

# Appendix: Modeling Dynamic Identities and Uncertainty in Social Interactions Bayesian Affect Control Theory

Tobias Schröder	Jesse Hoey	Kimberly B. Rogers
Institute for Urban Futures	David R. Cheriton School	Department of Sociology
Potsdam University	of Computer Science	Dartmouth College
of Applied Sciences	University of Waterloo	6104 Silsby Hall, Room 111
Kiepenheuerallee 5	Waterloo, Ontario,	Hanover, NH
14469 Potsdam, Germany	CANADA, N2L3G1	USA 03755
post@tobiasschroeder.de	jhoey@cs.uwaterloo.ca	krogers@dartmouth.edu

**Appendix to the article:** Tobias Schröder, Jesse Hoey and Kimberly B. Rogers. Modeling Dynamic Identities and Uncertainty in Social Interactions: Bayesian Affect Control Theory. *American Sociological Review*. Online June 24, 2016. DOI:10.1177/0003122416650963

## 1 Introduction

The following document gives the full resolution (vector graphics) figures for the main article, as well as the parameter settings for the simulations, and an extended set of simulation results for the Simulation 3 results (Figure 7).

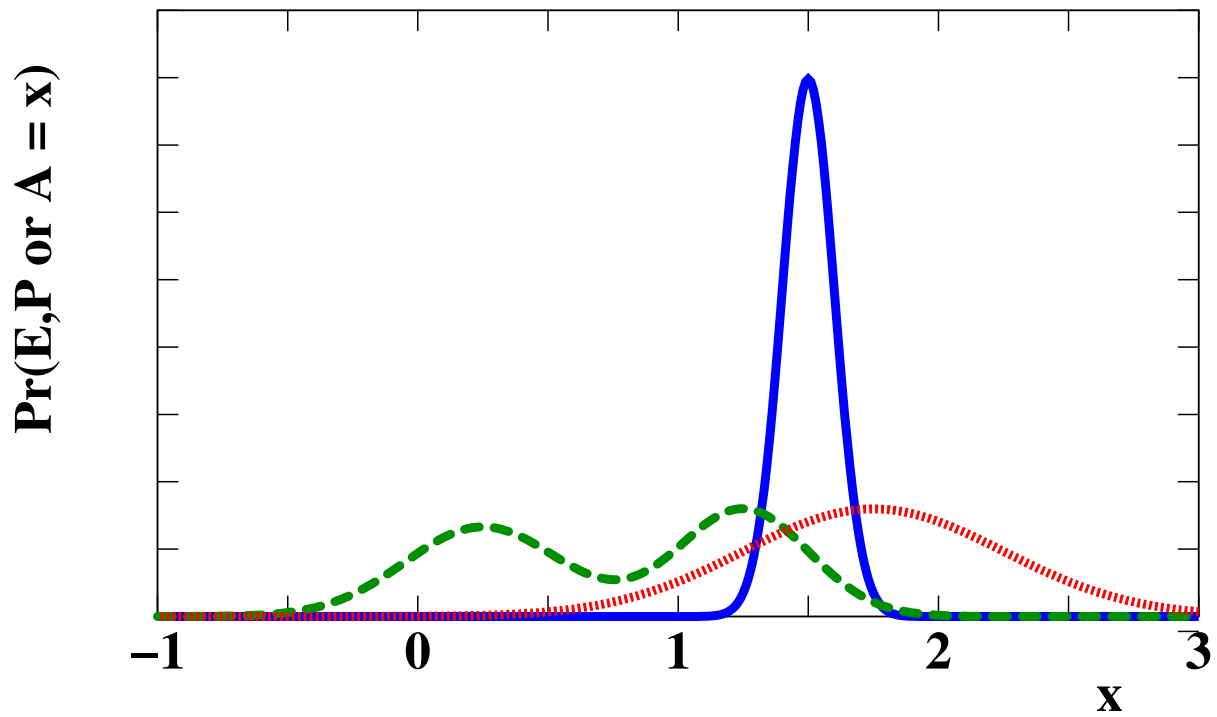


Figure 1: Identities Represented as Probability Distributions Along One Dimension of Affective Meaning (either E = evaluation, P = potency, or A = activity) Note: Solid (blue) line: an identity that is undispersed, so the actor has high confidence (low uncertainty) about it. Dotted (red) line: a more dispersed identity, so the actor is more uncertain about it. Dashed (green) line: a bimodal identity, so the actor has two concurrent and uncertain hypotheses about her identity.

