Diffusion of Innovations with Individual Preferences

Rational Choice vs Social Influence

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PhD(c) in Social Complexity Sciences, CICS, Santiago, Chile.

Motivation

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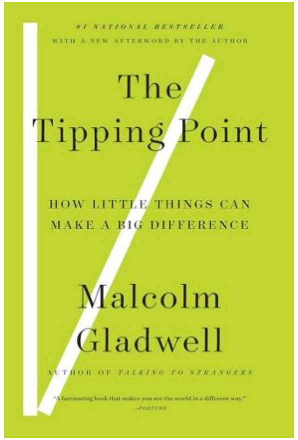
1. Hush Puppies rapid growth in 95’



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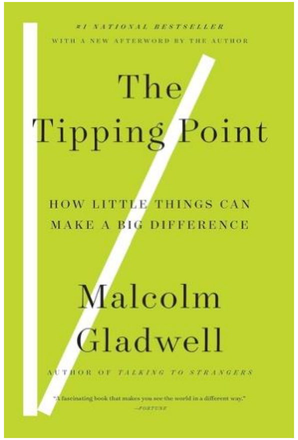

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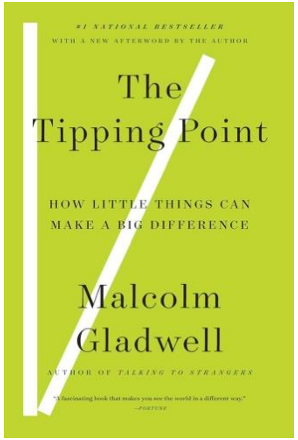

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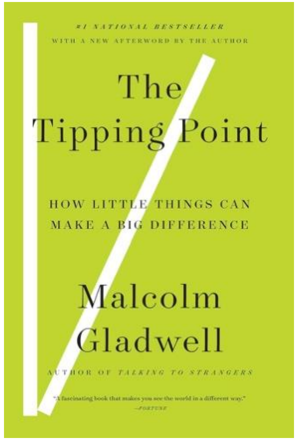

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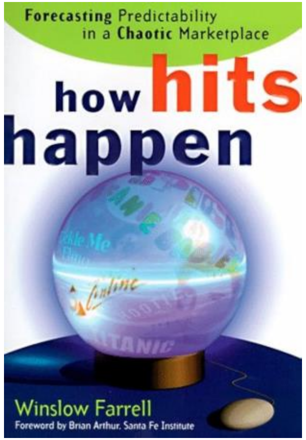

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1. Movies and Literature:
   1. The Full Monty
   2. Hootie & the Blowfish
2. Market Share:
   1. AT&T

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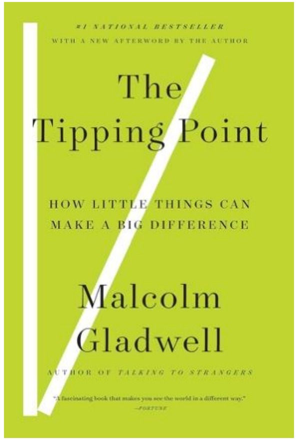

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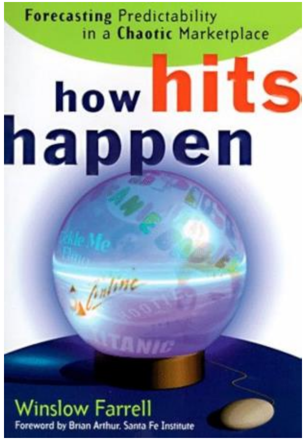

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these collective behaviors are studied as epidemics…

Previous works

Threshold Models of Collective Behavior[1]

Mark Granovetter
State University of New York at Stony Brook

Models of collective behavior are developed for situations where

HEALTH EDUCATION & BEHAVIOR

Special Issue: Modeling Social Dynamics

Diffusion/Contagion Processes on Social Networks

Health Education & Behavior
1–14

DOI: 10.1177/1090198120901497
journals.sagepub.com/home/heb
SAGE

Thomas W. Valente, PhD[1], and George G. Vega Yon, MS[1]

Previous works

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- Individuals are entirely characterized by
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0 *Individual's* q_i 1

Aversion to innovation

Propensity to innovations

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- Finally adopt if $q_t^i \leq \Gamma$.

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When it comes to peer influence, those dyads that are more similar to each other have greater influence [8].

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Some criticism has arisen due to the *'structural reductionism'* of these works:

- *"This literature often treats agents as cognition-free 'structural dopes,' operating like **relay stations** whose only purpose is to automatically respond to external stimuli."* [6]
- ***Fewer attention to more realistic setups.***

Addressing the flaws

We want to see the effect of word-of-mouth diffusion with:

- Plausible network topologies
- The right MUR distribution
- Tie-specific influence parameter $\alpha = \alpha_{ij}$

