Influence Model

- A Bayesian Network Approach for Human Interactions

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Overview

- What is influence?

- How to model and infer influence from observations?

“Influence”

- What is influence?
  “getting people to change their attitudes and behaviors.” [Katz and Lazarsfield 1955.]

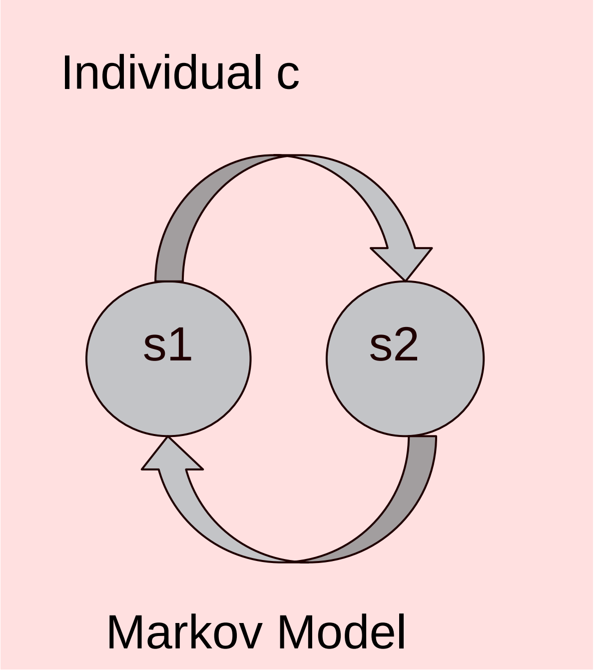
"Influence"

- Influence in statistical physics: voter model. [Krapivsky 1992].

$$W_k(S) \equiv W(s_k \to -s_k) = \frac{d}{4}\left(1 - \frac{1}{2d} s_k \sum_j s_j\right),$$

d	d-dimensional grid
s_k	node opinion (either 1 or 0)
$W_k(s)$	rate of opinion change
j node	k's neighbor nodes

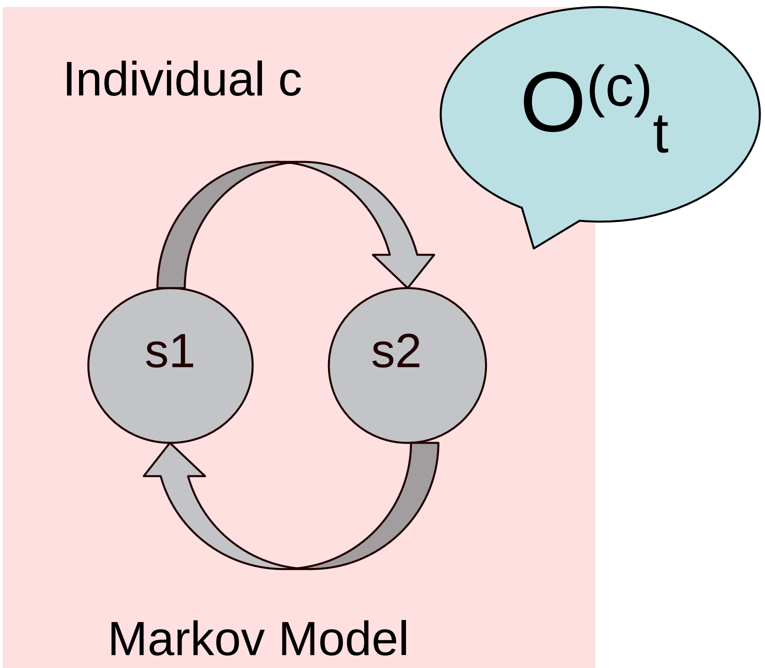
Influence Model



Agent *c*'s state at time *t*:

$$h_t^{(c)} = \{s_1, s_2\}$$

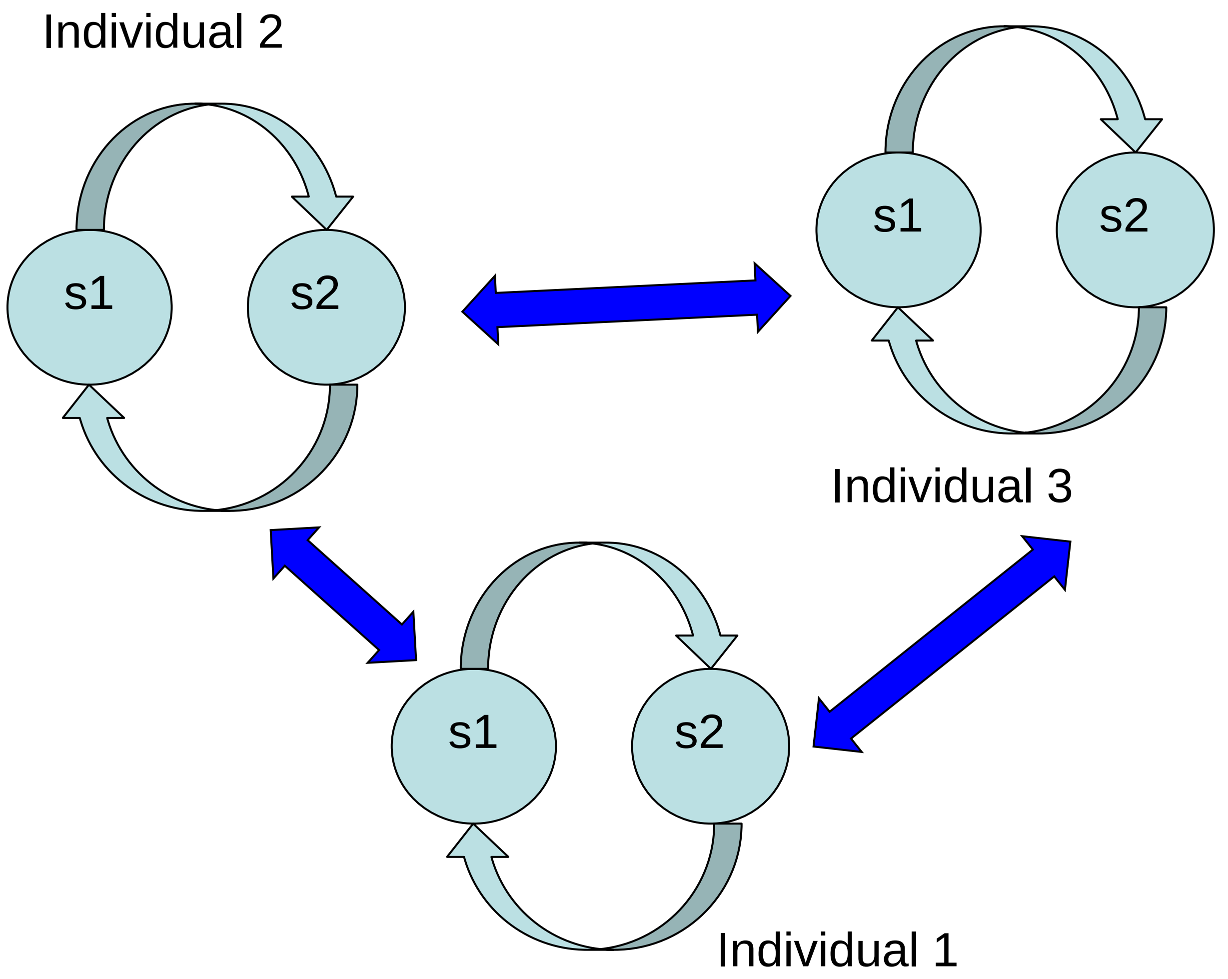
Influence Model

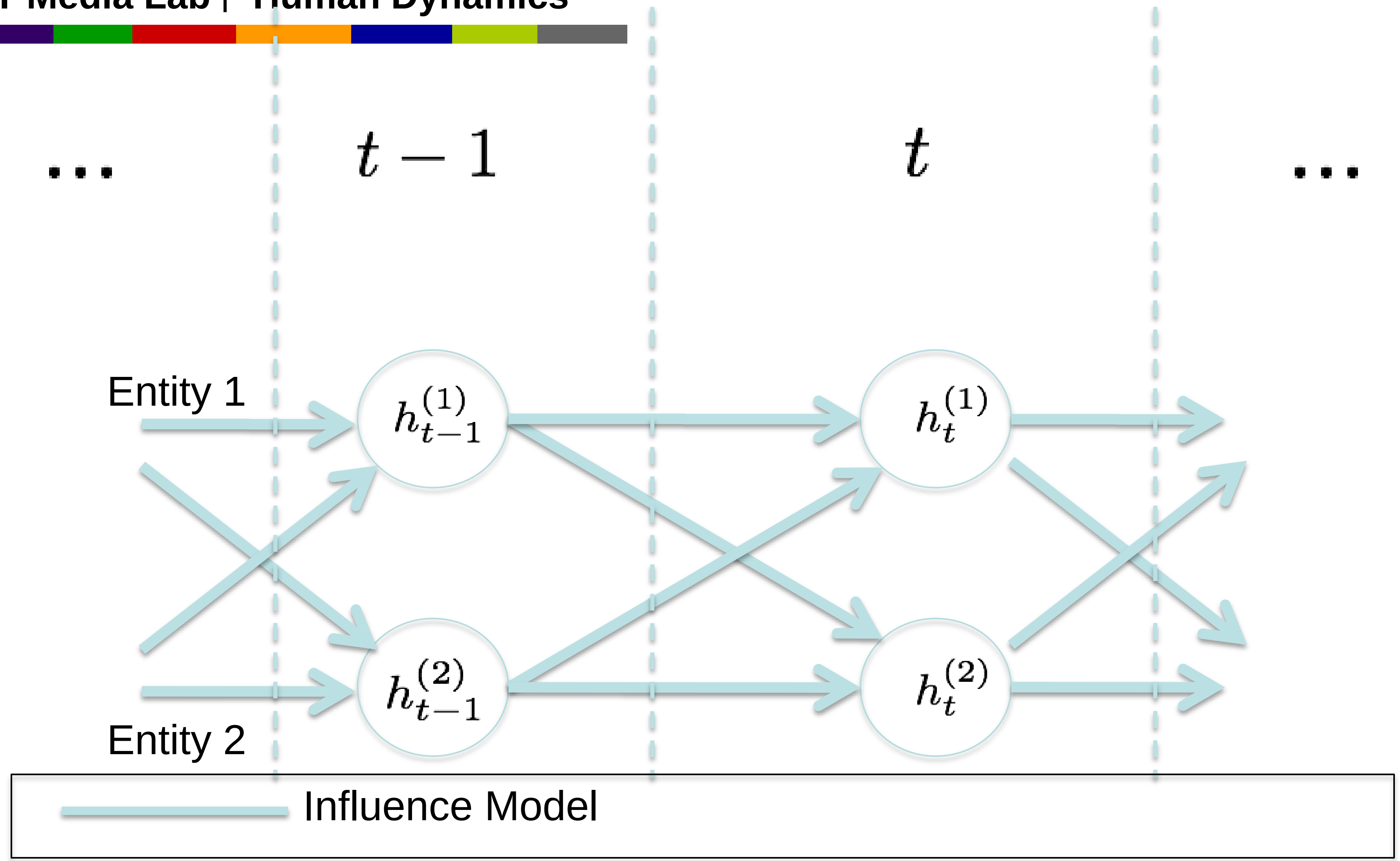


Each individual emit some signal at time *t* based on its current state $h_t^{(c)}$

$$\text{Prob}(O_t^{(c)} | h_t^{(c)})$$

Influence Model



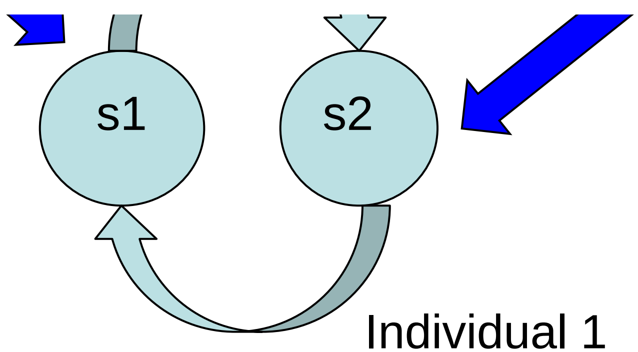


...
$t-1$
t
...
Entity 1
$h_{t-1}^{(1)}$
$h_t^{(1)}$
$h_{t-1}^{(2)}$
$h_t^{(2)}$
Entity 2
Influence Model

Influence Model

Individual 2

$$\mathrm{Prob}(h_t^{(c')} \mid h_{t-1}^{(1)}, \ldots, h_{t-1}^{(C)})$$



Individual 1

Existing Approaches

$$\mathrm{Prob}(h_t^{(c')}|h_{t-1}^{(1)}, \ldots, h_{t-1}^{(C)})$$

- Coupled HMM [Brand Oliver & Pentland'97]
  - # of states grow exponentially with C.
  - Easily over fitting.
- Interacting Group/Individual Model [Zhang et al NIPS'05]
  - Previous states change a group latent state variable; Current state is then influenced by this group latent state.
  - Lacking network structure.

Influence Model

$$\text{Prob}(h_t^{(c')}|h_{t-1}^{(1)},\ldots,h_{t-1}^{(C)}) = \sum_{c\in\{1,\ldots,C\}} \underbrace{\mathbf{R}_{c',c}}_{\text{tie strength}} \times \underbrace{\text{Prob}(h_t^{(c')}|h_{t-1}^{(c)})}_{\text{cond. probability}}$$

Influence Model

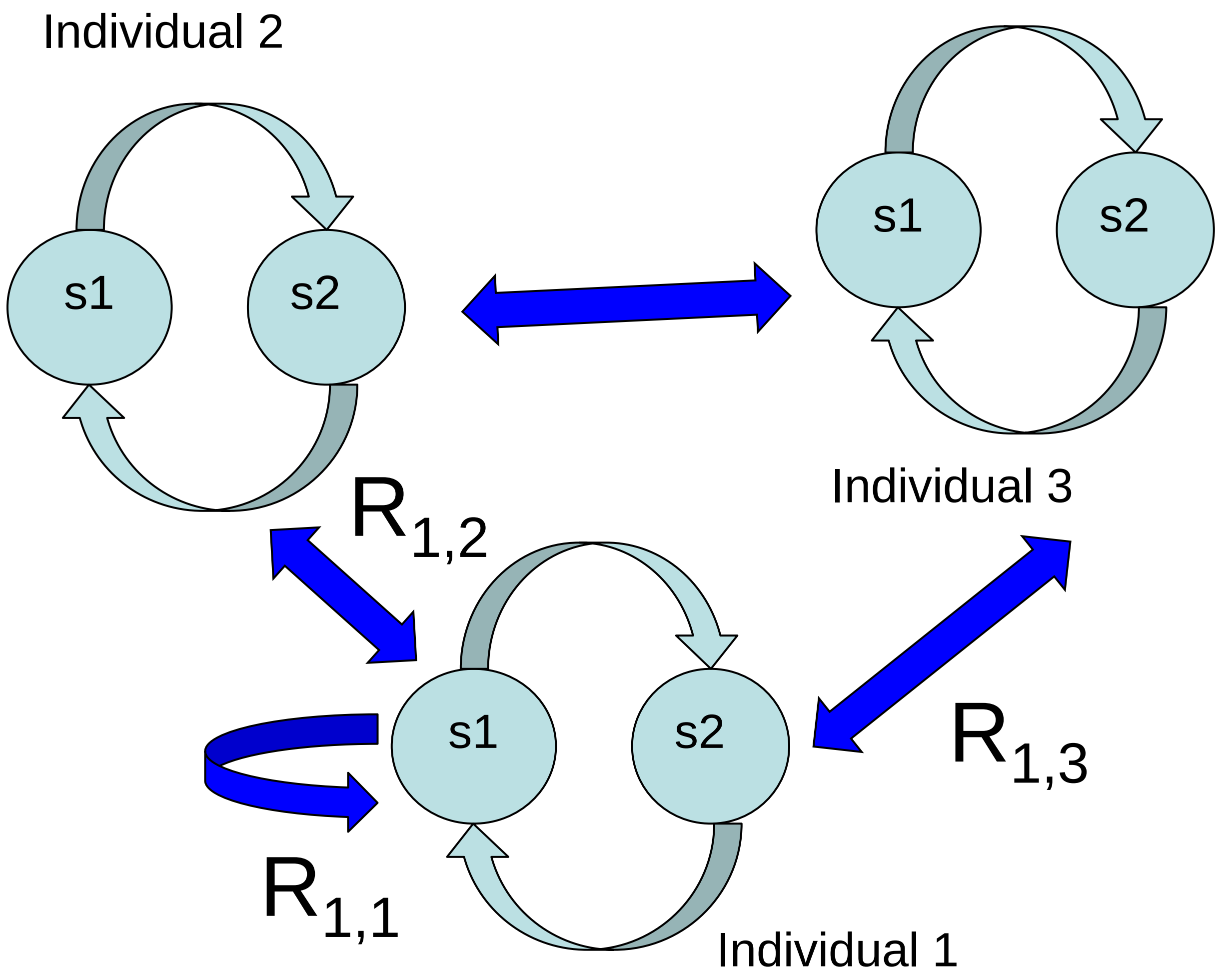
$$\mathrm{Prob}(h_t^{(c')}|h_{t-1}^{(1)},\ldots,h_{t-1}^{(C)}) = \sum_{c\in\{1,\ldots,C\}} \underbrace{\mathbf{R}_{c',c}}_{\text{tie strength}} \times \underbrace{\mathrm{Prob}(h_t^{(c')}|h_{t-1}^{(c)})}_{\text{cond. probability}}$$

	s_1	s_2
s_1	0.8	0.2
s_2	0.2	0.8

Influence Process

$$\mathrm{Prob}(h_t^{(c')} | h_{t-1}^{(1)}, \ldots, h_{t-1}^{(C)}) = \sum_{c \in \{1,\ldots,C\}} \underbrace{\mathbf{R}_{c',c}}_{\text{tie strength}} \times \underbrace{\mathrm{Prob}(h_t^{(c')} | h_{t-1}^{(c)})}_{\text{cond. probability}}$$

Influence Process



Example

100% Democratic
Individual 2

$R_{1,2} = 0.2$

$R_{1,1} = 0.1$

100% Republican
Individual 3

$R_{1,3} = 0.7$

Democrat, but 0.50 to switch to Republican

Me (Individual 1)

Example

$$\Pr(i_1 = \mathrm{R}) = 0.1 \times \Pr(\mathrm{R} \mid \mathrm{i}_1 = \mathrm{D}) + 0.2 \times \Pr(\mathrm{R} \mid \mathrm{i}_2 = \mathrm{D}) + 0.7 \times \Pr(\mathrm{R} \mid \mathrm{i}_3 = \mathrm{R})$$