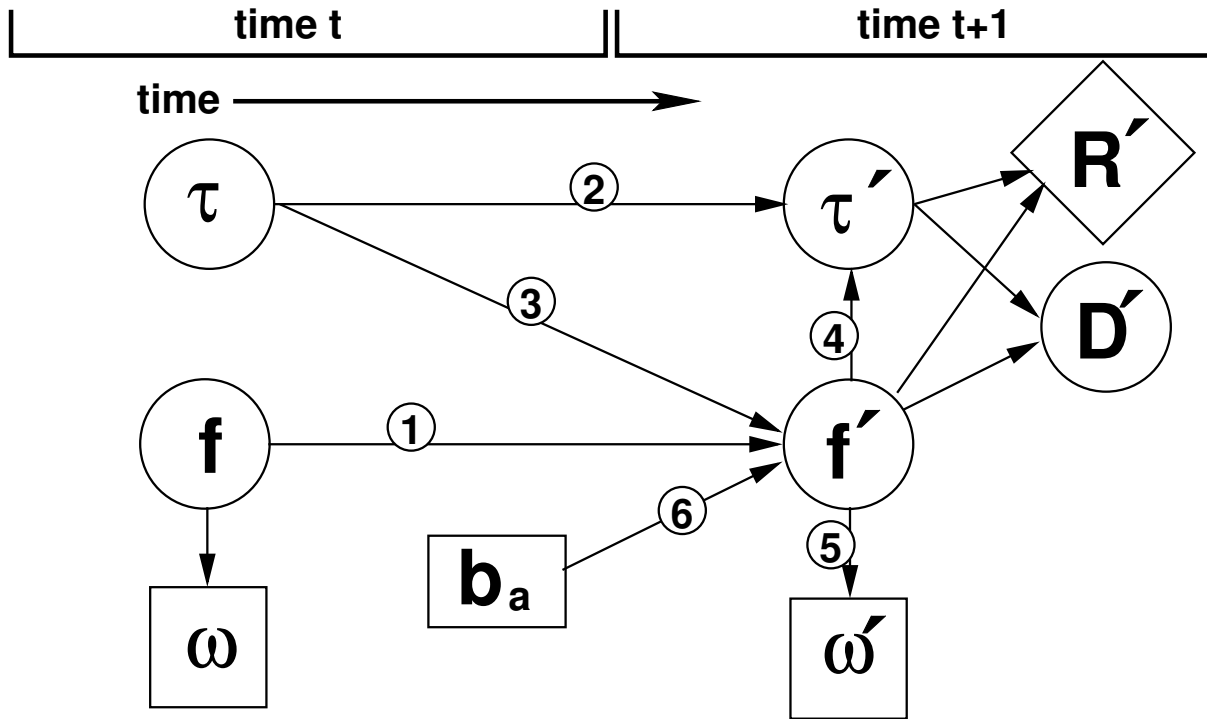


Figure 2: BayesACT as a Causal Dynamic Decision Network in which Arrows Are Interpreted as Causal Events. Square nodes = observables/actions. Circle nodes = chance variables. Diamond = reward function (Schacter 1988). Time is event driven; only two time slices are shown here, but the network is assumed to be “unrolled” through time indefinitely. Unprimed symbols refer to the current time step ( $t$ ); primes refer to the subsequent time step ( $t+1$ ).  $f, f'$  = fundamental sentiments,  $\tau, \tau'$  = transient impressions,  $\omega, \omega'$  = observable actions of the other agent (EPA vectors denoting affective interpretation of the action),  $b_a$  = actions of BayesACT agent (sets the behavior component of the fundamental sentiment,  $f$ ),  $D$  = Boolean variable that, if true, indicates that the affect control principle (deflection minimization) holds. Theoretically,  $D$  is always “true”.  $R$  = reward function.  $D$  and  $R$  are shown only at time  $t+1$  for clarity (they are also present at time  $t$ ). See the main text for detailed explanation of the relationships indicated by numbered arrows.