The model

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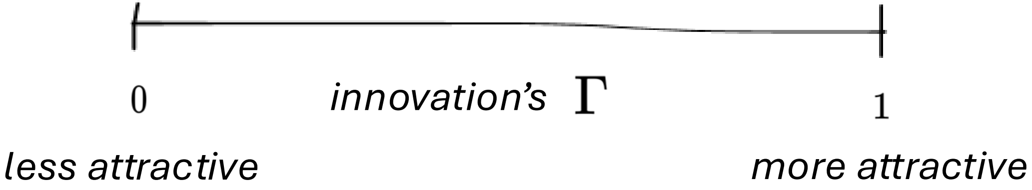
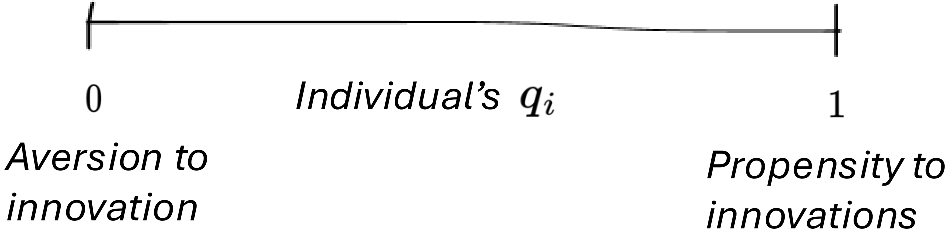


2. And individuals with *Minimum Utility Requirement* (MUR) $q_i \in [0,1]$.

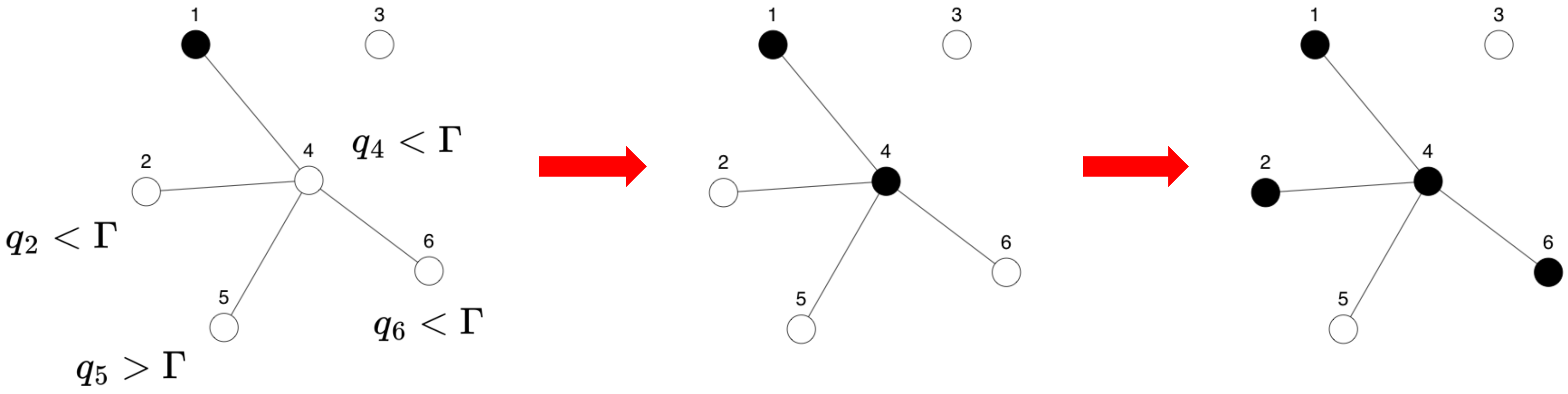


The model

Adoption can happen in two ways:

1) <u>Rational Choice:</u> i adopt if *Minimum Utility Requirement* ≤ *Intrinsic Utility Level*

$$q_i \leq \Gamma \qquad \Rightarrow a_i = 1$$



The model

2) Selective Social Influence:

$$E_i \equiv \frac{\sum_{j \neq i} \mathbf{X}_{ij} a_j}{\sum_{j \neq i} \mathbf{X}_{ij}}, \quad a_i = \begin{cases} 1 & \text{if } \tau_i \leq E_i \\ 0 & \text{otherwise} \end{cases}$$

The model

2) <u>Selective Social Influence:</u>

$$\tilde{E}_i \equiv \frac{\sum_{j\neq i} \mathbf{X}_{ij}\tilde{a}_j}{\sum_{j\neq i} \mathbf{X}_{ij}}, \qquad a_i = \begin{cases} 1 & \text{if } \tau_i \leq \tilde{E}_i \\ 0 & \text{otherwise} \end{cases}$$

Here, $\tilde{a}_i$ accounts for those infected individuals who are more influential:

$$\tilde{a}_i = 1 \quad \Leftrightarrow \quad a_i = 1 \wedge d_{ij} \leq h$$

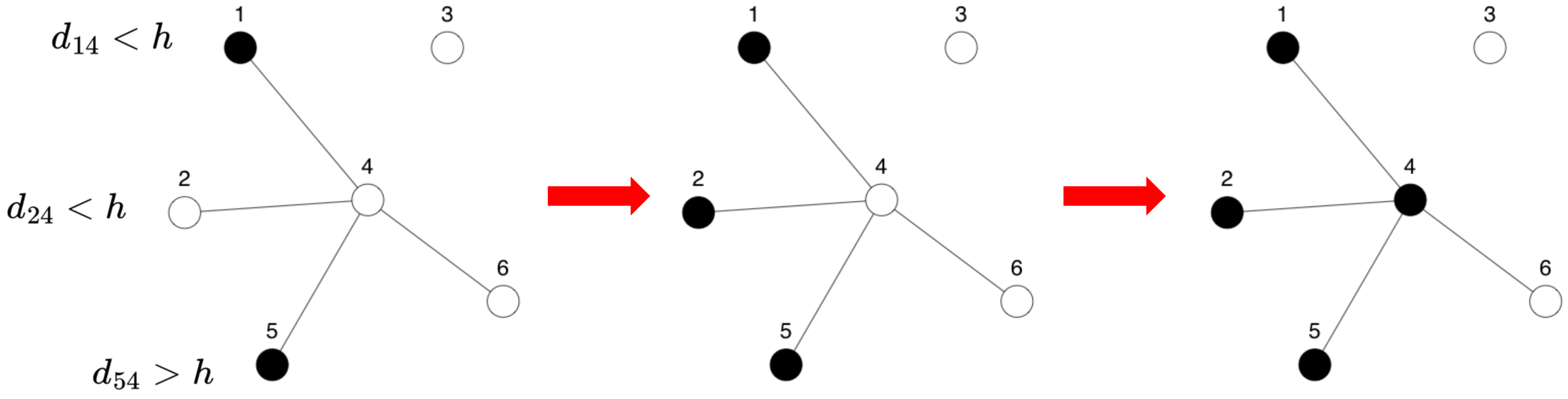
where:

1. d_{ij} is the social distance between individuals i and j,
2. h is the *Maximum Social Proximity* (MSP), which measures the flexibility to be influenced by a person with different demographics.

The model

2) <u>Selective Social Influence:</u>

Let's set $\tau_4 = 0.5$; then, because the variability among the ties [6]...



Setting up

Imputing network structure to a Survey

To run the simulations in a **plausible setup**, we should have a network with:

1) a representative socio-demographic distribution, and
2) a plausible distribution of the population's willingness to adopt.

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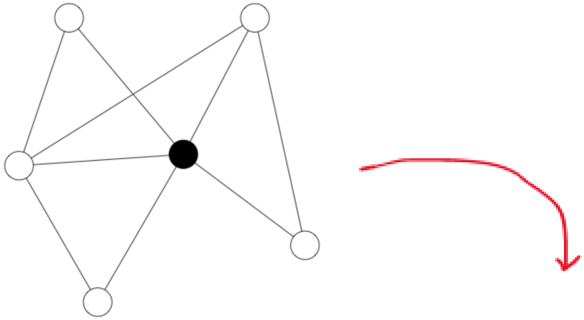
Following McPherson and Smith (2019) [7], you can impute a network structure on any other survey if that survey:

1) Is representative of the same population,
2) Has some basic demographic variables.



Homophilic strength in the m-th social dimension

Imputing network structure to a Survey

General Social Survey (GSS 2004):

1. Representative of the US population
2. Demographics:
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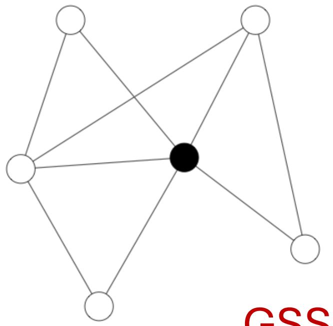
3. EGO data



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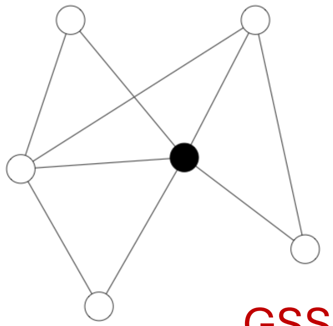

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3. ~~3. EGO data~~ ‘*Openness to Innovations*’ items

	id_1	id_2	id_3	...
Age	36	27	41	...
Educ	12	15	16	...
q_i	.54	.67	.32	...
...	...	...	...	...

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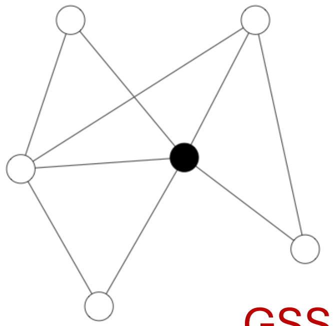

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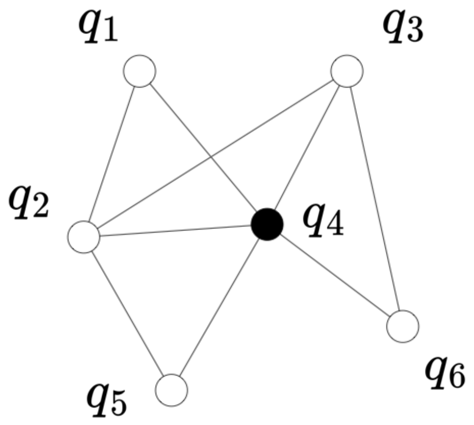

ATP 2014 +
Network structure

Imputing network structure to a Survey

Table 1. Case-Control Logistic Regression Predicting a Confiding Relationship based on General Social Survey Ego Network Data, 1985 and 2004.

