Social Influence & Learning Friedkin to Construct

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Social Influence

- Change in behavior and/or beliefs of ego due to
  - The network of relations in which ego is embedded
  - The behavior and/or beliefs of alters
- Three aspects
  - Conformity – changing to be more like others
  - Compliance – changing to do what others ask
  - Obedience – changing to do what others tell you to do and you perceive you have no choice
- While networks are used to study all three aspects only conformity is modeled

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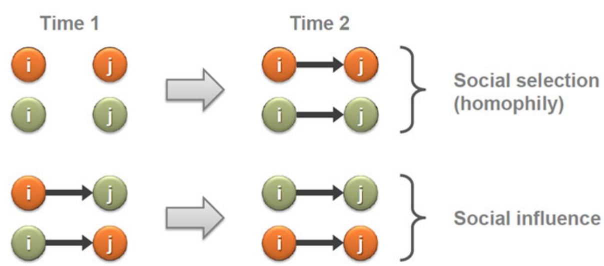
Social Selection, Social Influence

- 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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Social Influence Models

- 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:
- a) Individual characteristics
  - Gender, Age, Race, Education, Etc. Standard sociology
- b) Interpersonal influences
  - Actors negotiate opinions with others

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Social Influence Formalization

- **Social influence has been formalized by Noah Friedkin**
- **Key items**
  - **Each actor's initial preference/belief, $a_{ik}(0)$**
  - **Influence ties between actors, w_{ij}**
    - **Social network**
  - **Susceptibility each actor has to being influenced, s_i**

$$a_{ik}(1) = s_i(w_{i1}a_{1k}(0) + w_{i2}a_{2k}(0) + \cdots + w_{in}a_{nk}(0)) + (1 - s_i)(a_{ik}(0))$$

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Benefits of Freidkin's Model

See *Structural Theory of Social Influence*

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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Friedkin Formal Model

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

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

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 e, 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.

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

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

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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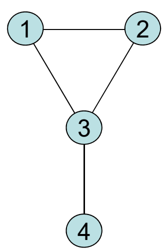
Alternative W's



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

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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:

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

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

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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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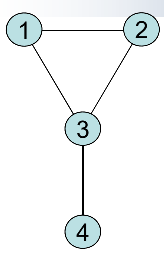
Over Time Example



	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

$\alpha = .8$

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

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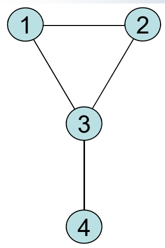
2nd Over Time Example



	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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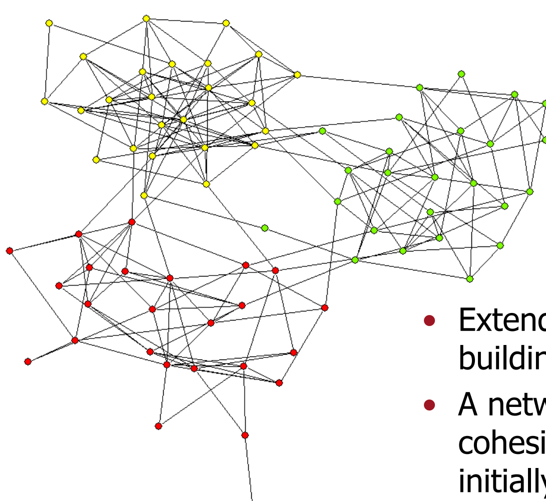
Basic Peer Influence Model



- Extended example: building intuition
- A network with three cohesive groups, and an initially random distribution of opinions