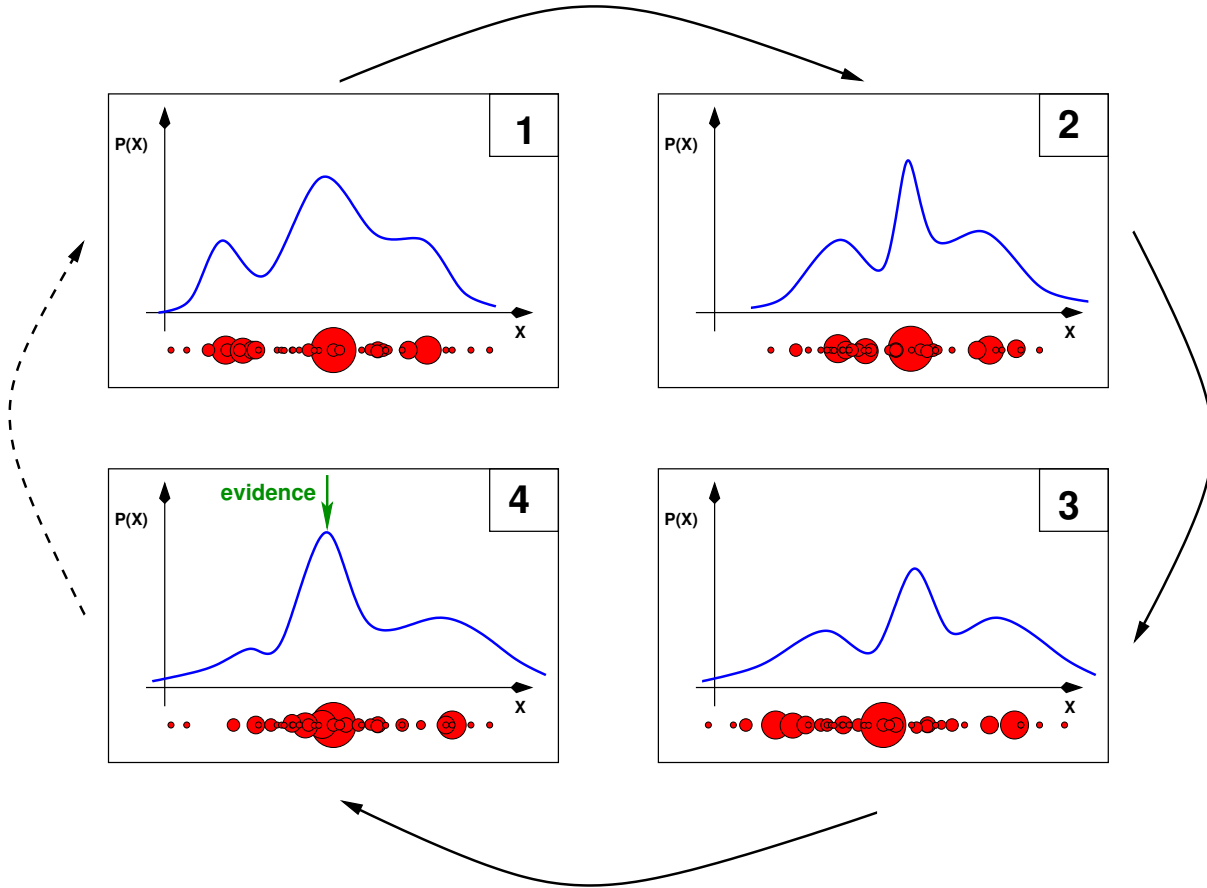


Figure 3: Sampling and Belief Update in BayesACT. Solid lines represent probabilistic identities along one affective dimension. Blobs represent the approximation of these probability distributions by the sampling technique explained in the main text. An update step starts at (1) with a current belief distribution. This is propagated through time according to the dynamics of BayesACT (including impression formation and stability of fundamentals) to step (2). Dynamics noise is then added causing the distributions to spread in step (3). This dynamics noise is due to the natural tendency of uncertainty to increase over time in the absence of evidence. Evidence is then received at step (4), and this “collapses” the distribution toward the evidence. Communication noise is taken into account at this step: the more certain an agent is about the evidence, the stronger the collapse. Finally, the distribution from step (4) replaces the one in step (1) (indicated by the dashed arrow) and the process starts over.

## 2 Simulations 1: Learning Identities

500 trials were run, with the following parameter settings:

param.	setting	meaning
$\alpha$	0.1	std. deviation of a diagonal uniform $\Sigma$ , the deflection potential covariance.
$\beta_a$	0.001	identity inertia for agent (std. dev)
$\beta_c$	0.001	identity inertia for client (std. dev)
$\beta_a^0$	2.0	initial identity std. dev. for agent
$\beta_c^0$	0.01	initial identity std. dev. for client
$\gamma$	0.1	model environment noise std. dev.
$\epsilon$	0.0	actual environment noise std. dev.
$N$	500	number of samples
$\sigma_r$	$N^{-1/3} = 0.126$	roughening noise
gender	male	gender of agent

