Unsupervised Learning of Dyadic Processes: Models, Methods, and Simulation

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Abstract. The dynamics that arise from dyadic processes, such as those observed in married couples, generate a cascade of effects—some good and some bad—on each partner, other family members, and other social contacts. Although the effects are well documented, the processes associated with the varied outcomes are not well understood. We currently have two methods of simulating dyadic interaction in married couples—an algorithm-based ABM and a particle filter. Although both work reasonably well, neither fully captures the dynamics of an evolving social process as well as we would like. Recently, we developed a third method of generating couple dynamics model using a Hierarchical Dirichlet Process Hidden semi-Markov Model (HDP-HSMM) (Johnson & Willsky, 2012). We review the how this technique generates plausible dyadic sequences that are sensitive to relationship quality and provides a natural mechanism for simulating micro-social processes.

Keywords: dyadic processes, micro-social dynamics, Hierarchical Dirichlet, Hidden semi-Markov Model

1 Introduction

Social scientists studying the dynamics of ubiquitous self–organizing dyadic processes—either as family units or merely actors in a fecundity play—have little insight into the critical features that predict, or even describe, sustained coupling. For humans, this is critically important: Evidence suggests that the marital relationship has unequivocal effects on health—good ones protect and buffer its constituents and bad ones are associated with having increased risk for physical maladies (Kiecolt-Glaser & Newton, 2001; Kiecolt-Glaser et al., 2005). This effect extends beyond the dyad—a distressed marriage is associated with a poor parent-child relationship, increased psychological problems in children, and

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should the relationship end, neither the children or the adults are immune—each endures greater stress and accompanying decreases in health (Fagundes et al., 2011) and financial stability.

Despite these consequences and decades of research dollars spent to examine, reduce, or prevent a distressed relationship, to date, marital researchers have only identified a few features of an interaction that are associated with marital distress. Moreover, during the past decade theoretical and technical advances allowed investigators in this area to extend the literature by capturing more and better audio, video, and physiological data across different tasks, settings, and length of observation. Yet aside from higher levels of negativity and more extended chains of negative reciprocity typically seen among distressed couples, few summary or sequential features of dyadic interaction consistently predict marital quality, and none predict marital outcome.

While investigators continue to be intrigued by the intricacies of interpersonal dynamics, the past decade of work has shown that these processes are not easy to study nor do scientists have a good understanding of them. In effect, 12-15 minutes of dyadic interaction generally provides substantial and sometimes predictive information about a couple, but the latent generating mechanisms underlying the dynamic processes associated with the cognitions, behaviors, and affect observed during the interaction are not known, nor has anyone tried to model them in real time. A goal in this area is to establish a set of key macro-level patterns, derived during micro-social processes, that have predictive validity beyond the observed constituent codes. Its hoped that the relevant micro-social features can predict either some proximal dyadic state or permit accurate population classification. In the language of computer science, this area of inquiry needs to find generating models of sequential latent processes, i.e., profiles of sequential movement across latent states with estimated probabilistic structures (Dunson, 2006). Fortunately over the last decade the study of latent generating processes has become a cornerstone of contemporary machine learning theory (Teh & Jordan, 2010). With the advent of faster computers, and theoretical advances in Bayesian methods, emphasis is now on discovering methods that capture temporal clustering and feature extraction in sequential data.

At the forefront of this area is the family of nonlinear hierarchical Bayesian techniques. For example, sequential and hierarchical Latent Dirichlet Allocation methodology (Gershman & Blei, 2011) now permits investigators to partition data into clusters (Teh et al., 2006) and sequence sensitive feature states (Emonet et al.,2011). Likewise, renewed interest in the traditional Hidden Markov Model (HMM) has resulted in several revised multi-state, hierarchical models that have the ability to capture time-sensitive latent state transition processes (see e.g., infinite HMM (Blei, Griffiths, and Jordan, 2010); Hierarchical Dirichlet Process-HMM (HDP-HMM), Teh & Jordan (2010)).