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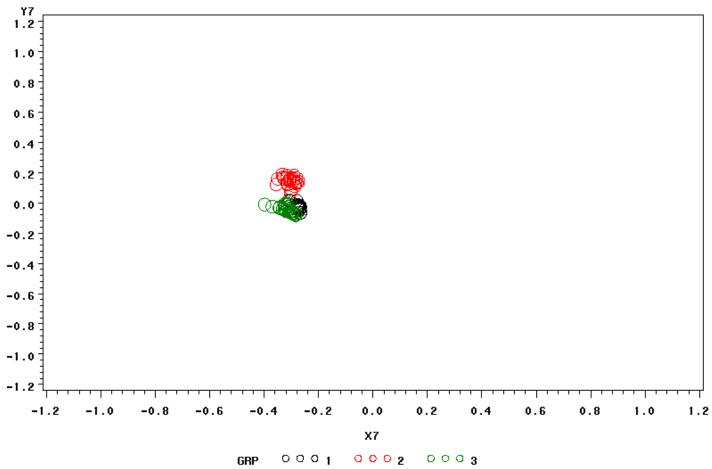
Social Influence
Your Beliefs are a Function of the Beliefs of those in Your Network



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Learning is Tied to Memory

- Organizational Learning
- Types
  - Collective
  - Transactive
  - Databases
  - Procedures & Rules
  - Roles & Structure
- Related ideas
  - Team mental models
  - Routines

- Agent Learning
- Types
  - Task
  - Transactive
  - Experience
  - Rules - procedures
  - Definitions
  - Context (frames,schemes)
  - Short/Mid/Long term
- Related ideas
  - Mental models
  - Knowledge base
  - Skill base

Issues:

Stories
Myths
Interpretation

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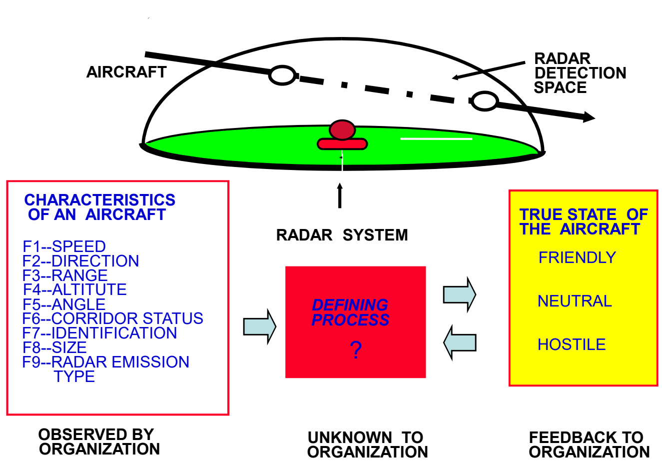
Goal Based: Radar Task



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Goal Based: Learning and Radar Task

- Agent has a set of categories
- If agent sees 3 bits
- 000
- 001
- 010
- 100
- 011
- 101
- 110
- 111
- A: Agent keeps track of number of times category seen
- B: Agent keeps track of number of times 0 was correct answer given that category
- The ratio of B to A is the Pa

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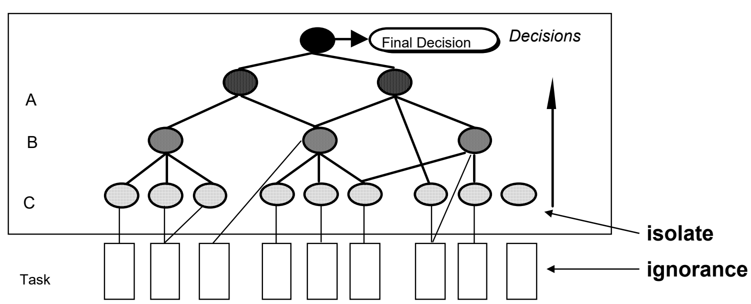
Operational Level