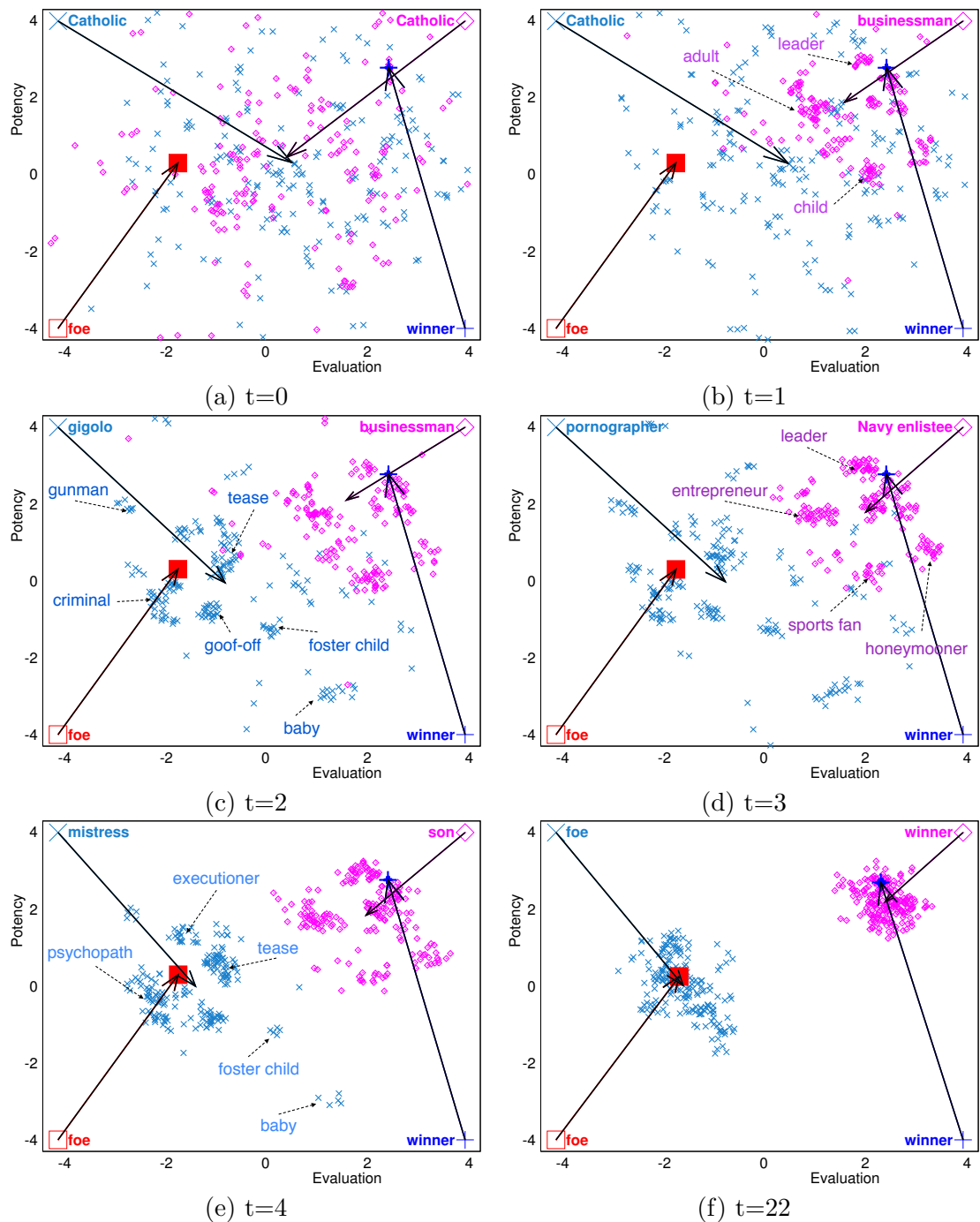


Figure 4: BayesACT Simulation of How Agents Learn about Their Mutual Identities. We used 200 samples for each agent. Only evaluation and potency axes are shown, although the simulation includes the activity dimension. Both agents start without any knowledge of the others identity. One agents beliefs about the identity of self/other are shown with blue/cyan plusses/crosses (+/x), the other agents beliefs are shown with red/magenta squares/diamonds ( $\square, \diamond$ ). Mean identities are shown as large versions of the same symbols and the closest label shown in the four corners. Black arrows link the mean identity label with the position in the plot. Smaller labels indicate significantly distinct clusters with dashed arrows for the agent being acted upon.

