Understanding Social Diffusion Dynamics Using Networked Cognitive Systems

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Overview

Network Science:
Individuals are connected to other individuals
Network topology
Diffusion is a function of an individual's connected neighbors
Cognitive Science:
Individuals process information from external input
Model of an individual
Diffusion is a function of how individuals process inputs

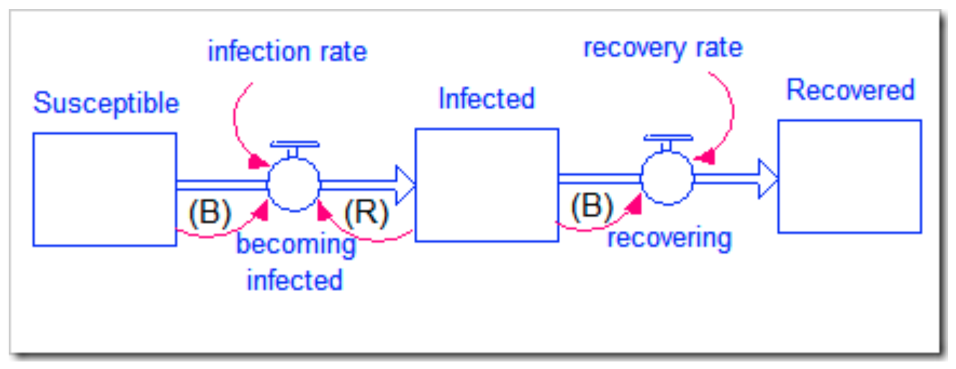
Multi-Agent Neural-Network (MANN)
A simulation platform to combine network science and cognitive science to explore social diffusion dynamics using a **networked cognitive systems approach**.

Agent-based modeling platform built in Python
Networks are created with networkx
Neural networks are created in using LENS (Light, efficient simulator)
Open Source under a MIT license

Table of criteria for qualifying as a system of behavior

Criterion	Description	Class
Process-Oriented / Mechanistic	Postulates mental constructs and their interactions	Operations
Dynamic	Representation of change over time and, potentially, interfaces dynamically with social contexts and environment	
Learning	Aspects of the model can change permanently over time	
Individual Differences	Has the capacity to represent systematic and theoretically important variation in behavior across individuals	Variation
Theoretical Grounding	Processes and constructs are grounded and constrained by neuroscientific psychical, or behavior economic theory	Development
Empirical Grounding	Proper comparison in empirical (most likely experimental) data to include testing of novel predictions. Ideally, a wide variety of experimental conditions would be considered	
Computational Implementation	A formal model of the operations and drivers of variation that also represents its theoretical basis in a way that is empirically comparable to human experiment and observation	

