



DCS/CSCI 2350
Social & Economic Networks

*How do diseases, behavior,
opinion, technology, etc.
propagate in a network?*

Cascading Behavior in Networks

Reading: Ch 19 of EK

Mohammad T. Irfan

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How Does Our Social Network Influence Our Behavioral Choices?

NSF Core Research Grant

“No man is an island” wrote the poet John Donne in 1624, meaning whether we like it or not, we are all connected. It’s an assertion that rings truer than ever in today’s networked world, and it’s a central theme of the research currently being done by computer scientist Mohammad Irfan and his colleagues.

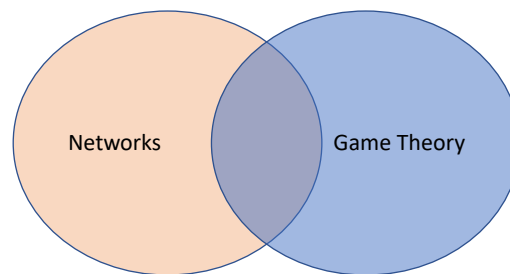
Assistant Professor of Digital and Computational Studies (DCS) and Computer Science (CS) Irfan recently helped to secure around half a million dollars in funding for an exciting multiyear project exploring human interactions in networks. The research could have implications for many fields, he says, from public health to energy pricing to finance to the analysis of congressional voting patterns.

The award was made by the National Science Foundation (NSF) and done in collaboration with Luis E. Ortiz of the University of Michigan—Dearborn, for a multiyear research initiative. It’s all part of a core NSF program called Information and Intelligent Systems, says Irfan, who is the project director (while Bowdoin is the lead organization.)



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My recent research



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My recent research

- [Influence in networks](#) (with Phillips'19 and Ostertag-Hill'20)
- [Power of context in influence networks](#) (with Gordon'17)
- [Influence in residential segregation](#)

<http://mtirfan.com/research>

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My recent research

- Congestion games
- Emergence of roles in multi-agent asset markets (with Albers'23)
- Cascades and overexposure (with Hancock'21 and Friel'22)

<http://mtirfan.com/research>

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Diffusion of innovations

- Studied in sociology since 1940s
- One's choice influences others

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Types of diffusion

- Indirect/informational effects – social learning
 - Photo/video going viral
- Direct-benefit effects
 - Technology adoption– Xbox/PS5, phone, fax, email, FB

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Examples

- Adoption of hybrid seed corn in Iowa
 - Ryan and Gross, 1943
- Adoption of tetracycline by US doctors
 - Coleman, Katz, and Menzel, 1966

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Shared ingredients in examples

- Indirect effects
- Adoption was high-risk, high-gain
- Early adopters had higher socioeconomic status
- Social structure was important– visibility of neighbors' activity

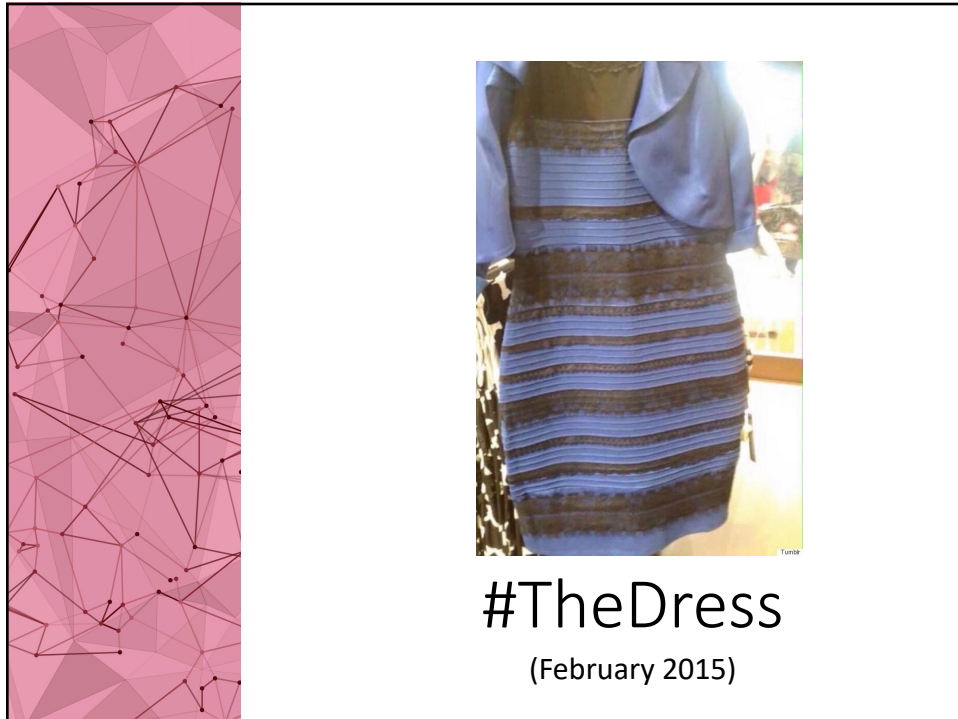
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Success
factors of
diffusion

