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Social Influence: Friedkin, Construct, Siena

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Social Influence

- Social influence models assume that individuals' opinions are formed in a process of interpersonal negotiation and adjustment of opinions.
  - Can result in either consensus or disagreement
  - Looks at interaction among a system of actors
- Attitudes are a function of two sources:
  - Individual characteristics
    - Gender, Age, Race, Education, Etc. Standard sociology
  - Interpersonal influences
    - Actors negotiate opinions with others

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Social Influence – Big Picture 0

- All three models we discuss today have underlying theory/methods and a tool that implements them
  - Friedkin's social influence theory and tools to implement it
  - The theory of Constructuralism and the simulation engine Construct
  - Siena as a method for estimating stochastic actor-oriented models based on panel data and Siena as a tool for doing the same

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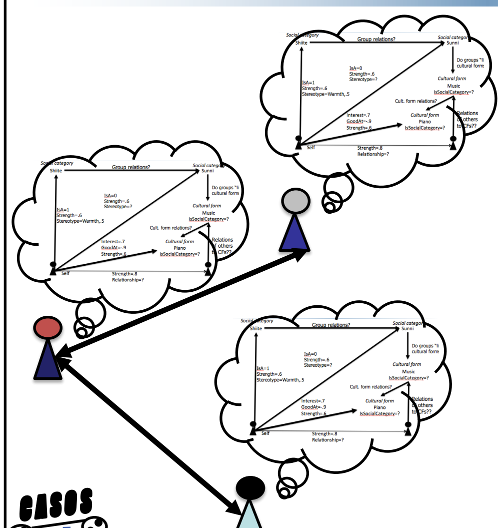
Social Influence – Big Picture 1



- The influence models we will discuss today are a way of bringing agency into the study of networks
- Humans have attributes, make decisions and have preferences, and all of these affect the end result

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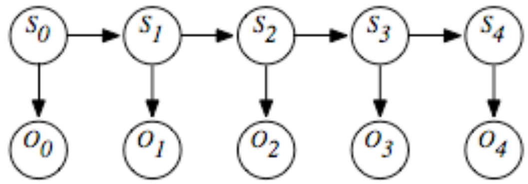
Social Influence – Big Picture 2



The social influence models we will study today all make *Markovian assumptions* about social processes

A Markov model assumes that everything we need to understand the current state of a system is given to us by the immediately previous state

The form of these assumptions and how they use available data define the approach

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Friedkin Formal (Markov) Model

$$\mathbf{Y}^{(1)} = \mathbf{XB}$$

$$\mathbf{Y}^{(t)} = \alpha \mathbf{W} \mathbf{Y}^{(T-1)} + (1-\alpha)\mathbf{Y}^{(1)}$$

$\mathbf{Y}^{(1)}$ = an N x M matrix of initial opinions on M issues for N actors

X = an N x K matrix of K exogenous variable that affect Y

B = a K x M matrix of coefficients relating X to Y

α = a weight of the strength of endogenous interpersonal influences

W = an N x N matrix of interpersonal influences

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$\mathbf{Y}^{(1)} = \mathbf{XB}$

Standard model for explaining anything: the General Linear Model.

The dependent variable (Y) is some function (B) of a set of independent variables (X).

For each agent:

$$Y_i = \sum_k X_{ik} B_k$$

Usually, one of the X variables is ε, the model error term.

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Basic Peer Influence Model

$$\mathbf{Y}^{(t)} = \alpha \mathbf{W} \mathbf{Y}^{(T-1)} + (1-\alpha)\mathbf{Y}^{(1)} \quad (2)$$

This part of the model taps social influence. It says that each person's final opinion is a weighted average of their own initial opinions

$$(1-\alpha)\mathbf{Y}^{(1)}$$

And the opinions of those they communicate with (which can include their own current opinions)

$$\alpha \mathbf{W} \mathbf{Y}^{(T-1)}$$

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… and the network aspect w

W is a matrix of interpersonal weights.
W is a function of the communication structure of the network,
Often a transformation of the adjacency matrix.

$$0 \le w_{ij} \le 1$$

$$\sum_j w_{ij} = 1$$

How the model is specified impacts w_{ii}
the extent to which ego weighs own current opinion
and the relative weight of alters

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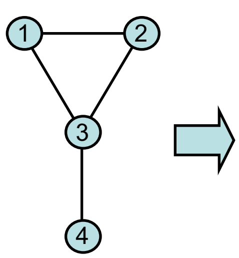
Alternative W's



Self weight:

Even

	1	2	3	4
1	1	1	1	0
2	1	1	1	0
3	1	1	1	1
4	0	0	1	1

	1	2	3	4
1	.33	.33	.33	0
2	.33	.33	.33	0
3	.25	.25	.25	.25
4	0	0	.50	.50

2*self

	1	2	3	4
1	2	1	1	0
2	1	2	1	0
3	1	1	2	1
4	0	0	1	2

	1	2	3	4
1	.50	.25	.25	0
2	.25	.50	.25	0
3	.20	.20	.40	.20
4	0	0	.33	.67

degree

	1	2	3	4
1	2	1	1	0
2	1	2	1	0
3	1	1	3	1
4	0	0	1	1

	1	2	3	4
1	.50	.25	.25	0
2	.25	.50	.25	0
3	.17	.17	.50	.17
4	0	0	.50	.50

Social Influence Cont.

$$\mathbf{Y}^{(t)} = \alpha \mathbf{W}\mathbf{Y}^{(T-1)} + (1-\alpha)\mathbf{Y}^{(1)}$$

When interpersonal influence is complete, model reduces to:

$$\mathbf{Y}^{(t)} = 1\mathbf{W}\mathbf{Y}^{(T-1)} + 0\mathbf{Y}^{(1)}$$
$$= \mathbf{W}\mathbf{Y}^{(T-1)}$$

When interpersonal influence is absent, model reduces to:

$$\mathbf{Y}^{(t)} = 0\mathbf{W}\mathbf{Y}^{(T-1)} + \mathbf{Y}^{(1)}$$
$$= \mathbf{Y}^{(1)}$$

Extending Social Influence Over Time

If we allow the model to run over t, we can describe the model as:

$$\mathbf{Y}^{(\infty)} = \alpha \mathbf{W}\mathbf{Y}^{(\infty)} + (1-\alpha)\mathbf{X}\mathbf{B}$$

The model is directly related to spatial econometric models:

$$\mathbf{Y}^{(\infty)} = \alpha \mathbf{W}\mathbf{Y}^{(\infty)} + \widetilde{\mathbf{X}}\beta + \varepsilon$$

Where the two coefficients (a and b) are estimated directly

Doreian, 1982, Sociological Methods and Research

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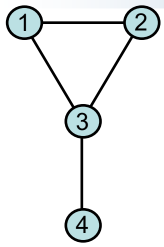
Over Time Example



	1	2	3	4	Y
1	.33	.33	.33	0	1
2	.33	.33	.33	0	3
3	.25	.25	.25	.25	5
4	0	0	.50	.50	7

$\alpha = .8$

Time:	0	1	2	3	4	5	6	7
ACTOR:1	1.00	2.60	2.81	2.93	2.98	3.00	3.01	3.01
2	3.00	3.00	3.21	3.33	3.38	3.40	3.41	3.41
3	5.00	4.20	4.20	4.16	4.14	4.14	4.13	4.13
4	7.00	6.20	5.56	5.30	5.18	5.13	5.11	5.10

Opinion

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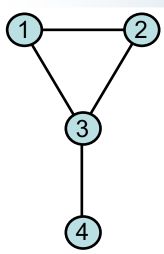
2nd Over Time Example



	1	2	3	4	Y
1	.33	.33	.33	0	1
2	.33	.33	.33	0	3
3	.25	.25	.25	.25	5
4	0	0	.50	.50	7

$\alpha = 1.0$

T: 0	1	2	3	4	5	6	7
1.00	3.00	3.33	3.56	3.68	3.74	3.78	3.81
3.00	3.00	3.33	3.56	3.68	3.74	3.78	3.81
5.00	4.00	4.00	3.92	3.88	3.86	3.85	3.84
7.00	6.00	5.00	4.50	4.21	4.05	3.95	3.90

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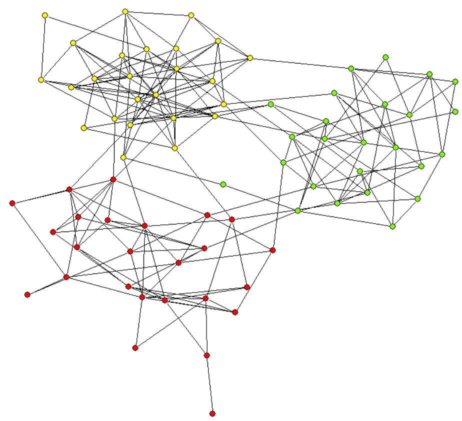
Building intuition