Variable	Model 1
Intercept	−14.456***
	(0.048)
Different race	−1.819***
	(0.077)
Different religion	−1.362***
	(0.044)
Different sex	−0.317***
	(0.025)
Education difference	−0.049***
	(0.002)
Age difference	−0.173***
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Year	−0.179***
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N (respondents)	3,001
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We can use those values and ERGM to get networks with:

1. The right topology,
2. The right structural homophily (realistic socio-demographic attributes),
3. The right distribution of your relevant variable (individual innovation propensity q_i).

Comprehensive Simulation Methodology

Using the ATP-networks (N=1000 nodes):

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Parameter Space Exploration:

- **IUL** (Γ): 41 levels (0.0 to 1.0).

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    - Means (μ_τ): 4 levels (0.3, 0.4, 0.5, 0.6).
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Scale of Simulation:

- 96 simulations for each combination of parameters
- Total simulations: $41 \times 13 \times 4 \times 4 \times 5 \times 96 \approx \underline{\underline{4 \times 10^6}}$!

Results

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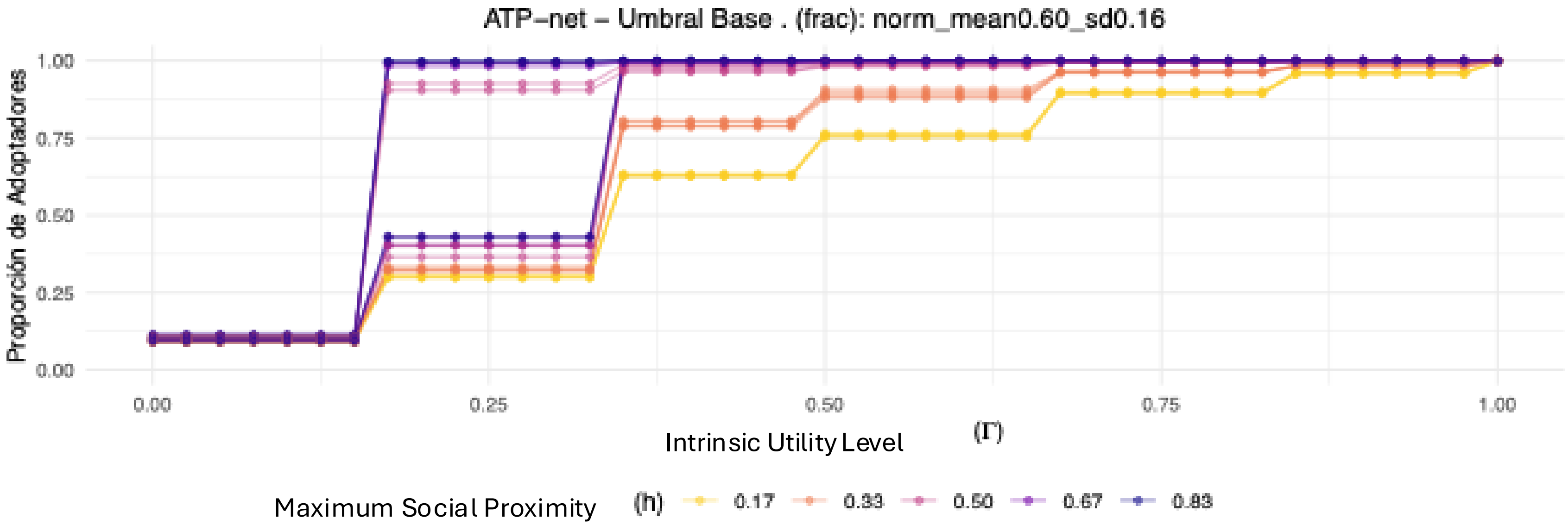
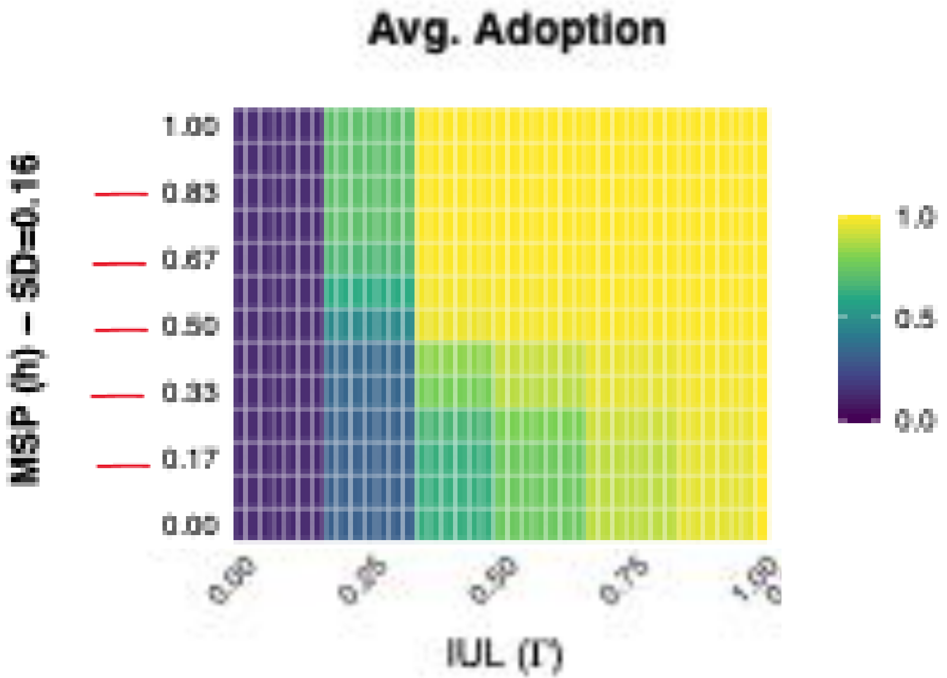

