

# Graph Bootstrap Percolation

## Case studies on selected graphs and algorithms

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# Introduction

## Graph Bootstrap Percolation

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### Introduction

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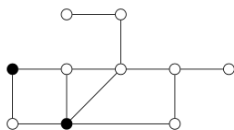
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Results

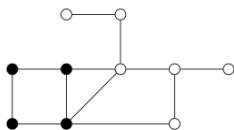
Consider the following activation process:

- Let  $G = (V, E)$  be a graph, whose vertices are in an "active" or "inactive" state. Fix a threshold  $k$  and choose a seed set  $A_0 \subseteq V$ .
- Denoting the adjacent vertices, or neighbors, of vertex  $v$  by  $N(v)$ , activations (also called infections) spread through the system as follows:

$$A_{i+1} = A_i \cup \{v \in V : |N(v) \cap A_i| \geq k\}$$



$A_0$



$A_1$

A simple example

# Motivation

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Bootstrap percolation can model spread in real

- Vertices and edges represent people and relationships, while the percolation process represents the spread of ideas, rumors, or trends.
- Which groups at minimum should be activated to achieve maximal influence throughout a community?
- How can we reduce the spread of ideas or rumors?

# Bootstrap percolation problems

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In the language of bootstrap percolation:

- Minimum contagious sets
  - What is the smallest possible seed set  $(S_0 \mid |S_0|)$  required to eventually infect an entire graph?
- Spread minimization
  - If we must initially infect a fixed number  $k$  of vertices, choose a seed set  $S_0 \subseteq V$  of fixed cardinality  $k$  such that the number of vertices that should be infected to minimize spread is minimized.

# Minimum contagious sets

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Let  $G(V, E)$  be a graph, and fix a threshold  $k$  percolation process.

- A contagious set is a seed set  $S_0$  that eventually infects the entire graph (i.e.,  $\langle S_0 \rangle = V$ ).
- A contagious set is called minimum if there is no smaller contagious set, and its size is denoted  $m(G, k)$ .
- Goal: Find  $m(G, k)$ .
- One solution: First, compute all possible contagious sets by exhaustively finding all seed sets  $S_0$  for which  $\langle S_0 \rangle = V$ . Then,  $m(G, k)$  is equivalent to the size of the smallest  $S_0$  (there may be more than one).

# Spread minimization

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Results

Let  $G(V, E)$  be a graph and fix a threshold  $k$  for the bootstrap percolation process. If we must initially infect a fixed number  $n$  of vertices (i.e., choose a seed set  $S_0 \subseteq V$  of cardinality  $|S_0| = n$ ) which vertices should be infected to minimize the size of the final infected set?

- For any seed set  $S_0 \subseteq V$ , we denote the size of the final infected set by  $|\langle S_0 \rangle|$ .
- Goal: Find a seed set  $S_0$  of size  $n$  that minimizes  $|\langle S_0 \rangle|$ .
- One solution: Compute  $|\langle S_0 \rangle|$  for all possible seed sets  $S_0$  of size  $n$  on the graph to find the smallest  $|\langle S_0 \rangle|$  by brute force.

# Challenges

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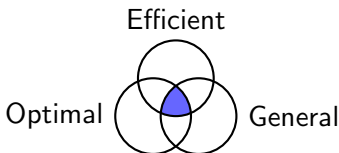
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- Spread minimization is believed to be NP-hard (this remains unproven)
- This implies there is unlikely to be an efficient general solution to the problem
- Hence, most approaches focus on specific cases (sacrificing generality) or finding a suboptimal solution
- Past work on the problem focuses on many specific cases supporting the suspected NP-hardness of the problem



# Some interesting cases

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In order to better understand bootstrap percolation through percolation processes on specific kinds of graphs

- Complete graphs
- Petersen graph
- Bipartite graphs



# Complete graphs

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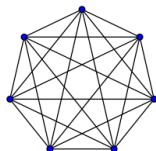
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In  $K_n$ , the complete graph of  $n$  vertices, each vertex is connected to every other vertex. Given a seed set  $S_0$  and a threshold  $k$ , whether any other vertices can be infected is possible.