Consider a network with three cohesive groups, and an initially random distribution of opinions:



(to run this model, use peerinfl1.sas)

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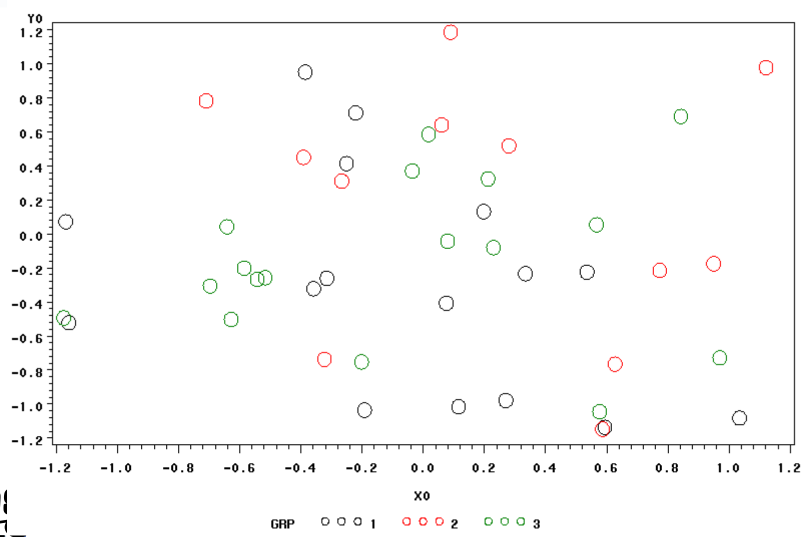
Simulated Peer Influence:
75 actors, 2 initially random opinions, Alpha = .8, 7 iterations



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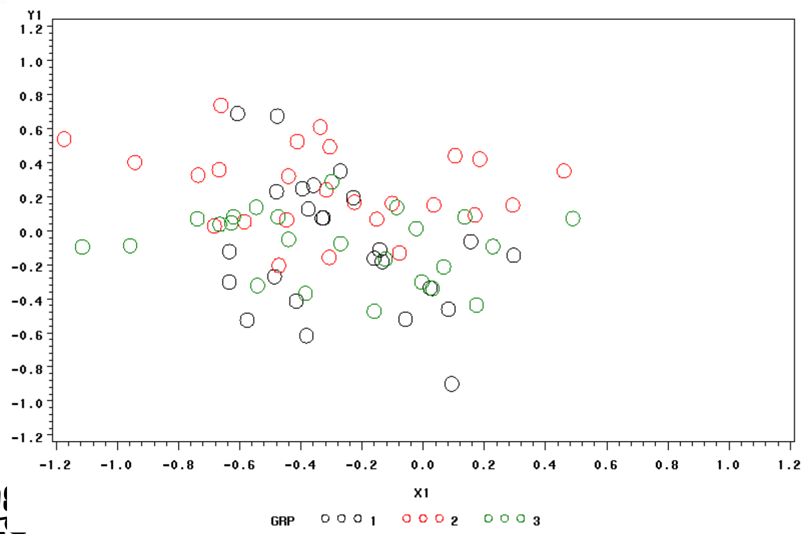

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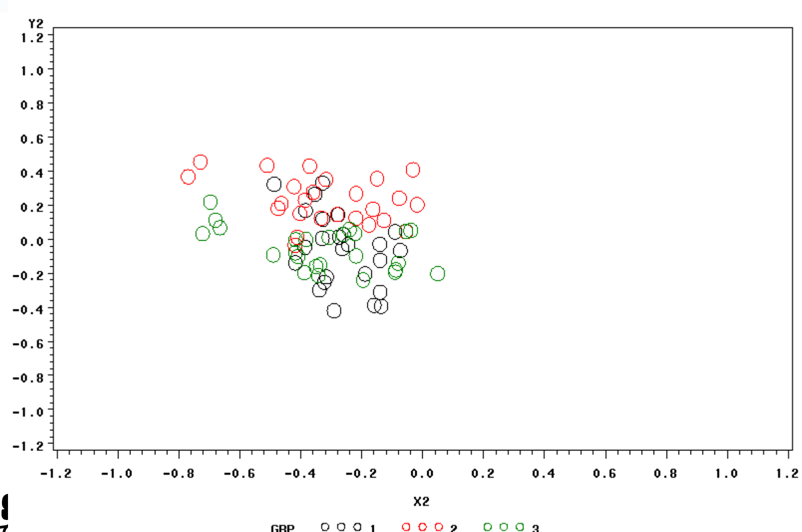

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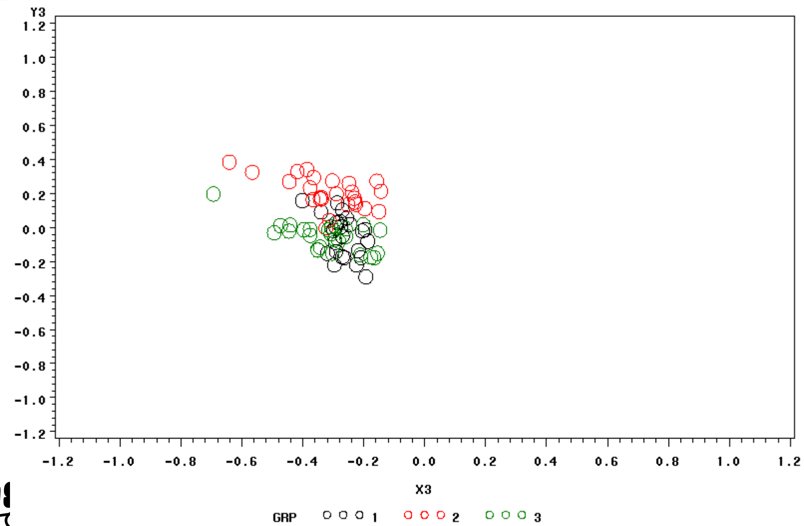

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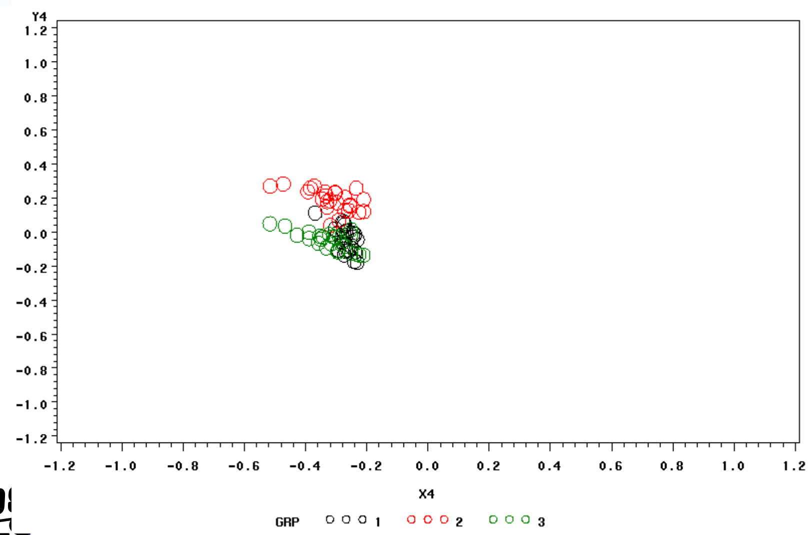

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Simulated Peer Influence:
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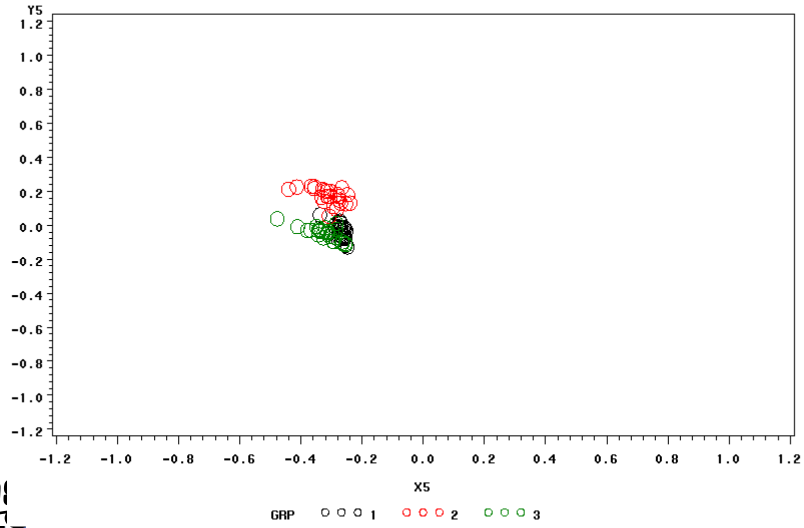