Diffusion of Innovations–
Everett Rogers (1995)

- Complexity
- Observability
- Trialability
- Compatibility

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Viral Facebook post (2013)



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Hush puppies (1995)



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Next

- Modeling diffusion
- Connection with the things we know
 - The strength of weak ties
 - Clustering

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Threshold models for diffusion

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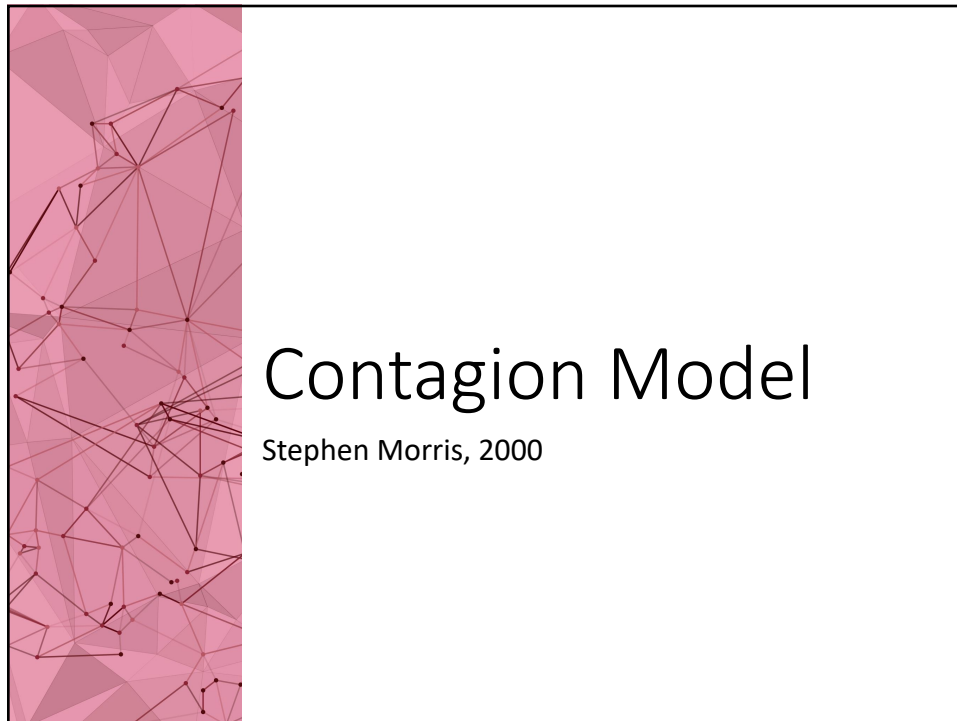
Precursor: Granovetter's model

- Mark Granovetter's threshold model of collective behavior (1978)
- An individual will adopt an action if at least **a certain number** (threshold) of other individuals adopt it
 - Riot example
 - General networks and distribution of threshold