Similarly, until recently HMMs were primarily used as tools in voice recognition (Rabiner, 1989) and later adopted for a diverse uses of other recognition tasks, ranging from social dynamics (Griffin, 2002) to hydrological time-series (Kehagias, 2004). In the last half-decade, development of new HMMs has incorporated a hierarchical nonparametric Bayesian approach; this adoption permits a greater range of use with real, somewhat messy, data (Fox et al., 2008; Johnson & Willsky, 2012). Most notability has been the attempt to parameterize the likelihood of state self-transitions (Fox et al., 2008); this, combined with the use of a Hierarchical Dirichlet process to generate priors and leave unspecified the expected number of states, permits the building of explicit-duration semi-Markov models. Such models are substantially more realistic of natural, dynamic stochastic processes.

In this presentation we will provide an overview of our current methods for modeling the dynamics of dyadic interaction and then show how the new machine learning techniques generate more accurate models and consequently more realistic simulations. We currently have two methods of simulating dyadic interaction in married couples—an algorithm-based ABM and a particle filter (described below). Although both work reasonably well, neither fully captures the dynamics of evolving social processes as well as we would like. Recently, we developed a third method of generating a couple dynamics model using a Hierarchical Dirichlet Process Hidden semi-Markov Model (HDP-HSMM) (Johnson & Willsky, 2012).

1.1 Preliminary Work

Our previous analysis of dyadic sequences focused on two fronts: (1) using unsupervised machine techniques - specifically, Hidden Markov Models - to extract observable features; and (2) building agent-based models that generate plausible interaction sequences. In the former case, Griffin (2002) used the data from 30 couples to develop a 10-state 4-symbol HMM that classified distressed from non-distressed couples with an accuracy rate of 91%; he found a decidedly different distribution in the observables for self-transitions and states transitions among non-distressed couples—there was substantially greater mutual positive affect during the middle phase of the sequence. Two aspects of this research are noteworthy. First, the classification rate of 91% is below expectation in a well developed HMM, but this value is acceptable (especially in this social science area) given the small sample size and low dimensional vector used to create the data string. Second, although no substantive conclusions were forwarded, results demonstrated that couple interactions were patterned and accurate learning and classification occurred without supervision.

In addition to using Hidden Markov Models to search for pattens within sequences, we have built two functioning ABMs of dyadic interaction. Our first attempt was an algorithm based model that simulated affect expression based on transition matrices derived for observed interactions (Griffin et al., 2004; Griffin & Li, 2012; see Figure 1).

Although the rule set (i.e., *if/then* statements) based model was simple and generally showed fidelity to the realized data, generated outcomes were inconsistent and often unwieldy. Next we built a simulation platform using a particle filter as the generating mechanism. A particle filter (i.e., sequential Monte Carlo (SMC)), is a model estimation technique based on simulation. It estimates the

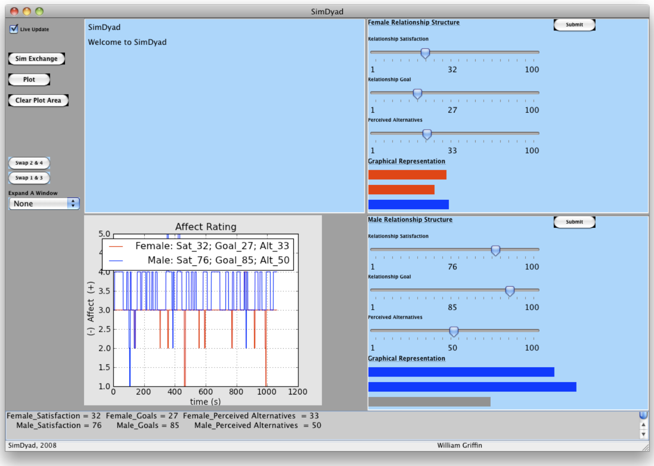

Fig. 1. User interface showing parameter sliderbars that modify interaction characteristics and a generated couple affect trace.