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Simulated Peer Influence:
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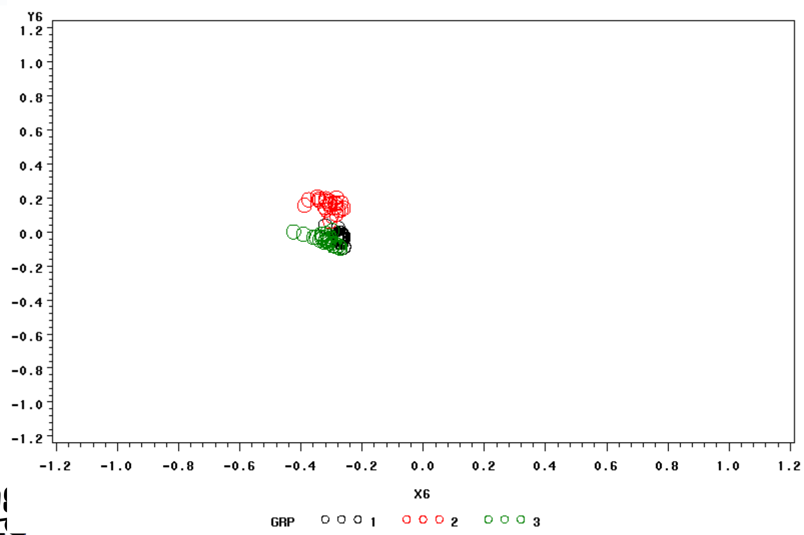

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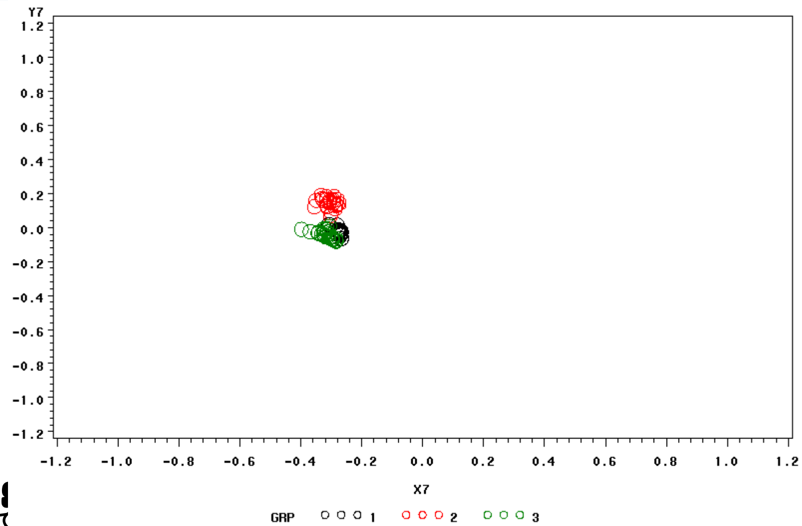

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Friedkin

- Freidkin claims in his *Structural Theory of Social Influence* that the theory has four benefits:
  - relaxes the simplifying assumption of actors who must either conform or deviate from a fixed consensus of others (public choice model)
  - Does not necessarily result in consensus, but can have a stable pattern of disagreement
  - Is a multi-level theory:
    - micro level: cognitive theory about how people weigh and combine other's opinions
    - macro level: concerned with how social structural arrangements enter into and constrain the opinion-formation process
  - Allows an analysis of the systemic consequences of social structures

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Construct

- Turn-based Dynamic-Network Agent-Based simulation model for examining information diffusion and social change
- First multi-agent network model in socio-cultural area
- Features
  - Co-evolution of social structure and culture
  - Co-evolution of agents and their societies
  - Co-evolution of social and knowledge networks
  - Agents learn through interaction
  - Agents need not be "people"
  - Multi-fidelity input is possible
    - Exact knowledge network
    - Group level probabilities
- Refactored in 2009 to use modern agent-based techniques and in 2012 into a "multi-level" system

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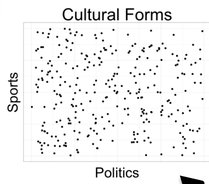
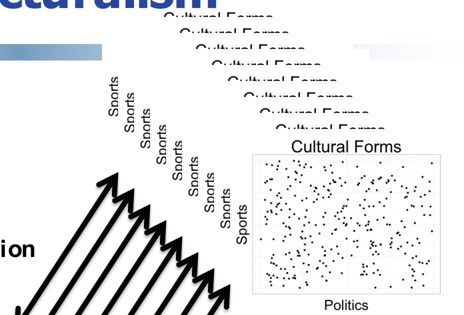
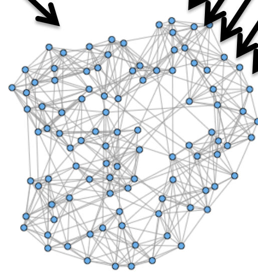
Constructuralism



Social interaction



As we interact with others, we learn new things and *construct* the knowledge of others



As we learn new things and update our perceptions of others, our preferences for whom to interact with change

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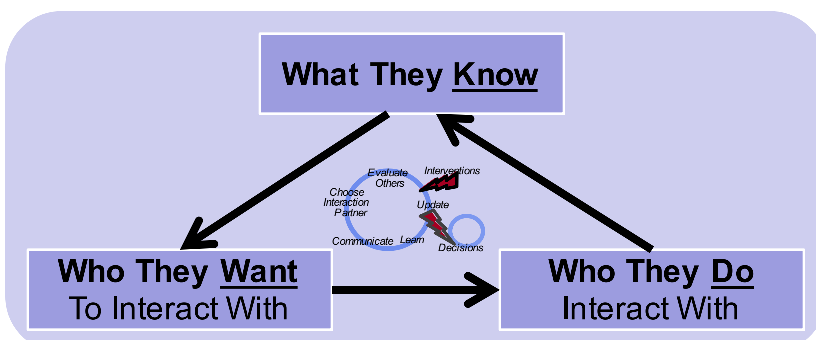
What is Construct?



- Construct is a sophisticated multi-agent simulation tool
  - the agents, social network, and knowledge base are dynamic
  - the effects studied are complex, varied, and highly non-linear

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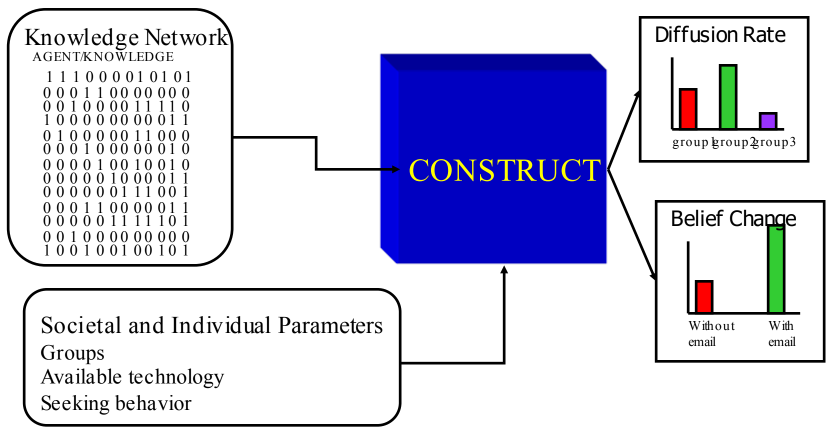
Construct – Basic IO



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Knowledge level approach to culture

- Cognitive mediation
- Extension of network analysis to knowledge
  - Theory of network change, with co-evolution of structure and culture
- Culture:
  - The snapshot - distribution of knowledge
  - The enactment - resultant procedures and actions
  - Mechanism concurrent learning of multiple pieces of information leads to differential rates of diffusion, consensus, performance, social stability depending on the specific distribution of knowledge that emerge
- Co-evolution: structure and culture, interaction and knowledge
  - Unanticipated impacts of IT at cultural level

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V1

The bare-bones Construct model

- Agents
  - All human
  - Interact only via relative similarity
  - Have transactive memory
- Knowledge is a binary string – AKik
  - If AKik=1 i knows k, else 0
  - Who knows what
  - Knowledge is task knowledge
  - Shared knowledge
    - If Akik=1 & Akjk = 1 then k is shared

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V1

Internal Mechanisms

- Communicate
  - Randomly pick information they know
  - Messages simple or complex
- Learn
  - Learning by being told
- Reposition
  - Relative similarity
- Choose partner
  - Need for communicative ease
  - Need to know

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V1

When Two Agents Interact

- If they can send
- They select message to communicate from the facts they know
- Message = 1 "fact" – a "k"
- All facts equally likely to be selected to communicate
- If the agent can receive the agent learns the communicated fact just in case they didn't already know it