Example

$$\Pr(i_1 = \mathrm{R}) = 0.1 \times \Pr(\mathrm{R} \mid \mathrm{i}_1 = \mathrm{D}) + 0.2 \times \Pr(\mathrm{R} \mid \mathrm{i}_2 = \mathrm{D}) + 0.7 \times \Pr(\mathrm{R} \mid \mathrm{i}_3 = \mathrm{R})$$

Influence from myself

influence form individual 2

influence from individual 3

Example

$$\Pr(i_1 = \mathrm{R}) = 0.1 \times \Pr(\mathrm{R} \mid \mathrm{i}_1 = \mathrm{D}) + 0.2 \times \Pr(\mathrm{R} \mid \mathrm{i}_2 = \mathrm{D}) + 0.7 \times \Pr(\mathrm{R} \mid \mathrm{i}_3 = \mathrm{R})$$

Influence from myself

influence form individual 2

influence from individual 3

$$\Pr(i_1 = \mathrm{R}) = 0.1 \times 0.5 + 0.2 \times 0 + 0.7 \times 1 = 0.75$$

Social Network and Influence Matrix

Research shows that the influence strength value from the influence matrix has strong correlation ($R=0.92$, $p<0.001$) with the individual centrality in the social network[Choudhury&Basu 2002].

Influence Model

We’ve gathered a lot of individual observations time series from:

The influence model toolkit provides a simple approach to understand influence dynamics from these data.

Inference

From only observations, the influence model is able to infer the following parameters automatically:

- Influence matrix R.
- Cond. probability. i.e.: How each individual influences others.

$$\text{Prob}(h_t^{(c')} | h_{t-1}^{(1)}, \ldots, h_{t-1}^{(C)}) = \sum_{c \in \{1,\ldots,C\}} \underbrace{\mathbf{R}_{c',c}}_{\text{tie strength}} \times \underbrace{\text{Prob}(h_t^{(c')} | h_{t-1}^{(c)})}_{\text{cond. probability}}$$

- A Toy Example

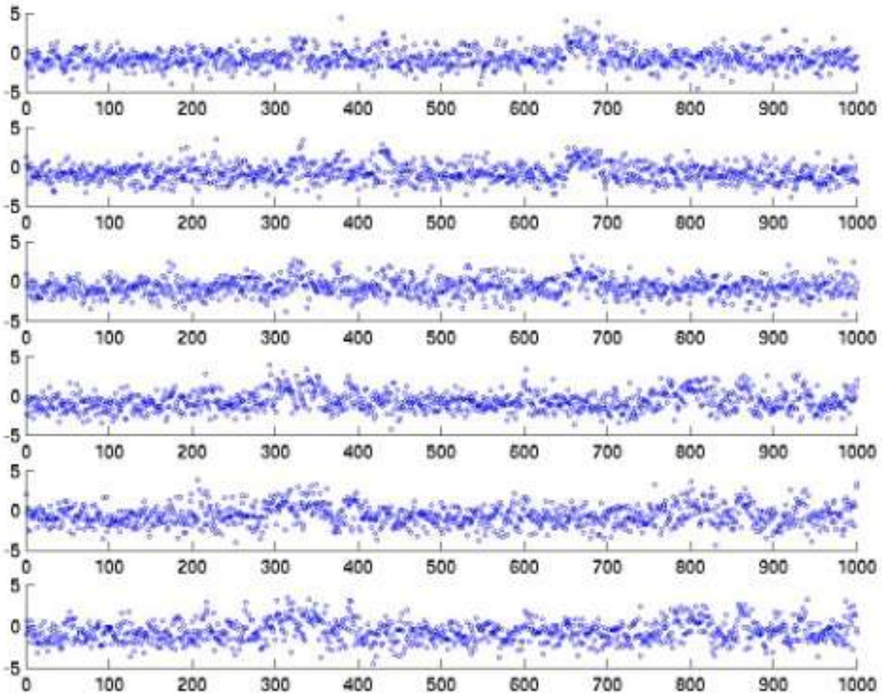
- Introduction to the Influence Model Toolbox

Wen Dong

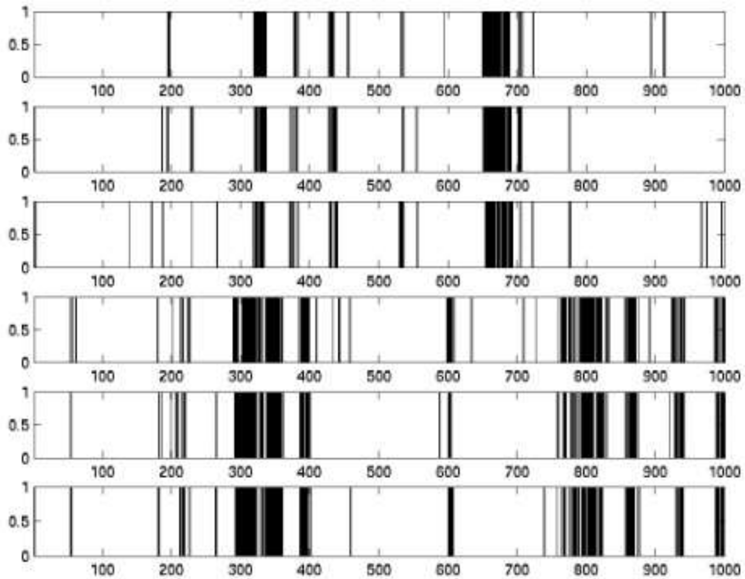
Example: Agent Network

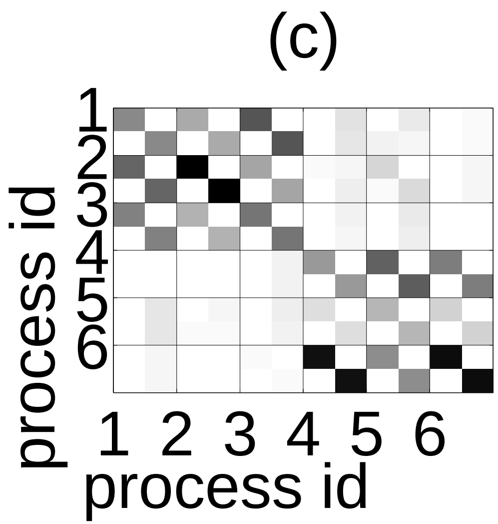
- We are given:
  - Agents interact in unknown way
  - Each agent takes 2 latent states (s1 and s2)
  - Observations of agent states have errors
- We want to find:
  - How agents interact?
  - What are the true agent latent states at different time *t*?

Observations about Agents have errors and missing data



Influence model removes errors and discovers network structure simultaneously



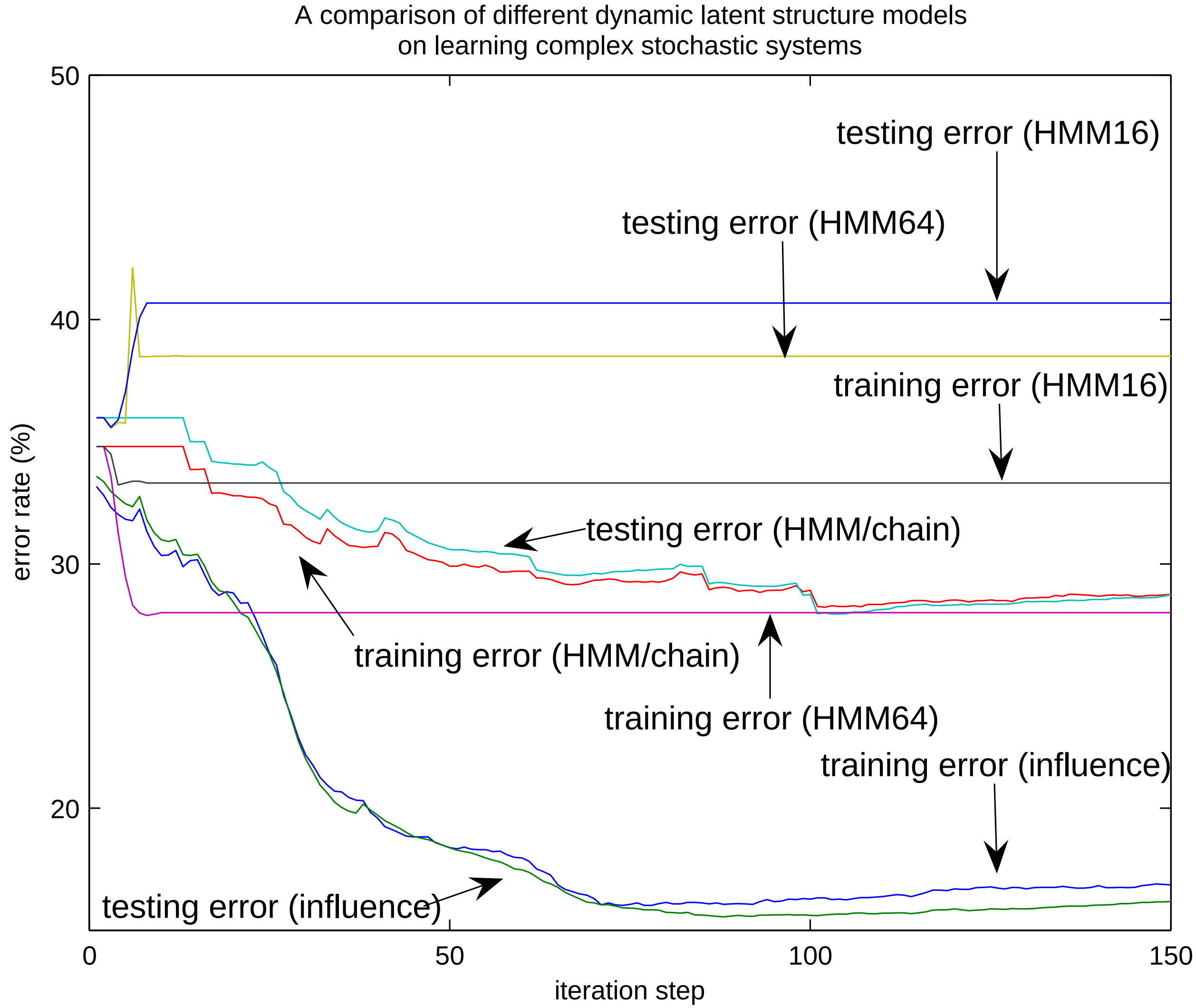


Latent structure network example.