sequence of hidden parameters based on the observed data. The model interface is shown in Figure 2; sliderbars allow the user to vary relevant parameters of the putative process. Using the particle filter, we developed a data driven model that allowed the viewer to examine how small changes in relationship quality shifted the trajectory of the interaction. Whereas the initial ABM focused on expressed affect, the particle filter simulated verbal and nonverbal exchanges. This model illustrates how the observable features of an evolving interaction vary in real-time depending on each individual's self-report of relationship quality, aspirations, and goals. A typical output is shown in Figure 3; as expected, with small differences in the aforementioned parameters, each instantiation generates a different, yet probabilistically constrained, behavioral series. We learned several things from this work: first, algorithms derived from extant data can generate complex evolving processes that provide inconsistent facsimiles to realized data; and (2) particle filters provide a good method of generating plausible sequences but are not intended to invoke theoretical opportunity for the investigator, they simply generate a good trace; and (3) although HMMs are well developed mathematically, traditional use of the methodology requires the investigator to assume time-invariant state distributions and a fixed, known number of states. We know that in a dynamical system, by definition, time in state is the critical feature; likewise, descriptions and models of different systems require differing number of states.

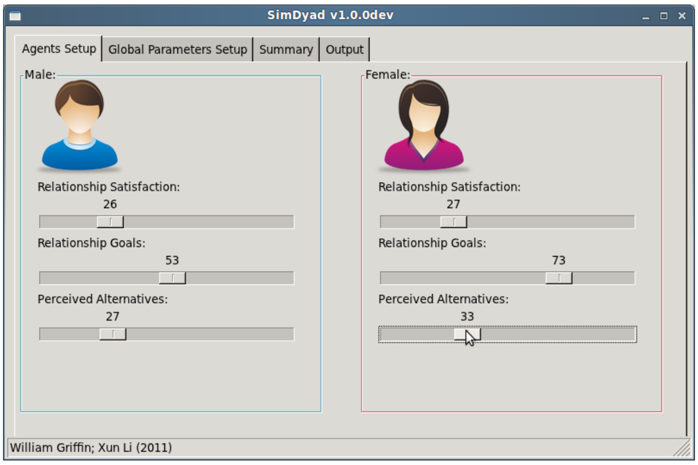

Fig. 2. User interface showing parameter sliderbars that modify interaction characteristics.

2 HDP-HSMM

The standard Hidden Markov Model (HMM; Rabiner, 1989) is an excellent general method of discovering latent structures in sequential data (Griffin, 2002), as long as the assumed process is simple (e.g., the state durations were time invariant or the number of states were known a priori). Fortunately, with increased investigations of real-world complex datasets, the standard HMM has been transformed over the last decade: computer scientists have created numerous sequential analytic techniques that are sensitive to the nuances of evolving latent structures (e.g., infinite HMMs) akind to the type seen in micro-social dynamics (Gershman & Blei, 2011). Among these is the Hierarchical Dirichlet Process Hidden Markov Model (HDP-HMM; Teh et al., 2006). The hierarchical Dirichlet process (HDP) models the dependence among groups through sharing the same set of discrete parameters. Yet its assumption of exchangeability make it inappropriate for sequential data; fortunately this restrictive assumption spurred new models that are appropriate for time sensitive data (Blei & Lafferty, 2006; Dunson, 2006). For example, Fox, Willsky, and colleagues (2008) were able to extend the standard HDP by introducing a method of parameterizing the self-transition bias, the state persistence problem, which in turn, allowed them to develop a fully nonparametric HMM - effectively removing the need to specify, a priori, the number of states associated with a system. This method, termed the Sticky HDP-HMM, despite being a radical improvement, suffered the same duration distribution constraint as the standard HMM: state durations are time-invariant.

Fortunately Johnson & Willsky (2012) quickly extended the work of Fox et al. (2008) by combining semi-Markovian ideas with the Stickly HDP-HMM to construct a general class of models that incorporated duration distributions. The

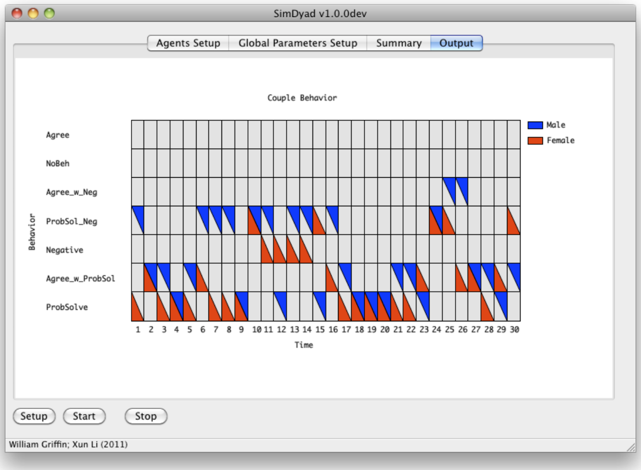

Fig. 3. Model output showing a sex coupled sequence over 30 time units.