ATP–net – Umbral Base . (frac): norm_mean0.60_sd0.16
Proporción de Adoptadores
1.00
0.75
0.50
0.25
0.00
0.00
0.25
0.50
0.75
1.00
Intrinsic Utility Level
(Γ)
Maximum Social Proximity
(h)
0.17
0.33
0.50
0.67
0.83

Results



Avg. Adoption
MSP (h) – SD=0.16
1.00
0.83
0.67
0.50
0.33
0.17
0.00
0.00
0.25
0.50
0.75
1.00
IUL (Γ)
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0.5
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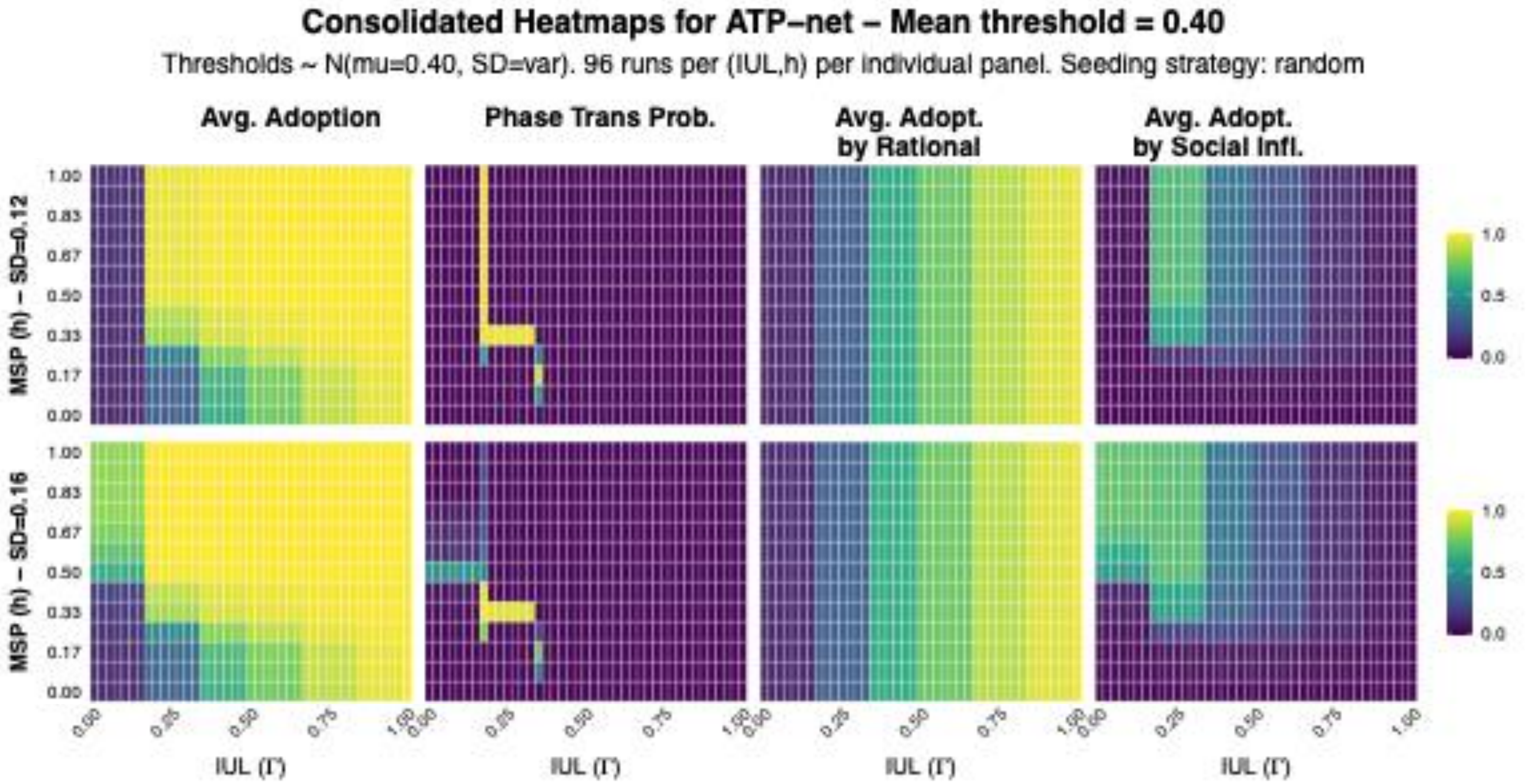

