

Modeling Affect Dynamics in Dyadic Interactions Using Differential Equation Models

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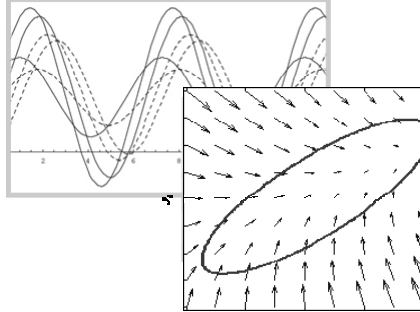
Outline

- Dynamics of Dyadic Interactions Project
- Patterns of fluctuations (e.g., emotions) over time
- Theoretical models of affective dynamics in dyads
- Fitting differential equation models to empirical time series data
- Results
- Conclusions and future directions

Dynamics of Dyadic Interactions Project

- Develop models for examining time-related associations between two individuals in an interacting system
- Identify patterns of dynamics in dyadic interactions
- Use those patterns as predictors of future outcomes of the system

DYNAMICS OF DYADIC INTERACTIONS PROJECT



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DDIP – Data Collection

- Phase 1: Lab visit
 - Demographic and psychological measures
 - Experimental tasks – physiological data
- Phase 2: Daily questionnaire of emotions 60 – 90 consecutive days
- Phase 3: Follow-up at 1 and 2 years to examine stability and quality of relationship

Daily Questionnaire

Indicate to what extent you have felt this way today

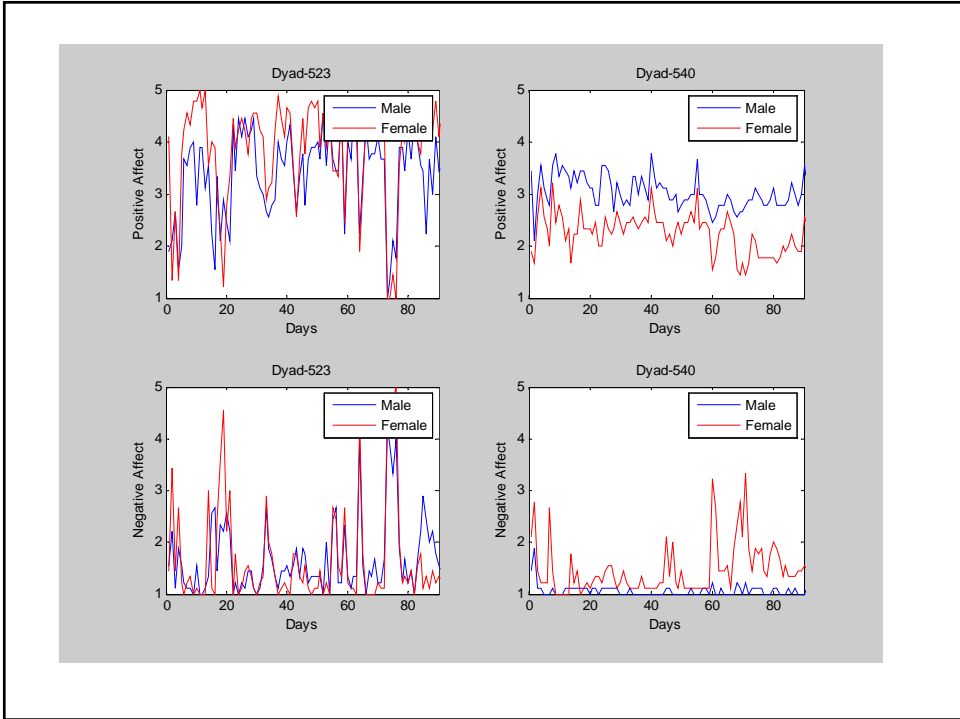
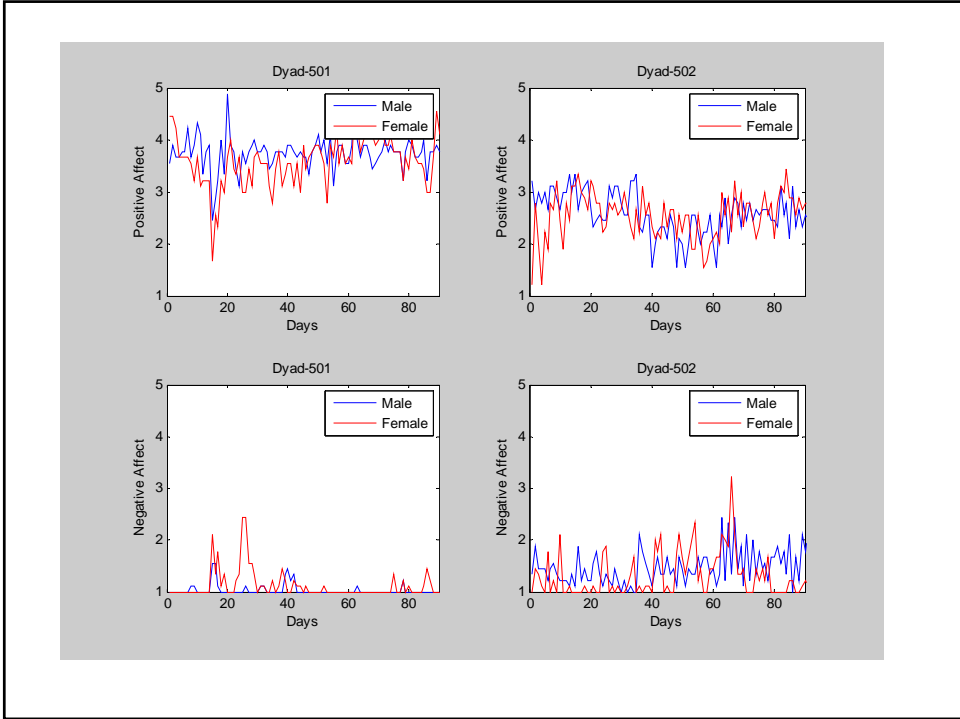
1 2 3 4 5
very slightly a little moderately quite a bit extremely
or not at all