- Organizational Structure - command
- Resource Access Structure - control

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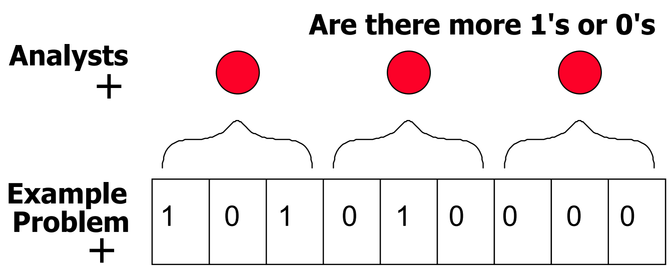
Binary Choice



Correct Decision -- 0
Task Complexity -- 9

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Bayesian Learning

- A probabilistic view of learning based on *Bayes Theorem.*
  - *Bayes Theorem: P(h | D) = P(D | h) * P(h) / P(D)*
  - *hi, i {1, ..., n}* denotes a set of hypotheses.
  - *D denotes a set of data*
  - *P(hi | D) denotes the probability of the correctness of hypothesis hi, given the additional information D*
- Assumes that there is a set of hypotheses, each having a certain probability of being correct.
- Additional information changes the probabilities from a learner's point of view.
  - Strengthen and weaken
- Goal: find the hypothesis with the highest probability of being correct, given a specific piece of information - h' := max[P(D | hi) * P(hi)]

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Practical Notes on Bayesian Learning

- Assumption of independence rarely met – but system still works ok
- Computational intensive – so approximation approaches are used
- Bayesian networks (belief or causal networks) are not Bayesian learning
- Bayesian learning often used to estimate neural networks
- Bayesian learning often used to estimate hidden markov models

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How do Multi-agent learning systems differ?

- Degree of decentralization
  - Distributedness or parallelism
- Interaction specific features
  - Level of interaction
  - Persistence of interaction
  - Frequency of interaction
  - Pattern of interaction
  - Variability of interaction
- Involvement specific features
  - Relevance of involvement
  - Role played during involvement
- Goal specific features
  - Type of improvement that is tried to be achieved by learning
  - Compatibility of the learning goals pursued by the agents

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And …

- Learning method
  - Rote learning
  - Learning from instruction and advice taking
  - Learning from examples and practice
  - Learning by analogy
  - Learning by discovery
- Learning feedback
  - Supervised learning
    - Feedback specifies the desired activity of the learner
    - Match the desired action
  - Reinforcement learning
    - Feedback specifies the utility of the actual activity of the learner
    - Maximize utility
  - Unsupervised learning
    - No explicit feedback
    - Find useful and desired activities based on trial and error and self-organizing

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Learning and Multi-agent Systems

- Stand-alone learning –
  - Agent learns in a solitary way independent of other agents
- Interactive learning –
  - Learning activities of individual agent influenced by others
    - Delayed
    - Accelerated
    - Redirected
    - Made possible
- Alternative Terms
  - Mutual learning, cooperative learning, collaborative learning, co-learning, team learning, social learning, shared learning, pluralistic learning, organizational learning

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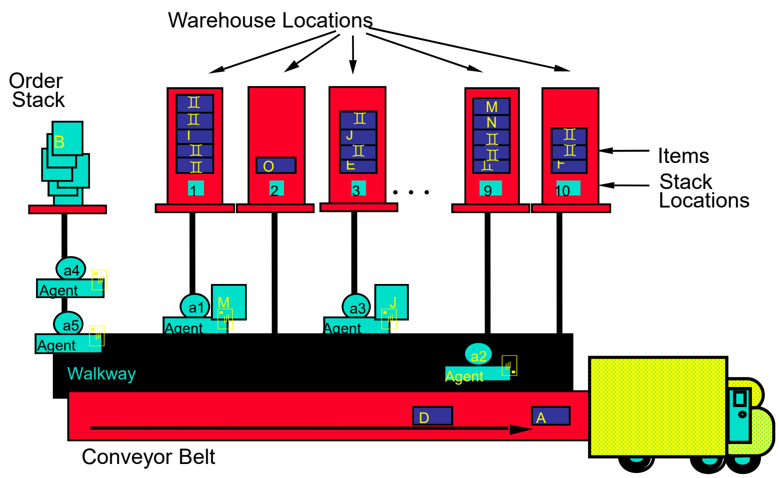
Social + Goal Based Learning: Warehouse Task



