26th annual INCOSE international symposium
Edinburgh, UK
July 18 - 21, 2016

Influencing Message Propagation in a Social Network Using Embedded Boolean Networks

A Demonstration Using Agent-Based Modeling

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Objective

- Validate previous research on embedding Boolean networks into an existing agent-based system to influence its behavior
- Re-use Boolean networks to generate similar dynamics in a new target system
- Target systems generated by agent-based model of the Twitter financial community[1]

[1] Yang, S. Y., Liu, A., & Mo, S. Y. K. 2014b. “Twitter Financial Community Modeling Using Agent Based Simulation.” In *Computational Intelligence for Financial Engineering & Economics (CIFEr), 2014 IEEE Conference on,* 63-70: IEEE..

General Approach

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- Design Boolean networks with desired properties (e.g. x of y nodes active)
- Couple networks to agent decision-making processes in target system
- Pre-designed BN dynamics influence expression of agent rules
- Limit system’s state space

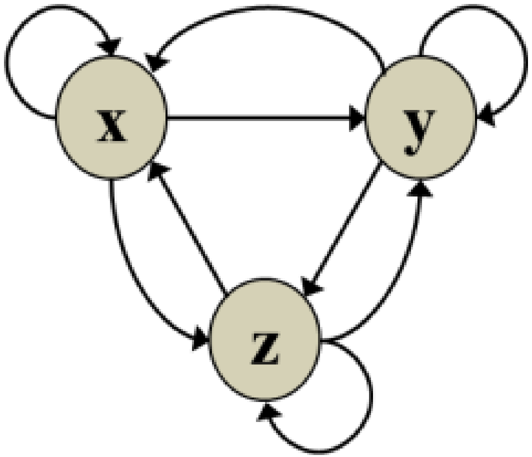
RBN Overview

- Random Boolean networks (RBNs) originally proposed as an investigative model to study genetic regulatory networks[1]
- Hypothesis: a self-organizing mechanism beyond natural selection that limits the number of existing cell types
- RBNs demonstrate this possibility

[1] Kauffman, S. (1969). Metabolic stability and epigenesis in randomly constructed genetic nets. *Journal of Theoretical Biology*, 22(3), 437-467.

RBN Overview

- Directed graph - *n* nodes
- Each node has *k* input edges – assigned randomly
- Each node has logical state –> xyz(t) = 010



Boolean Network
n=3, k=3

RBN Overview

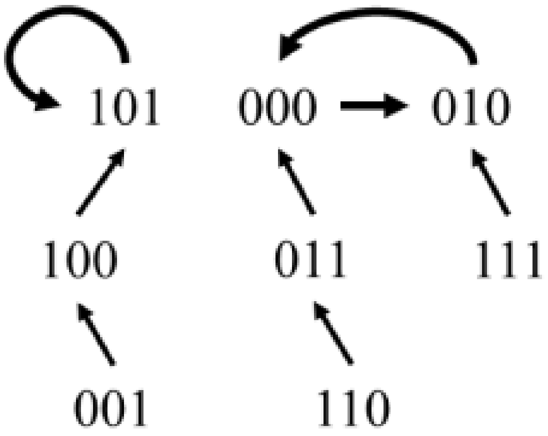
- Each node has randomly assigned Boolean function
- Current states and Boolean function determine next states
- 1-to-1 mapping
- Synchronous updates

xyz(t)	*xyz(t+1)*
000	010
001	100
010	000
011	000
100	101
101	101
110	011
111	010

State Transition Table

RBN Overview

- Finite network size and 1-to-1 mapping leads to revisiting a previous state
- Attractor: set of states forming a cycle
- Point and cycle attractors



State Transition Diagram

RBN Overview

- Paths to attractors represent transient behaviors
- Attractors determine BN’s steady state behavior
  - Point Attractors -> static behavior
  - Cycle Attractors -> sequence of behaviors
- Can have many, different attractors in a BN

