Influence Modeling of System Interactions

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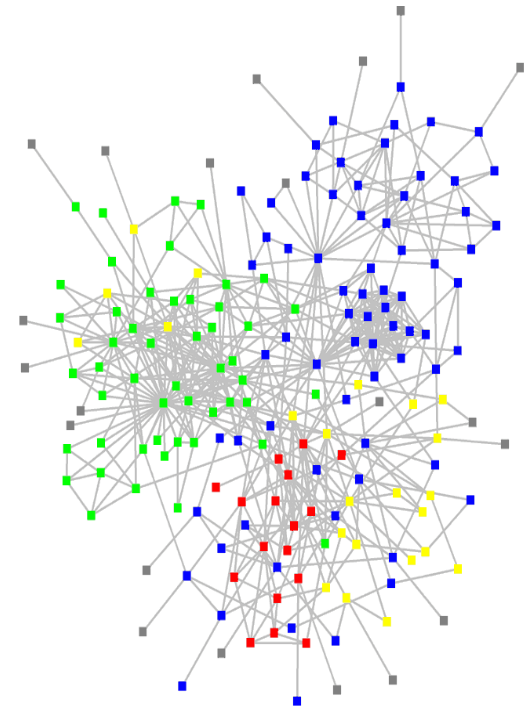
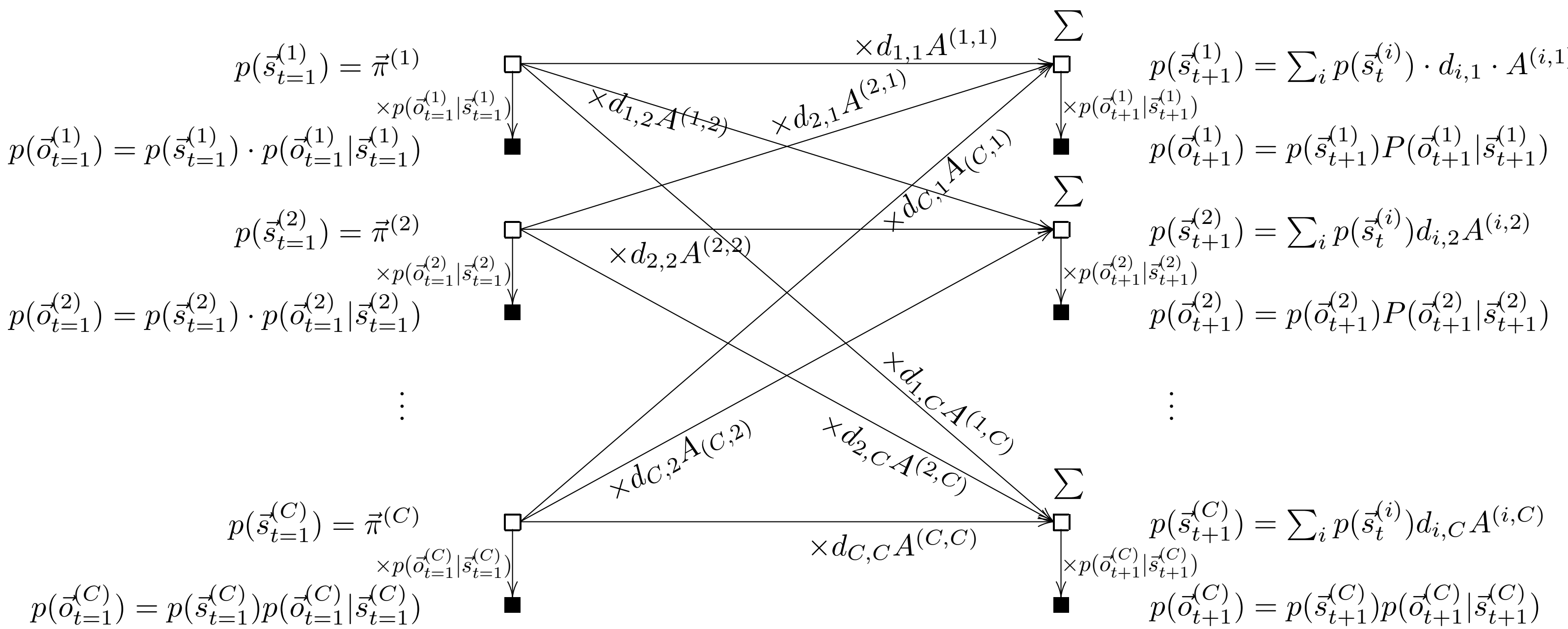
What is an influence model?