recent models are well described in the aforementioned references. Our work uses the models developed by Johnson and Willksy. Our goal of extracting patterns from sequential data is conceptually and quantitatively similar to their search for structure in the real and synthetic data used in their paper. Where they used multiple time-series for household appliance data we inserted husband and wife sequence data. Likewise, our simulations are written in Python, as is their publicly available code, thus it was easily modified to fit our research questions, output plots, and GUI.

3 Methods

3.1 Sample

Recruitment Thirty married couples responded to newspaper advertisements offering twenty-five dollars for participation in a study on marital communication. The initial sample was recruited from among married couples living in the metropolitan Phoenix area. In the first wave, 40 participants (20 couples) were recruited. One couple was dropped because of invalid data. Five of the remaining 19 couples reported marital distress. Because five couples are an insufficient number for group comparison (e.g., distressed vs. nondistressed) and comprehensive statistical analysis, the second recruitment effort specifically targeted distressed couples. The modified newspaper advertisement asked couples to participate in the study if they felt their marriages were distressed. Of the 11 married couples recruited in the second wave, nine marriages qualified as distressed and two as nondistressed. In sum, 14 distressed and 16 nondistressed married couples participated in the study.

3.2 Data Collection

Upon arrival at the Marital Interaction Lab, couples were greeted by the lab assistant and then seated in a room constructed to resemble a small living area containing prints, curtains, plants, and two chairs in the center of the room. Two unobtrusive, partially concealed, remotely controlled cameras were mounted on the walls at head level behind each chair. All audiovisual and mixing equipment was controlled from a room adjacent to the interaction. Video signals were combined producing a split-screen image; audio was obtained from lavaliere microphones worn by each spouse.

3.3 Problem Solving Task

After completing informed consent forms, couples were given the Areas of Disagreement questionnaire (i.e., standard Strodbeck's revealed differences task). Each marital partner selected and ranked a list of potential disagreement areas typically associated with marital relationships, according to how much they disagreed and for how long they had disagreed. Couples were then instructed on how to use the Affect Generation computers in the lab (see below). After they became familiar with the procedure, they returned to their chairs. With the lab assistant's help, the couple selected the three most common topics from the list of problem areas and agreed to discuss them. The lab assistant then instructed the couple to engage in a 12-minute discussion and attempt to resolve the issues. This is a common task used to evoke interaction in married dyads. Controlling the audio and video equipment from the adjacent room, the lab equipment operator recorded the couples' conversation.

3.4 Affect Generation

After completing the conversation, lab assistants escorted marital partners to their respective seats at the Affect Generation computers. The lab assistant left the room and each spouse then simultaneously reviewed and rated his or her own affect while watching a videotaped split-screen playback of the interaction. Separated by a partition and wearing audio headsets, husbands and wives could not see or hear their spouse while reviewing the videotaped interaction. A study using similar methodology for recalled self-report of affect reported validity for the procedure with respect to observational coding.

The videotape was played back through a specially configured microcomputer using software that overlays a 9-level, color-coded, vertical bar on each color video monitor. This overlay was positioned beside the face on the monitor of the spouse reviewing the tape. The affect rating ranges from extreme negative (red), through neutral (gray) to extreme positive (blue), and is controlled by a personal computer mouse. Extreme negative is at the monitor bottom, neutral is at mid-monitor, and extreme positive is at the top of the monitor. The width of the bar varies at each affect level (5 pixels increments) corresponding to the intensity of the affect, neutral being the thinnest. The widest affect level is 28 pixels wide (1.5 cm). As the reviewer moves the mouse, the affect bar is highlighted corresponding to the degree and direction of the affect. For example, as the individual's affect rating becomes more negative (positive), the mouse is pulled back (pushed forward) and the appropriate affect level becomes highlighted, and as the highlighted area moves further from neutral, the width of the level expands to reflect intensity. During the review of the tape, and viewing only his or her own rating, each individual is asked to move the mouse to reflect affective experience during the interaction (i.e., "How were you feeling at each moment?") In this context, affect refers to the speaker's assessment of an internal reference to the meaning of "feeling" (i.e., over a continuum from positive to negative). Software records the location of the bar position every second, providing a continuous measure of affect throughout the interaction. Average ratings are referenced to a reduced 9-point scale: $8 =$ extreme negative, $4 =$ neutral, and $0 =$ extreme positive.