<input type="checkbox"/> interested	<input type="checkbox"/> irritable
<input type="checkbox"/> distressed	<input type="checkbox"/> alert
<input type="checkbox"/> excited	<input type="checkbox"/> ashamed
<input type="checkbox"/> upset	<input type="checkbox"/> inspired
<input type="checkbox"/> strong	<input type="checkbox"/> nervous
<input type="checkbox"/> guilty	<input type="checkbox"/> determined
<input type="checkbox"/> scared	<input type="checkbox"/> attentive
<input type="checkbox"/> hostile	<input type="checkbox"/> jittery
<input type="checkbox"/> enthusiastic	<input type="checkbox"/> active
<input type="checkbox"/> proud	<input type="checkbox"/> afraid

Indicate to what extent you have felt this way about your relationship today

1 2 3 4 5
very slightly a little moderately quite a bit extremely
or not at all

<input type="checkbox"/> sad	<input type="checkbox"/> loved
<input type="checkbox"/> emotionally intimate	<input type="checkbox"/> happy
<input type="checkbox"/> trust	<input type="checkbox"/> discouraged
<input type="checkbox"/> committed	<input type="checkbox"/> doubtful
<input type="checkbox"/> blue	<input type="checkbox"/> loving
<input type="checkbox"/> physically intimate	<input type="checkbox"/> lonely
<input type="checkbox"/> trapped	<input type="checkbox"/> angry
<input type="checkbox"/> free	<input type="checkbox"/> deceived
<input type="checkbox"/> argumentative	<input type="checkbox"/> socially supported



Models for Dyadic Interactions

- Many approaches
- Growth curve models, multilevel models, cross-lagged regression models, dynamic factor analysis, exploratory approaches (among others)

- Differential equations

$$dx/dt = f(x, y)$$

$$dy/dt = f(y, x)$$

- They explicitly consider the two members of a dyad as an interdependent system
- They express change as a continuous process

Models for Dyadic Interactions

- Gottman et al. (2002)

$$W_t = \alpha_{0w} + \alpha_{1w} W_{t-1} + I_W (H_{t-1})$$

$$H_t = \beta_{0h} + \beta_{1h} H_{t-1} + I_H (W_{t-1})$$

- Boker & Laurenceau (2006); Steele & Ferrer, (under review)

$$\ddot{w}(t) = \eta_w w(t) + \zeta_w \dot{w}(t) + \gamma(\eta_h h(t) + \zeta_h \dot{h}(t)) + e_{\ddot{w}}(t)$$

$$\ddot{h}(t) = \eta_h h(t) + \zeta_h \dot{h}(t) + \gamma(\eta_w w(t) + \zeta_w \dot{w}(t)) + e_{\ddot{h}}(t)$$

Models for Dyadic Interactions

- Felmlee & Greenberg (1999); Felmlee (2006)

$$dx/dt = a_1 \cdot (x^* - x) + a_2 \cdot (y - x)$$

$$dy/dt = b_1 \cdot (y^* - y) + b_2 \cdot (x - y)$$

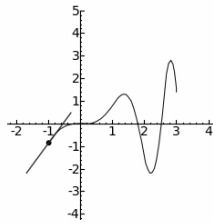
- Predator/Prey Model (Chow et al., 2007)

$$\dot{x}_t = r_x x_t - a x_t \cdot y_t$$

$$\dot{y}_t = -r_y y_t + b x_t \cdot y_t$$

Differential Equation Models

Determining rate of change via derivatives



Estimation DFE Models

- Pooled cross-section and time-series data and use Weighted Generalized Least Squares
- Filtering procedures such as the Kalman filter (Kalman, 1960; Julier et al., 1995)
- ReBEL (Recursive Bayesian Estimation Library; Van der Merwe, 2003)
- Ox, Winbugs, DEDiscover
- ODE procedures in R and SAS

DFE Models for Dyadic Interactions

- Theoretical models of dyadic interactions (Felmlee & Greenberg, 1999; Felmlee, 2006)
- Four dynamic systems models of dyadic interactions based on the general model