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V1

Construct V1 Model

ACTION

$$\text{Interact}_{ij}(t) = f(\text{Availability}_i(t), \text{ProbInteract}_{ij}(t))$$

$$\text{Communicate}_{jik}(t) = f(\text{ProbInteract}_{ij}(t), AK_{jk})$$

ADAPTATION

$$AK_{i*}(t+1) = AK_{i*}(t) + \text{Communicate}_{jik}(t)$$

MOTIVATION

$$\text{ProbInteract}_{ij}(t) = \frac{\text{SharedFacts}_{ij}(t)}{\sum_{h=1}^{I} \text{ShareFacts}_{ih}(t)}$$

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Interaction Style - Need for Communicative Ease

V1

- Relative similarity = how much i shares with j divided by how much i shares with all others
- AKik is knowledge network
  - Knowledge network is agent by knowledge ("facts")
- Expected interaction based on relative similarity

$$RS_{ij} = \frac{\sum_{k=0}^{K} (AK_{ik} * AK_{jk})}{\sum_{j=0}^{I} \sum_{k=0}^{K} (AK_{ik} * AK_{jk})}$$

I = max number of agents
K = max number of ideas, facts, pieces of knowledge

$$\text{Global Cutoff} = \sum_{i=0}^{I} \sum_{j=0}^{I} RS_{ij} \;/\; (I * (I - 1))$$

If $RS_{ij} \geq$ Cutoff the Expected interaction = 1
else 0

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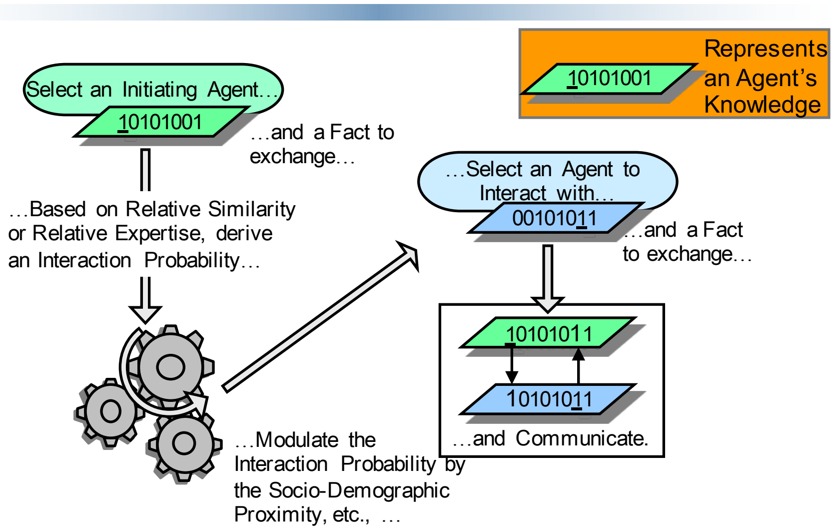
What Drives Interaction



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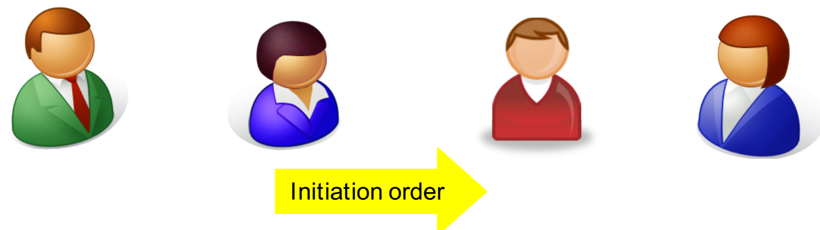
Select Initiation Order



- Initiation order is random in each time period
  - it will be different for each time period, and not tied to previous period
- Agents can initiate interaction more than once
  - but interactions occur at different times and do not occur all at once
- Initiation order has no bearing on facts transmitted or received

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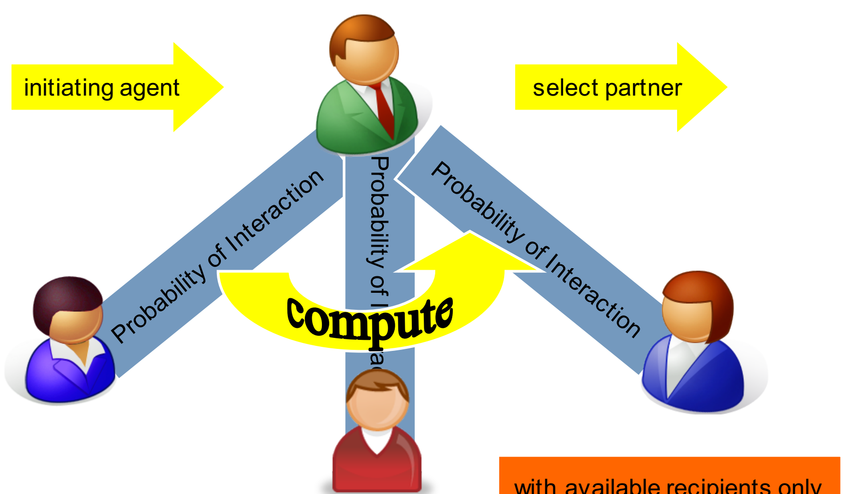
Diadic Interaction Mechanism



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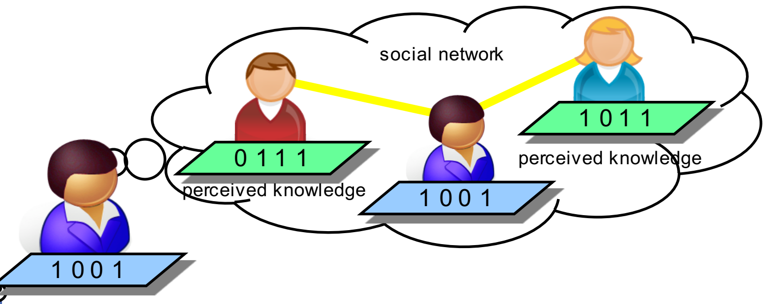
Human Agents Are Boundedly Rational

- Agents in Construct are boundedly rational actors
  - their cognitive abilities are bounded, meaning that they cannot possess or process all information about others perfectly
  - their social abilities are also bounded, meaning that they may not possess or process all information about their social setting



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Information Diffusion

- Information Diffusion: The process by which knowledge moves through a social group
  - Knowledge can be of varying "sizes" – but the "size per bit" should be consistent in each simulation. "James was seen with Sally at Seviche" can be a knowledge bit, as can "F-22 Pilot Operations", but they should not be the same number of bits inside the same simulation.
  - Social Groups are defined by the networks of interacting actors. This makes the simulation **network-centric**.

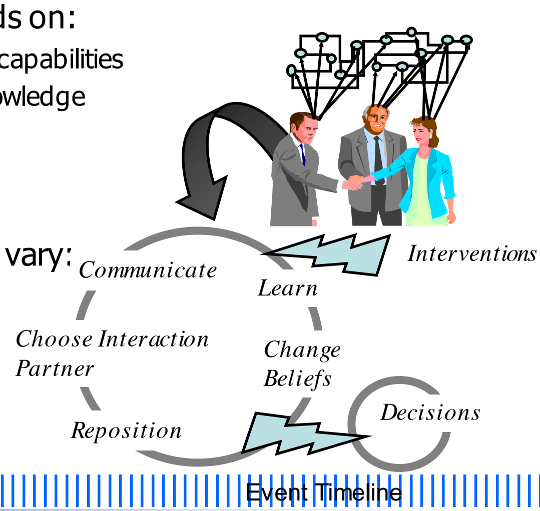
V1

Measuring Stability

- Model generates new meta-matrix each time period
- Quiescence – no change occurs in this meta-matrix
- If forgetting or personnel change or … - quiescence cannot occur
- Relative stability – lack of radical changes – behavior is same on average during a window
- Even without forgetting etc. time between 90% and 100% arbitrary – depending on the chance of the last fact being communicated
- Stability is reached when at 90% of final value is good compromise

The "Construct" Simulation Engine

- Agent behavior depends on:
  - Information processing capabilities
  - Amount and type of knowledge
  - Beliefs
  - Decision procedure
  - Media available
- Knowledge and beliefs vary:
  - Across agents
  - Across tasks



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Multi-Level Behavior and Responses

Model Primitives

Individual
- Agents
- Interaction
- Cognitive limitations
- Behavioral limitations
- Social limitations
- Knowledge
  - Transactive memory
- Beliefs
- Decisions
- Risk taking
- Timing

Collective
- Groups
- Social Structure
  - The network
- Culture
  - Shared beliefs
  - Shared knowledge

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Key Networks In Construct

	Agents	Knowledge	Beliefs	Tasks	Groups	Dummy (attributes)
Agents	interaction sphere ntwk	knowledge network	belief network	task assign. ntwk	agent group ntwk	agent type network
Know-ledge			belief weight ntwk	requirement network	knowledge group ntwk	
Beliefs			association network (*)			
Tasks				precedence network (*)		
Groups						
Dummy						

note: there are multiple agent x agent, agent x knowledge, agent x time networks

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Belief Dispersion

- Belief Dispersion: The change in beliefs of actors in a social group over time.
  - Beliefs cannot be evaluated for truth.
  - Knowledge can contribute to or deny a belief.
    - Belief: "Cats are better house-pets for a family than dogs."
    - Supporting Evidence: "Cats tend to live longer than most breeds of dog."
    - Contrary Evidence: "Most cats must have explicit socialization training early if they are going to be as affectionate as most breeds of dogs."

