the LDBM gets better with more context, the influence model improves from 1-gram to 2-gram but slightly drops in accuracy from 2-gram to 3-gram. One reason for this could be the coarse sampling of control parameters while another could simply be the sparsity in learning 3-grams in bigger models. We note that our best performing model matches the best Recurrent Neural Network (RNN)-based accuracy obtained by Tseng et al in [5]. This points to complementary gains from improved L2B models [5] and from incorporating interlocutor dynamics as in this work.

We also examined which (α, β) configuration in the influence model and α in the LDBM performed best in different test folds. This can provide insight into how relevant each stream of information is, on average. The histogram of best



(a) *LDBM 1,2,3-gram* (b) *Influence 1-gram*

(c) *Influence 2-gram* (d) *Influence 3-gram*

Figure 2: *Histogram of best parameter configurations for 1,2,3-gram LDBM and Influence models*

configurations for both models is shown in figs. 2a to 2d. It is interesting to note that the best performing model, the 2-gram influence model, overwhelmingly picked α=β=1, implying equal importance of all the information streams. This too stresses the importance of incorporating the spouse's feedback when studying a rated speaker's Negative behavior.

5.2. Parameters to Outcomes Mapping Results

The 1-D histogram relates to interpersonal influence in the following way: $\gamma = 0$ denotes equal contribution of the rated speaker's past behavior as the spouse. $\gamma > 0$ corresponds to the speaker's past behavior being more dominant than the spouse whereas $\gamma < 0$ denotes the reverse. In order to check if the outcome histograms are generated from different distributions, we fit a Gaussian distribution to each one.

We obtained fits with a mean value of 0.2, 0.16, -0.18 and 0.05 for outcomes 1, 2, 3 and 4 respectively; all gaussians exhibit a high variance. We see that couples with the best outcome 4 have a mean γ closest to 0, signifying equal influence, while couples with the worst outcome 1 have a mean γ farthest from 0, signifying one person's influence dominating the other's. These results are encouraging enough to warrant further investigation in future.

6. Conclusions & Future Work

In this work, we proposed a model of how a speaker's behavior changes over time as a result of interacting with their partner. Our approach described a generative process of how one person is perceived based on what they said and how this perception relatively affects the other in conjunction with their own past behavior. By achieving higher accuracy over a single-speaker model on the task of classifying Negative behavior for Couples Therapy, we demonstrated the effectiveness of incorporating information from both participants in a conversation.

In addition, we investigated if our model could provide insights into how interaction dynamics relate to the long-term quality of a couple's relationship. We found that some outcomes tend to be associated with how proportionately a speaker is affected by their partner's perceived behavior with respect to their own past behavior.

As part of future work, we will implement comprehensive optimization of the model while also jointly training all components in it. We also plan on investigating which behaviors benefit from influence modeling and which ones don't and why. Another area where our model can potentially be improved is in replacing discrete behavior states with continuous ones such as in the Kalman filter or recursive neural networks. We will also investigate incorporating our more recent advances in language-to-behavior mapping as in [5].

We also plan on further investigating the relation between influence parameters and outcomes with the help of the extensions mentioned above - refined estimation of parameters and for all behaviors - as well as by jointly analyzing the influence parameters and states.

7. Acknowledgments

The U.S. Army Medical Research Acquisition Activity, 820 Chandler Street, Fort Detrick MD 21702-5014 is the awarding and administering acquisition office. This work was supported by the Office of the Assistant Secretary of Defense for Health Affairs through the Psychological Health and Traumatic Brain Injury Research Program under Award No. W81XWH-15-1-0632. Opinions, interpretations, conclusions and recommendations are those of the author and are not necessarily endorsed by the Department of Defense.

8. References

[1] M. Mikulincer, V. Florian, P. A. Cowan, and C. P. Cowan, "Attachment security in couple relationships: A systemic model and its implications for family dynamics," *Family process*, vol. 41, no. 3, pp. 405–434, 2002.

[2] P. G. Georgiou, M. P. Black, and S. S. Narayanan, "Behavioral signal processing for understanding (distressed) dyadic interactions: some recent developments," in *Proceedings of the 2011 joint ACM workshop on Human gesture and behavior understanding*. Scottsdale, AZ: ACM, 2011, pp. 7–12.

[3] S. Narayanan and P. G. Georgiou, "Behavioral signal processing: Deriving human behavioral informatics from speech and language," *Proceedings of the IEEE*, vol. PP, no. 99, pp. 1 –31, 2013.

[4] M. P. Black, A. Katsamanis, C.-C. Lee, A. Lammert, B. R. Baucom, A. Christensen, P. G. Georgiou, and S. S. Narayanan, "Automatic classification of married couples' behavior using audio features," in *Proceedings of InterSpeech*, 2010.

