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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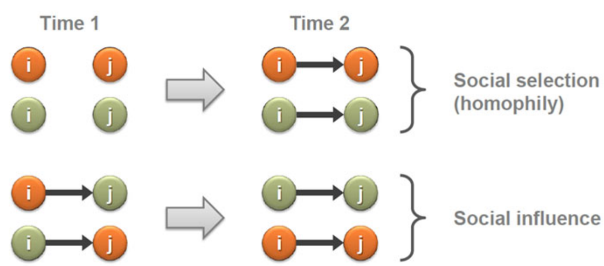
Social Selection, Social Influence

- 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

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

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

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.

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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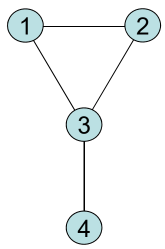
Alternative W's



	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

Self weight:

Even

	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

2*self

	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

degree

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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:

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

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

Doreian, 1982, Sociological Methods and Research

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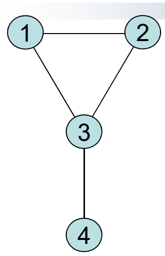
Over Time Example



	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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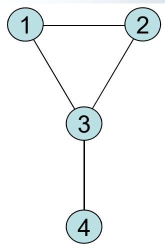
2nd Over Time Example



	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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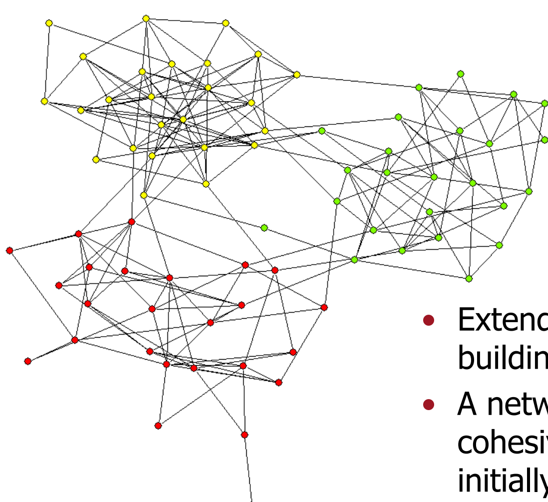
Basic Peer Influence Model



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

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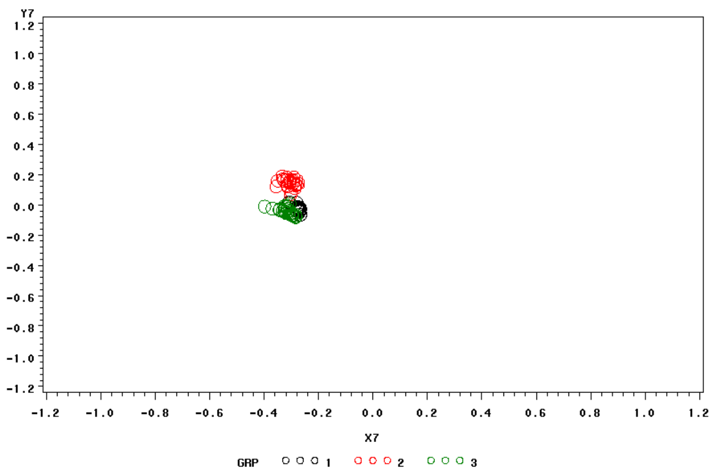
Social Influence
Your Beliefs are a Function of the Beliefs of those in Your Network



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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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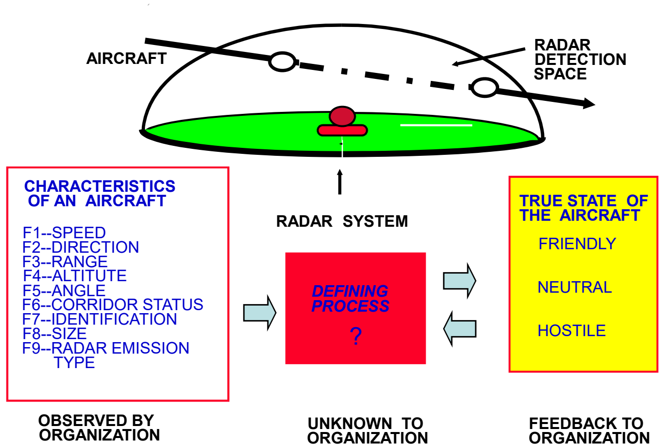
Goal Based: Radar Task