Consolidated Heatmaps for ATP–net – Mean threshold = 0.40
Thresholds ~ N(mu=0.40, SD=var). 96 runs per (IUL,h) per individual panel. Seeding strategy: random
Avg. Adoption
Phase Trans Prob.
Avg. Adopt. by Rational
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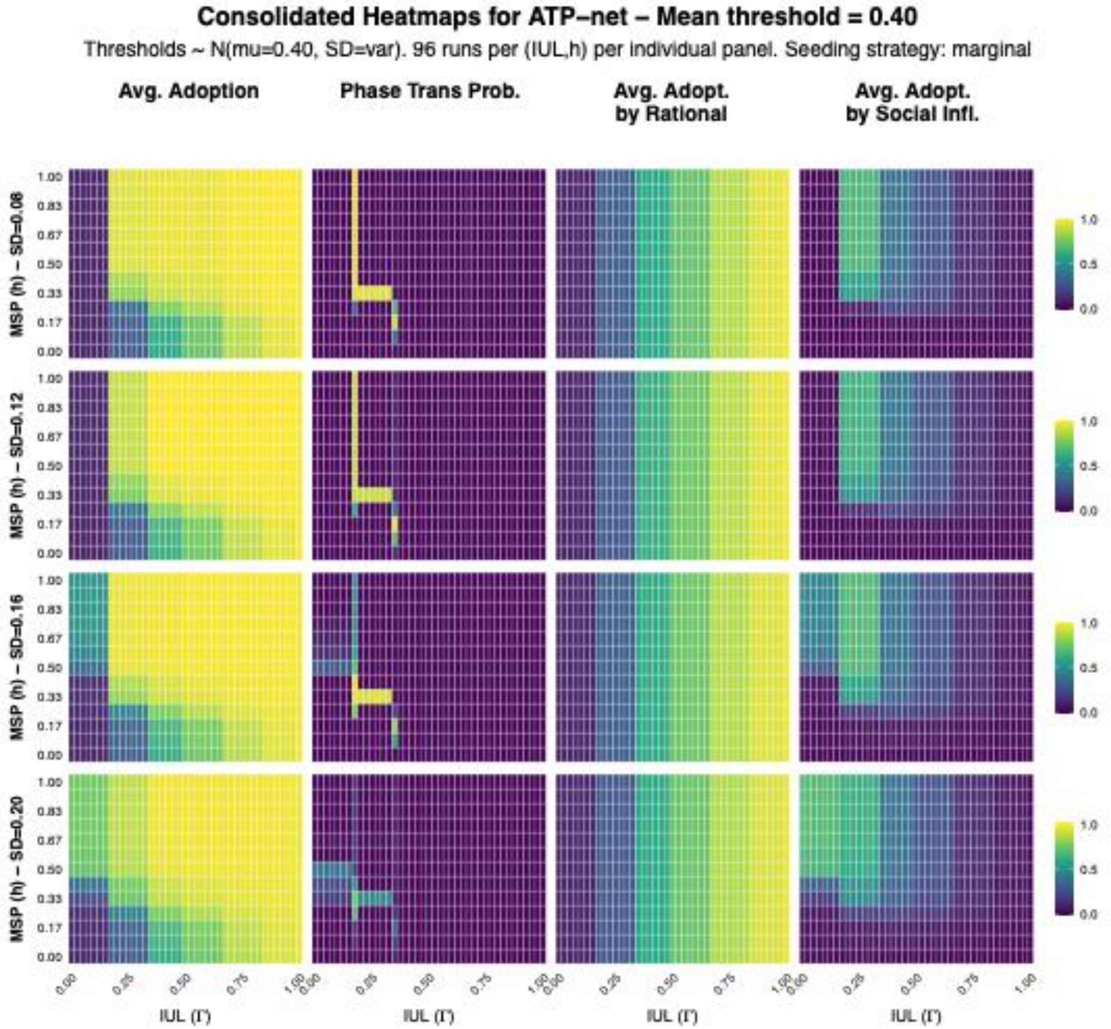
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Avg. Adoption