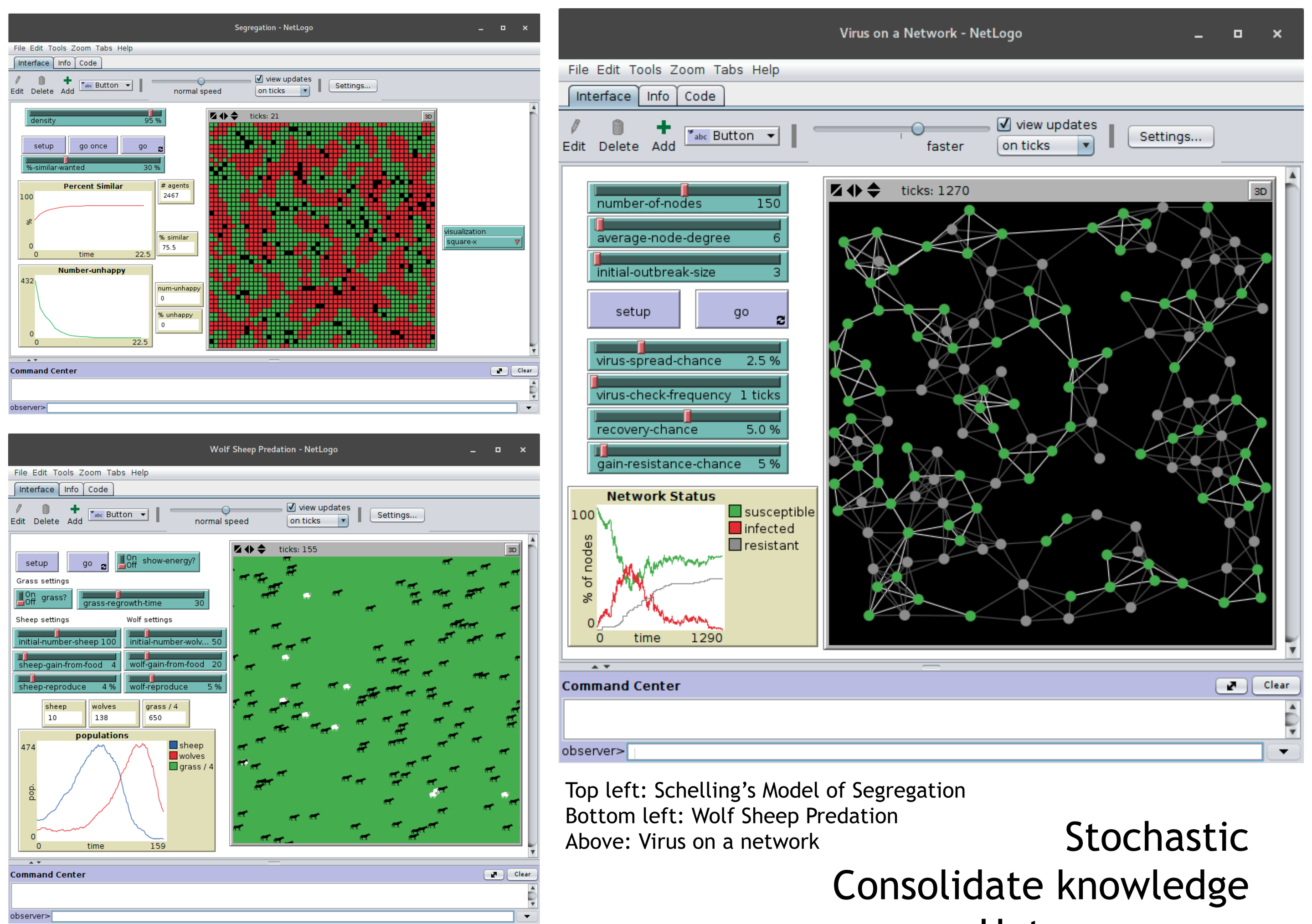
Compartmental Models



$$\frac{dS}{dt} = -bS(t)I(t)$$
$$\frac{dI}{dt} = bS(t)I(t) - kI(t)$$
$$\frac{dR}{dt} = kI(t)$$

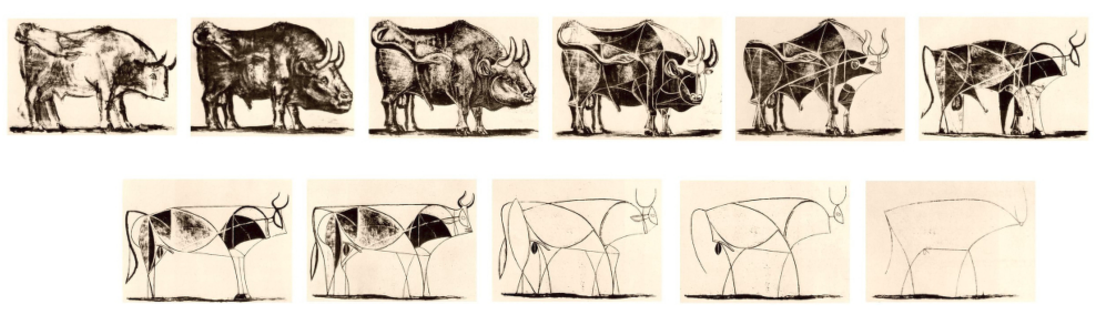
Relatively Simple
Deterministic
System Dynamics
Homogeneous

Agent-Based Models



Top left: Schelling's Model of Segregation
Bottom left: Wolf Sheep Predation
Above: Virus on a network

Stochastic
Consolidate knowledge
Heterogeneous



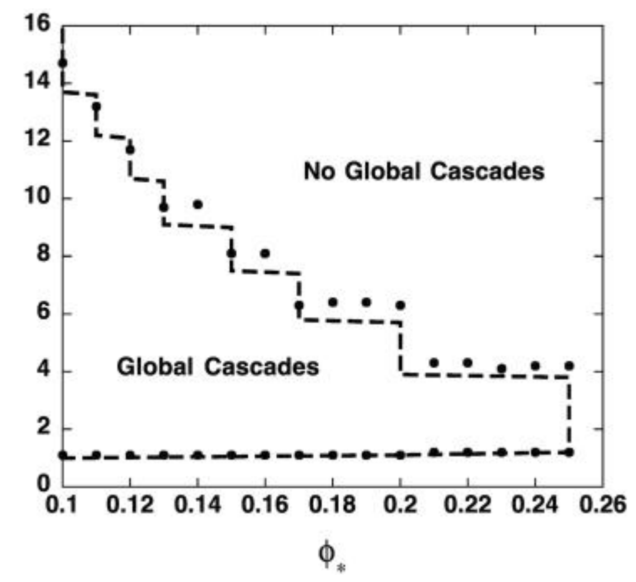
Picasso's "The Bull" Lithographs 1-11: An analogy for the detail in an ABM to the overall system dynamics in an Compartmental Model