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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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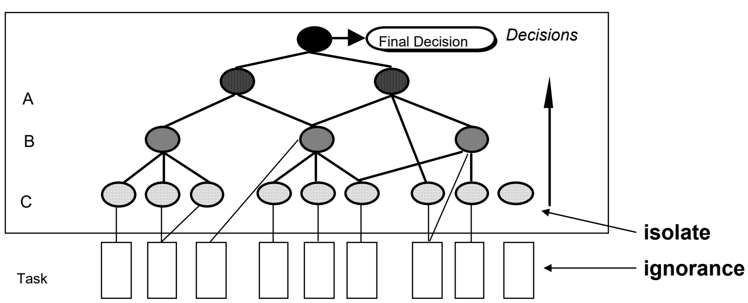
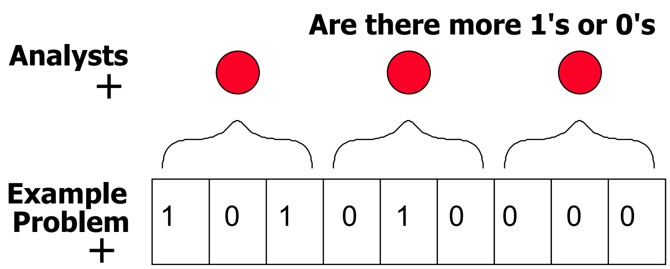
Operational Level



- Organizational Structure - command
- Resource Access Structure - control

Binary Choice



Correct Decision -- 0
Task Complexity -- 9

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

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

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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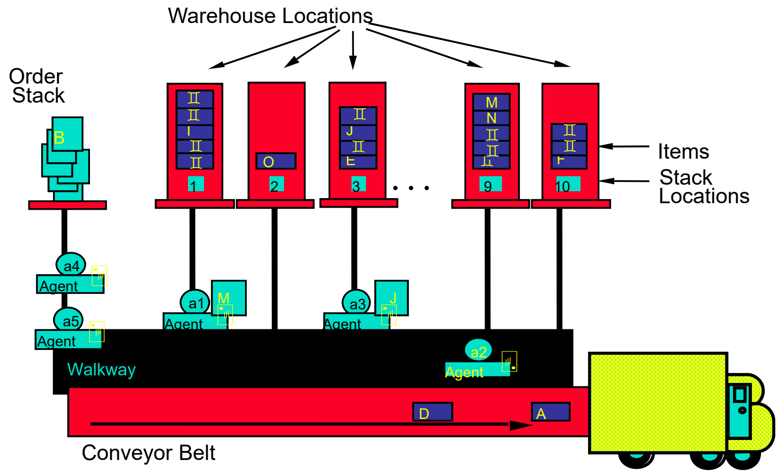
Social + Goal Based Learning: Warehouse Task



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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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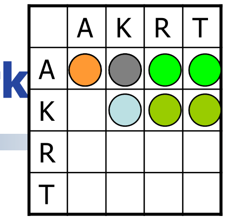
Learning and Network



- 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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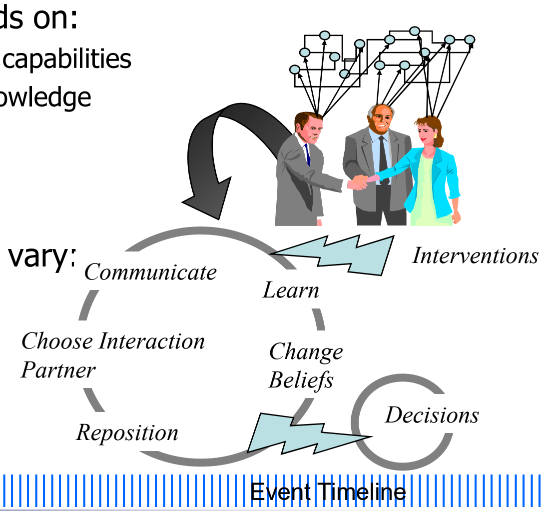
The "Construct" Simulation Engine

- 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

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

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

ADAPTATION

$$AK_{i*}(t+1) = AK_{i*}(t) + Communicate_{jik}(t)$$

MOTIVATION

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

V2

Basic Model + Beliefs

ACTION

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

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

ADAPTATION

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

MOTIVATION

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

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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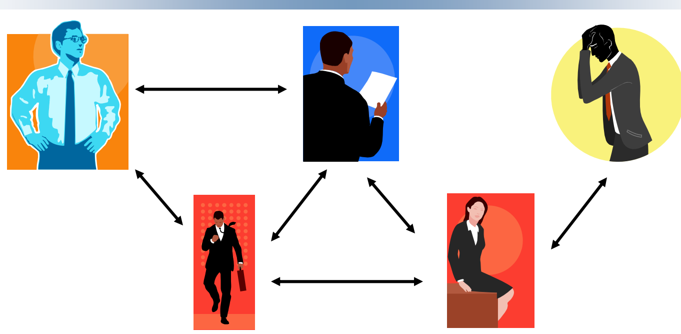
Agents Can Have Specific Interaction Spheres