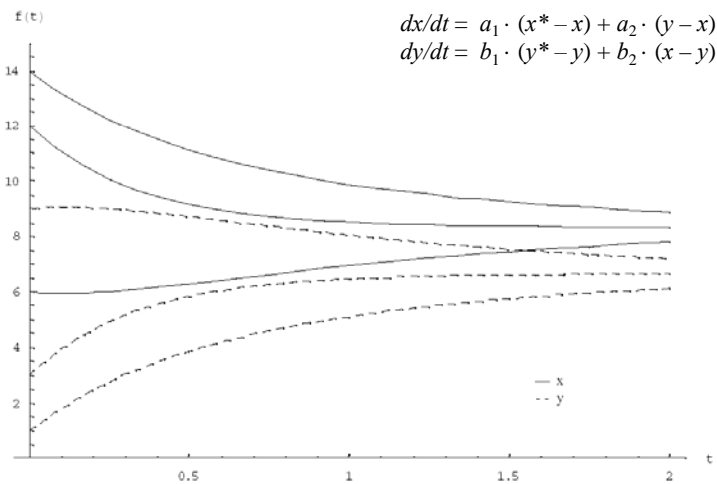
$$dx/dt = a_1 \cdot (x^* - x) + a_2 \cdot (y - x)$$

$$dy/dt = b_1 \cdot (y^* - y) + b_2 \cdot (x - y)$$

Fundamental Assumptions

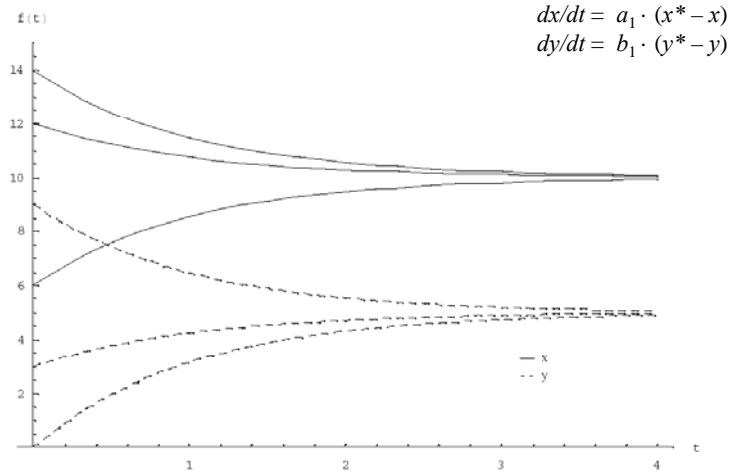
- Dyads form dynamic and interactive systems
 - The relationship of couples changes over time
 - Individuals in couples influence each other
- Change takes place in a continuous manner
- The model coefficients are constant over time

DFE Models for Dyadic Interactions



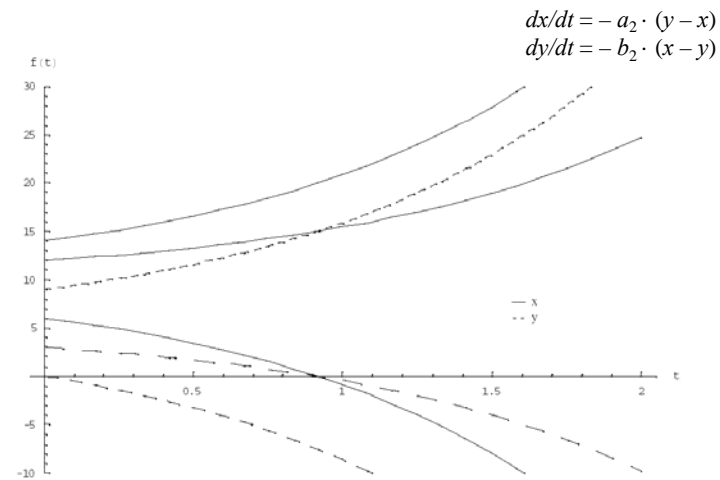
Model 1: Both members are cooperative

DFE Models for Dyadic Interactions



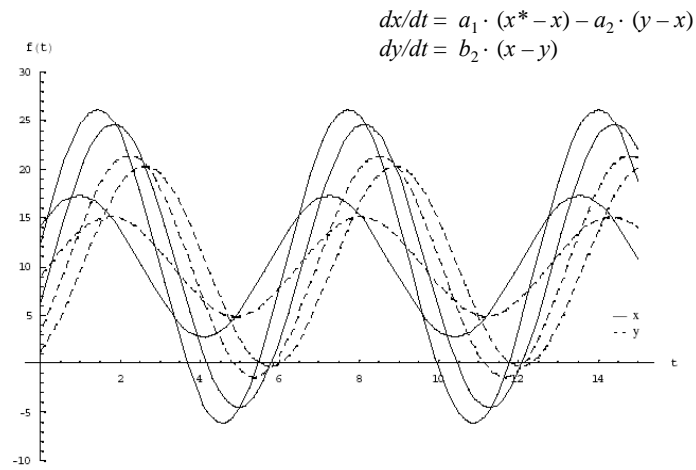
Model 2: Both members are independent

DFE Models for Dyadic Interactions



Model 3: Both members are contrarians

DFE Models for Dyadic Interactions



Model 4: One uncooperative (x) and one dependent (y)

Data Analysis

- Positive affect, negative affect
- Proportional affect
positive / (positive + negative)
- PROC Model (SAS)
- FIML estimation

Fitting ODE in SAS

```
TITLE 'Model 1: Cooperative system (.70 ideal)';
PROC MODEL DATA = paff_ode_inits;
  BY dyad_id;
  PARM a1=.1 a2=.1 b1=.1 b2=.1;
  RESTRICT a1 > 0;
  RESTRICT b1 > 0;
  RESTRICT a2 > 0;
  RESTRICT b2 > 0;

  dert.faf = a1*(.7 - faf) + a2*(maf - faf);
  dert.maf = b1*(.7 - maf) + b2*(faf - maf);

  FIT faf maf / FIML
  OUT = dypos_m1_out
  OUTALL OUTEST = dypos_m1_est;
RUN;
```