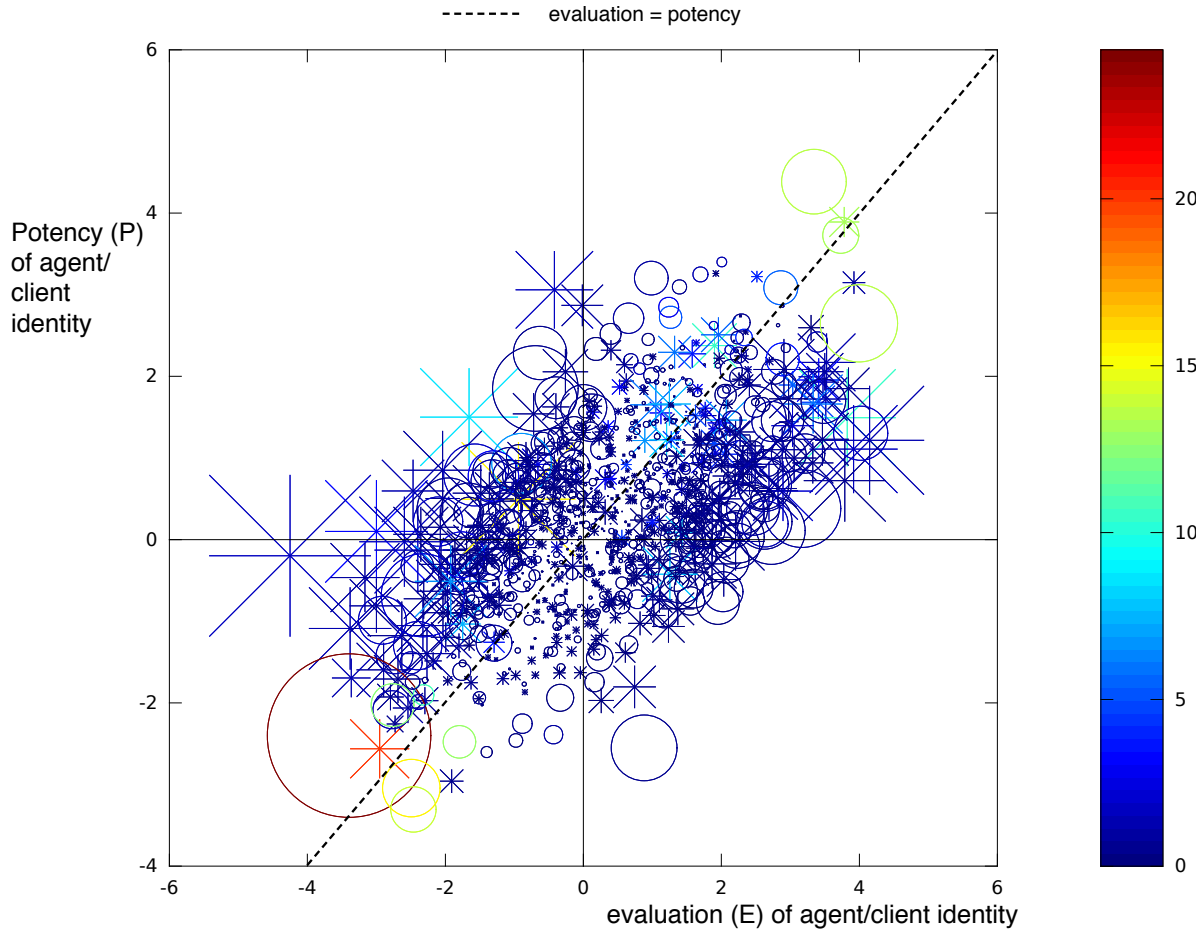


Figure 5: Learning Identities in BayesACT as a Function of Evaluation and Potency of an Agent’s True Identity. The figure shows 500 trials. The stars are for one agent, the circles are for the other, and they are positioned at the agents true identity. The area of the stars/circles is proportional to the mean squared Euclidean distance between the true identity and the BayesACT estimate thereof after 20 iterations; that is, bigger stars/circles are harder-to-learn identities. The color gives the standard deviation. The mean/standard deviation is taken over 10 experiments per trial with the same true identities, but with randomly initialized distributions (samples). The dashed line shows where  $E = P$ .

### 3 Simulations 2: Multiple Identities

500 trials were run, with the following parameter settings:

param.	setting	meaning
$\alpha$	0.1	std. deviation of a diagonal uniform $\Sigma$ , the deflection potential covariance.
$\beta_a$	0.01	identity inertia for agent (std. dev)
$\beta_c$	0.001	identity inertia for client (std. dev)
$\beta_a^0$	0.01	initial identity std. dev. for agent
$\beta_c^0$	0.01	initial identity std. dev. for client
$\gamma$	0.1	model environment noise std. dev.
$\epsilon$	0.0	actual environment noise std. dev.
$N$	1000	number of samples
$\sigma_r$	$N^{-1/3} = 0.1$	roughening noise
gender	male	gender of agent