- We view a sensor network as information flow from behavior rules to noisy observations.
  - behavior rules: cooperation, social structure, common schedule, common sense, etc.
  - Observations: audio, accelerometer, visual, IR, blue-tooth, GPS, cell tower usage, etc.
- We want to reverse the project from noisy observations back to behavior rules
  - Temporal information of individual agents contributes to understanding of the network dynamic structure.
  - Understanding of the network dynamic structure contributes to inference the dynamics of individual processes.



From http://www.orgnet.com/email.html

A graphical model representation of an influence model



A graphical model representation of the influence model. The left column represents basis step, and the right column induction step. Shadowed squares are observable, while un-shadowed unobservable. Our task is to learn the parameters and latent states from observations

Inference of an influence model

$$\vec{\alpha}_t^* = \begin{cases} \vec{\pi}_{1\times\sum m_c} & ,t=1 \\ \vec{\alpha}_t^* \cdot H \cdot \text{diag}[\vec{b}_t], & t>1 \end{cases}$$

$$N_t = \prod_c \left(\sum_{i=1}^{m_c} \vec{\alpha}_{t,i}^*\right) \cdot \begin{pmatrix} \frac{1_{m_1\times m_1}}{\sum_{i=1}^{m_1} \vec{\alpha}_{t,i}^*} & & \\ & \ddots & \\ & & \frac{1_{m_C\times m_C}}{\sum_{i=1}^{m_C} \vec{\alpha}_{t,i}^*} \end{pmatrix}$$

$$\vec{\alpha}_t = \vec{\alpha}_t^* \cdot N_t$$

$$\vec{\beta}_t = \begin{cases} \vec{1}_{\sum m_c \times 1} & ,t=T \\ \vec{\alpha}_t^* \cdot H \cdot \text{diag}[\vec{b}_t], & t<T \end{cases}$$

$$\vec{\gamma}_t = \vec{\alpha}_t \cdot \text{diag}[\vec{\beta}_t]$$

$$\vec{\xi}_{t-1\to t} = \text{diag}[\vec{\alpha}_t] \cdot H \cdot \text{diag}[\vec{b}_t] N_t \cdot \text{diag}[\vec{\beta}_t]$$

$$p(\vec{o}) = \prod_c \left(\sum_{i=1}^{m_c} \vec{\alpha}_{t,i}^*\right)$$

Sufficient statistics update

$$A_{i,j} = \text{normalize}\left[\sum_{t=2}^{T} \vec{\xi}_{t-1\to t}\right]$$

$$S = \begin{pmatrix} 1_{1\times m_1} & & \\ & \ddots & \\ & & 1_{1\times m_C} \end{pmatrix}$$

$$d_{i,j} = \text{normalize}\left[S \sum_{t=2}^{T} \vec{\xi}_{t-1\to t} S^{\mathrm{T}}\right]$$

$$\vec{\pi}^{(c)} = \text{normalize}[\vec{\gamma}_{t=1}]$$

$$p(\vec{o}^{(c)} \mid \vec{s}^{(c)}) = \text{normalize}\left[\sum_t \vec{\gamma}_t^{(c)\mathrm{T}} \vec{\delta}^{(c)}_{y_t, \vec{o}^{(c)}}\right]$$