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V1

Agents

- Agents are information processors (IP)
  - Learn
  - Communicate – send information
  - Make decisions
  - Initiate interaction
  - Process information
  - Forget
- Information Technologies are agents
- Information Technologies are enhancers to agents
- Agents have knowledge
  - What agents do is a function of IP capabilities and amount of knowledge
- There are classes of agents
  - Agent classes vary based on processing capabilities
    - Humans - learn, process, initiate interaction, send, forget, 1:1
    - Databases - learn, process, send, 1:1
    - Books send, 1:N

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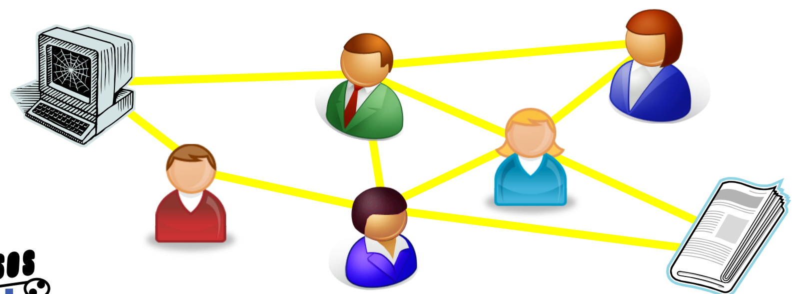
Agents Can Be Human or Non-Human

- Agents are often human but do not have to be
  - the type of each agent in the simulation can be specified
  - often, non-humans are represented as different types of agents
  - most non-human agents cannot initiate communication, but must wait for a human to contact them



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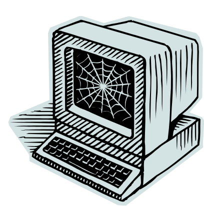
Agents Can Be Non-Human

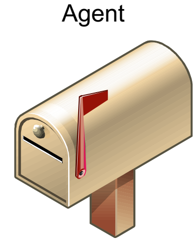
- Non-human agents can provide info to the humans
  - they can serve as sources for specific information
- Interaction with non-human agents can be restricted
  - features like literacy, internet access, and other mechanisms can restrict how agents can learn information from the non-humans

Print Media Agent

Web Page Agent



Mail Agent



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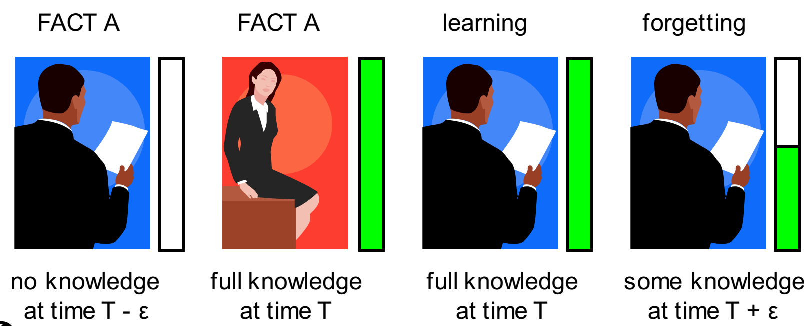
Agents Can Have Knowledge

- The "meaning" of the knowledge is user-defined
  - knowledge can be binary- or real- valued
  - knowledge can be learned as well as forgotten
  - individual agents have different learning, forgetting rates



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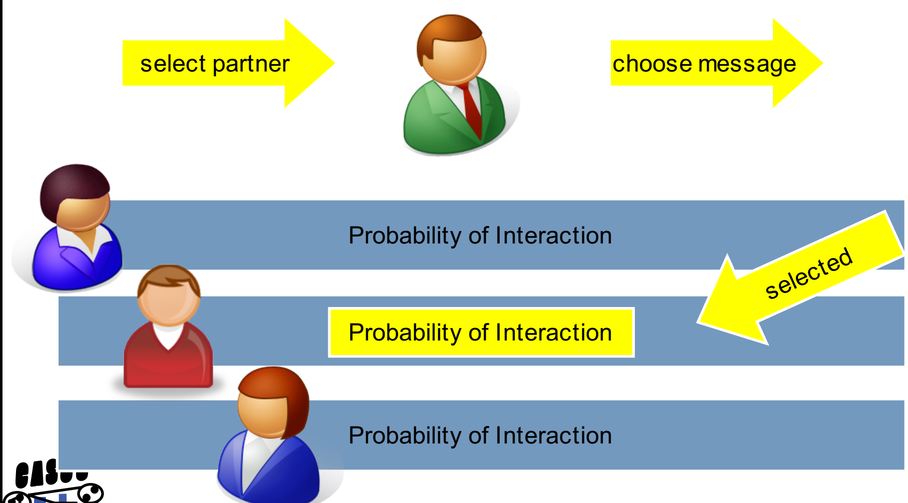
Partner Selection



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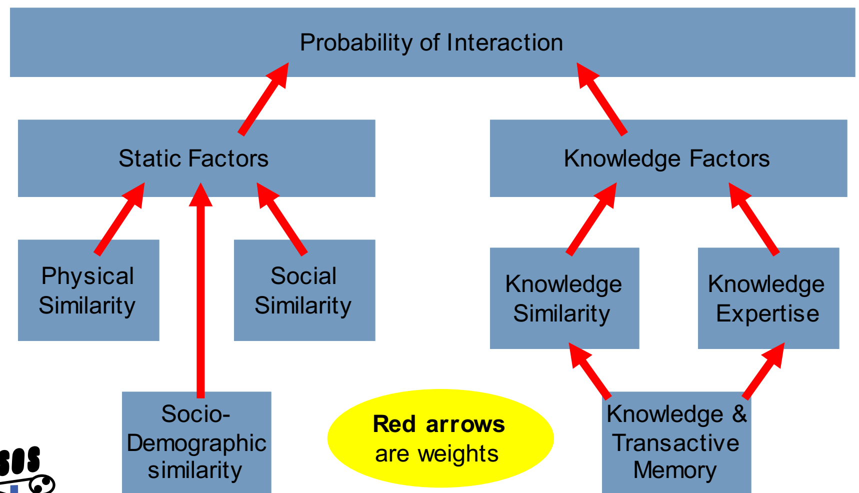
Computing Interaction Probabilities in Construct



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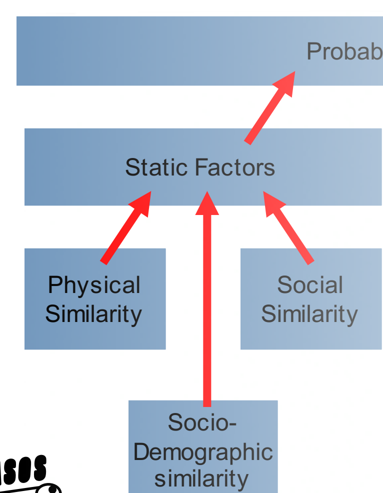
Static Factors



- Physical similarity
  - how close two agents are
  - can use a distance function
  - closer -> higher probability
- Socio-demographic similarity
  - computed from attributes
  - represent salient qualities
  - overlap -> higher probability
- Social similarity
  - catch-all for other features
  - can be ignored if not needed
  - more -> higher probability

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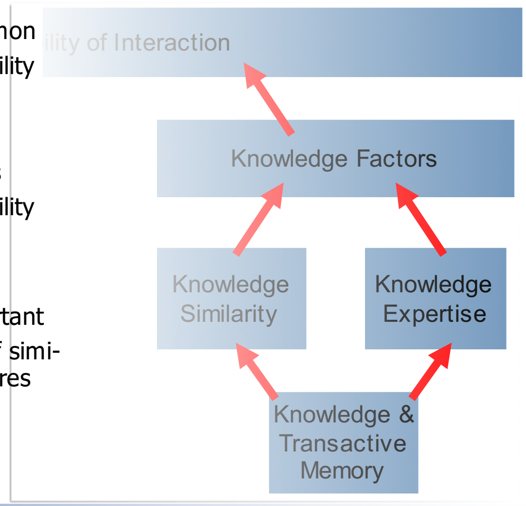
Knowledge Factors