RBN Overview

- Variations of Boolean networks
  - Probabilistic
  - Semi- and Asynchronous
  - Varying number of inputs
  - Multi-level states
  - Non-random network topologies

Twitter Model

- Network of agents ("Twitters") based on a "following" relationship
- Three agent classes: Broadcasters, Acquaintances, and Odd Users

Twitter Model

- Probability distributions for agent behaviors derived from empirical evidence[1]
- Build representative networks and simulate messaging that takes place in the community
- Can vary network structure to experiment with messaging in different networks

[1] Yang, S. Y., Mo, S. Y. K., & Zhu, X. 2014a. "An Empirical Study of the Financial Community Network on Twitter." In *Computational Intelligence for Financial Engineering & Economics (CIFEr), 2014 IEEE Conference on,* 55-62: IEEE.

Twitter Model

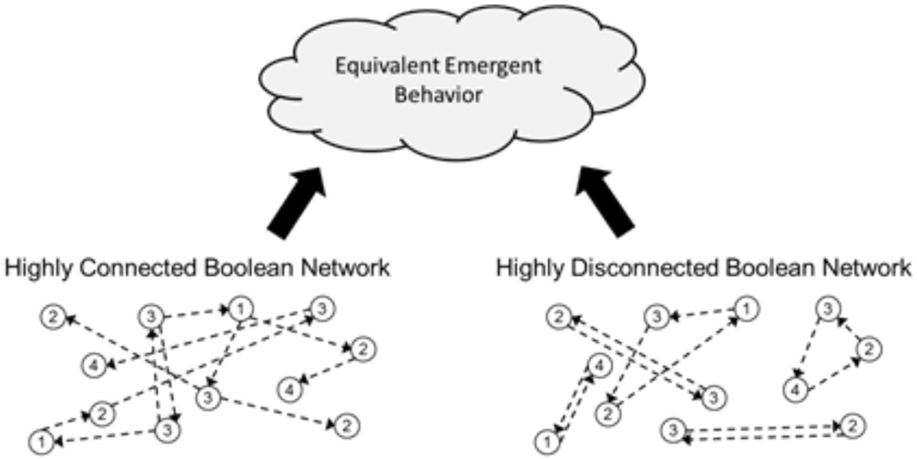
- Recreates 2013 Associated Press hoax incident and the resulting impact on the financial markets
- Propagation characteristics of hoax message are included in the model
- Manually removed high centrality nodes and measured impact on spread of hoax message

BN in a Social Network

- Use BNs from previous research to inactivate most central nodes in finance community target systems
- Compare results to manually modified networks to validate BN's influence on hoax message spread

Implementation

- Difficult to implement a large BN
  - 2^n state space growth
- Use small BN "blocks" that produce required state transitions and attractors



Implementation

- New variables for each Twitter
  - state of the BN node associated with a Twitter
  - list of connected Twitters that represent the incoming edges in BN (separate from follower links)
  - list of ordered outputs from assigned Boolean function
  - centrality value of the Twitter
- Use state variable to enabled/disabled existing retweeting procedure

Implementation

- New procedures
  - read file of centrality values
  - select and remove a percentage of Twitters with the highest centrality values
  - select and inactivate a percentage of Twitters with the highest centrality values by replacing their Boolean functions

Simulation Setup

- Generated two networks using Twitter financial community model
- Ratio of Twitter classes (B / A / O)
  – (0.10 / 0.85 / 0.05) and (0.20 / 0.50 / 0.30)
- Ratio of A to A and A to O links
  – (0.75 / 0.25) and (0.50 / 0.50)

Simulation Setup

- Import scenario configuration files
- Remove / inactivate Twitters
  - 0% to 30% with highest centrality in 5% steps
- Start simulation and initiate hoax message
- Stop and record % message spread
- Scenarios run 100 times, results averaged