Phase Trans Prob.
Avg. Adopt. by Rational
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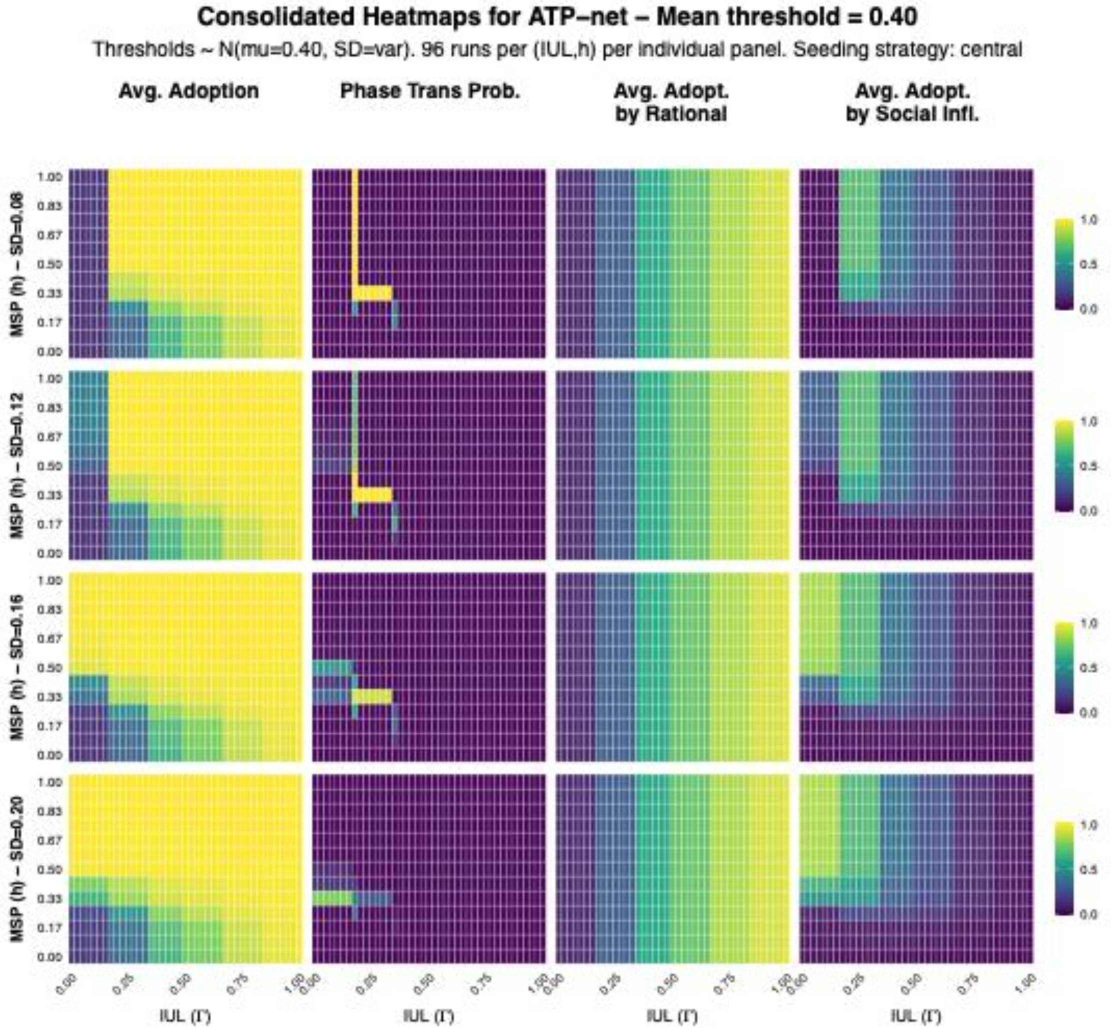
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IUL (Γ)
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0.00 0.25 0.50 0.75 1.00
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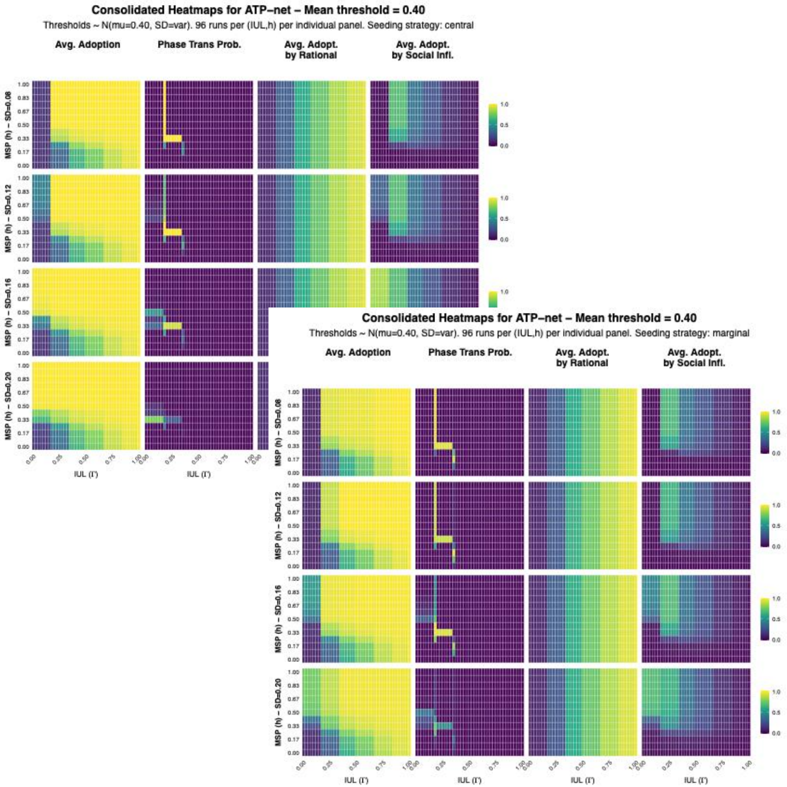
Results