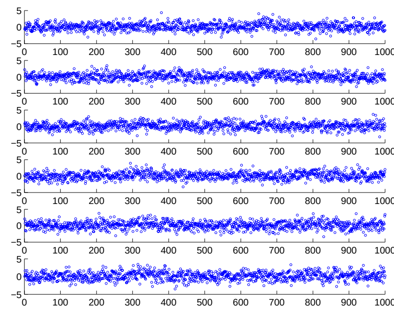
$$\mu^{(c)} = \frac{\sum_t \vec{\gamma}_t^{(c)\mathrm{T}} \vec{o}_t^{(c)}}{\sum_t \vec{\gamma}_t^{(c)\mathrm{T}} 1_{m_C\times 1}}$$

$$\sigma^{(c)2} = \frac{\sum_t \vec{\gamma}_t^{(c)} \vec{o}_t^{(c)\mathrm{T}} \vec{o}_t^{(c)}}{\sum_t \vec{\gamma}_t^{(c)\mathrm{T}} 1_{m_C\times 1}} - \mu^{(c)\mathrm{T}} \mu^{(c)}$$

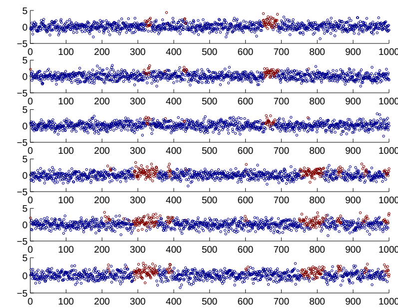
Parameter estimation

Inferences on power station network dynamics

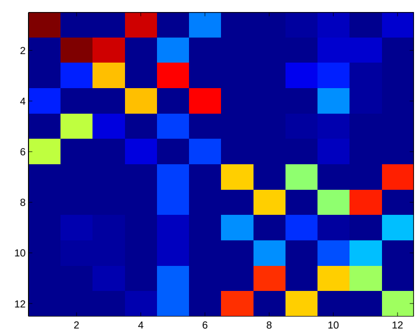
- (a) shows 1000 consecutive observations of 6 influencing Markov processes. What is their interaction as well as their individual latent state sequences behind the observations?
- The understanding of the individual behaviors and the understanding of the system structure contribute to each other.
- (b), (c) show the reconstructed latent state sequences and the system structure from the first 250 observations for each processes using the influence model, (d) shows the generating latent state sequences.