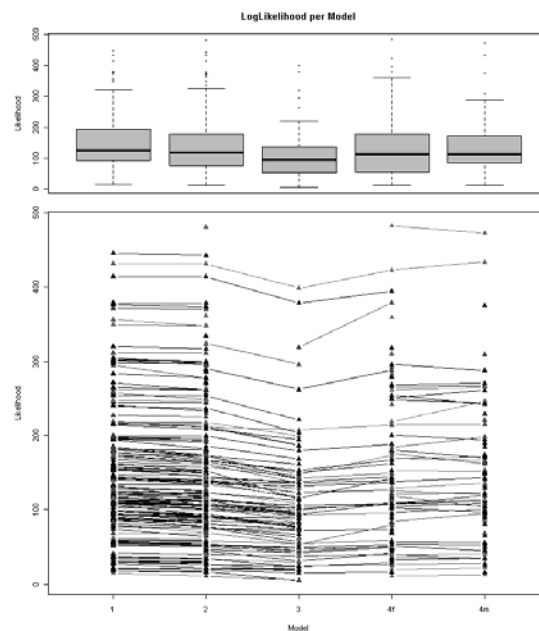
Data Analysis (cont.)

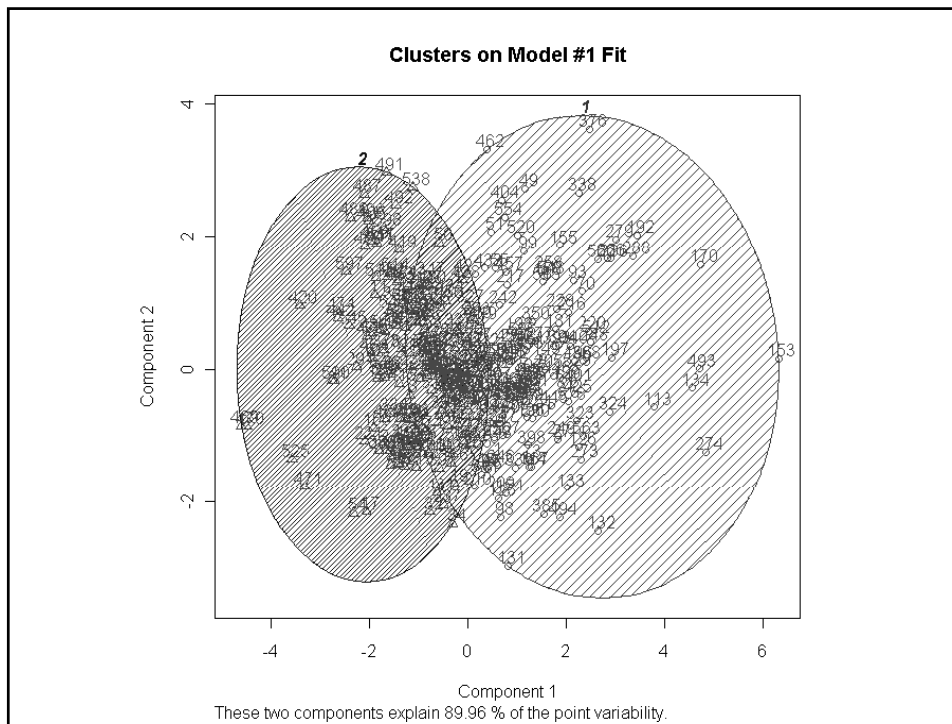
- Fit of all models to time series from each dyad separately ($N_{dyads} = 300$)
- Fit comparison across models for each dyad
- Assignment of dyads to dynamic system types
- Summary of model parameters across dynamic types

Results

- Model Fit:
 - 140 dyads showed one model as best fit
 - 159 showed a differential fit pattern
- *K*-means cluster analysis with 2 clusters per model ("fit" and "non-fit" cluster)
- Used the cluster means and selected the group with the highest loglikelihood as a group – best fitting group for that model
- Comparison of dyads in the best fit group for multiple models and forced them into the model with the highest loglikelihood