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Social + Goal Based Learning: Learning and Warehouse Task

- Agent has mental model of warehouse
- Learning by observation
  - As agent goes to stack it memorizes what it sees
- Learning by being told
  - As agent asks where is X
  - Answers from others are incorporated
  - Agent can't recall whether it was told or discovered information
- Trust learning
  - Agent has degree of trust in others
  - If asks agent y where is x
  - If agent y says x is at location b
  - If ego goes to b and x is not there, ego's trust in y changes to distrust
  - If other's say y is a liar ego's trust turns to distrust

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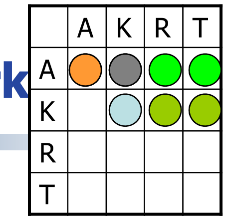
Learning and Network



- Learning alters the information network
- Learning alters the knowledge network
- As the knowledge network changes, individuals change who they interact with
  - Relative similarity
  - Knowledge seeking
- Which changes who can handle what resources and tasks
- Learning can alter how well agents can use resource and do tasks
- Which can change what knowledge is used for which resources or tasks
- Which changes who interacts with whom
- Which changes who knows what
- We can measures changes in organizational learning
  - By measuring changes in knowledge network
  - By measuring the cascades that follow

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Social Learning
Social Influence Models

- $y = aWy + Xb + e$

- Where:
- y is a vector of self's and other's attitudes or beliefs
- X is a matrix of exogenous factors
- W is a weighting matrix denoting who interacts with whom
- a is a constant
- b is a vector (individualized weights)
- e is a vector of error terms

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Social Learning Construct & Learning

- Agent memory is a binary string of length N
- A message is a binary string of length M (M << N)
- Agent's Communicate
  - Randomly pick information they know
  - Messages simple or complex (1 or more bits)
- Agent's learn
  - Learning by being told
  - Agent learns by changing value in memory to 1 if it is a 1 in string
  - Memory is updated to match information passed
- Agent's can forget
  - Cells in memory can be changed

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Construct

- 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
- Currently being extended to a multi-level system

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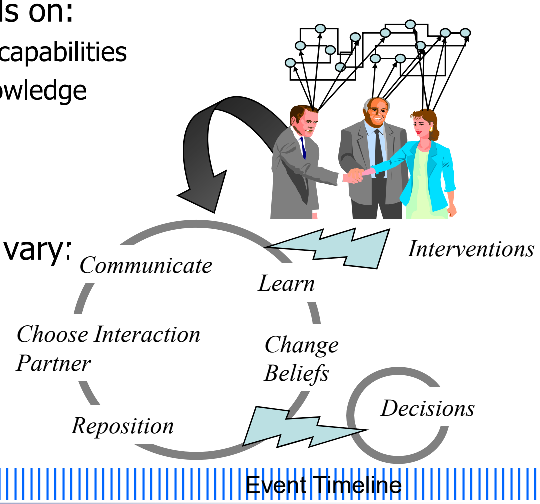
The "Construct" Simulation Engine

- 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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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**.

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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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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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V1

Knowledge

- 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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V2

Basic Model + Beliefs

ACTION

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

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

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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V1

Interaction Style - Need for Communicative Ease

- 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

$$RSij = \frac{\sum_{k=0}^{K} (AKik * AKjk)}{\sum_{j=0}^{I} \sum_{k=0}^{K} (AKik * AKjk)}$$