[5] S.-Y. Tseng, S. N. Chakravarthula, B. R. Baucom, and P. G. Georgiou, "Couples behavior modeling and annotation using low-resource lstm language models." in *INTERSPEECH*, 2016, pp. 898–902.

[6] S. N. Chakravarthula, R. Gupta, B. Baucom, and P. Georgiou, "A language-based generative model framework for behavioral analysis of couples' therapy," in *Acoustics, Speech and Signal Processing (ICASSP), 2015 IEEE International Conference on*. IEEE, 2015, pp. 2090–2094.

[7] B. Xiao, P. Georgiou, Z. E. Imel, D. Atkins, and S. Narayanan, ""Rate my therapist": Automated detection of empathy in drug and alcohol counseling via speech and language processing," *PLOS ONE*, December 2015.

[8] C.-C. Lee, C. Busso, S. Lee, and S. S. Narayanan, "Modeling mutual influence of interlocutor emotion states in dyadic spoken interactions," in *Tenth Annual Conference of the International Speech Communication Association*, 2009.

[9] Z. Yang and S. Narayanan, "Modeling mutual influence of multimodal behavior in affective dyadic interactions," in *Acoustics, Speech and Signal Processing (ICASSP), 2015 IEEE International Conference on*. IEEE, 2015, pp. 2234–2238.

[10] W. L. Cook and D. A. Kenny, "The actor–partner interdependence model: A model of bidirectional effects in developmental studies," *International Journal of Behavioral Development*, vol. 29, no. 2, pp. 101–109, 2005.

[11] K. J. Baucom, B. R. Baucom, and A. Christensen, "Changes in dyadic communication during and after integrative and traditional behavioral couple therapy," *Behaviour research and therapy*, vol. 65, pp. 18–28, 2015.

[12] C.-C. Lee, A. Katsamanis, B. R. Baucom, P. G. Georgiou, and S. S. Narayanan, "Using measures of vocal entrainment to inform outcome-related behaviors in marital conflicts," in *Signal & Information Processing Association Annual Summit and Conference (APSIPA ASC), 2012 Asia-Pacific*. IEEE, 2012, pp. 1–5.

[13] M. Nasir, B. R. Baucom, P. Georgiou, and S. Narayanan, "Predicting couple therapy outcomes based on speech acoustic features," *PloS one*, vol. 12, no. 9, p. e0185123, 2017.

[14] S. B. Berns, N. S. Jacobson, and J. M. Gottman, "Demand–withdraw interaction in couples with a violent husband." *Journal of Consulting and Clinical Psychology*, vol. 67, no. 5, p. 666, 1999.

[15] A. Christensen, D. Atkins, S. Berns, J. Wheeler, D. Baucom, and L. Simpson, "Traditional versus integrative behavioral couple therapy for significantly and chronically distressed married couples," *Journal of Consulting and Clinical Psychology*, vol. 72, no. 2, pp. 176–191, 2004.

[16] C. Heavey, D. Gill, and A. Christensen, "Couples interaction rating system 2 (cirs2)," *University of California, Los Angeles*, vol. 7, 2002.

[17] J. Jones and A. Christensen, "Couples interaction study: Social support interaction rating system," University of California, Los Angeles, Technical manual, 1998.

[18] K. J. Baucom, M. Sevier, K. A. Eldridge, B. D. Doss, and A. Christensen, "Observed communication in couples two years after integrative and traditional behavioral couple therapy: outcome and link with five-year follow-up." *Journal of consulting and clinical psychology*, vol. 79, no. 5, p. 565, 2011.

[19] P. G. Georgiou, M. P. Black, A. Lammert, B. Baucom, and S. S. Narayanan, ""That's aggravating, very aggravating": Is it possible to classify behaviors in couple interactions using automatically derived lexical features?" in *Proceedings of Affective Computing and Intelligent Interaction*, Memphis, TN, USA, 2011.

[20] A. Stolcke, "Srilm-an extensible language modeling toolkit," in *Seventh international conference on spoken language processing*, 2002.

[21] A. P. Dempster, N. M. Laird, and D. B. Rubin, "Maximum likelihood from incomplete data via the em algorithm," *Journal of the royal statistical society. Series B (methodological)*, pp. 1–38, 1977.

[22] S. N. Chakravarthula, B. Xiao, Z. E. Imel, D. C. Atkins, and P. G. Georgiou, "Assessing empathy using static and dynamic behavior models based on therapist's language in addiction counseling," in *Sixteenth Annual Conference of the International Speech Communication Association*, 2015.