In this method of affect retrieval, each affect has a subjective reference that is unique to the rater, within the context of the interaction, given the dyad's history. For each individual there is only an internal template referencing a positive, a neutral, or a negative affect state. In effect, an internal state that is pleasant to one individual may be only neutral to another. Moreover, because it is self-report, it could be argued that such a recall procedure provides a good proxy of the true affect state, and requires less inference than other, outsider perspective data collection procedures (see Griffin, 2002; Griffin et al., 2004 for complete details).

4 Results

Initially, the couples were sorted by reported marital satisfaction level and placed into 3 categories: High, Medium, and Low. Each category contained 10 couples. As expected those couples placed in the middle group straddled the accepted cut-off score that is usually used to distinguish distressed from non-distressed couples. We thought that it was more informative to generate results across a continuum of satisfaction levels rather than to simply break the couples into the usual distressed-nondistressed groups.

Table 1. High Satisfaction: Group 1. This table shows all inferred states along with their expected durations plus the means values of the male (D1) and female (D2) affect ratings.

State	Duration: λ	D1:μ	D2:μ	D1:Var	D2:Var	Cov
0	12.625	4.0	0.0	0.530	0.008	0.006
1	10.493	4.0	4.0	0.387	0.303	0.159
2	14.678	0.0	4.0	0.003	2.626	0.009
3	8.783	2.0	0.0	0.008	0.006	0.000
4	5.868	1.0	0.0	0.008	0.008	-0.000
5	38.263	6.0	7.0	1.129	0.331	0.157
6	10.752	2.0	2.0	0.008	0.010	0.003
7	6.809	3.0	5.0	0.012	0.938	0.002
8	30.682	7.0	2.0	0.164	0.899	0.013
9	9.210	4.0	3.0	0.424	0.284	0.056
10	18.457	1.0	3.0	0.003	1.368	0.004
11	12.932	3.0	3.0	0.020	0.224	0.004
12	18.815	7.0	5.0	0.989	0.970	-0.216
13	19.900	0.0	1.0	0.006	0.008	0.000
14	8.704	2.0	4.0	0.006	1.544	-0.001
15	11.732	2.0	7.0	0.311	0.161	0.080
16	0.744	3.0	5.0	3.548	2.716	1.709
17	15.586	2.0	1.0	0.277	0.003	0.004
18	17.030	0.0	0.0	0.006	0.006	-0.000
19	5.898	4.0	1.0	0.862	0.009	0.006

The analysis began by running the HDP-HSMM on each satisfaction group as a collective whole; that is, data were added, couple-by-couple, into a common pool so that a general model could be generated for the whole of the group at each category level. Data consisted of male affect rating and female affect rating. Next, at the group level, a general system structure emerged in the form of state values for dimension 1 (i.e., male) and dimension 2 (i.e., female), along with variance and covariance structure; in addition, the model generates the expected duration for each derived state (note: greater detail is provided below). Next, each couple's realized data were used as observation data and the group model was asked to generate a data sequence that corresponded with the extant data using the states and durations available to it. As analyses progressed, it was apparent that within group variance made it difficult to qualitatively and quantitatively characterize couple behavior by group satisfaction level.

Consequently we then took each couple's data sequences and generated a sequential singular value decomposition (SVD) time-series, and applied a clustering analysis (Ward's criteria) on these within-group time-series. Using these results, we formed two homogeneous subgroups within each level of distress. All analyses were repeated at the level of subgroups; the High satisfaction group had subgroups with $n = 7$ and 3, Medium was 6 and 4, and Low was 6 and 4. Although additional information about parameter choices will be given at the presentation, it should be noted that the number of maximum states was 20; although analyses were run with much higher values, the number of states needed to capture the dynamics of the system across all groups averaged about 13–17 states. All the analyses presented here are based on resampling of 10,000; that is, to generate a plausible distribution of values to estimate a sequence, the model makes 10,000 pulls from a distribution that is consistent with the estimated parameters values.

