Dynamic Statistical Models of Collective Social Network Behavior

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Motivation

- Social networks are heterogeneous and dynamic
- Social computation techniques provide controlled experiments on social networks
- **Goal 1:** Cluster actors in a social network by identifying similar behavior
- **Goal 2:** Predict collective network behavior based on network structure

Social Computation Data

- Experiments at UPenn ask participants to perform graph computations
- Participants can only see their immediate neighbors
- 36 participants, varied network structures

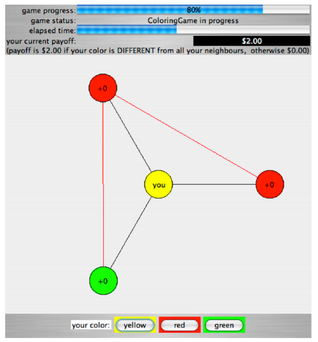


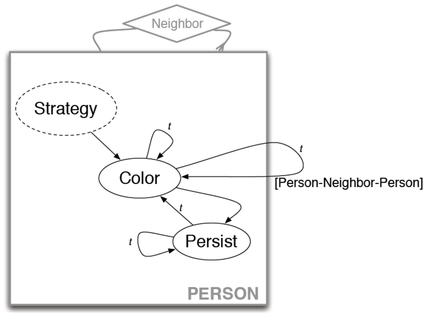
Figure from S. Judd *et al,* 2010.

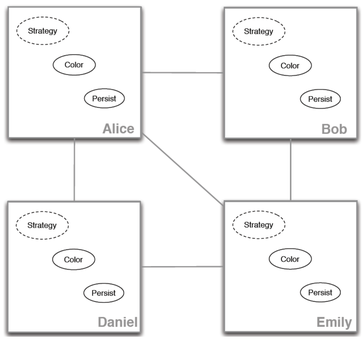
- Static network structure for each experiment
- Tasks are either to color the graph, or to come to a consensus in limited time

Figure from S. Judd *et al,* 2010.

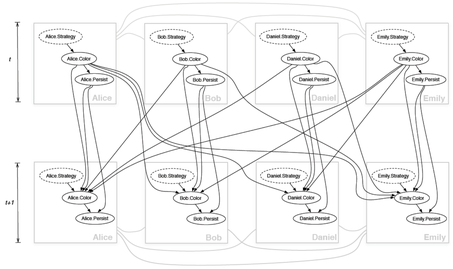
Relational Approach

- Participants' actions are dependent on their neighbors in the network
- Start by designing a model template for individual behavior





- Create relational skeleton from the experiment's network structure and location of individuals within the network
- Combine model and skeleton to build a dynamic Bayesian network



Evaluation

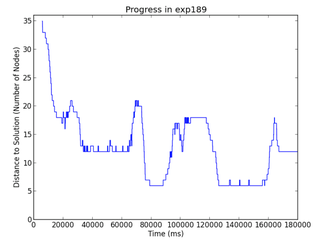
- Quantitatively measure collective behavior
- Rank real data by hardness, and rank simulated experiments
- Compare using Spearman's rank correlation coeff cient

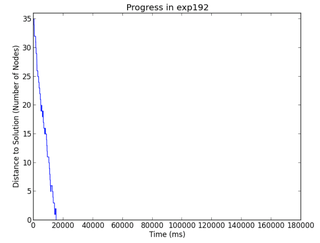
Summary

- Data from social computation experiments provides a unique opportunity to model social network behavior
- We can attempt to account for interactions within a social network using a relational approach

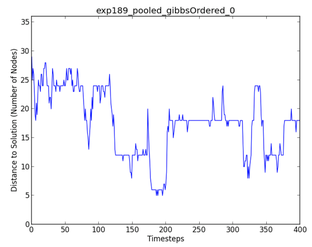
Preliminary Results

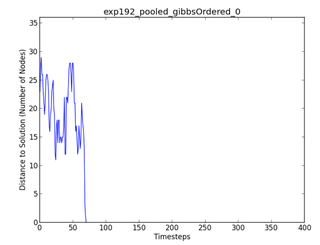
- Real data:





- Individuals all use same strategy:
  - Spearman coefficient of 0.56





- Individuals all use different strategies:
  - Spearman coefficient of 0.08
  - Modify matching criteria