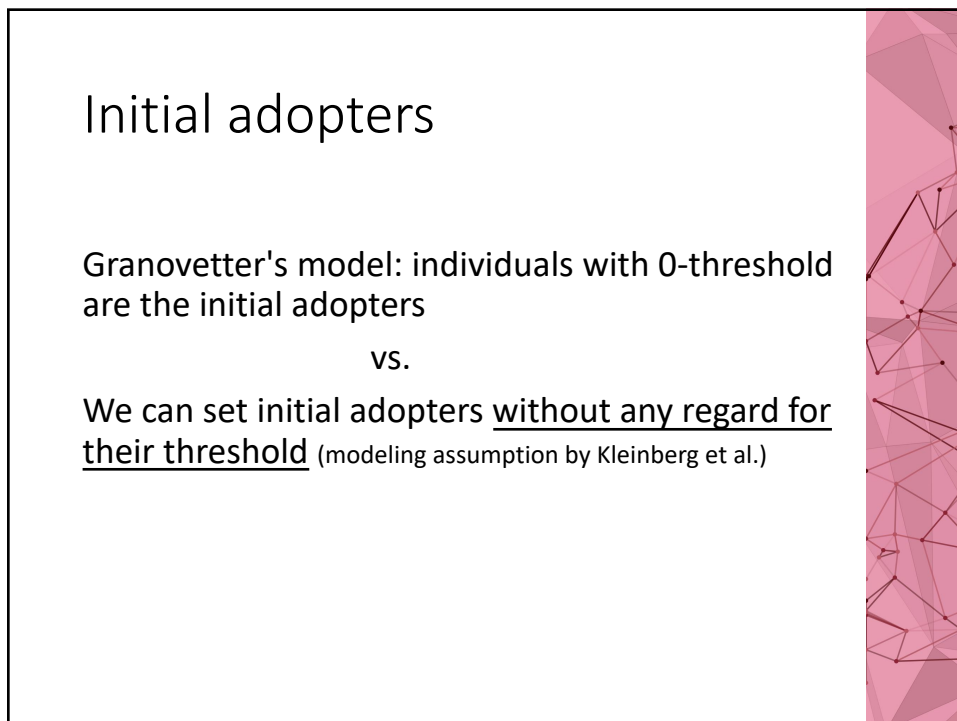
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- Collective behavior: Relatively spontaneous, unstructured, extra-institutional behavior of a fairly large number of individuals. (Goode)
 - Residual field in sociology
- Collective action: People acting together in pursuit of common interests. (Tilly)
 - 1990s to date

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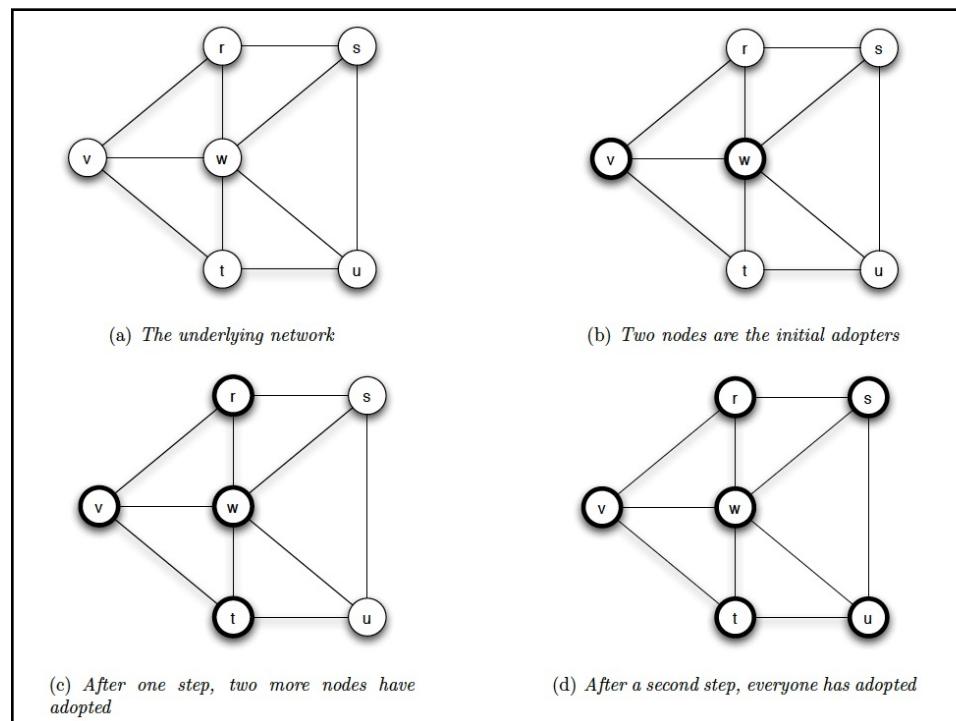


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Example: switching from B to A