- The influence model can normally attain around ***95% accuracy*** in predicting the latent states for each processes.
- The reconstructed influence matrix has only ***9% relative difference*** with the original one.
- Using only the observations of other processes, we can predict a process's state with ***87% accuracy***.

Dong, Pentland

Influence model has the right balance between model complexity and model power



How to use our influence model code

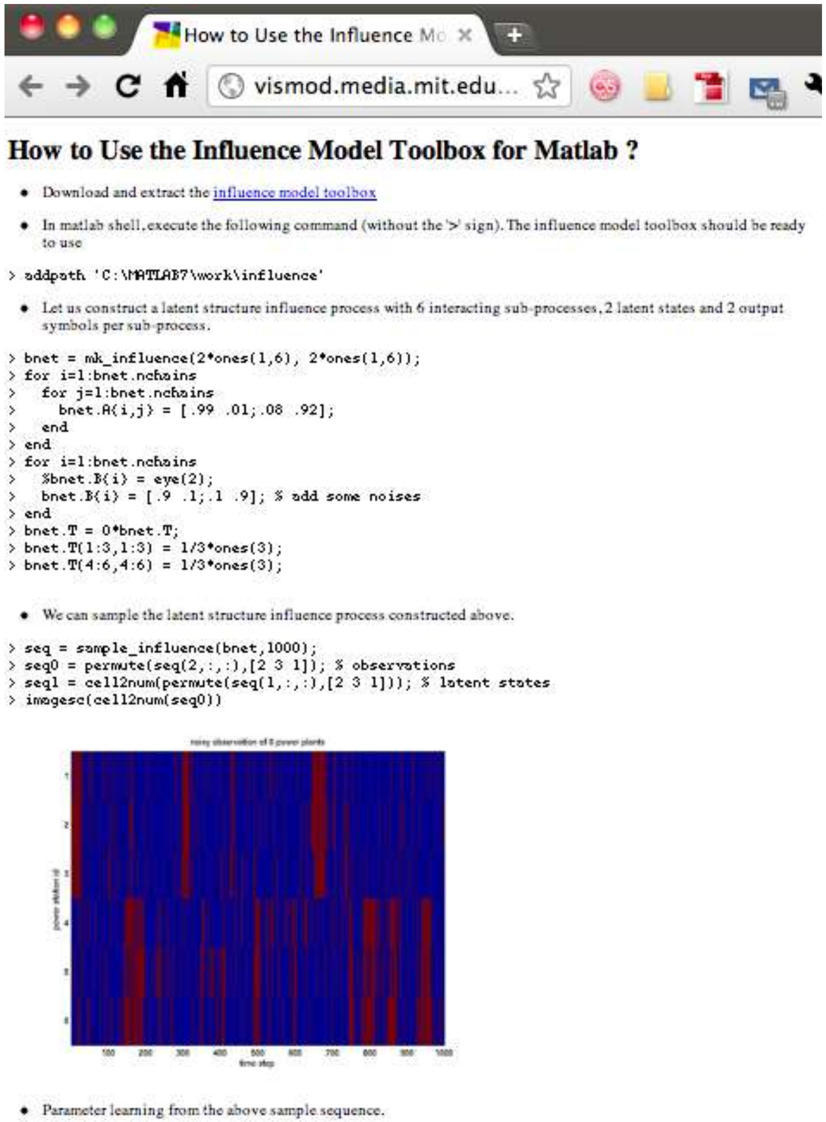
- Construct a model
- Synthesize a sample path
- Make inference
- Learn parameters
- Make predictions

http://vismod.media.mit.edu/vismod/demos/influence-model/software-usage.htm

How to use our influence model code

```
% construct influence model
bnet1 = mk_influence(2*ones(1,6), 2*ones(1,6));
% prepare for inference
engine = influence_inf_engine(bnet1);
% make inference
bnet1 = learn_params_influence(engine,seq0,50);
%
engine1 = influence_inf_engine(bnet1);
seq2 = influence_mpe(engine1,seq0);
imagesc(seq2)
```

http://vismod.media.mit.edu/vismod/demos/influence-model/software-usage.htm



How to Use the Influence Mo ×

vismod.media.mit.edu...

How to Use the Influence Model Toolbox for Matlab ?

- Download and extract the influence model toolbox
- In matlab shell, execute the following command (without the '>' sign). The influence model toolbox should be ready to use

```
> addpath 'C:\MATLAB7\work\influence'
```

- Let us construct a latent structure influence process with 6 interacting sub-processes, 2 latent states and 2 output symbols per sub-process.

```
> bnet = mk_influence(2*ones(1,6), 2*ones(1,6));
> for i=1:bnet.nchains
>   for j=1:bnet.nchains
>     bnet.A(i,j) = [.99 .01;.08 .92];
>   end
> end
> for i=1:bnet.nchains
>   %bnet.B(i) = eye(2);
>   bnet.B(i) = [.9 .1;.1 .9]; % add some noises
> end
> bnet.T = 0*bnet.T;
> bnet.T(1:3,1:3) = 1/3*ones(3);
> bnet.T(4:6,4:6) = 1/3*ones(3);
```

- We can sample the latent structure influence process constructed above.

```
> seq = sample_influence(bnet,1000);
> seq0 = permute(seq(2,:,:),[2 3 1]); % observations
> seq1 = cell2num(permute(seq(1,:,:),[2 3 1])); % latent states
> imagesc(cell2num(seq0))
```

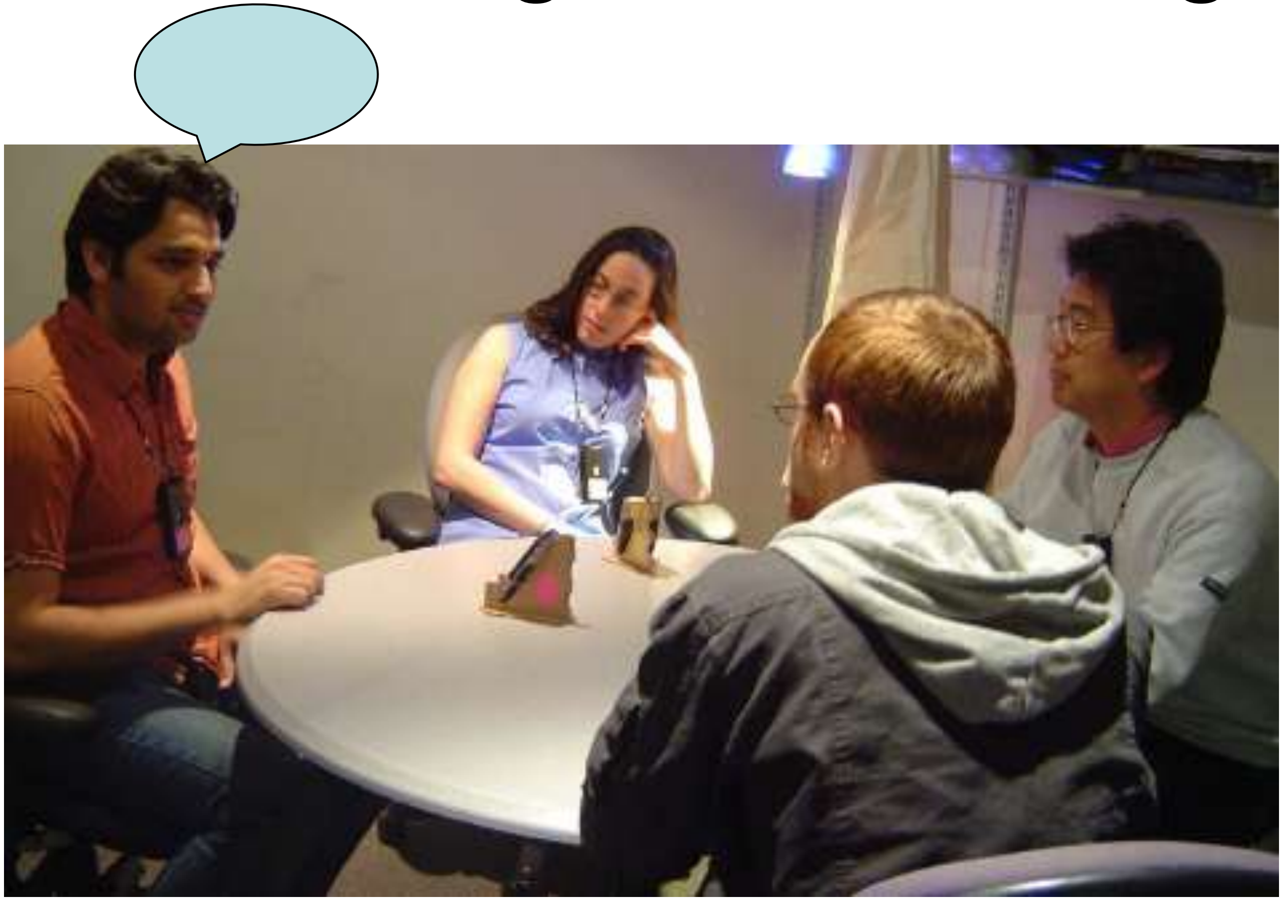
- Parameter learning from the above sample sequence.