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

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

If $RSij \geq$ Cutoff the Expected interaction = 1
else 0

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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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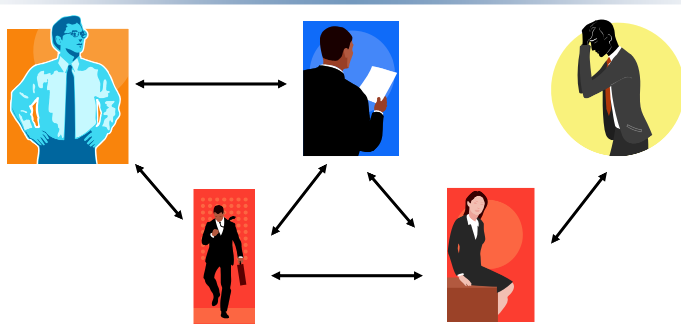
Agents Can Have Specific Interaction Spheres



- 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

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Social Influence & Transactive Memory

- Who is in your network
  - People
  - Groups
  - Generalized other
- Transactive Memory
  - My memory of who
    - Knows who
    - Is doing what
    - Has what characteristics

Three Tiers of Knowing

- **Personal**: I know this individual and have specific perceptions about what they do and do not know.
- **Group**: I do not know this individual, but I have perceptions about groups to which I believe they belong.
- **Global**: I do not know this individual, and I do not have perceptions about the groups to which I believe they belong.

Memory is limited

- Memory of others is limited to a small handful
- Most knowledge is at group level
  - Social cognition
- Social influence models need to be adapted to the meory model of influence
- Doing so is a win
  - Makes dynamic network simulation models
    - More accurate
    - Faster

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Improved SI

Stylized facts of Construct and Construct-SC			
Designed	Citation	Construct	Construct-SC
Individuals interact with others.		X	X
People interact with others based on their perceptions of them.		X	X
Individuals reason about a generalized other.	Mead 1925		X
Individuals have perceptions of groups.	Stryker 1980		X
Perceptions of unknown individuals are based on their known group affiliations.	Tajfel and Turner 1979		X
Group perceptions can be informed by interactions with members of that group.	Carley 1991		X

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Stylized facts of Construct and Construct-SC			
Emergent	Citation	Construct	Construct-SC
Information diffusion has an S-Shaped Curve.	Rogers 2010	X	X
Heterogeneous groups more likely than homophilous groups to discover novel information from outside	Granovetter 1983; 2005	X	X
Groups with some heterogeneity outperform purely homophilous groups.	Ancona & Caldwell 1992	X	X
Individuals are more likely to interact in-group than out-group.	Blau 1977; Tajfel & Turner 1979	X	X
Improvement in task competency of cliquish groups will have increasing marginal variation.	West et al 1999		X
Our perceptions of others are often based upon things such as expected roles, social norms, and social categorizations.	Greenwald & Banaji 1995; Heise 1979; 2007		X
Arbitrary and meaningless distinctions between groups can trigger a tendency to favor own group at the expense of others.	Tajfel et al. 1971		X
Transactive memory should preserve computational resources.	Wegner 1995		X

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Social Influence Theory

Social Influence Theory

- Goal: Remote detection of WMD capability, & desire to develop,
- Goal: Identification of states that can impact response
- Challenges
  - Size, secrecy & dual-use nature of technology
- Approach
  - Network change model combining
  - Validation using historical data
  - Dynamic network big data computational techniques for streaming data

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Social Influence Theory

Security Model – Social Influence + capability + threat

- Original Friedkin model1: $y^t = AWy^{t-1}-(1-A)y^1$
  - A: Amount that actor y influenced by others (matrix)
  - wij: Amount of weight that actor i places on j's opinion
  - y1: Opinion at time 1
- Adapted to account for differences:
  - Countries motivated to develop nuclear weapons if threat perceived
  - Countries with nuclear weapons discourage others from developing
  - Hostilities increasing motivation and alliances decreasing motivation

Hostile Country with Nuclear Weapons	Allied Country with Nuclear Weapons	Attitude Impact	Opinion Impact
Yes	Yes	Weakly increase	0.25
No	No	Strongly decrease	-0.5
Yes	No	Strongly increase	0.5
	Yes	Weakly decrease	-0.25