Loglikelihood per Model

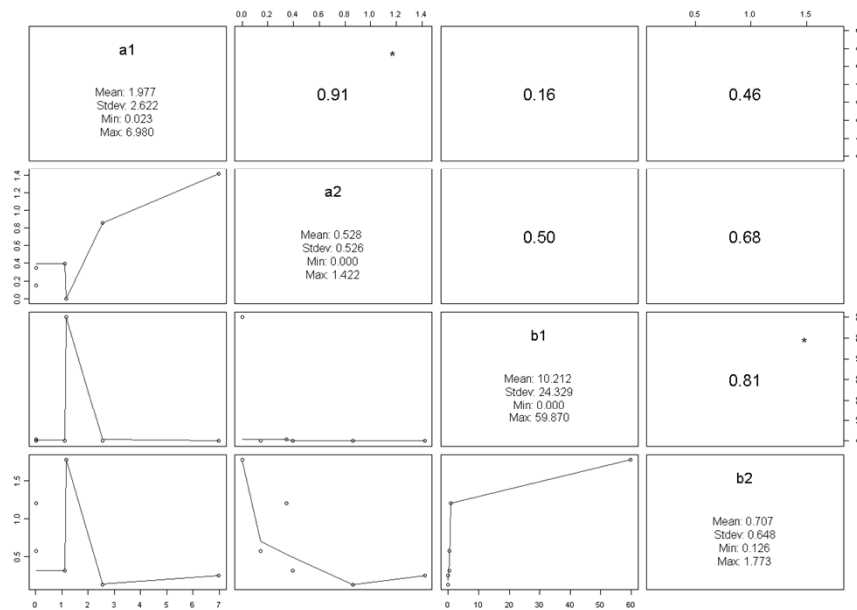




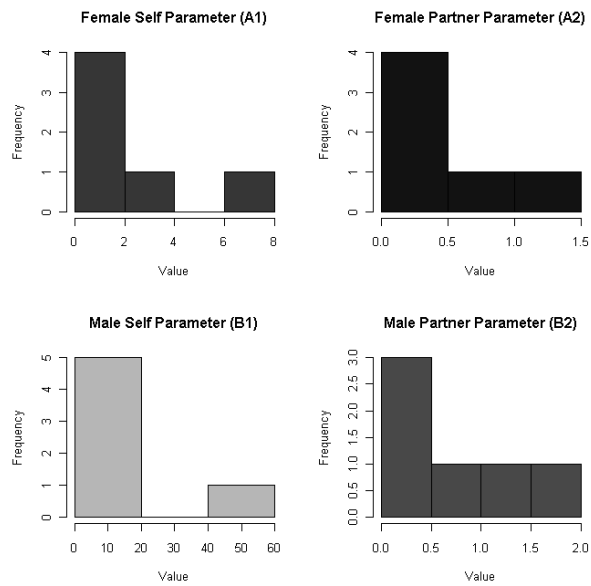
Results (cont.)

- Model #1: 6 dyads
- Model #2: 77 dyads
- Model #3: 11 dyads
- Model #4a: 42 dyads (female uncooperative w/ male dependent)
- Model #4b: 4 dyads (male uncooperative w/ female dependent)

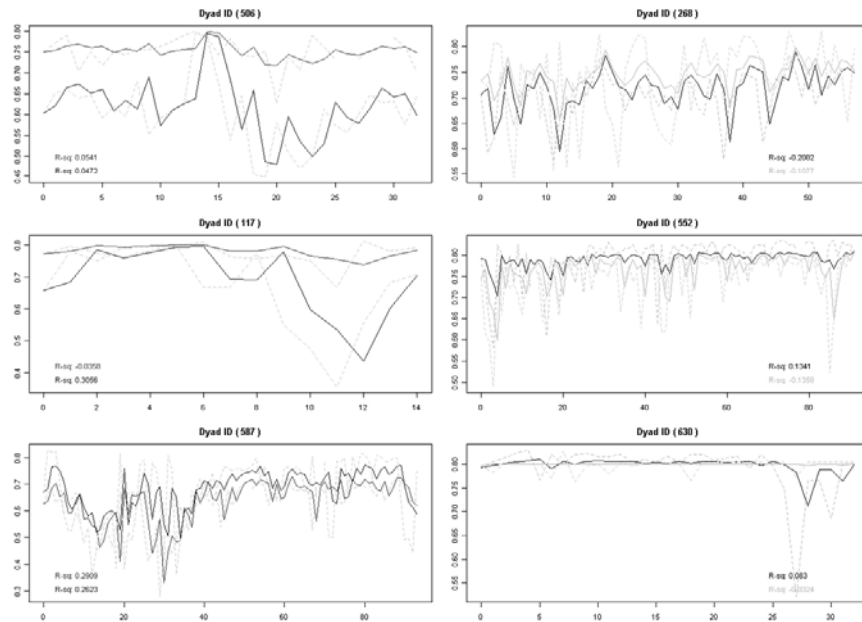
Parameter Estimates – Model 1



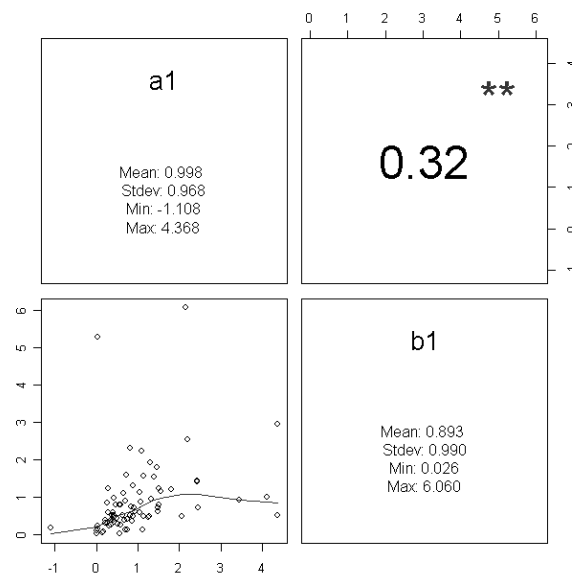
Parameter Histograms – Model 1



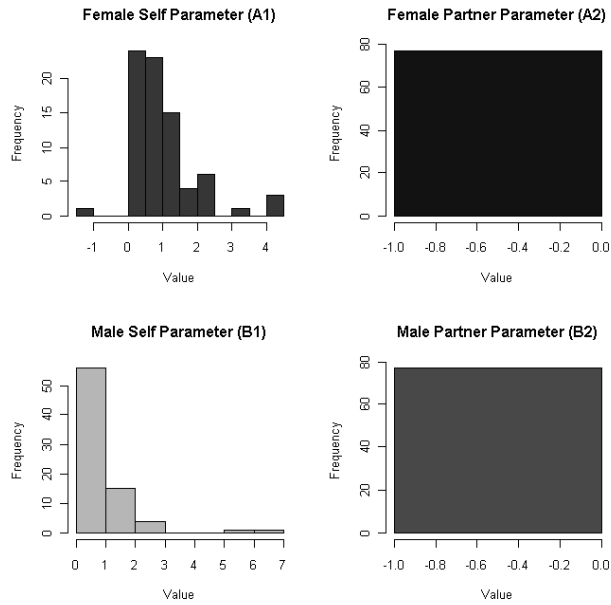
Predicted Trajectories vs. Observed Data – Model 1