Predicting Turn-Taking

Predicting Turn-Taking

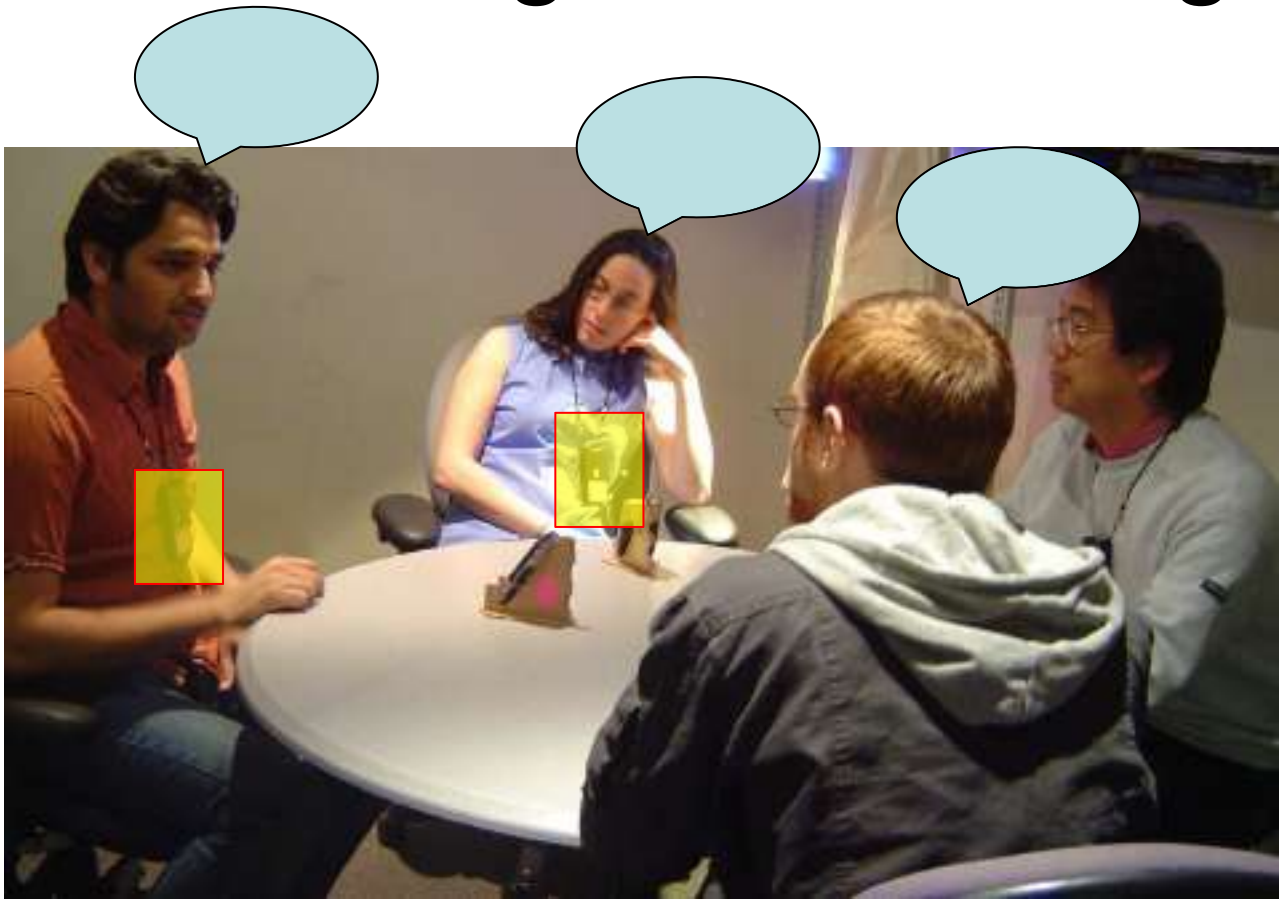
CATEGORY	TASK DESCRIPTION
CO+PS	Four people perform a problem solving task in the same room.
CO+BS	Four people perform a brainstorming session in the same room.
DS+PS	Four people perform the same problem solving task in two rooms with Skype.
DS+BS	Four people perform the same brainstorming session in two rooms with Skype.

Predicting Turn-Taking



Predicting Turn-Taking

Predicting Turn-Taking



Predicting Turn Taking

Input: individual's badge audio signal (volume and variations)

Hidden states: whether individual is speaking or not speaking

Influence: one person speaking behavior influences other people's speaking behavior

Prediction: we train model and sample the next state to predict who speaks next.

Predicting Turn Taking

$$\mathrm{Prob}(h_t^{(c')}|h_{t-1}^{(1)},\ldots,h_{t-1}^{(C)}) = \sum_{c\in\{1,\ldots,C\}} \underbrace{\mathbf{R}_{c',c}}_{\text{tie strength}} \times \underbrace{\mathrm{Prob}(h_t^{(c')}|h_{t-1}^{(c)})}_{\text{cond. probability}}$$

$$\Downarrow$$

$$\mathrm{Prob}(h_t^{(c')}|h_{t-1}^{(1)},\ldots,h_{t-1}^{(C)}) = \sum_{c\in\{1,\ldots,C\}} \mathbf{R}^{r_t}{}_{c',c} \times \mathrm{Prob}(h_t^{(c')}|h_{t-1}^{(c)}).$$