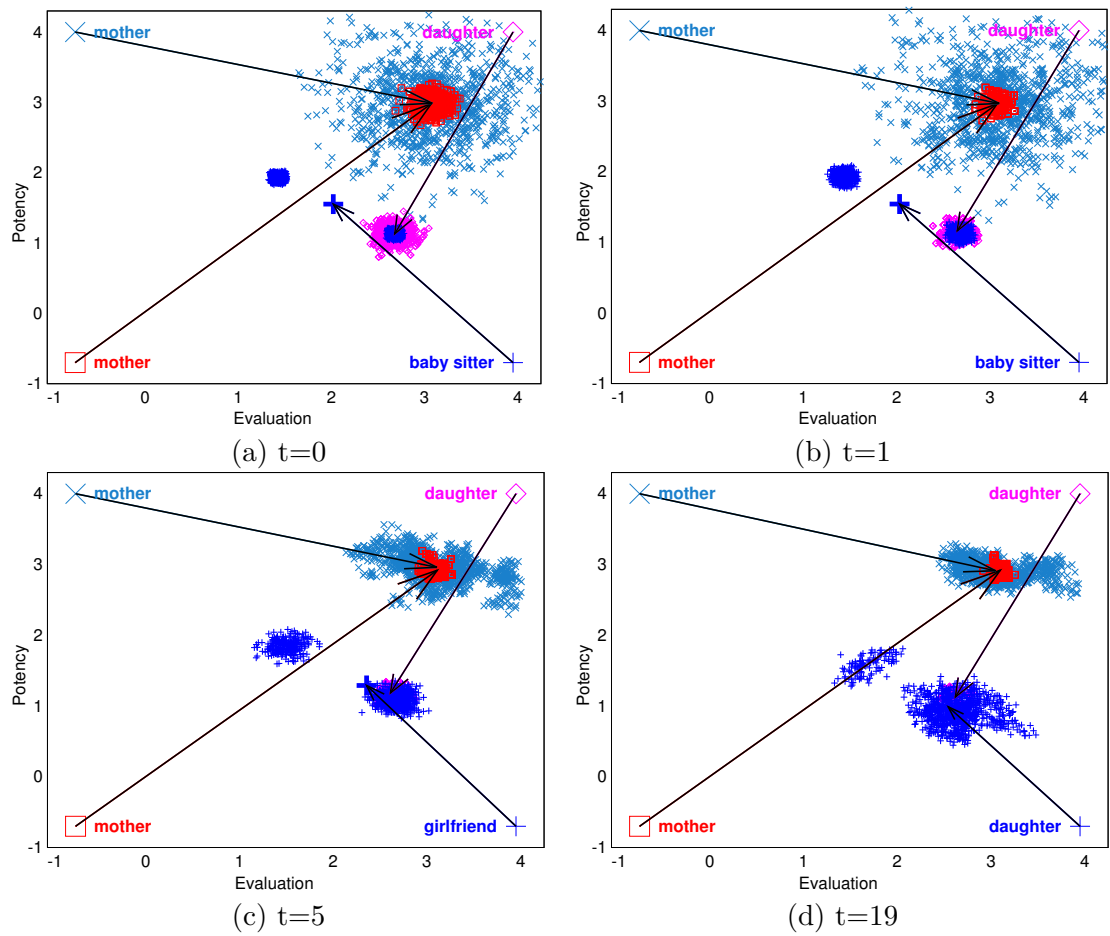


Figure 6: BayesACT Simulation of Multiple Identities Governing Social Interaction. Interaction with “mother.” We used 1,000 samples for each agent. Blue agent has multiple identities, one of which (daughter) is made more salient through interaction with red agent (mother). Labels show the closest match of the mean of each agents identity distribution, taken from female dictionary data.