- Initially, everyone does B
- Payoff parameters: $b = 2$, $a = 3$
- Threshold for switching to A, $q = 2/5 = 40\%$
- We will set two initial adopters of A and "play out" the diffusion

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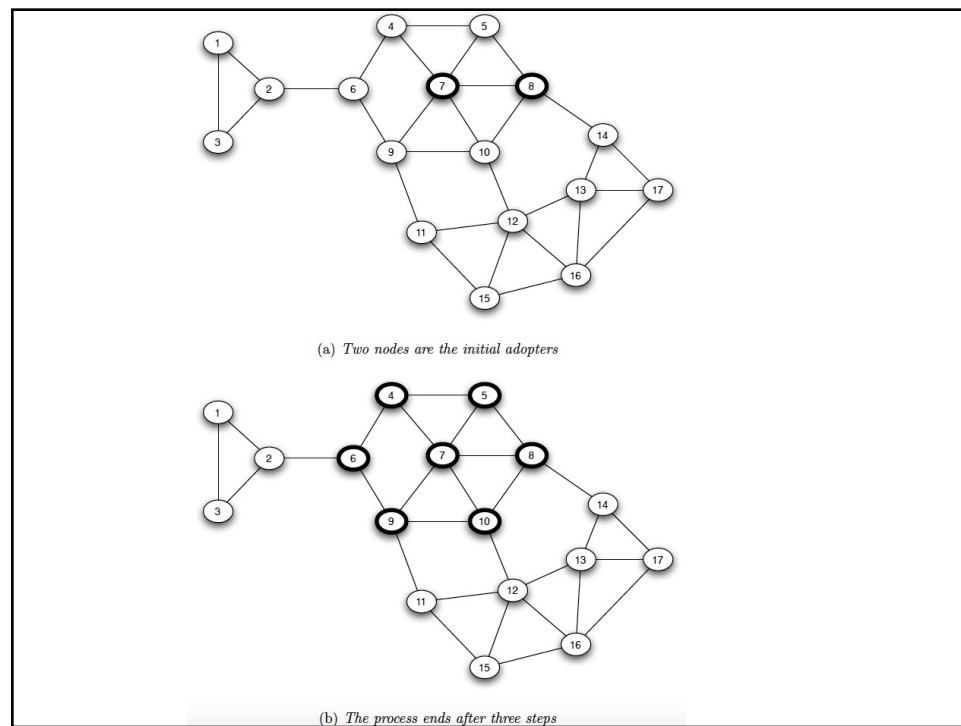


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Complete cascade

- **Def.** A set of initial adopters causes a "complete cascade" if everyone adopts the new action at the end of diffusion.
 - Always happens?

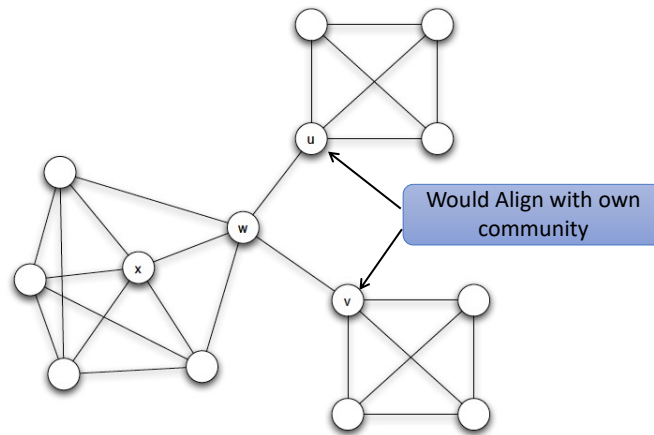
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Diffusion and strength of weak ties

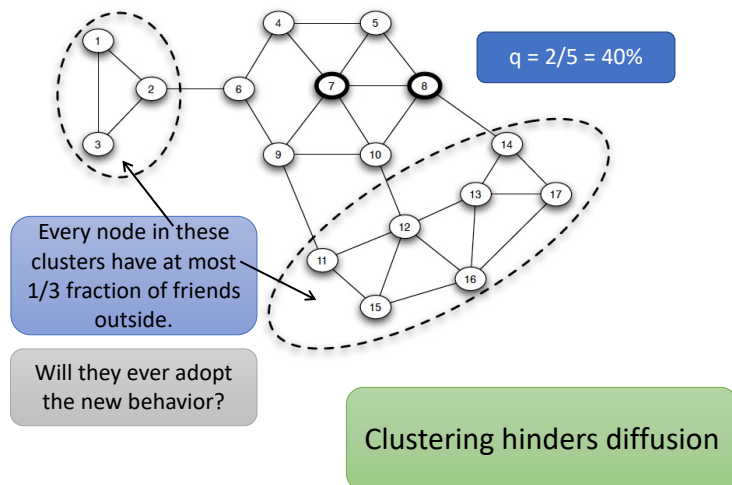
- Weak ties are conveyors of information
- But cannot “force” adoption of behavior



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Diffusion and clustering

- Does clustering help or hinder diffusion?