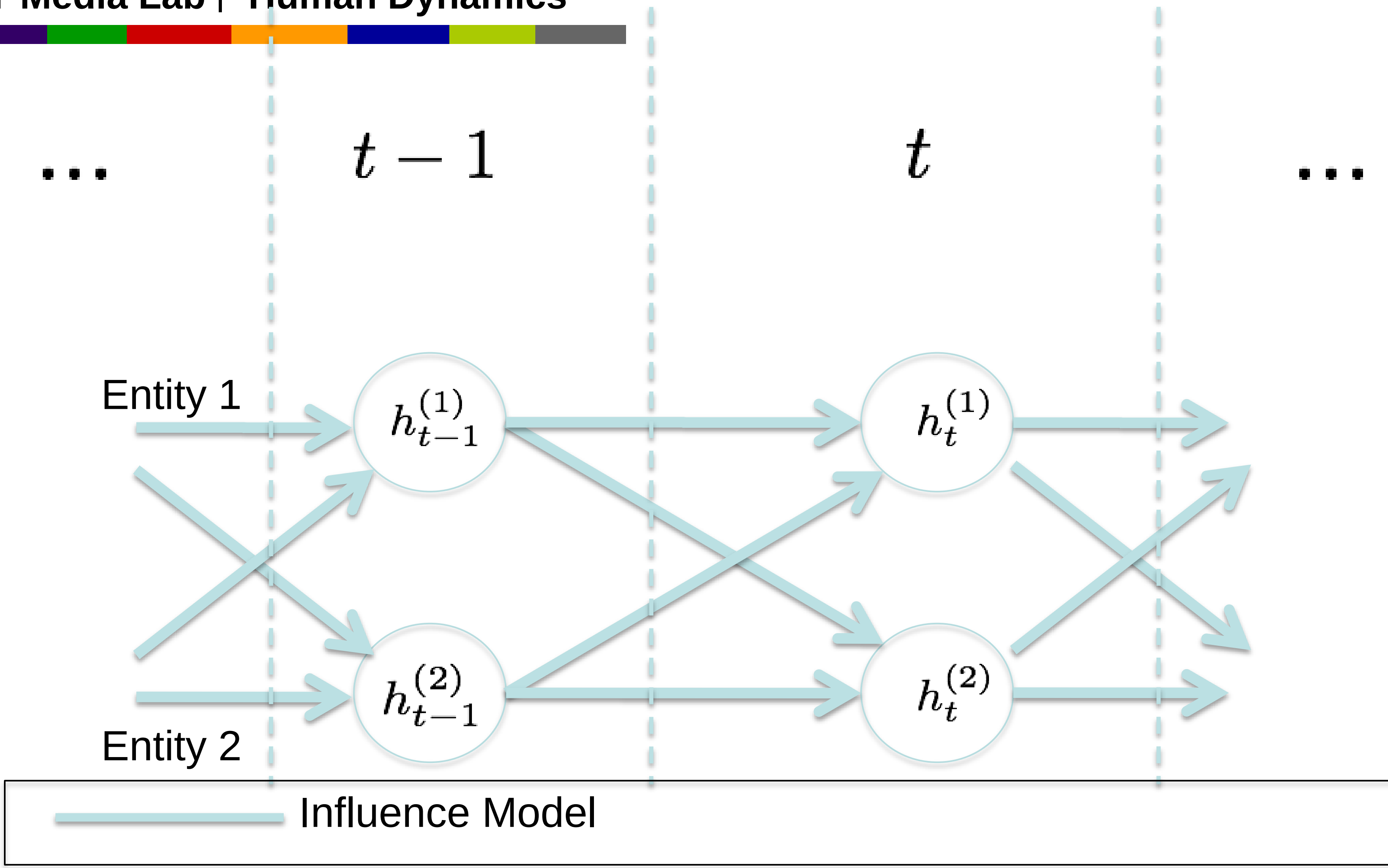
Predicting Turn Taking

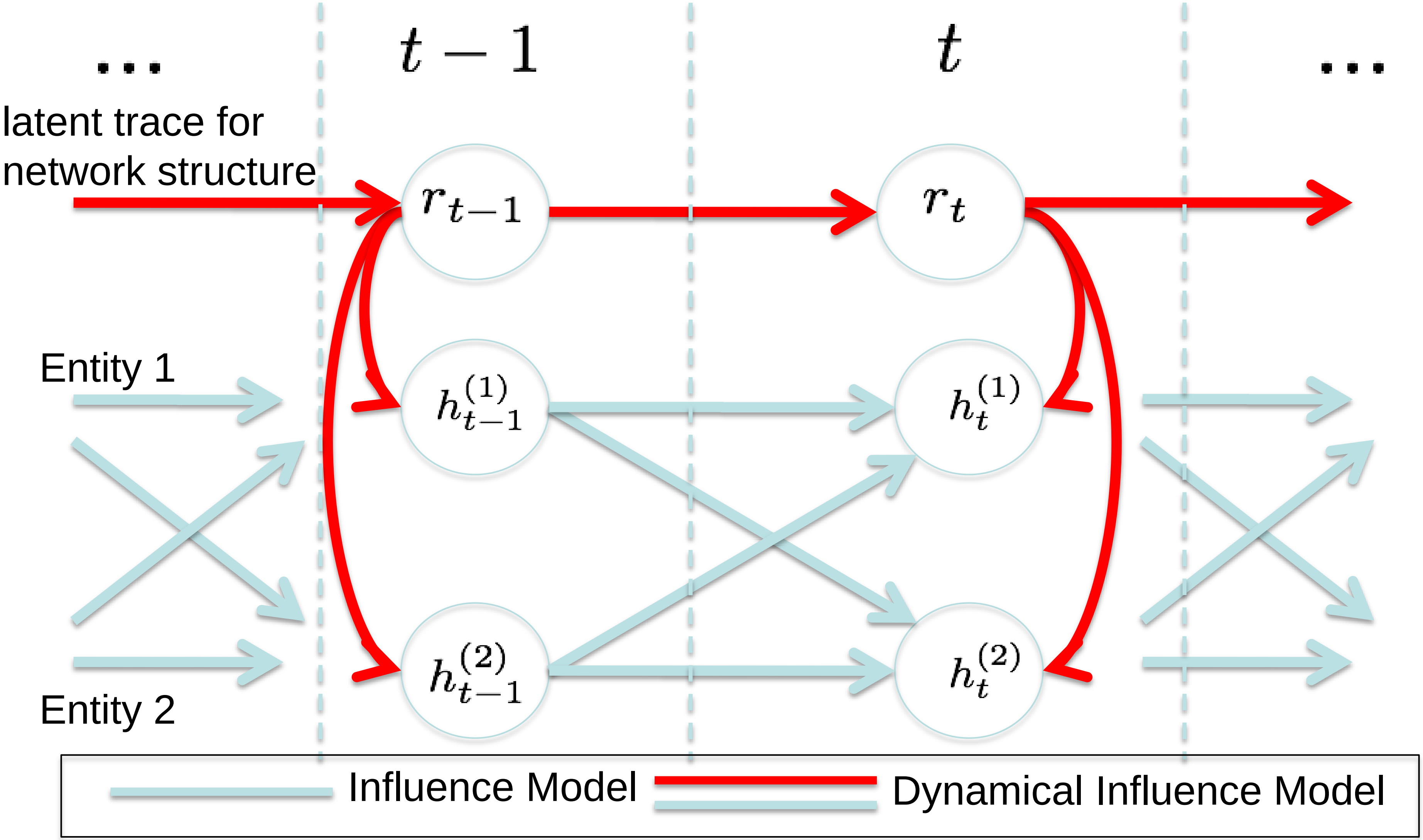
$$\text{Prob}(h_t^{(c')} | h_{t-1}^{(1)}, \ldots, h_{t-1}^{(C)}) = \sum_{c \in \{1,\ldots,C\}} \underbrace{\mathbf{R}_{c',c}}_{\text{tie strength}} \times \underbrace{\text{Prob}(h_t^{(c')} | h_{t-1}^{(c)})}_{\text{cond. probability}}$$

$$\Downarrow$$

$$\text{Prob}(h_t^{(c')} | h_{t-1}^{(1)}, \ldots, h_{t-1}^{(C)}) = \sum_{c \in \{1,\ldots,C\}} \mathbf{R}^{r_t}{}_{c',c} \times \text{Prob}(h_t^{(c')} | h_{t-1}^{(c)}).$$

$$R \Longrightarrow R^1, \ldots, R^J$$


...
$t-1$
t
...
Entity 1
$h_{t-1}^{(1)}$
$h_t^{(1)}$
$h_{t-1}^{(2)}$
$h_t^{(2)}$
Entity 2
Influence Model


...
$t-1$
t
...
latent trace for network structure
r_{t-1}
r_t
Entity 1
$h_{t-1}^{(1)}$
$h_t^{(1)}$
$h_{t-1}^{(2)}$
$h_t^{(2)}$
Entity 2
Influence Model
Dynamical Influence Model

Predicting Turn Taking

	ACCURACY ALL SAMPLES				ACCURACY COMPLEX INTERACTION SAMPLES			
METHODS	**DS+BS**	**DS+PS**	**CO+BS**	**CO+PS**	**DS+BS**	**DS+PS**	**CO+BS**	**CO+PS**
TESLA	0.41	0.42	0.32	0.25	0.44	0.37	0.37	0.17
NN	**0.58**	0.60	0.48	0.50	**0.47**	0.47	0.38	0.26
Ours(J=1)	0.45	**0.67**	**0.75**	**0.63**	0.45	0.56	**0.77**	0.62
Ours(J=2)	0.46	0.58	0.65	0.34	**0.47**	0.58	0.67	0.46
Ours(J=3)	0.50	0.60	0.55	0.48	**0.47**	**0.73**	0.65	**0.65**

Traffic in Road Network

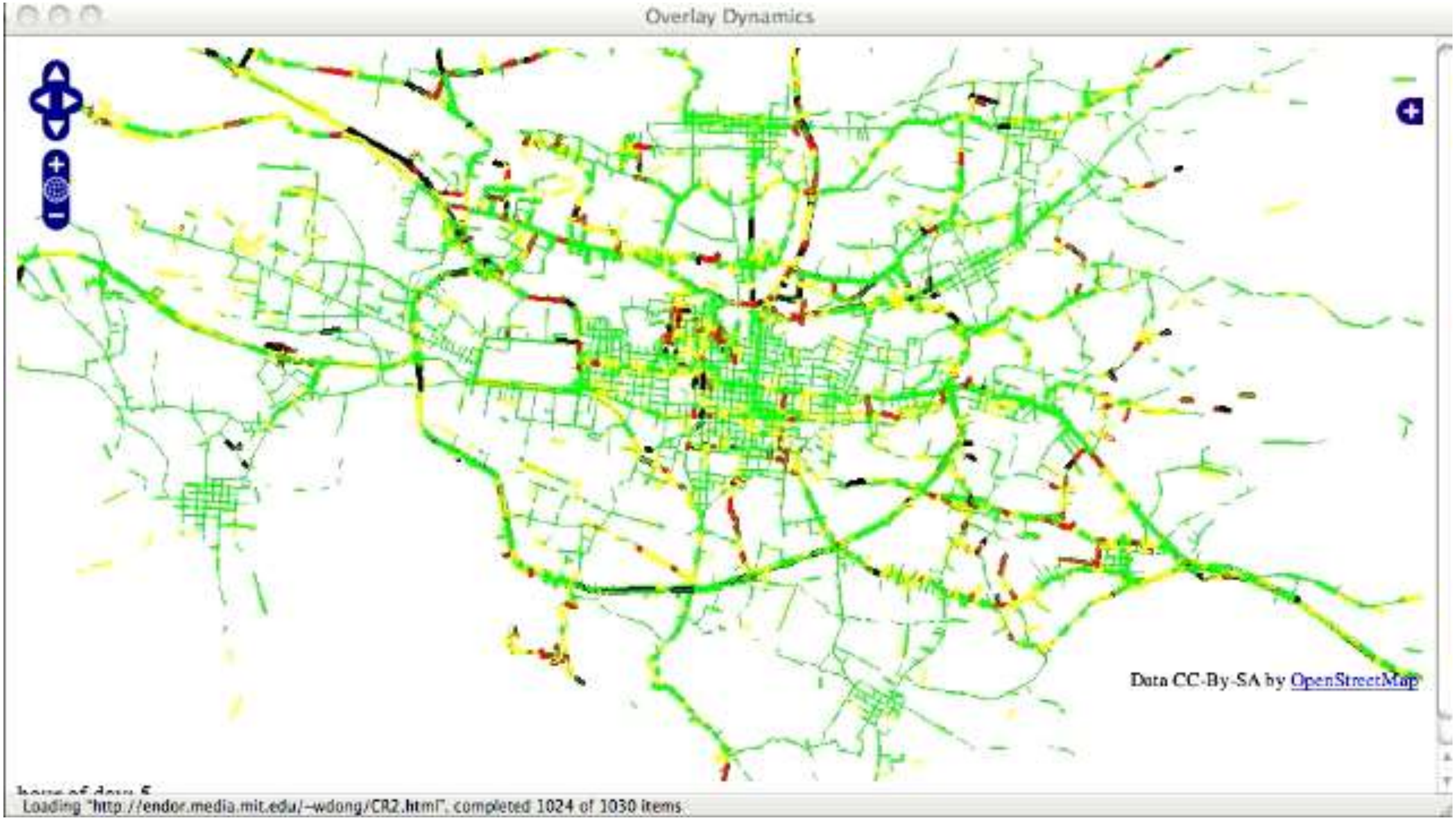
Traffic correlation among roads enables us to

- estimate traffic by tracking a few vehicles
- predict traffic by simulating the interaction

Example: Traffic in Road Network

- Given:
  - time and location of 1000 cars in Costa Rica.
- Find:
  - Correlation of traffic among roads
  - Traffic predictions.