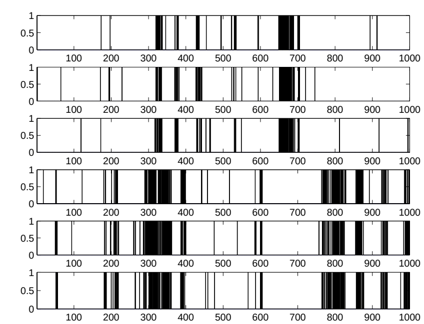
(a) observation



(b) reconstructed

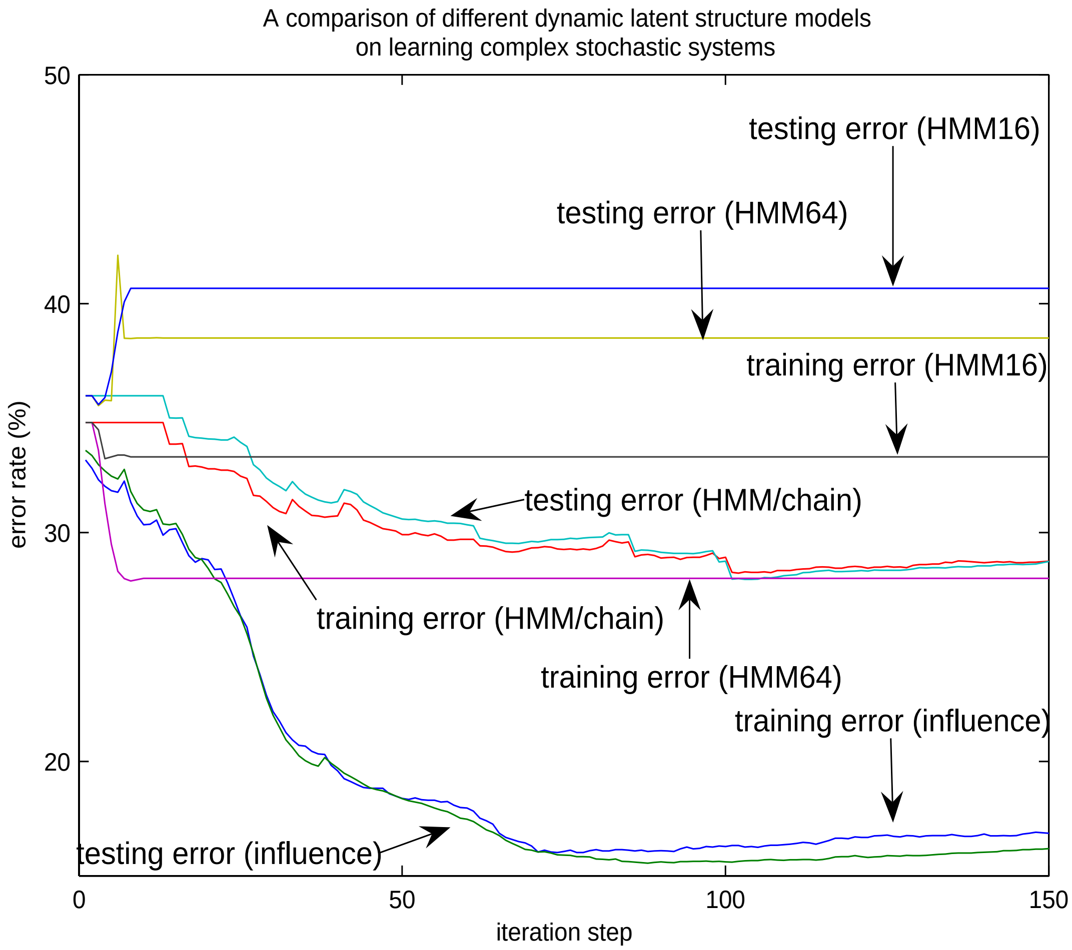


(c) structure



(d) original

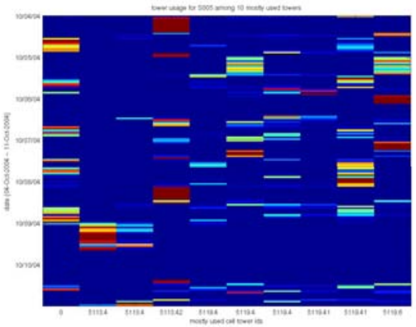
Inference from noisy measures



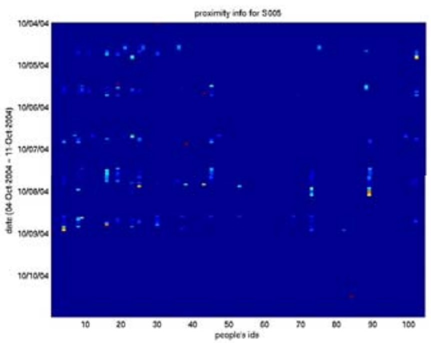
Inferences on Mobile Phone Networks

(data collected by Nathan Eagle)

- (a) shows a subject's cell tower usage during one week (y axis) among 10 mostly used cell towers (x axis). Cell tower usage data reflects people's geographical information.
- (b) shows a subject's proximity with other subjects (x axis) during one week (y axis). Proximity data reflects people's togetherness.
- What can be inferred by putting individuals' data together ?