- Knowledge similarity
  - how much info in common
  - more -> higher probability
- Knowledge expertise
  - how much other knows
  - more -> higher probability
- Knowledge weights
  - make some facts important
  - affect the calculation of similarity and expertise scores



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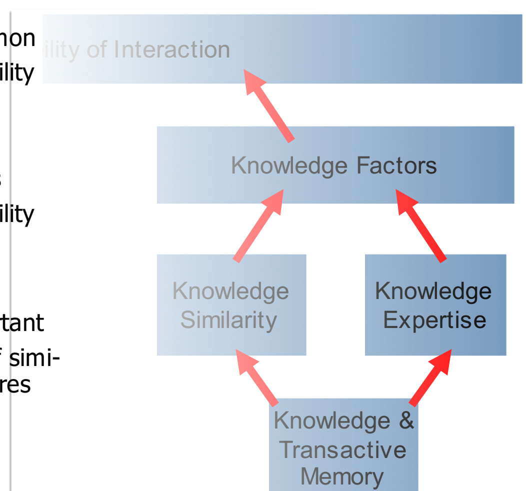

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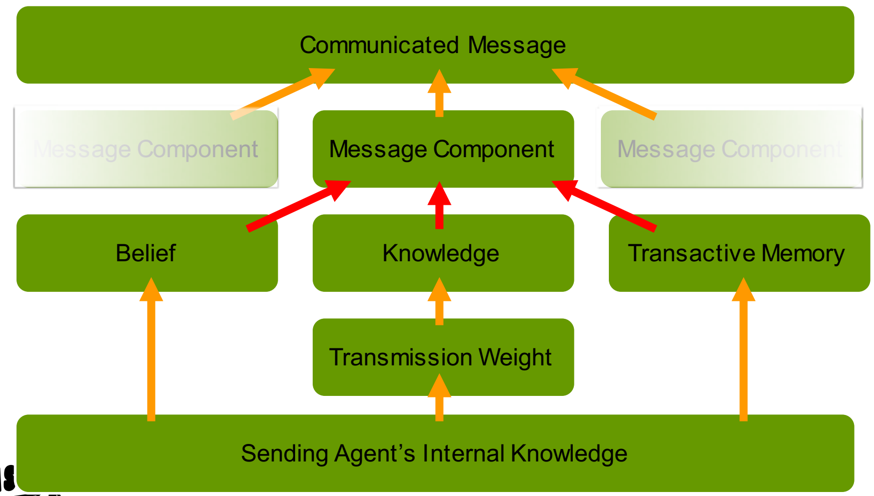
Selecting Messages in Consturct



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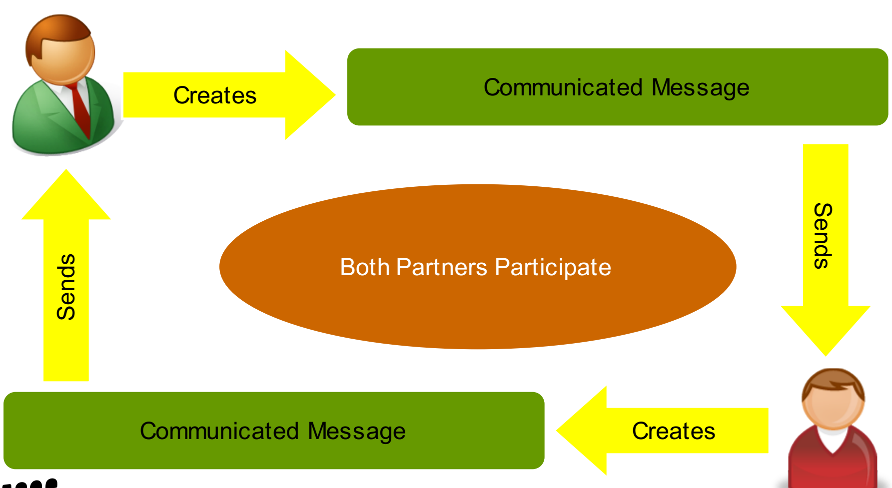
Sending Messages in Construct



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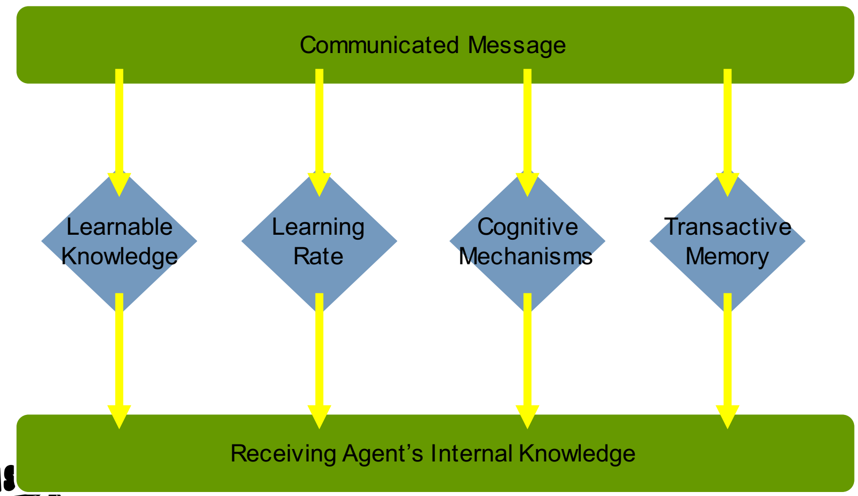
Learning



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V1

Behavioral Outcomes

- Diffusion
  - At time "x" how many people know fact 1
  - At time "x" how many people know 5 facts
  - At time "x" how many people know all the facts
- Consensus
  - At time "x" how many people have the same opinion about y
- Performance Accuracy
  - At time "x" what percentage of the tasks are analyzed correctly by the majority
  - Variation – simple, medium and complex task that vary in number of bits

Stability Rates

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V1

Accuracy

- Task is a binary classification task
  - String of 1's and 0's
- Goal is to determine if there are more 1's or 0's
- The task string = the number of facts
- Each person observes those task bits for which they have information
  - If individual knows Sik then individual can read Tjk
- If for the bits observed the person see's more 1's than 0's then decide 1 else 0
- The group's decision is the majority decision
- The true answer is calculated given the actual task bit strength
- Performance accuracy is percentage correct across 25 tasks each time period

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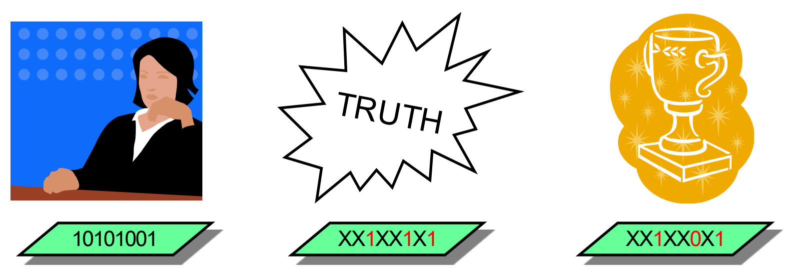
Agents Can Perform Tasks



- Agents compare their knowledge with pre-defined truth
  - if agents have relevant knowledge, they use it in the task
  - if agents lack a piece of knowledge, they guess
  - multiple agents can collaborate on a task
  - collaboration on tasks can increase similarity among agents

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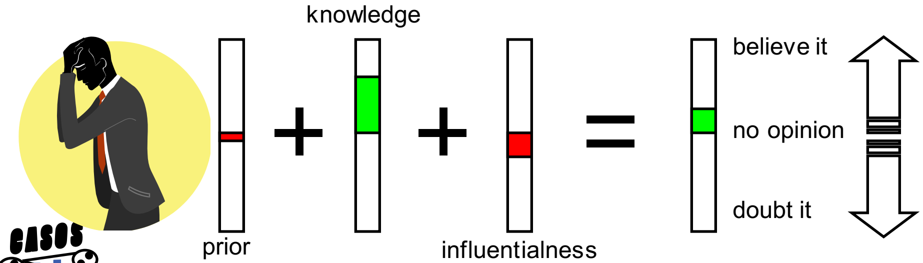
Agents Can Have Beliefs

- Beliefs represent agreement with a principle
- Beliefs are a function of several factors
  - current knowledge
  - priors, including immediate past beliefs
  - composition of interaction sphere
  - influentialness of others and individual susceptibility to influence



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V2

Basic Model + Beliefs

ACTION

$$Interact_{ij}(t) = f(Availability_i(t), ProbInteract_{ij}(t))$$

$$Communicate_{jik}(t) = f(ProbInteract_{ij}(t), Known_{jk})$$

ADAPTATION

$$Known_{i*}(t+1) = Facts_{i*}(t) + Belief_{i*}(t) + Communicate_{jik}(t)$$

MOTIVATION

$$ProbInteract_{ij}(t) = \frac{SharedFacts_{ij}(t) + SharedBelief_{ij}(t)}{\sum_{h=1}^{I} ShareFacts_{ih}(t) + SharedBelief_{ih}(t)}$$