- If  $|S_0| < k$ , no vertices have  $k$  or more infected neighbors, so no spread occurs. Hence  $|S_\infty| = |S_0|$ .
- Otherwise,  $|S_0| \geq k$ , and all vertices have  $|S_0|$  infected neighbors. Therefore, the entire graph becomes infected in the next step, and  $|S_\infty| = |V|$ .



$K_7$ , the complete graph of 7 vertices

# Petersen graph

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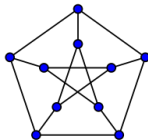
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The Petersen graph is a peculiar graph with 10 edges. It is helpful to divide its vertices into two sets: the "inner" vertices and the "outer" vertices.



The Petersen graph

We examined outcomes for  $|\langle \cdot \rangle_0|$  with threshold  $\theta$  for different seed sets  $S_0$ .

# Petersen graph

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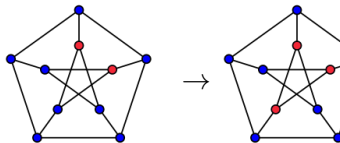
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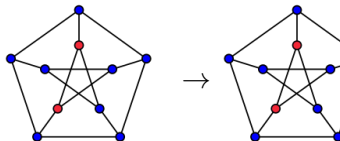
Results

Considering the "inner" vertices when  $|I_0| = 2$

- Selecting two nearby vertices results in at least one subsequent infection.



- Selecting not so nearby vertices as  $I_0$  results in no subsequent infections, and  $|\langle I_1 \rangle| = |I_0|$ .



# Petersen graph

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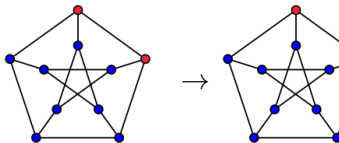
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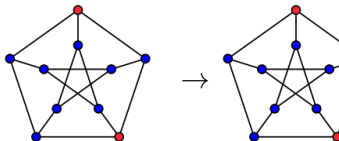
Results

Considering the "outer" vertices when  $|I_0| = 2$

- Selecting two nearby vertices results in no infections.



- Selecting not so nearby vertices as  $I_0$  results in one subsequent infection, and  $|I_1| = 3$



# Petersen graph

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Results

Why does this happen?

- There is an automorphism on the Petersen graph that preserves its shape, and maps the inner vertices to the outer vertices.
- Any choice of two nearby inner vertices maps to two nearby outer vertices that are not so nearby.
- Therefore, the opposite rule applies after an automorphism.

# Bipartite graphs

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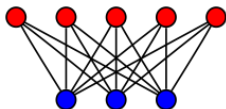
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Results

A bipartite graph  $K_{m,n}$  is a graph whose vertices are split into two disjoint subsets  $A$  and  $B$ , where  $|A| = m$  and  $|B| = n$ .

- A bipartite graph is called complete if every vertex in  $A$  connects to every vertex in  $B$ .
- Percolation on the complete bipartite graph  $K_{m,n}$  is defined similarly to the complete graph  $K_n$ .
- We explored percolation on bipartite graphs by studying the percolation process on complete bipartite graphs for different combinations of  $m$  and  $n$ .



The complete bipartite graph  $K_{m,n}$

# Complete bipartite graphs

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Results

For  $m, n \geq k$ , a large enough and well distributed subset of vertices will infect the entire graph  $K_{m,n}$ .