Understanding and Improving Road Network Dynamics



http://endor.media.mit.edu/~wdong/CR2.html

Better Traffic Prediction with Fewer Input

- 15% more accurate than Google Traffic
- Tracked only 1000 cars

Modeling the Structure of Collective Intelligence

A mathematical model of interpersonal interaction can describe group problem solving.

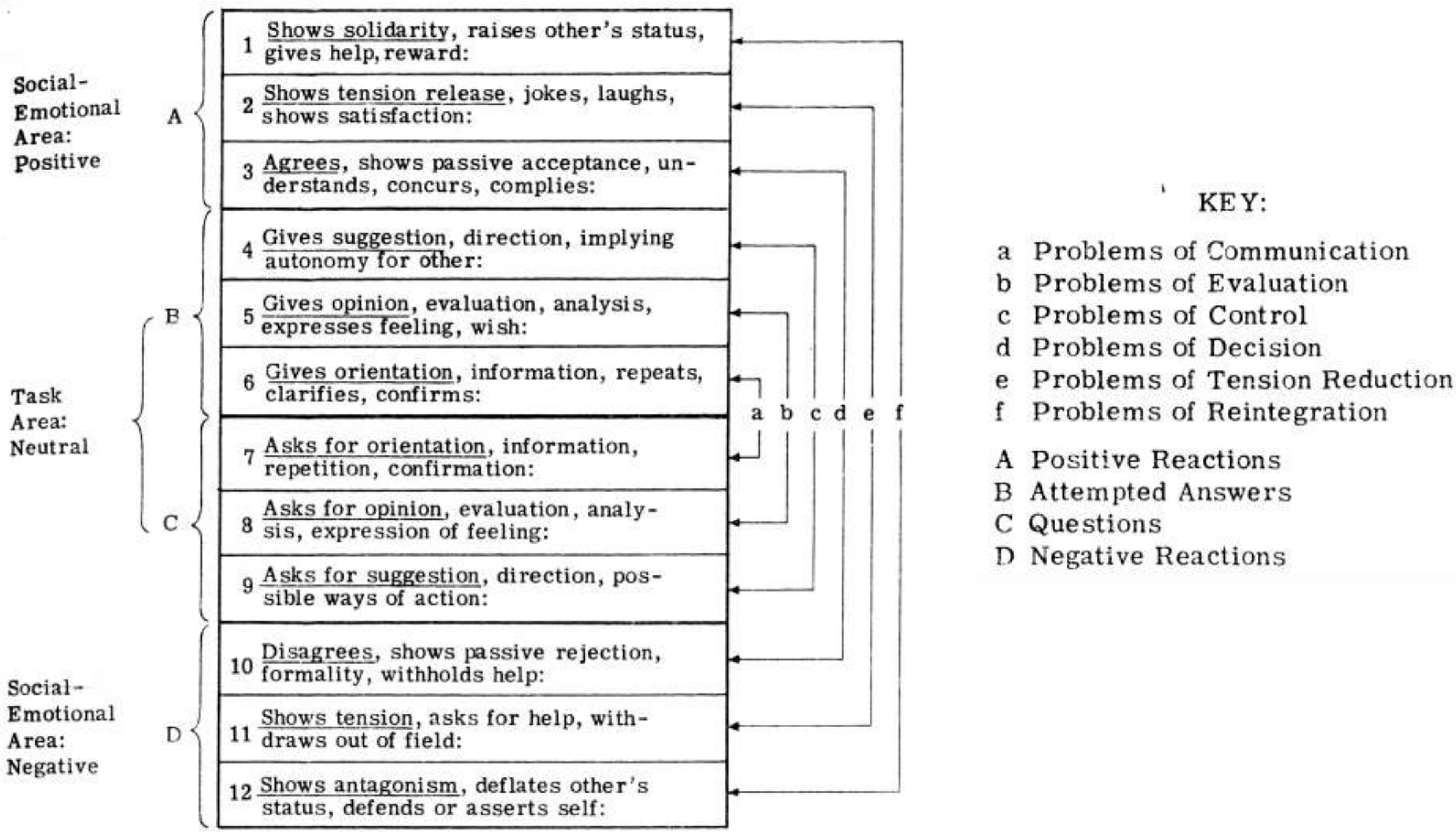
A non-parametric model can be inferred from observing many people solving the same problem.

Automated tools can measure problem solving performance.

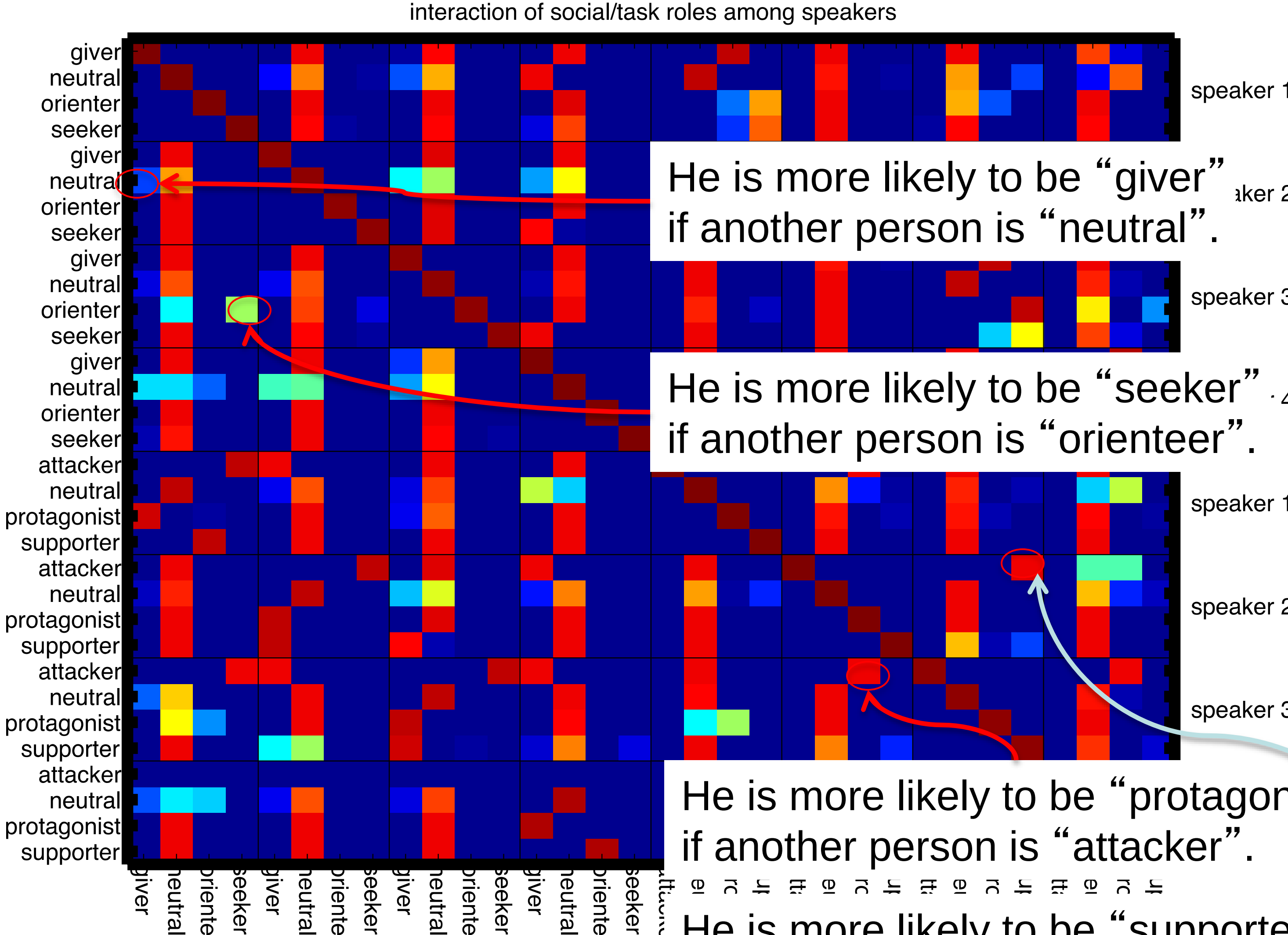
We hope to be able to predict and improve performance.