1. Friedkin, *A Structural Theory of Social Influence* (1998)

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Social Influence Theory

Extended Numerical Model

- $y^t = A(1Hy^{t-1} - 0.25Fy^{t-1} - 0.5HFy^{t-1}) - (1-A)y^1$
  - y^t: Country intent to acquire nuclear weapons at time t
  - A: Actor influence matrix (log of GDPs)
  - H: Hostility network
  - F: Alliance network
  - y^1: Whether countries have nuclear weapons
- The generalized version of this model:

$$y^t = A(C_H H y^{t-1} - C_F F y^{t-1} + C_{HF} HF y^{t-1}) - (1-A) y^1$$

Parameter	Init. Value	Range	Rationale
C_H	1	[-1,1]	Extent of external hostility influence on domestic action
C_F	0.25	[-1,1]	Extent of external ally influence on domestic action
H, F	H, F	H+, F+	H+ considers extended hostility network; F+ considers extended alliance network.

Fit CH, CF, and CHF from historical data

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Social Influence Theory

Data Sources

- Weight (A): use GDP from World Bank
- : Alliance network: Correlates of War
  past 5 or 10 years
- : Hostility network International Crisis
  Behavior dataset of inter-state conflict
  past 5 or 10 years

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Disagreements over exact dates in nuclear history data

Validation

Acquire	Meyer (1942-80)	Jo & Gartzke (1941-02)		Singh & Way (1945-2000)	
	Decide	Program	Possession	Explore	Pursue
USA	1942-	1942-	1945-	*	*
Russia	1942-	1943-	1949-	*	1945-
UK	1947-	1941-	1952-	1945-	1947-
France	1956-	1954-	1960-	1946-	1954-
China	1957-	1956-	1964-	1955-	1955-
Israel	1968-	1955-	1966-	1949-	1958-
India	1964-66 1972-	1964-5 1972-	1988-	1954- 1975-	1964- 1980-
S. Africa	1975-	1971-90	1979-91	1969-	1974-
Pakistan		1972-	1987-	1972-	1972-

Validation is difficult as ground truth is uncertain

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Statistics Assessing the Security Model

Validation

- Precision and Recall Statistics:
  - **P**recision: $t_p/(t_p + f_p)$ 'relevance'
  - **R**ecall: $t_p/(t_p+f_n)$ 'accuracy'
  - F1 Statistic: 2**pr**/(**p+r**)

t_p is "True Positive"
f_p is "False Positive"
f_n is "False Negative"

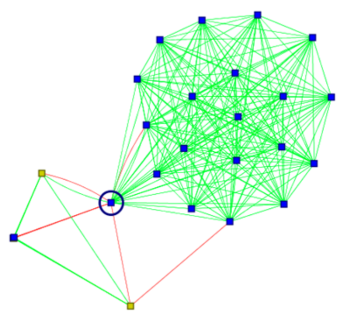
- Dynamic analysis of security model
  - 5 year increments starting in 1969
  - Non-Proliferation Treaty signed in 1968
  - Comparison using multiple sources of 'ground truth'

Engineering based science of validation does not hold as basic assumptions such as process stationarity do not hold