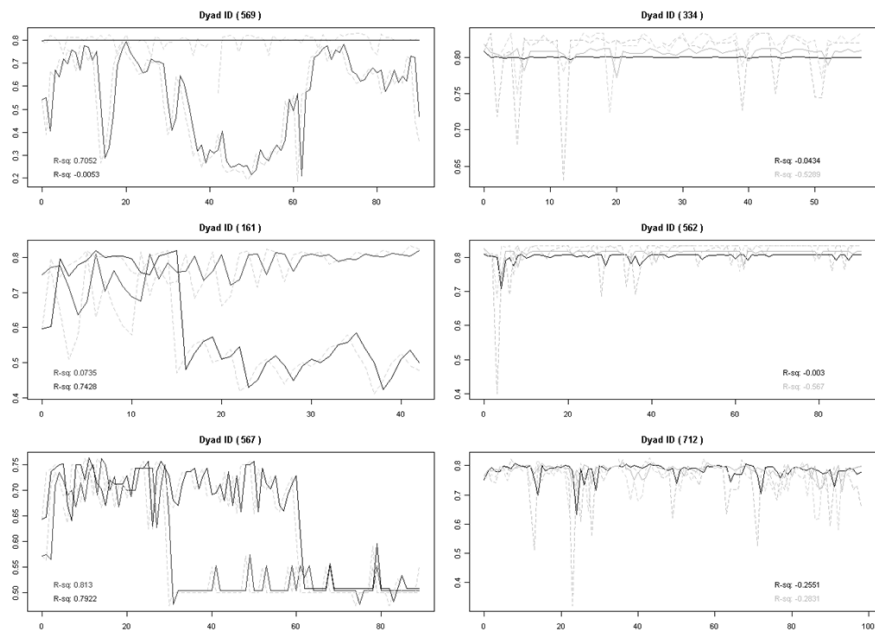
Parameter Estimates – Model 2



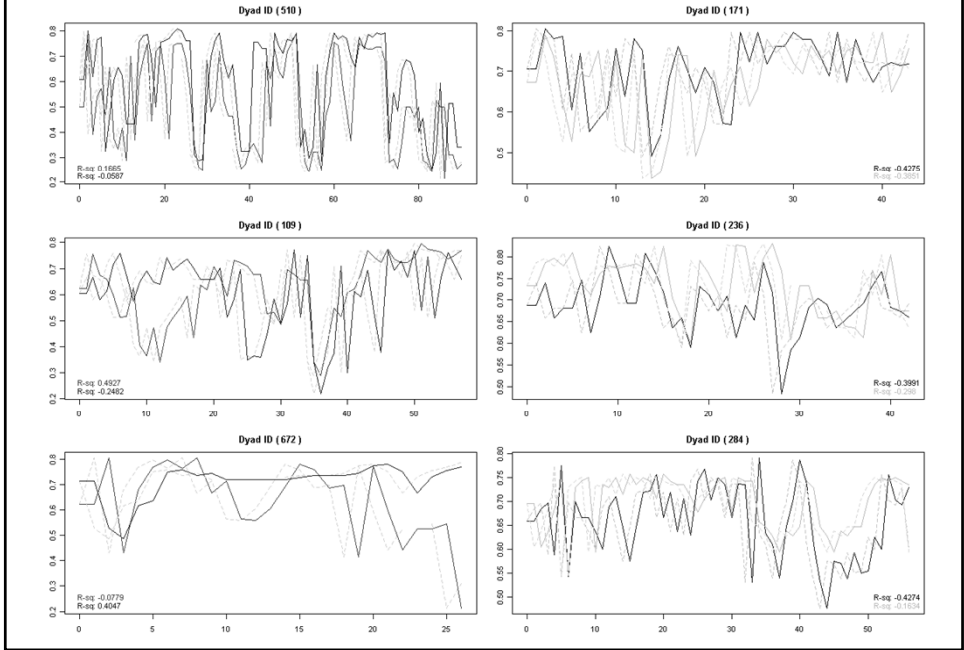
Parameter Histograms – Model 2



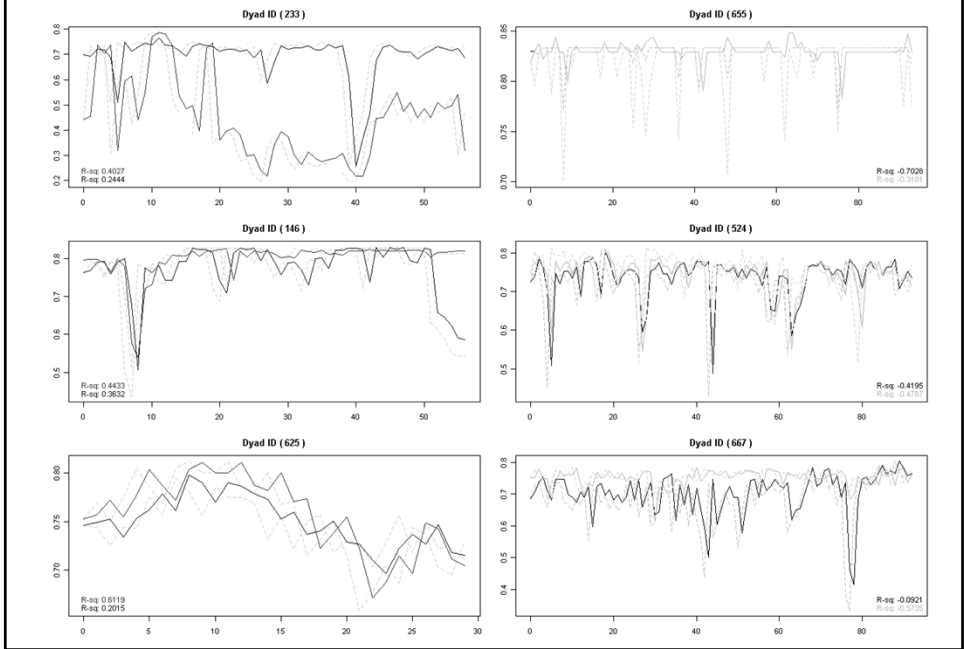
Predicted Trajectories vs. Observed Data – Model 2