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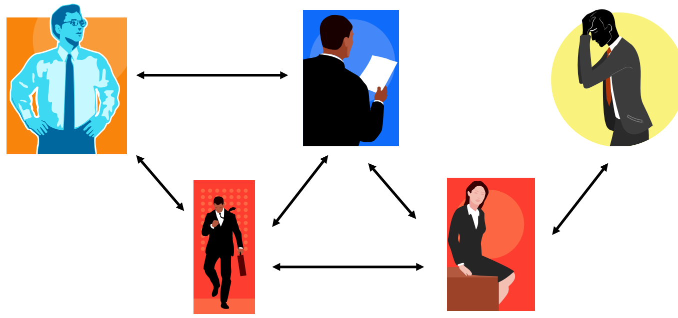
Agents Can Have Specific Interaction Spheres



- Agents may have pre-specified interaction spheres
  - agents only interact with those in sphere, not with all others
  - agents outside this sphere can affect the central agent by passing knowledge through a series of intermediaries

CASOS

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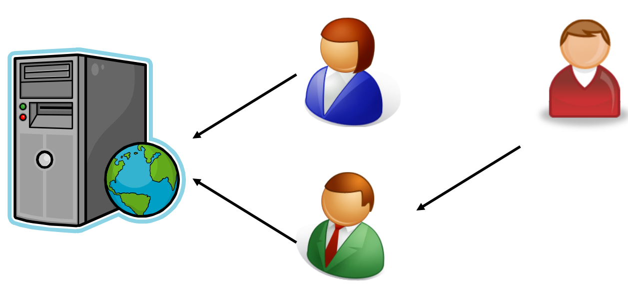
Agents Can Interact Multiple Times

- Agents can initiate or receive communication (or both)
  - initiators actively seek out interaction partners
  - receivers passively wait for an initiator to contact them
  - Interactions result in an exchange of knowledge, beliefs, or TM
- Some agents initiate or receive multiple times



CASOS

CASOS

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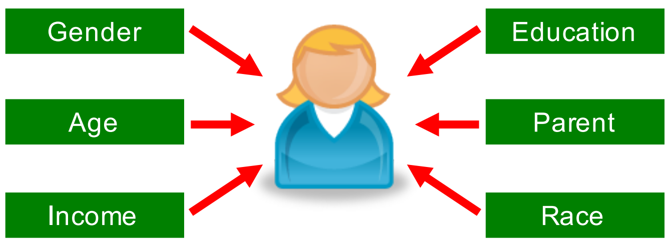
Agents Can Have Socio-Demographic Attributes

- Socio-demographics capture salient characteristics
  - information can be used to determine interaction probabilities
  - agents prefer to interact with those who are similar to them



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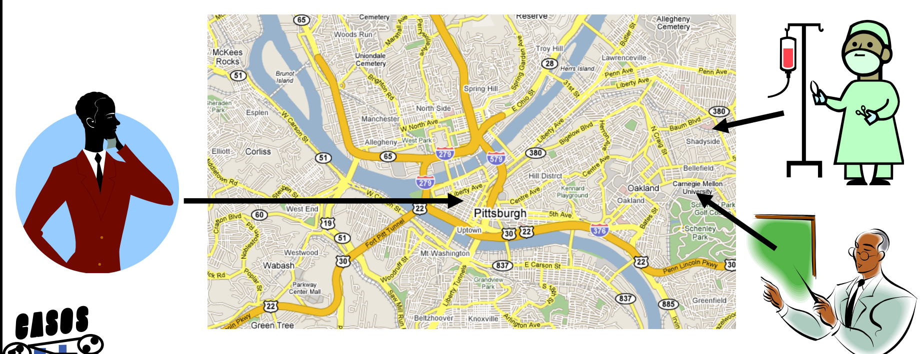
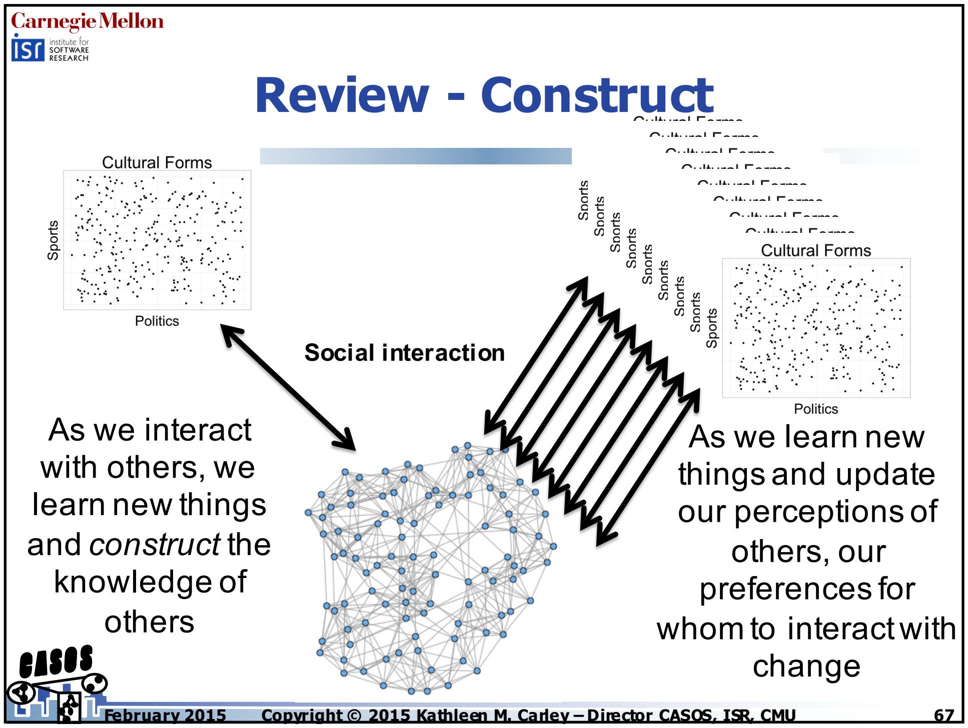
Agents Can Have Proximity Measures

- Agents have physical proximities to other agents
  - agents who are physically close will be more likely to interact
- Agents have social proximities to represent other factors
  - social proximity can represent professional similarity, for example





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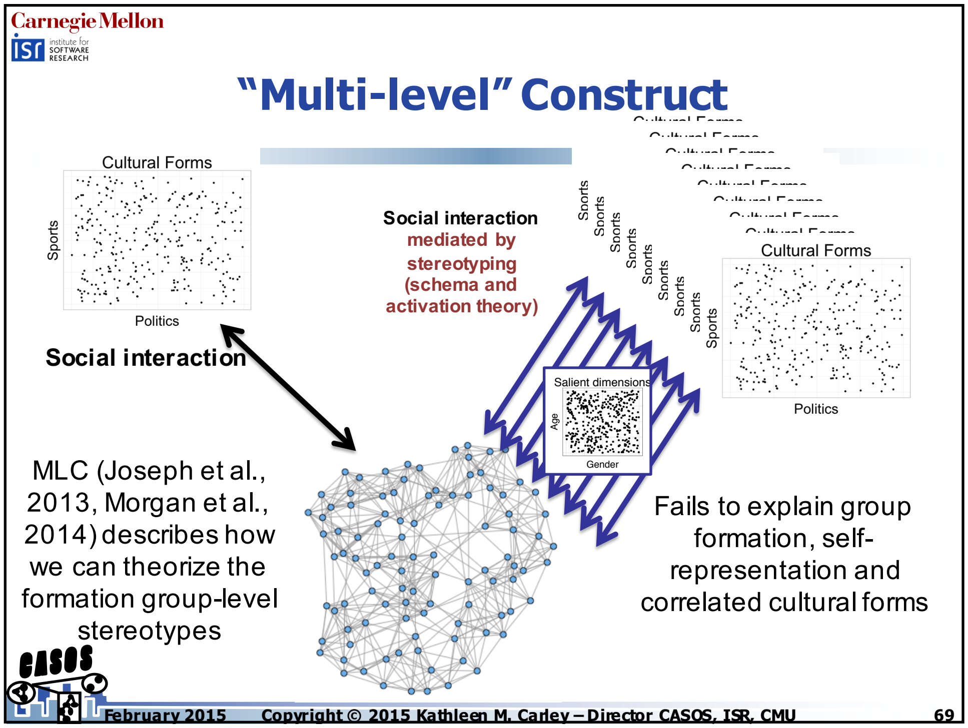
Is there anything wrong with Construct?