Binary Models with Externalities

Network science approach
ABM where agents (individuals) are connected to one another
Random, Small-world
Each agent has a binary outcome
Local dependencies: connected neighbors that are different
Fractional threshold: proportion of neighbors different
Heterogeneous: not all agents have the same parameters
Look for information flow through network (global cascades)
Simple model that can be used to explain multiple phenomena
fads, riots, crime, competing technologies, spread of innovation, conventions, and cooperation

Degree (z)	Threshold (φ)	Vulnerability
High	High	Low
High	Low	High
Low	High	Low
Low	Low	High

Above: Table showing the vulnerability (i.e., how likely an agent will change states) given its degree and threshold

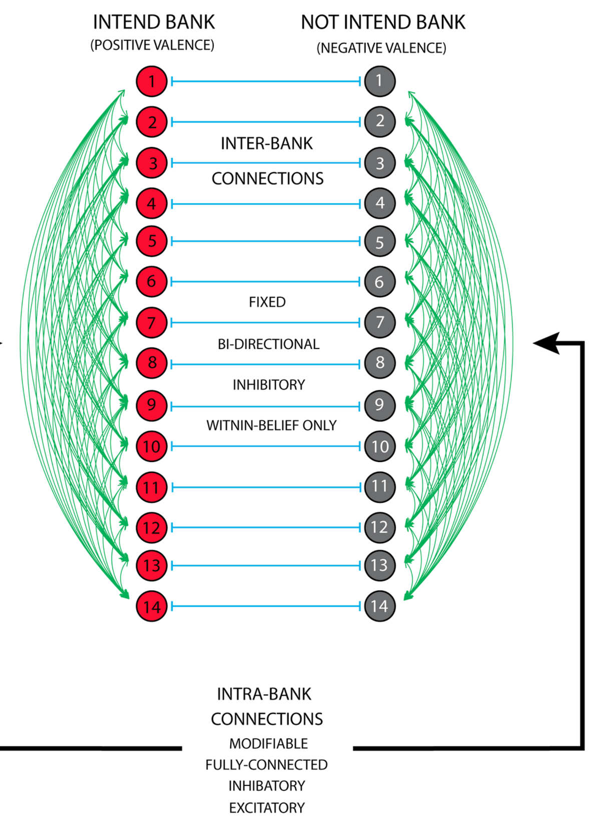


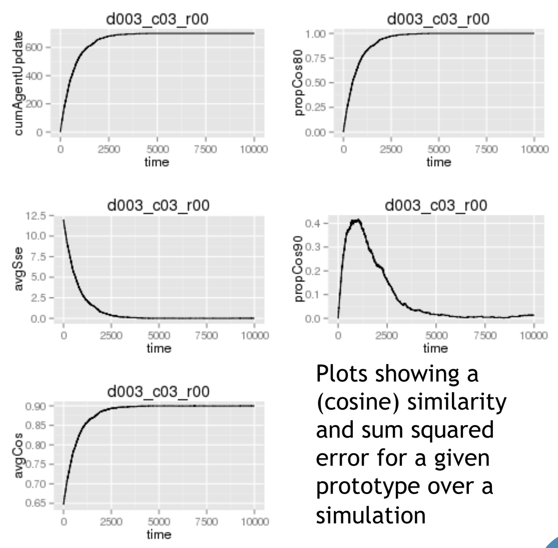
Left: Theoretical threshold for global cascades from the Watts 2002 paper. For a given threshold, ϕ, and average number of neighbors, z, where the cascade condition is satisfied (analytical solution)

MANN Model

Decisions and behaviors are binary, but the process of making a decision and performing an action is not.