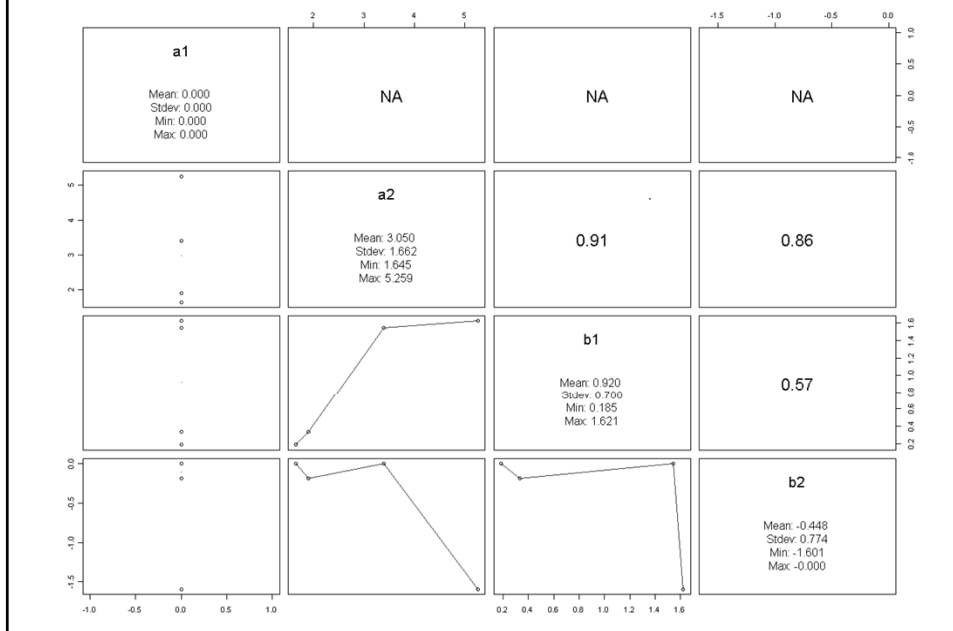
Predicted Trajectories vs. Observed Data – Model 3



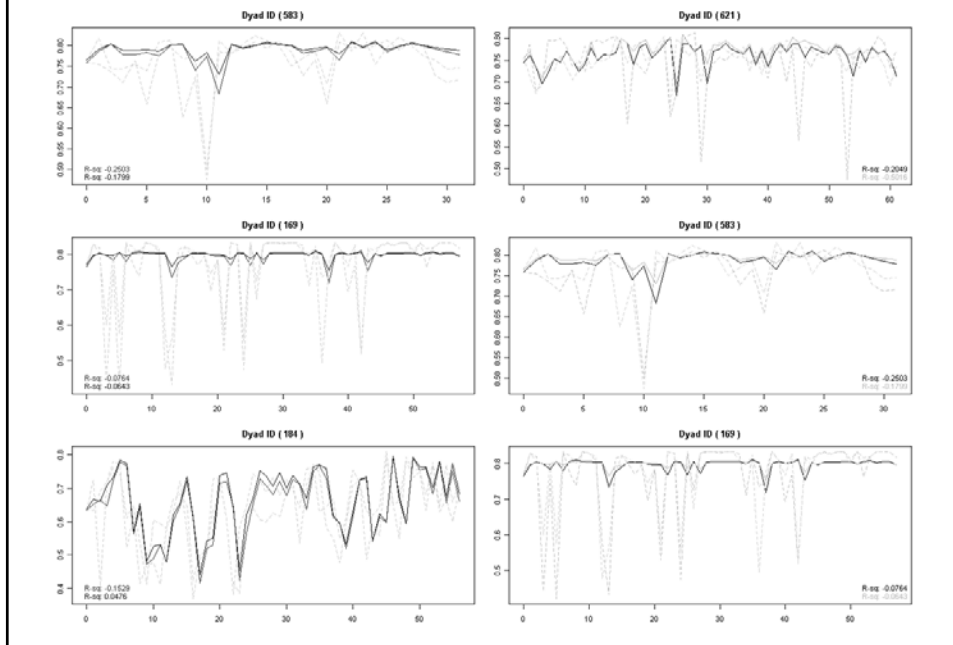
Predicted Trajectories vs. Observed Data – Model 4a