4.1 Example Output

Our analyses generate numerous indices characterizing the dyadic processes associated with each group and subgroup, these include: (1) a system level overview of the inferred states including their expected durations along with the state variance/covariance structure. Table 1 shows the output for high satisfaction couples, group 1; (2) the model also generates a generic sequence consistent with the values of the inferred system structure in addition to a subject-by-subject output showing the observation distributions, a plausible state by duration sequence, distributions of durations, and an inferred multi-dimensional affect trace (i.e., male, female). Figure 4 illustrates these features stacked vertically by subject; and (3) finally, the model generates a state transition matrix along with an emission matrix ([state,observable] joint matrix). These two matrices provide the probabilistic structure needed to simulate sequential observable behavior expected in a system. Aside from their computational value, they also provide visual information; for example, Figure 5 shows two generated transition matrices for high martial satisfaction couples, subgroup 1 is shown on the left and subgroup 2 is shown on the right. Although both reflect a 20 state system, as modeled, state composition is unique to each group (e.g., Table 1 shows subgroup 1), nonetheless it is easy to see that in subgroup 1, state 16 acts as an attractor within the system whereas subgroup 2 shows a lot of variability in their movement across states. Again, note that both subgroups are in the same satisfaction group and yet as the clustering analyses suggested, and subsequently verified by the model, within group differences must be accounted for when simulating these types of processes.

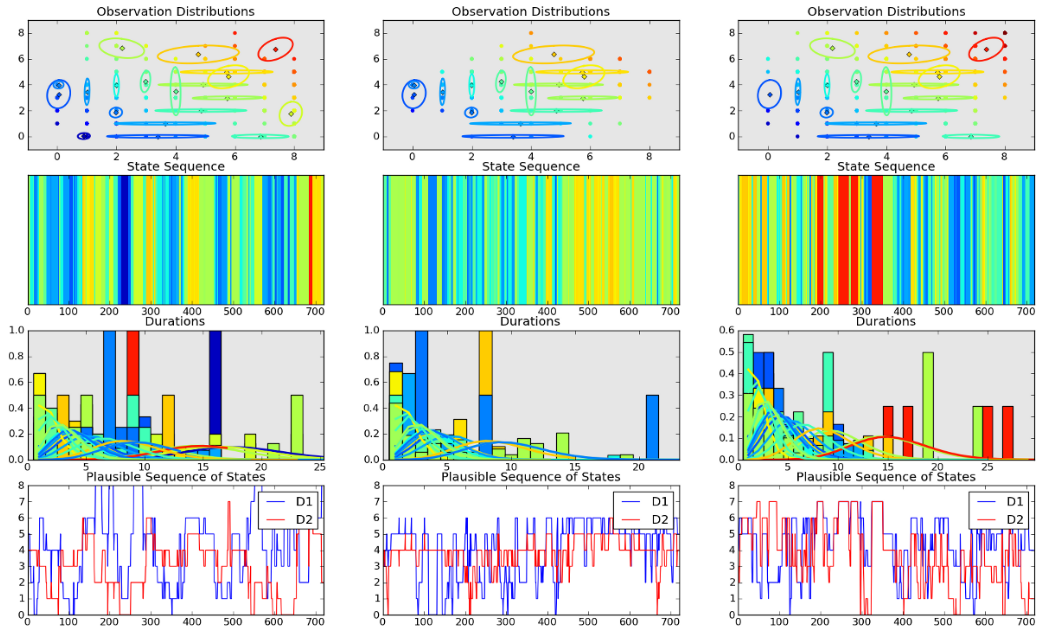

Fig. 4. High Satisfaction: Group 2; features shown are observation distributions, inferred sequence with duration estimate, duration distributions, and plausible couple affect trace. Cooler colors indicate more positive affect.