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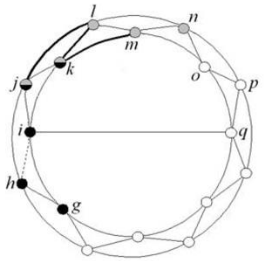
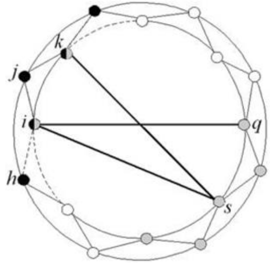
- Social influence plays a relevant role in adoption, even for configurations where the innovation is **not particularly attractive**.
- The model offers consistent results across several parameter configurations.
- The regions where social influence is on are separated abruptly by **first-order phase transitions**.

Previous works

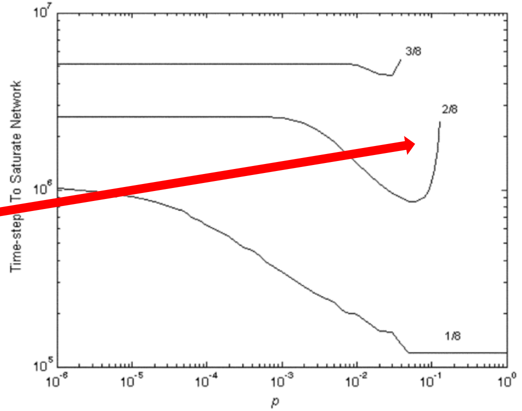
Centola & Macy 2007 [3]

- While the rewiring is higher:



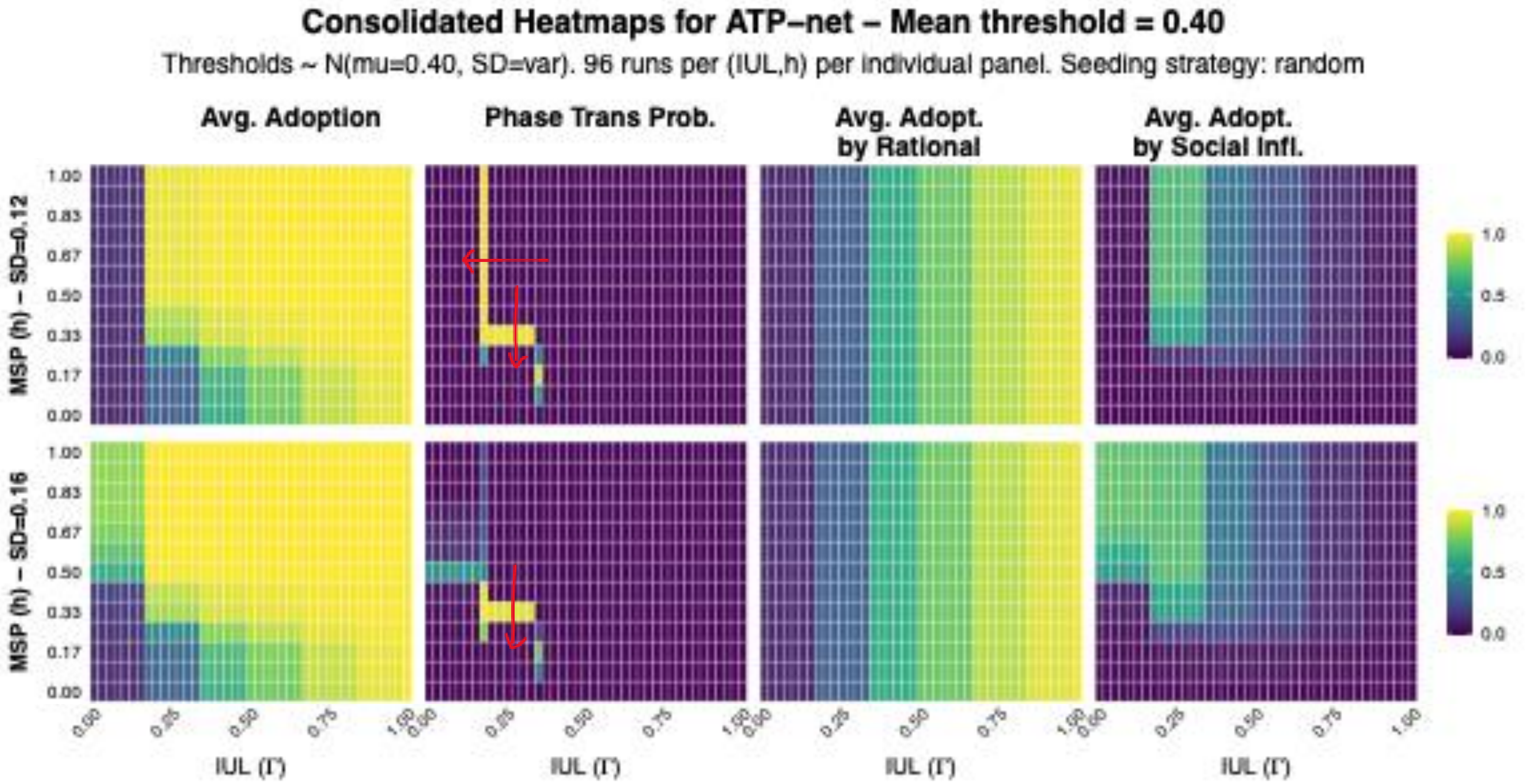


- We get an abrupt barrier in diffusion:



Pure structural phase transition

Results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So, what have we learned?

- Social influence plays a relevant role in adoption, even for configurations where the innovation is **not particularly attractive**.
- The model offers consistent results across several parameter configurations.
- The regimens where social influence is on are separated abruptly by **first-order phase transitions**.
- There are non-structural barriers to word-of-mouth diffusion.

Thanks!

All the results are available
on the GitHub repository !

References

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Conclusion

Future steps:

1. Simulate competitive dynamics to see if the characteristics of the seed nodes are more important than the attractiveness of the innovation itself.

2. Impute low thresholds to those individuals with high q_i :

Openness to innovation == Lower social influence requirements

Phase Transitions