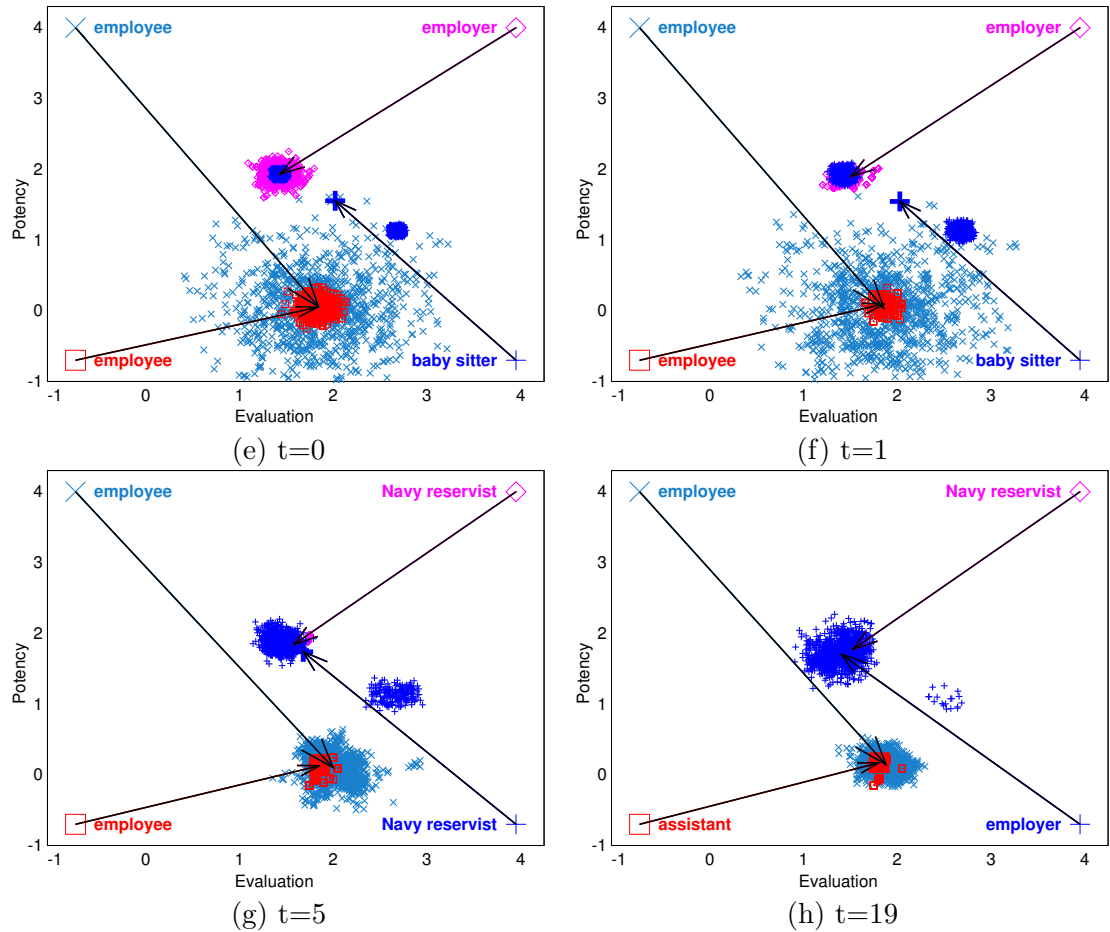


Figure 7: BayesACT Simulation of Multiple Identities Governing Social Interaction. Interaction with “employee.” We used 1,000 samples for each agent. Blue agent has multiple identities, one of which (employer) is made more salient through interaction with red agent (employee). Labels show the closest match of the mean of each agents identity distribution, taken from female dictionary data.

## 4 Simulations 3: Emergence of Structure

500 trials were run, with the following parameter settings:

param.	setting	meaning
$\alpha$	0.1	std. deviation of a diagonal uniform $\Sigma$ , the deflection potential covariance.
$\beta_a$	0.001	identity inertia for agent (std. dev)
$\beta_c$	0.001	identity inertia for client (std. dev)
$\beta_a^0$	2.0	initial identity std. dev. for agent
$\beta_c^0$	2.0	initial identity std. dev. for client
$\gamma$	0.5	model environment noise std. dev.
$\epsilon$	0.01	actual environment noise std. dev.
$N$	1000	number of samples
$\sigma_r$	$N^{-1/3} = 0.1$	roughening noise
gender	male	gender of agent