- 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 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)

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			

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

Validation

Disagreements over exact dates in nuclear history data

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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Validation

Statistics Assessing the Security Model

- 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

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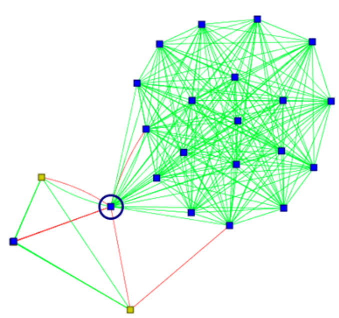
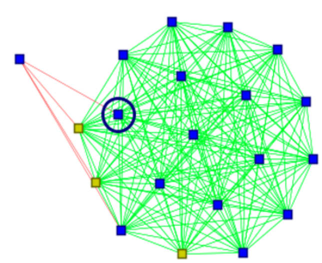
Social Influence Theory

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

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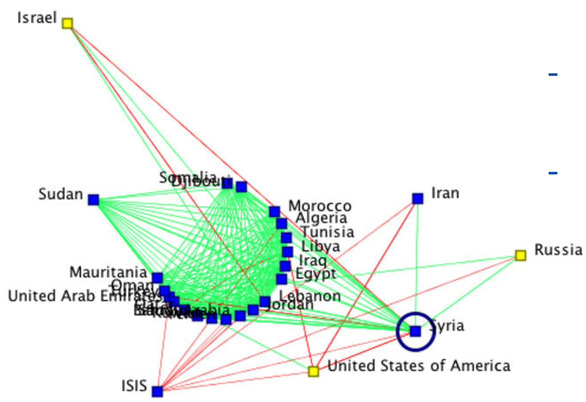
Social Influence Theory

Hotspots (I)



Syria

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

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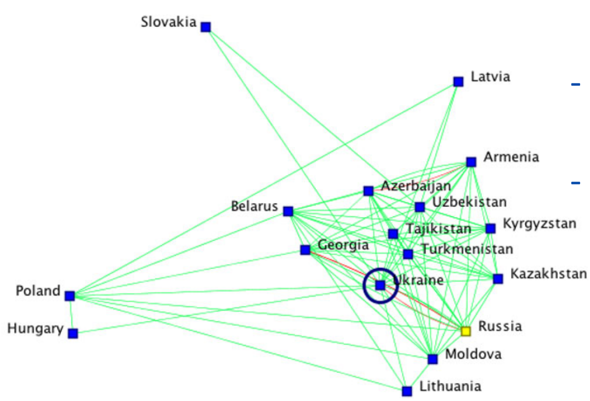
Social Influence Theory

Hotspots (II)



Ukraine

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

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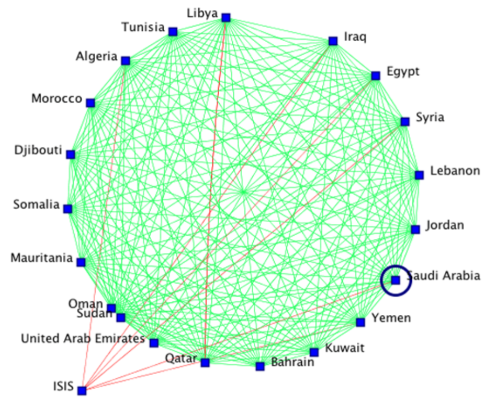
Embedded in Alliances (I)

Social Influence Theory



Saudi Arabia

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

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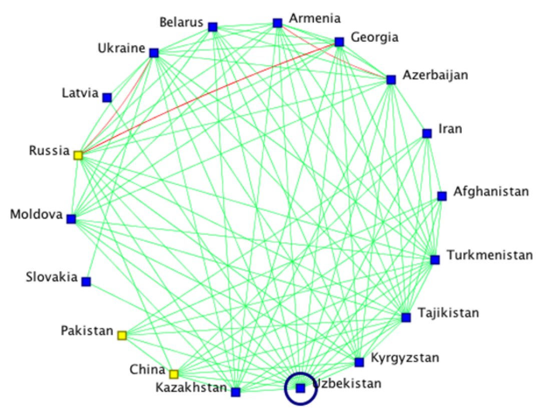
Embedded in Alliances (II)

Social Influence Theory



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