- Socially Unrealistic
  - Effective "working memory" has so far been shown to be a narrowly bounded property- maintaining an accessible store of knowledge for all of these alters ascribes too much cognitive power.
  - Also…?
- Computationally Infeasible (at city-scale!)
  - Unless interaction spheres are severely restricted, remembering all similarity/expertise bits will rapidly exceed working memory
- Result is smaller simulations with highly restricted interaction spheres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"Multi-level" Construct
Cultural Forms
Sports
Politics
Social interaction
Social interaction
mediated by
stereotyping
(schema and
activation theory)
Sports
Cultural Forms
Politics
Salient dimensions
Age
Gender
MLC (Joseph et al., 2013, Morgan et al., 2014) describes how we can theorize the formation group-level stereotypes
Fails to explain group formation, self-representation and correlated cultural forms
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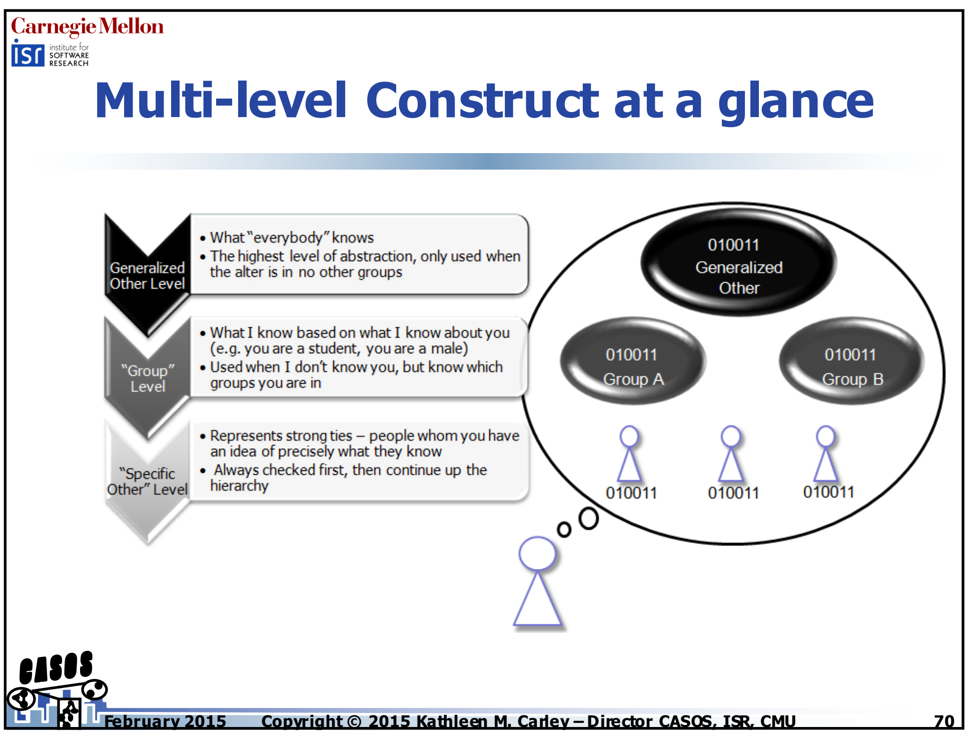
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Multi-level Construct at a glance
Generalized Other Level
• What "everybody" knows
• The highest level of abstraction, only used when the alter is in no other groups
"Group" Level
• What I know based on what I know about you (e.g. you are a student, you are a male)
• Used when I don't know you, but know which groups you are in
"Specific Other" Level
• Represents strong ties – people whom you have an idea of precisely what they know
• Always checked first, then continue up the hierarchy
010011 Generalized Other
010011 Group A
010011 Group B
010011
010011
010011
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How Does Construct Compare to Other Similar Models?

- Construct is a social network simulator
  - it is one of many tools developed to understand how individuals and societies evolve in complex settings
  - Construct focuses on modeling realistic social networks, and strives to model the connections as accurately as possible
- Construct is a meso-level social simulation model
  - it has strong representation of cognitive properties, though it is not a cognitive architecture per se like SOAR or ACT-R
  - it also has support for a large number of interacting agents, though it is not a swarm-like model like SWARM
  - thus, Construct provides the best of both worlds, as it allows for cognitive agents to interact in complex social environments
- Construct is a turn and agent-based simulation tool, useful for modeling information and belief diffusion.

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- Kathleen M. Carley, 1991, "A Theory of Group Stability," American Sociological Review, 56.3: 331-354. Available from: http://www.jstor.org/stable/2096108. Reprinted in Organizational Networks Research, 2011, Martin Kilduff Diageo & Andrew V. Shipilov (Eds), Sage.
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Siena

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Sienna Assumptions

- Actors have agency which allows them to change:
  - Their **outgoing links** (create new ones, dissolve existing ones, do nothing)
  - Their **attributes** (increase/decrease/keep levels, change/keep categories)
- All actors have **full knowledge** about the network & attributes of others.
- Ties are not transient events,
  - Ties are **states**, relatively stable with a tendency to endure over time.
- The changing network is seen as an outcome of a **Markov process**:
  - the current state of the network (not past ones!) probabilistically predicts its next state.
- Continuous time parameter **t** observed at **K** discrete moments t1, t2… tK
- Observation 1 is not modeled – it is the process starting value.
- At any given time, one probabilistically selected actor gets the opportunity to change an outgoing tie (add new, drop existing, do nothing).

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Basic Approach

- Assume a network of size **n** observed at **k** points in time.
- What are the **mechanisms** driving the **network change** over time?
  - How does the network structure influence actor characteristics over time?
  - Think about it theoretically
- Given those mechanisms, what are the **effects** we should include: structure (e.g. transitivity), covariates (e.g. homophily), behavior (e.g. influence)
  - What network metrics should you include
- **Simulate networks** based on initial parameter values.
  - Compute statistics for the simulated networks and compare with those from the observed networks.
  - Update parameter values to make the average of simulated statistics as close as possible to the statistics obtained from the observed network.
- Generate networks based on final parameter estimates.
  - Use those to check that the average statistics are close to the observed (target) values.
  - Calculate a **convergence t-ratio** for deviation between the two.
- You check **goodness of fit** with regard to **auxiliary statistics** – ones not included in rhw model.
  - If the model is good, the simulated networks will be similar to the observed one.
  - You want no significant difference.

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Change Determination

- Network evolution is modeled in small units: micro-steps (one actor, one tie change).
- The change depends on two functions:
  - **Rate function** – when (how often) can actor **i** make a decision? Models the speed with which the dependent variable will change.
  - **Objective function** – what decision will actor **i** make? Tells us how likely an actor is to change the network in a particular way.
- The **Objective function** can be defined as the sum of:
  - **Evaluation Function** – evaluate the network after **adding** a tie
  - **Endowment function** – evaluate the network after **dissolving** a tie
- *Issue - the dissolution of a tie may not be the opposite of creating one.*
  - *e.g. the benefit of creating a reciprocal ties could be smaller than the loss associated with dissolving a reciprocal tie*

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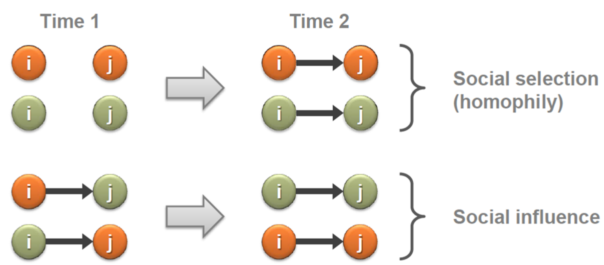
Social Selection, Social Influence

- Social selection: Bob & Jane become friends because they share certain characteristics
- Social influence: Because they are friends, Bob comes to share Jane's characteristics
- The two are very difficult to distinguish looking at a single point in time



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Where to Get Siena

Siena: www.stats.ox.ac.uk/~snijders/siena

- Maintained by Tom Snijders, University of Oxford
- RSiena Manual
- RSiena sample scripts
- RSiena package on CRAN
- RSienaTest on R-Forge

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Comparison to SIENA/ergm

- SIENA assumes an actor-oriented model.
- Actors have a series of objective functions they seek to optimize, as well as co-variates.
- The logit probability of a link is a function of actor objective functions and covariates.
- If only one observed network is present (cross sectional) then an ergm is used.
- **This approach does not model the data, rather it seeks to identify when network behavior changes from some dynamic equilibrium.**

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Comparison to SIENA/ergm

- Stability: LPM , ergm, repeated measures
- Evolution: SIENA, multi-agent simulation, or both
- Shock: Change detection in real-world applications
  Multi-agent simulation for experimentation
- Mutation: Change detection coupled with SIENA for real world applications
  Multi-agent simulation for experimentation