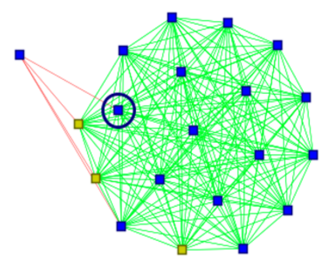
CASOS

Social Influence Theory

Stylized Networks



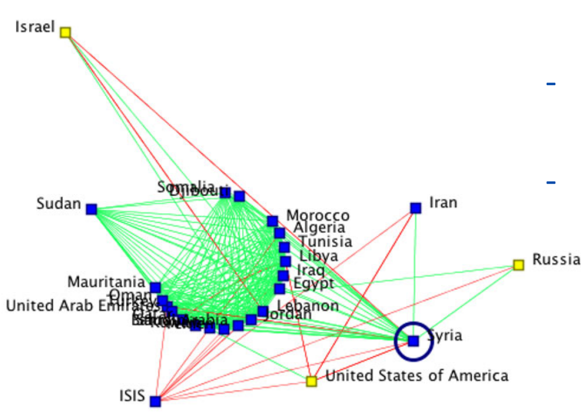
Motivated to develop nuclear capability: conflicts with nuclear weapons states (yellow)



Not motivated to develop nuclear capability: embedded in alliances providing conventional security

Social Influence Theory

Hotspots (I)



Syria

- Competing alliances and hostilities
- Regional, international forces and actors influencing decisions

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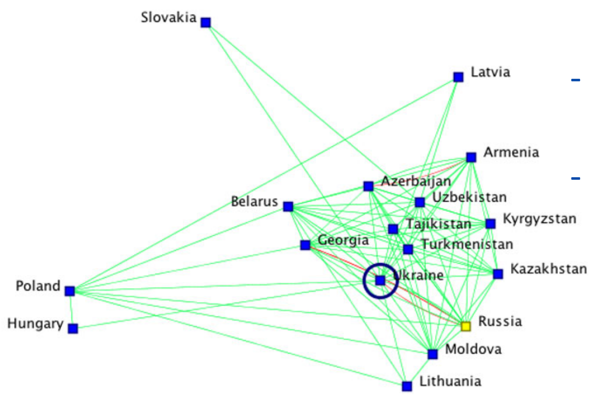
Social Influence Theory

Hotspots (II)



Ukraine

- Overlapping sets of alliance networks
- On cusp of other nuclear powers getting involved, would significantly decrease stability

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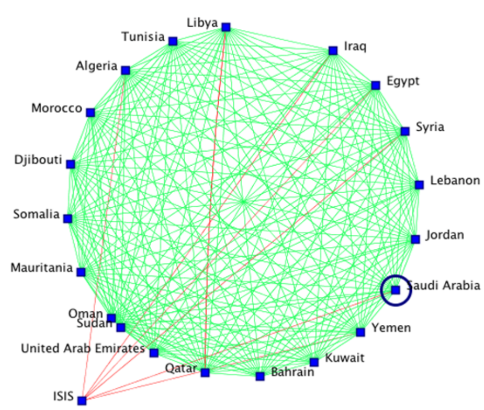
Social Influence Theory

Embedded in Alliances (I)



Saudi Arabia

- Embedded in Arab League
- Dynamic sensitivity analysis shows low motivation for developing nuclear capability

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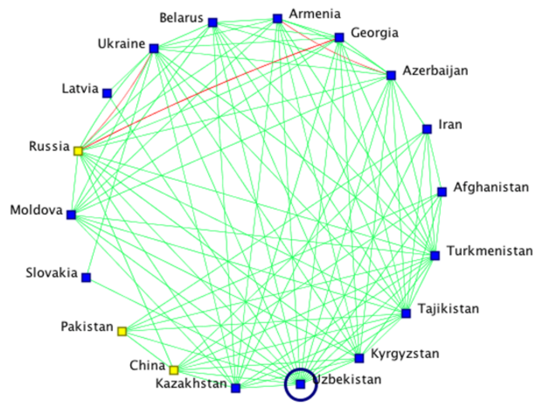
Social Influence Theory

Embedded in Alliances (II)



Uzbekistan

- Overlapping sets of alliances
- In multiple alliances with nuclear weapons powers, low motivation for developing nuclear capability

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Extending to Groups and Stakeholders

Why Extend Social Influence Theory beyond states?

- Example: Syria with and without ISIS
- In modern world, groups and stakeholders may have interest in WMDs and may modulate states' interest in developing and using WMDs