Bales' Interaction Process Analysis

Chart 1. The system of categories used in observation and their major relations.



Roles combine with each other in useful ways, hence we can infer roles from the roles of others



He is more likely to be "giver" if another person is "neutral".

He is more likely to be "seeker" if another person is "orienteer".

He is more likely to be "protagonist" if another person is "attacker".

He is more likely to be "supporter" if another person is "supporter".

Quantifying Group Problem Solving with Stochastic Analysis

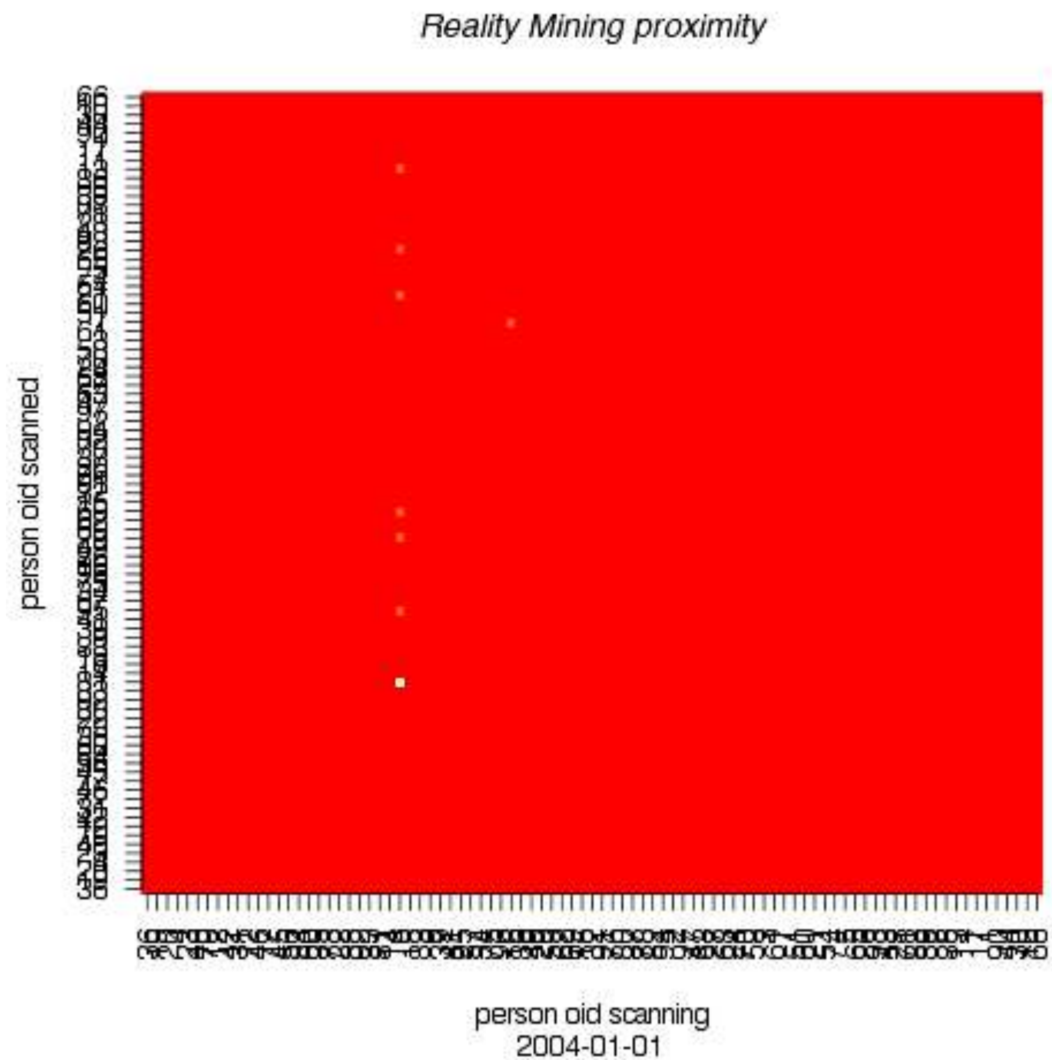
We model how **different group performance levels** are related to **different transition probabilities among "events"** in a stochastic process of group discussion, and study the characteristics of productive groups through **sampling a trained stochastic process for typical behavior**, such as in the following derived table.

Our approach could account for 40% to 60% of performance, and could be easily extended to include more features.

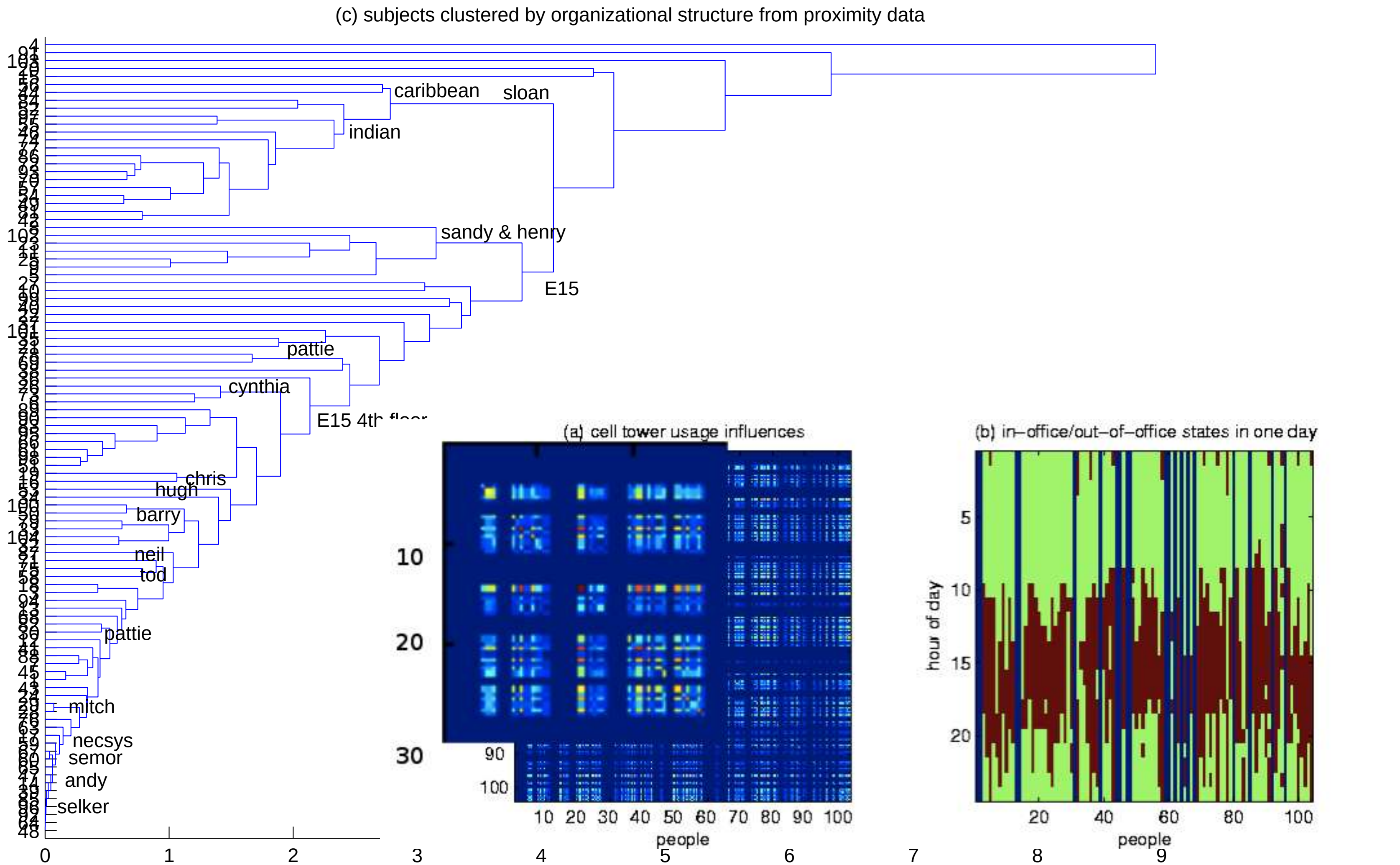
brainstorming requires faster turns, more sentences, shorter sentences, more speaker overlap.

percentile	number of sentences	sentences per person per minute	average sentence length	speaker transitions	speaker overlap
25%	250	10.6	2	4	0.8
50%	300	12.3	1.5	5	1.2
75%	350	14.0	1.2	7	1.4

Organizational Behavior has Periodical and clustering pattern



We can use influence model to track organizational behavior



Conclusion

- We introduce the basic influence model, a open-source toolbox and a few examples.
- We show that many complex social systems can be modeled using the influence model.
- We show that the influence model can be applied to understand group dynamics and collective intelligence.

Limitation

- The influence model is still a Bayesian graph model:
  - Computational intense for inference.
  - Require a lot of training data.
  - 1^{st} order Markov property.
  - General machine learning problems.
- The influence model only relies on individual observations:
  - Leveraging existing network data may be beneficial.

Code and Papers

- Code
- http://vismod.media.mit.edu/vismod/demos/influence-model/index.html

- Papers
- http://hd.media.mit.edu/TechnicalReportsList.html

- Contact
- pentland@mit.edu