Parameter Estimates – Model 4b

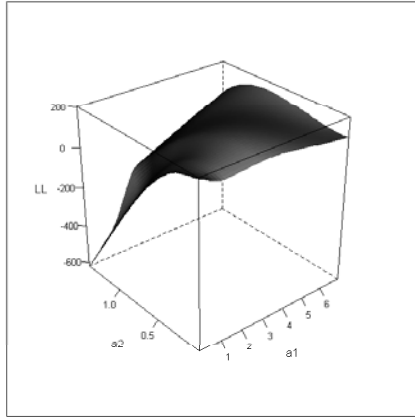


Predicted Trajectories vs. Observed Data – Model 4b



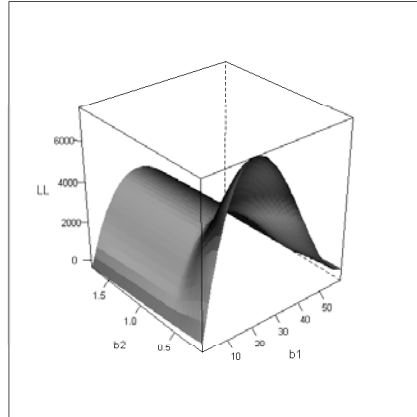
R-Square Surfaces – Model 1

Log Likelihood by Female parameters



a_1 & a_2

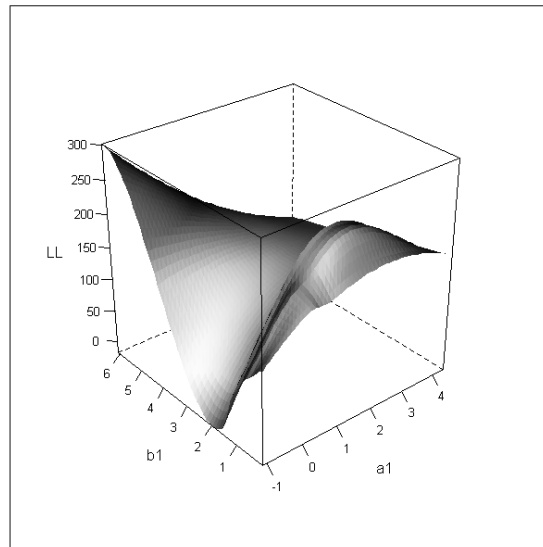
Log Likelihood by Male parameters



b_1 & b_2

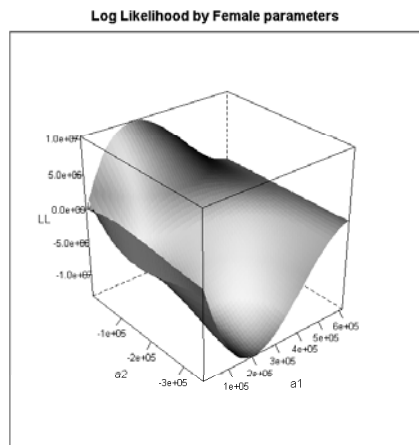
R-Square Surfaces – Model 2

Log Likelihood by Female & Male parameters

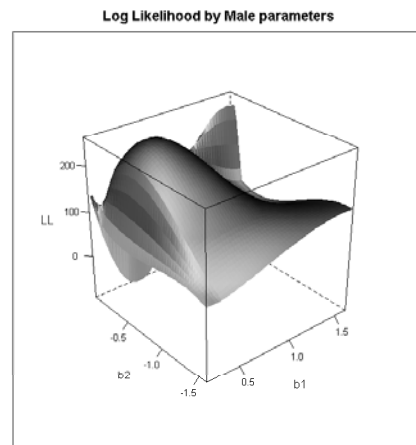


a_1 & b_1

R-Square Surfaces – Model 4



a1 & a2



b1 & b2

Conclusions

- The results from these analyses are informative about affective dynamics
- But it is difficult to summarize information from the individual (i.e., dyad) to the group
- These analyses were guided by theoretical models; without any theory this summary is harder
- Theoretical models of dyadic interactions – based on “ideal” affect; other models are also possible
 - Gottman, Levenson, Fredrickson

Benefits of DFE for Time Series Data

- They are useful for representing processes that change in a continuous fashion
- They can account for multiple and complex change patterns with relatively concise models
- They consider equilibrium points in the system explicitly
- They model individual's behavior as a function of the system
 - If two individuals form an interdependent system, the long-term behavior of the dyad develops in a unique way over time

Extensions

- Change might be discontinuous, with multiple equilibrium points, and nonstationarity
- Change can be motivated by forces outside the system (e.g., in response to external events)
- Individuals (and couples) can have multiple emotional set points
- Complex models that include interactions and nonlinearities

Extensions (cont.)

- Random effects in the parameters to account for variability in the dynamics
- Correlates of dynamic parameters with relevant factors (e.g., attachment, type and length of relationship)
- Prediction by dynamics parameters of future outcomes in the system (e.g., relationship quality and stability)

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