(a) Cell tower usage distributions

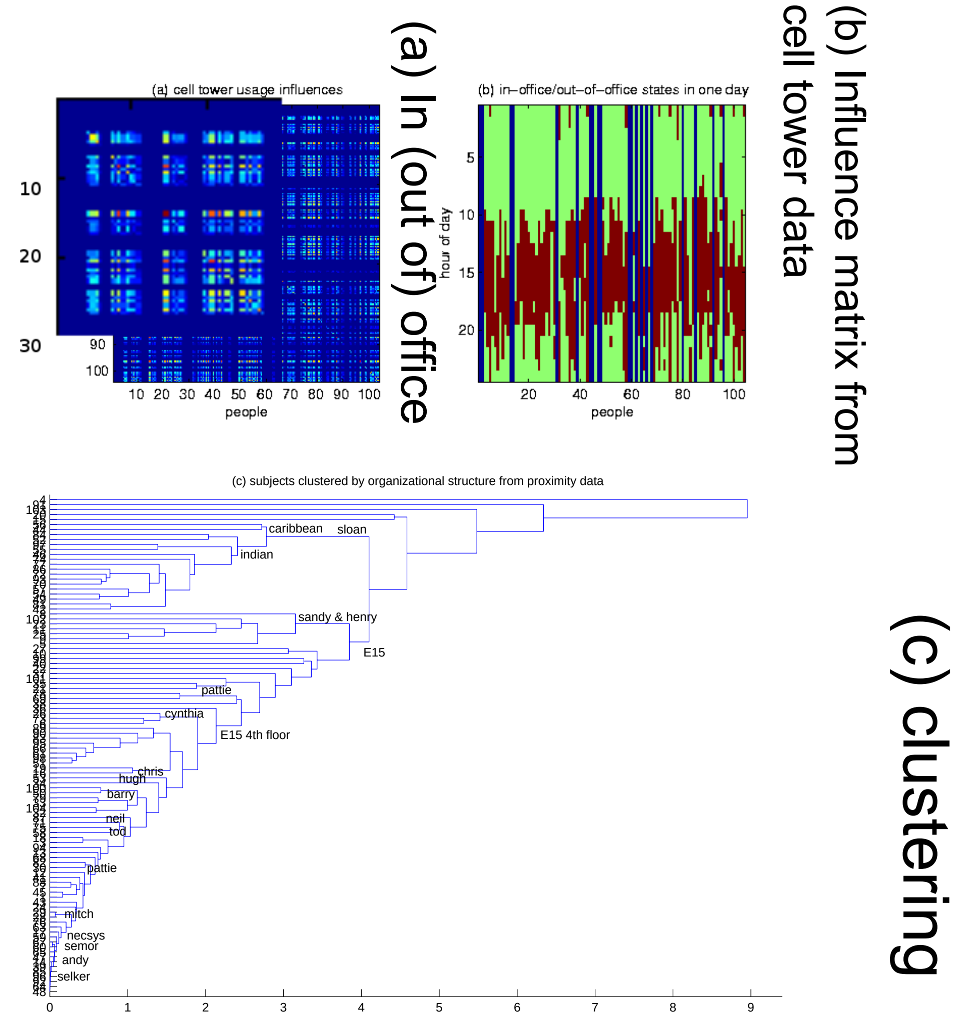


(b) Bluetooth proximity

Inferences on Mobile Phone Networks

(data collected by Nathan Eagle)

- We can infer whether a subject is in the office or out of office wither better precision, as shown in (a).
- We can locate strongly self-influencing persons as either new students or advisors (b)
- The structure we reconstructed resembles the academic research group structure with 3 outliers, corresponding to abnormal cell phone usage. (c)



Benefit of Using Influence Model

- Summarizing the observations
- Mutually annotating each other’s observations.
- Incorporating temporal information
- Can be used to find the dynamics of a community as a whole.

Bibliography

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