- If  $|S_0| < k$ , every vertex in  $K_{m,n}$  has less than  $k$  neighbors and remains inactive.
- If  $|S_0| \geq k$ ,  $S_0$  can be entirely in subset  $V_1$  or  $V_2$ .
  - If  $S_0$  is chosen to be in subset  $V_1$ , subset  $V_2$  has  $|S_0| \geq k$  infected neighbors and its vertices are activated during the first iteration of percolation.
  - During the second iteration, all vertices in  $V_1$  have  $|S_0| \geq k$  infected neighbors and be activated.

# General bipartite graphs

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Results

For any general bipartite graph  $K_{m,n}$ ,  $m \geq n$ , if we can choose a seed set such that no new vertices are activated during the percolation process.

- For a graph where  $m, n \geq \lceil \frac{|V|}{2} \rceil$ , split the vertices in half. If the seed set is odd sized, let the difference be 1 vertex.
- For a graph where  $n < \lceil \frac{|V|}{2} \rceil$ , activate all vertices in as much of subset A as necessary.



# Erdős–Rényi random graphs

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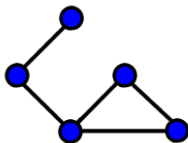
Results

The Erdős–Rényi graph is a random graph represented by  $G = G(n, p)$ .  $n$  is the number of vertices and  $p$  is the associated probability.

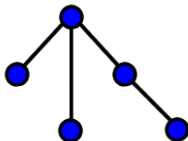
- Edges of all possible combinations of vertices in  $G$  with probability  $p$
- We examined only the cases in which this was a connected graph – any isolated vertex must be in the seed set to ever get activated
- Con: Does not accurately portray social c

# Example of Erdős–Rényi graphs

- Two possible Erdős–Rényi graphs for  $G(5, 0.3)$
- All possible edges among 5 vertices are selected with probability 0.3



$G_1$



$G_2$

# Stochastic block model

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A stochastic block model (SBM) graph is the union of two Erdős–Rényi graphs  $G_1$  and  $G_2$ . There is an activation probability  $q$  and two different communities  $G_1$  and  $G_2$ .

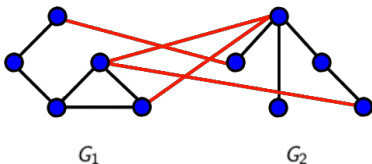
- We have a graph  $G = (n_1, n_2, p_1, p_2, q)$
- $n_i$  is the number of vertices per graph
- $p_i$  is the probability per graph for intra-community edges
- $q$  is the probability for inter-connected edges between communities  $G_1$  and  $G_2$

# Example stochastic block model graph

## Graph Bootstrap Percolation

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- We union the two Erdős–Rényi graphs from
- Edges between vertices of different communities with probability  $q$



# Stochastic block model

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In Bootstrap percolation on the stochastic block model (Torrìsi, Giovanni Luca, Michele Garetto, and E. 2022), asymptotic bounds are given for  $p$  in terms of  $n$  and  $k$ .

$$1/n_i \ll p_i \ll 1/(n_i^{1/k})$$

Additionally, a critical number of seeds per component is given in terms of  $p$ ,  $n$ , and  $k$ .

$$g_i = 1 - \left( \frac{1}{k} \right) \left( \frac{(k-1)!}{n_i p_i^k} \right)^{\frac{1}{k-1}}$$

- When the size of the seed set  $|S| = g_i$  reaches a certain threshold, a "phase transition" in which the graph is reached.

# A brute-force approach

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We generated computations to observe the behavior of bootstrap percolation in the SBM model which includes many cases. Generating these computations would allow us to see how choosing a random seed set performs. We set the following parameters,

- $n_1 = n_2$  and  $p_1 = p_2$
- Sizes for  $n$  of 10, 50, 100, 500, 1000 vertices
- $2 \leq |S_0| \leq 4$  and  $2 \leq k \leq 4$
- $k$  is bounded below by  $|S_0|$
- $q$  is a constant multiple of  $p$
- 40  $p$ -values bounded between  $1/n_i$  and  $1/n_j$