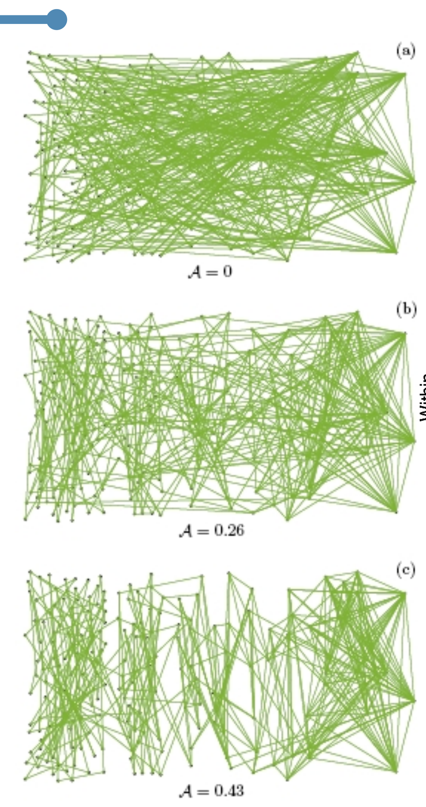
- **Neural networks:** allow us to use multi-dimensional agents, not just a simple binary agent.
- **Auto Associative Neural Network:** learn and reproduce an identity(prototype) given a portion of inputs
- **Theory of Reasoned Action:**
  Beliefs ➡ (Attitudes and Social Context) ➡ Intention ➡ Behavior



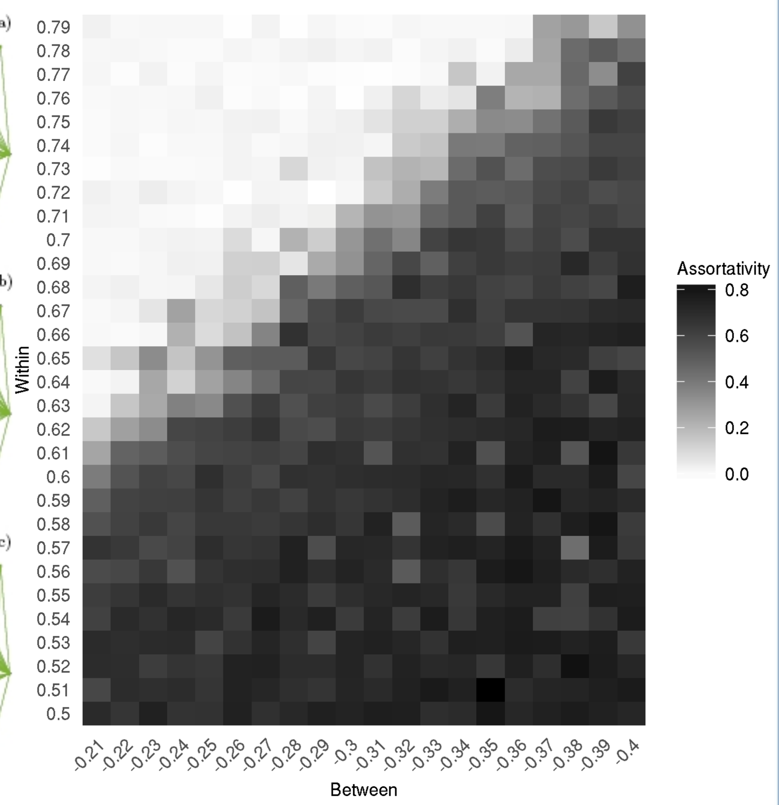


Plots showing a (cosine) similarity and sum squared error for a given prototype over a simulation

Left: Visualization of an Auto Associative Neural Network (recurrent neural network with constraint satisfaction). Each "row" represents a belief towards a behavior, where the left side represents the positive "feelings", and the right side, the negative "feelings"



Right: Figure from the Wikipedia page on network assortativity. It is reproduced here to give a sense of how assortativity values relate to network topology



Far Right: The neural network needs to be initiated with values for the weights. Figure shows varying values for the between and within starting weights for the neural network.
Each "cell" represents a pair of **weight values** and the **average assortativity** at the end of a simulation (t = 100) over **10 simulations**.
This represents the **degree of clustering for a given intension**.
The phase transition shown in the heatmap is characteristic of **complex systems**

Further Research and Developments

- Integrating systems of behavior with systems of populations
- How to measure information flow
- How to map fractional thresholds
- How to provide inputs to nodes
- How to summarize MANN data

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VirginiaTech Biocomplexity Institute

This poster (and references): https://github.com/chendaniely/2017_ser_poster
MANN code: https://github.com/chendaniely/mann2, https://github.com/chendaniely/mann2_simulations, https://github.com/chendaniely/mann

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