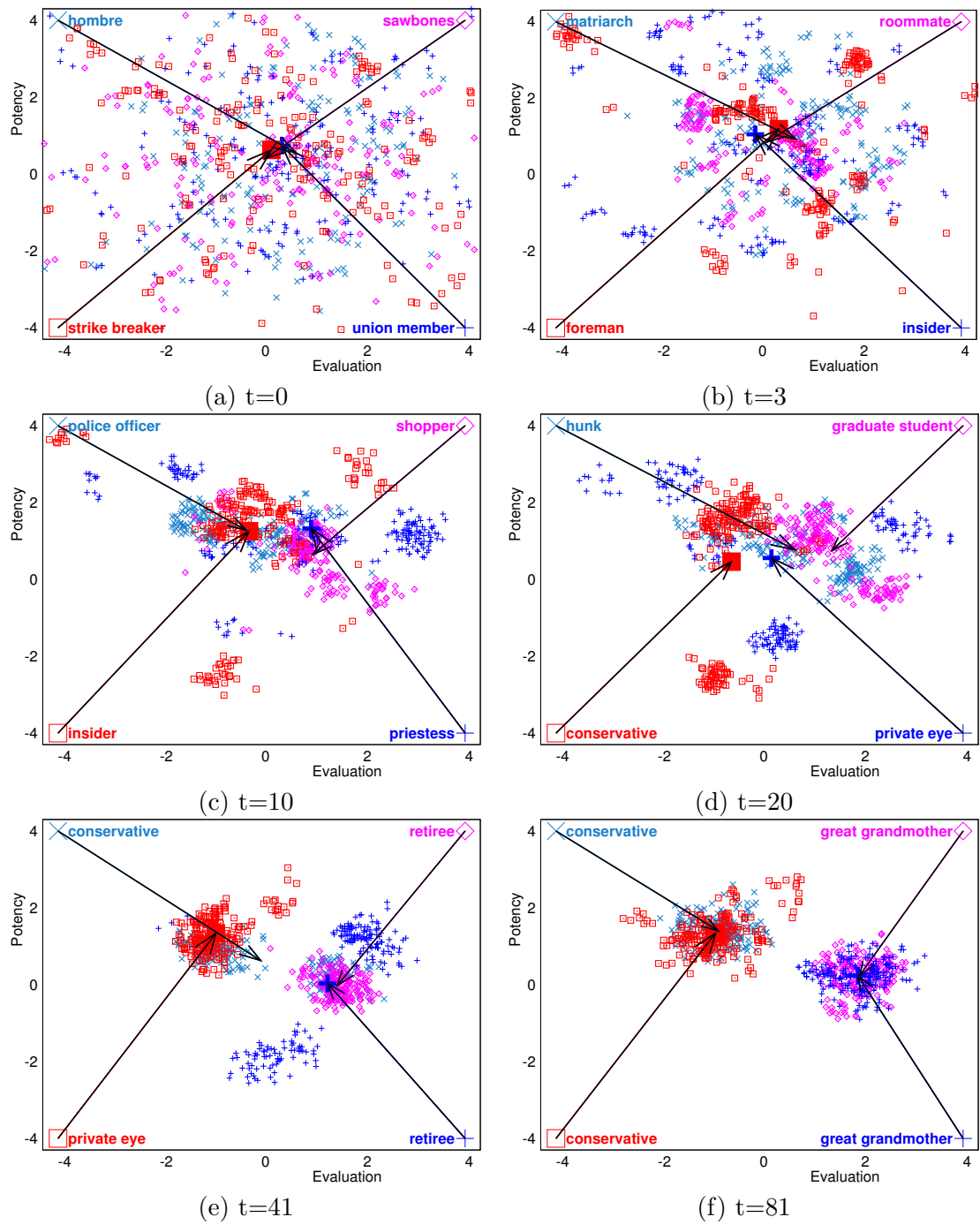


Figure 8: BayesACT Simulation of Emerging Role Relations. We used 200 samples for each agent. Only evaluation and potency axes are shown, although the simulation includes the activity axis. Both agents start without any knowledge of their own or the others identity. One agents beliefs about the identity of self/other are shown with blue/cyan pluses/crosses (+/x), the other agents beliefs are shown with red/magenta squares/diamonds ( $\square$ ,  $\diamond$ ). The mean identities are shown as large versions of the same symbols, and the closest labels are shown in the four corners (for time steps beyond  $t = 10$ ). Black arrows link the mean identity label with the position in the plot. Smaller labels indicate significantly distinct clusters with dashed arrows.

The series of plots on the following pages shows the final distributions after 100 iterations, starting from maximally dispersed identity distributions for both self- and other- identity ( $\mathbf{f}_a$  and  $\mathbf{f}_c$ ) for both agents. In each plot, the samples for the self-identity  $\mathbf{f}_c$  of the two simulated agents are shown as “red” and “blue” filled circles. The samples are plotted in the space of evaluation (x) and potency (y). The activity axis is shown by the brightness of the circles: brighter samples are more active. If  $a \in [-4.3, 4.3]$  is the activity of a sample, then the color of the filled circle (as an  $[R, G, B]$  triple, each color specified in  $[0, 1]$ ) is  $[0, 0, \frac{1-a}{1+e^{-\frac{a}{2}}}]$  for the “blue” agent and  $[\frac{1-a}{1+e^{-\frac{a}{2}}}, 0, 0]$  for “red” agent.

We looked through these plots (500 in total) and counted the number in which we could clearly see that there was one “blue” cluster that was distinct from one “red” cluster. If one of the two clusters was not visible, then it was not counted as a distinction. This could happen because the plots only show the range  $[-6, 6]$  and some cluster may have diverged outside this region, or the two clusters are one on top of the other. Of the 500 trials, we counted 421 (84%) in which a clear distinction could be seen.

The mean difference between the mean identity for the two agents was as follows for different value of the environment noise  $\epsilon$ :

dimension	$\epsilon$				
	0.01	0.05	0.1	0.5	1.0
Evaluation	$1.72 \pm 1.33$	$1.78 \pm 1.44$	$1.71 \pm 1.40$	$1.95 \pm 1.47$	$2.02 \pm 1.55$
Potency	$2.45 \pm 1.88$	$2.42 \pm 1.81$	$2.50 \pm 1.85$	$2.72 \pm 1.89$	$3.03 \pm 2.10$
Activity	$1.93 \pm 1.59$	$2.01 \pm 1.60$	$1.99 \pm 1.55$	$2.10 \pm 1.63$	$2.34 \pm 1.73$