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What are the factors for a widespread diffusion?

- Initial adopters
- Network structure
- Threshold value q
 - Quality of product– payoff parameters a and b
- Example: viral marketing

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More general models

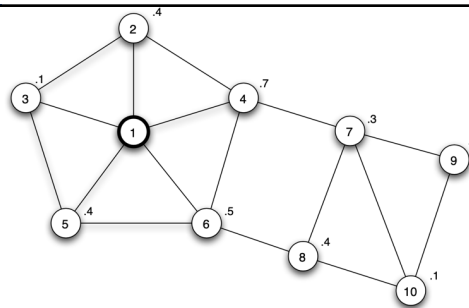
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Cascades with heterogeneous thresholds

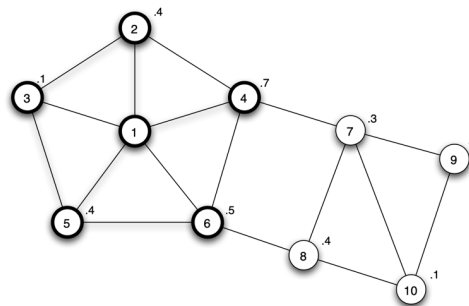
		w	
		A	B
v	A	a_v, a_w	$0, 0$
	B	$0, 0$	b_v, b_w

- Node v 's threshold = $b_v/(a_v + b_v)$
 - Same calculation as before

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(a) One node is the initial adopter



(b) The process ends after four steps

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Further extension: linear threshold model

All friendships are not the same!
=> influence

Reference: Handout (on Canvas)

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Influence maximization problem

Given $k > 0$, select a set of k initial adopters so that the spread of the *new behavior* is maximized

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Cascades and Overexposure in Social Networks: The Budgeted Case