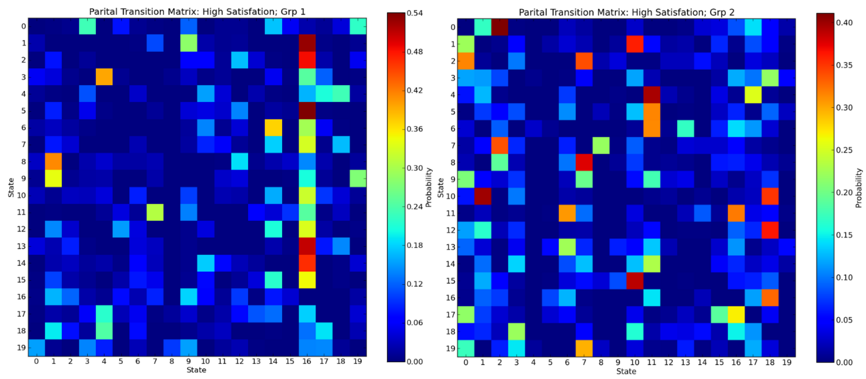

Fig. 5. Transition matrices for high satisfaction subgroup 1 (left) vs. subgroup 2; diagonal self-transitions have been removed to visually enhance cross state transitions values.

5 Conclusion

We developed a method of modeling complex dyadic processes using state-of-the-art unsupervised learning techniques. The HDP-HSMM provides all the information needed to generate data driven complex, yet realistic, simulations of dyadic and small group dynamics. It constructs states, transitions matrices, emission matrices, and expected durations—all the ingredients needed to generate realism in simulations. We will demonstrate how this can be done using married couples who report a wide range of satisfaction levels. Effectively showing how contemporary machine learning techniques can be used by computational social scientists to generate complex social dynamics.

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A ODD

A.1 Overview: Purpose

We are modeling dyadic processes, consisting of behavior and affect, in married couples. This is not an simulation - instead it is a method of modeling the assumed process. With this model we generate the parameter values that can be used in an ABM or, depending on the context and need, it is sufficient as a model of the micro-social dynamics. It is well established that dyads - either e.g., married couples, or mother-child pairings, interact in ways that convey the quality of the relationship. The methods used in this model are new, untested, and somewhat difficult to understand but they have the potential to provide substantial insight into latent generating mechanisms associated marital quality. If successfully implemented, the methods provide:

- procedures for generating simulation parameters,
- possible ways to discover algorithms associated with marital interaction,
- a step-by-step procedure for discovering behavioral and affect motifs in dyadic processes.

A.2 Overview: Entities

With the framework of this model there are, I think, 3 entities:

- the couple: male, female
- the laboratory where the interaction occurs
- the problem solving task used by the couple that generates the interaction

A.3 Overview: State Variables

There are two:

- Behavior: verbal, nonverbal
- Affect: extreme positive to extreme negative

A.4 Overview: Scale

Realized data and the model are based on 12-15 minute interactions; this is a standard time frame for these data collection episodes

A.5 Overview: Process

Couples are invited to a laboratory to participate in a research project. They are asked to converse about problems in the relationship. The conversation is recorded; behaviors are coded by external observers, and affect is generated by each member of the couple during a review session. These data are used in the model. In this presentation, we used the male and female affect sequence, 720 data points, as dimension 1 and dimension 2, respectively. These data are a 2-dimensional representation of the system, from which patterns are extracted using the HDP-HsMM methods.

A.6 Design Concepts:

This is a method of generating parameter values associated with a model of micro-social dynamics and not a way of simulating those dynamics, at least not in the traditional sense. Consequently, many of the sub-categories within this section of not directly applicable. However, we envision the values being generated within a typical run as being plug-in ready for a simulation. Thus there are a couple of method features that should be noted.

The objective is to identify interaction patterns that are associated with marital quality. Specific quantitative output enable us to do that; they are:

- State identification (including variance and covariance structures)
- State transition matrices
- Emission matrices (state, observable joint matrix)
- Expected duration per state

From these we can use contemporary data analytic or visualization techniques to discover motifs that discriminate across marital satisfaction levels.

A.7 Details:

Given that this is a modeling method and not a simulation, the subcomponents of this section of not applicable.