Simulation Results

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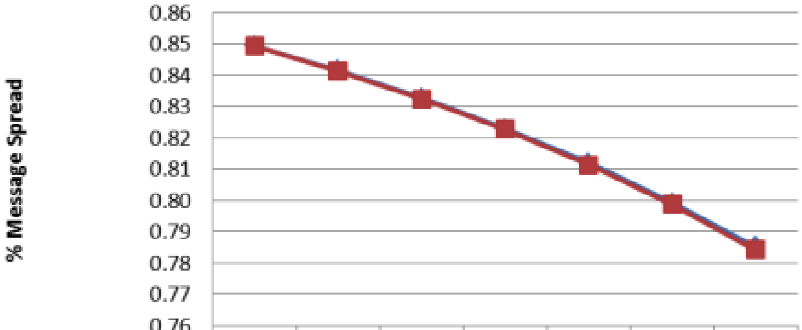
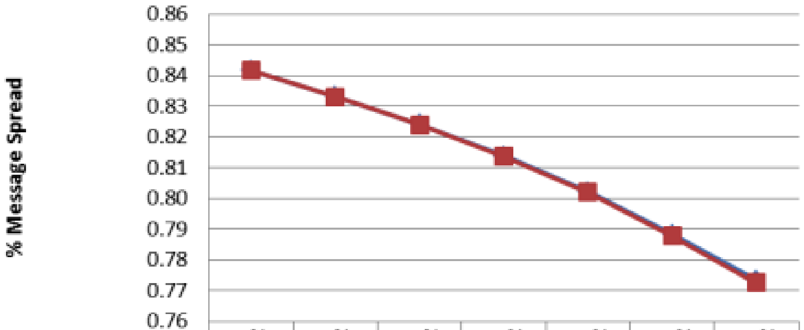


	0%	5%	10%	15%	20%	25%	30%
out degree	0.8493	0.8416	0.8328	0.8229	0.8119	0.7993	0.7854
out degree BN	0.8493	0.8413	0.8324	0.8227	0.8113	0.7988	0.7842

% Removed or Inactivated

Scenario #1
Out-Degree Centrality



	0%	5%	10%	15%	20%	25%	30%
out degree	0.8416	0.8332	0.8241	0.8138	0.8023	0.7884	0.7736
out degree BN	0.8416	0.8331	0.8239	0.8136	0.8020	0.7879	0.7725

% Removed or Inactivated

Scenario #2
Out-Degree Centrality

Simulation Results

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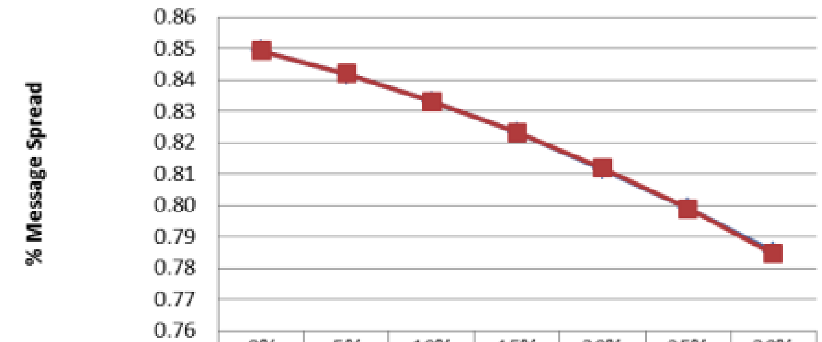
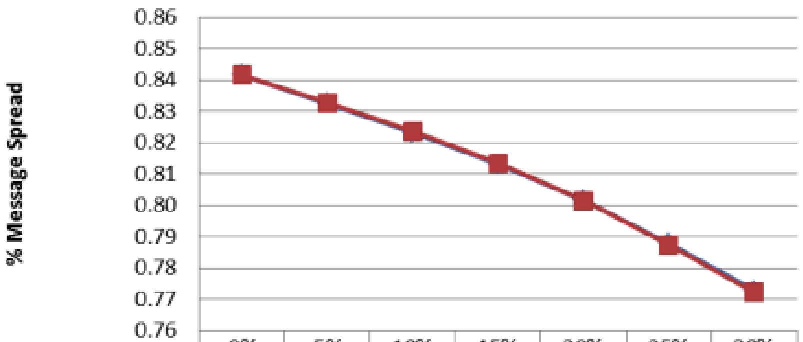