Mohammad T. Irfan

Kim Hancock



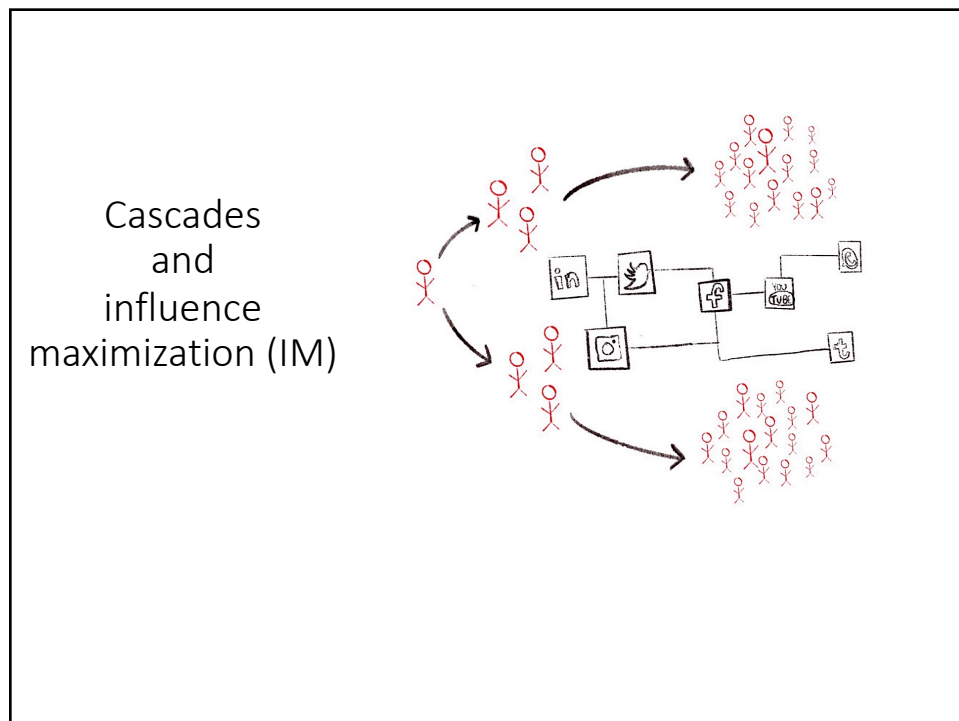
Laura M. Friel





Paper Link

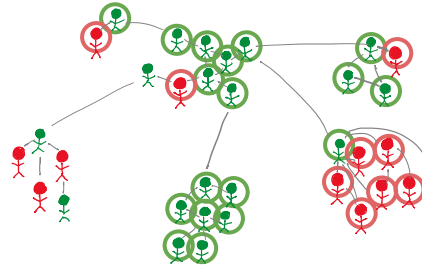
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Overexposure

Green: accepting node
Red: rejecting node



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How do we select a set of initial adopters (or seeds) that will **maximize** the spread of influence while **minimizing** overexposure?

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Unbudgeted seeding

Abebe, Adamic, and Kleinberg (**AAK**), AAAI 2018

- Polynomial-time algorithm for the unbudgeted case
- Proved hardness of the budgeted case

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How do we select up to k initial adopters that will maximize the spread of influence while minimizing overexposure?

[Paper Link](#)

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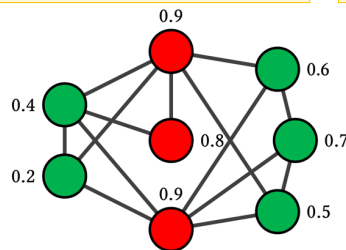
Modeling overexposure (AAK)

- Undirected, unweighted graph
- Each node: a criticality parameter, θ_i
- Product appeal, ϕ

Accepting node: $\phi \geq \theta_i$

Rejecting node: $\phi < \theta_i$

Product appeal = 0.7



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Propagation model (AAK)

Accepting node:
Sends information to ALL
neighbors.

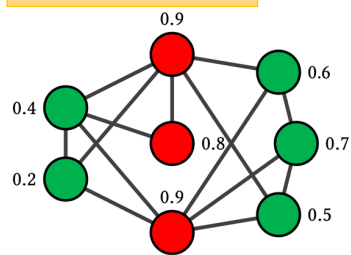
Rejecting node:
Does not send to anybody.
Inflicts global cost!

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Overexposure problem

Given budget k ,
 maximize **payoff** = # of accepting – # of rejecting
 nodes reached

Example (budget, $k = 1$)



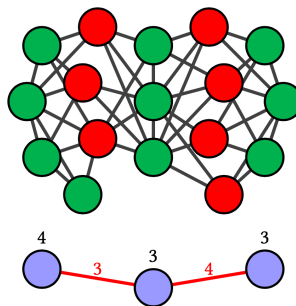
Select left: payoff = 2 – 3 = -1

Select right: payoff = 3 – 2 = 1

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Cluster graph formulation

Assumption: A rejecting node cannot be at the boundary of more than two clusters of accepting nodes.



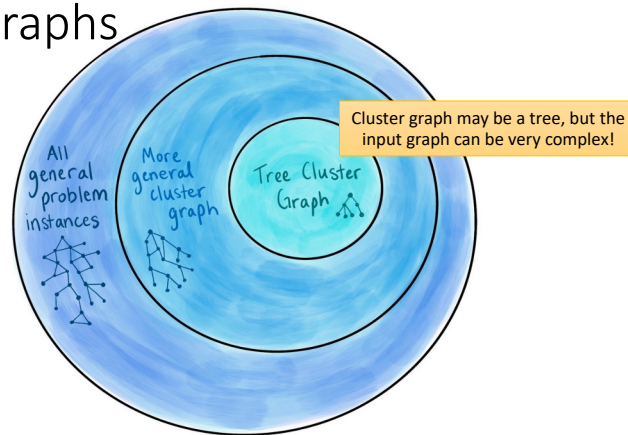
Input graph

Cluster graph

Simple cluster graph for
 very complex input graph

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Algorithms for classes of cluster graphs



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Lower quality products need smarter algorithms to avoid overexposure.

Higher quality products can be coupled with extremely simple and fast greedy algorithms.

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