# SBM computations, 10 vertices

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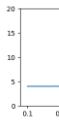
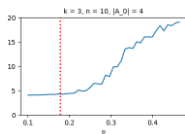
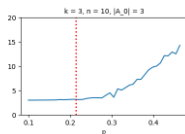
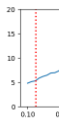
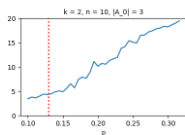
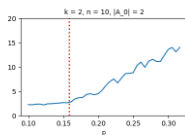
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Randomly chosen seed sets for  $n =$

# SBM computations, 1000 vertices

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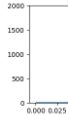
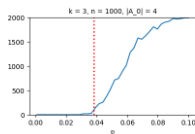
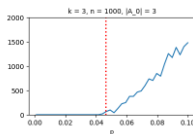
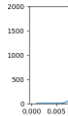
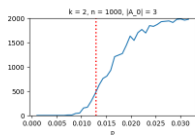
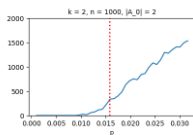
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The red dotted line indicates when the critical  $g_i$  is reached and equal to  $| \mathcal{O} |$  for some value

be derived by solving for  $p$  in  $g_i = 1 - \frac{1}{k} \left( \frac{(k-1)}{r} \right)^{r-1}$   
randomly chosen seed set, it can be seen that,

- When  $| \mathcal{O} | < g_i$ , there is little to no spread
- When  $| \mathcal{O} | > g_i$ , we see the phase transition  
 $| \langle \mathcal{O} \rangle |$  gets larger
- So far, it looks like percolation in the SBM performs accordingly to defined bounds!

# An algorithmic approach

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An attempt to choose  $\rho_0$  based on degree of vertices in different ways. We hoped to minimize the number of edges between active and inactive vertices

- There are two simple cases - picking the largest degree vertices, and picking the smallest degree vertices
- Can either also choose to infect the neighbors of the chosen vertices or not
- Looked into our own algorithm that chooses vertices with "greatest degree less than remaining"

# Algorithms, 10 vertices

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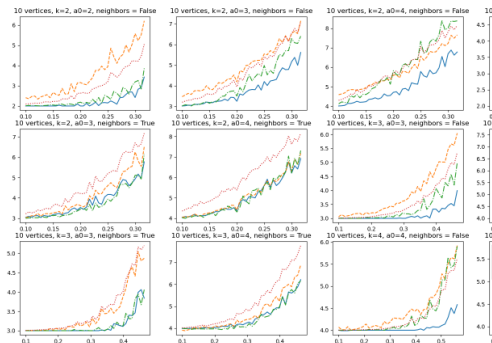
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The algorithms on random graphs of 10

# Algorithms, 1000 vertices

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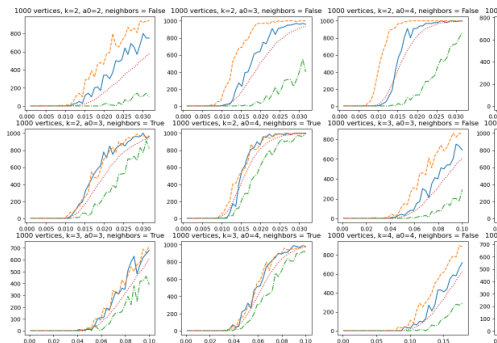
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# Results

## Graph Bootstrap Percolation

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### Results

Empirically, choosing the vertices with smallest considering neighbors is the best algorithm for activation of a random graph

- Considered the same p-values as in the SE
- 10 vertex case is unique, potentially due to
  - Higher variance
  - Both  $|V_0|$  and  $k$  being close to the number

# Next Steps

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We plan to continue looking into the algorithm to better understand the probability behind why certain algorithms perform as they do, and how likely they are to perform within a certain threshold.

# Questions

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Thank you!  
Any questions?