	0%	5%	10%	15%	20%	25%	30%
closeness	0.8493	0.8418	0.8331	0.8232	0.8114	0.7990	0.7851
closeness BN	0.8493	0.8419	0.8330	0.8233	0.8118	0.7990	0.7846

% Removed or Inactivated

Scenario #1
Closeness Centrality

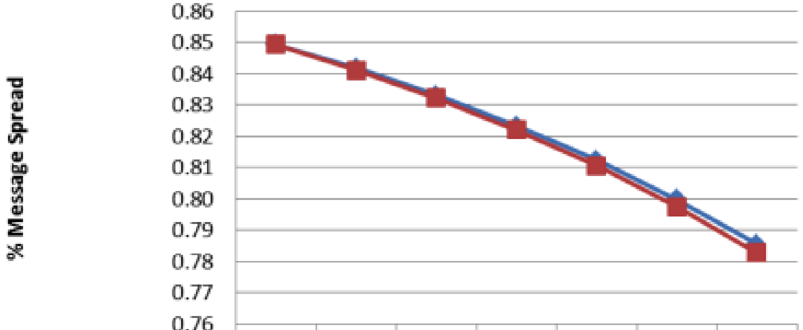


	0%	5%	10%	15%	20%	25%	30%
closeness	0.8416	0.8325	0.8232	0.8131	0.8016	0.7879	0.7727
closeness BN	0.8416	0.8327	0.8236	0.8135	0.8014	0.7873	0.7722

% Removed or Inactivated

Scenario #2
Closeness Centrality

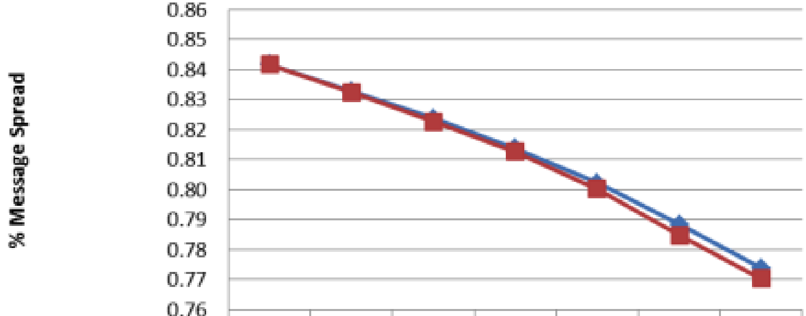
Simulation Results



	0%	5%	10%	15%	20%	25%	30%
betweenness	0.8493	0.8417	0.8331	0.8232	0.8124	0.7998	0.7855
betweenness BN	0.8493	0.8411	0.8321	0.8220	0.8105	0.7976	0.7828

% Removed or Inactivated

Scenario #1
Betweenness Centrality



	0%	5%	10%	15%	20%	25%	30%
betweenness	0.8416	0.8327	0.8237	0.8136	0.8022	0.7884	0.7739
betweenness BN	0.8416	0.8323	0.8225	0.8126	0.8002	0.7848	0.7704

% Removed or Inactivated

Scenario #2
Betweenness Centrality

Conclusions

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- Validated prior research on BNs
  - Reusable self-organizing mechanisms
  - Influence existing agent-based systems
- Key elements:
  - Design attractors for desired state space
  - Coupling BN state to agent decision rules

Future Research

- Application to real world systems
- New design methods for large BNs
- Context switching
  - Responding to different stimuli
  - Creating sequences of behaviors