

Information Cascades on Arbitrary Topologies

Jun Wan, Yu Xia, Liang Li and Thomas Moscibroda

Presented by Oliver Richter

Influence

you can make a difference

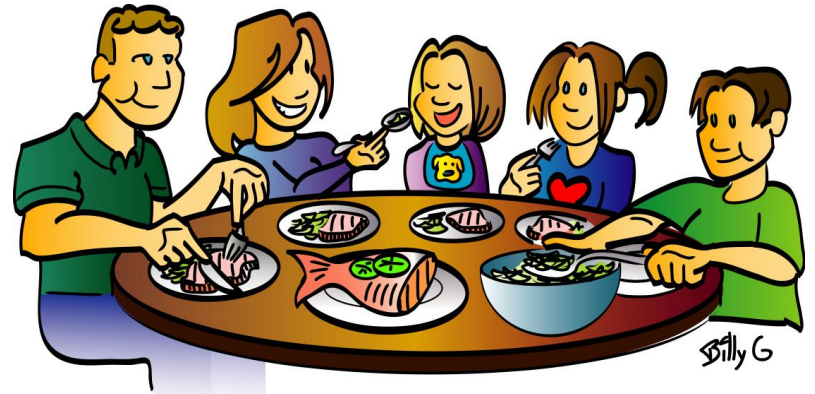


Example Restaurant

Option A



Option B



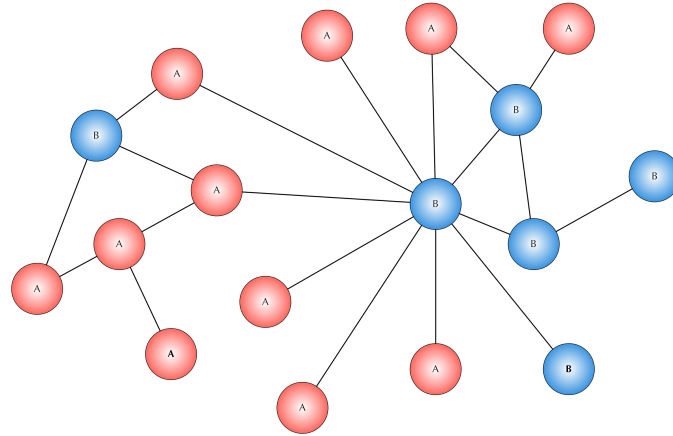
Other Examples



Fashion



Mass movements



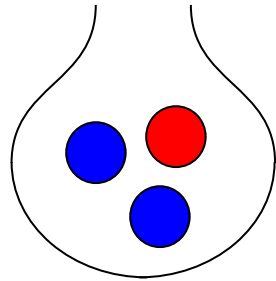
Voting



Books

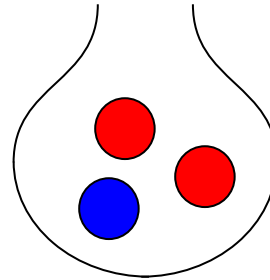
The Model

50% chance



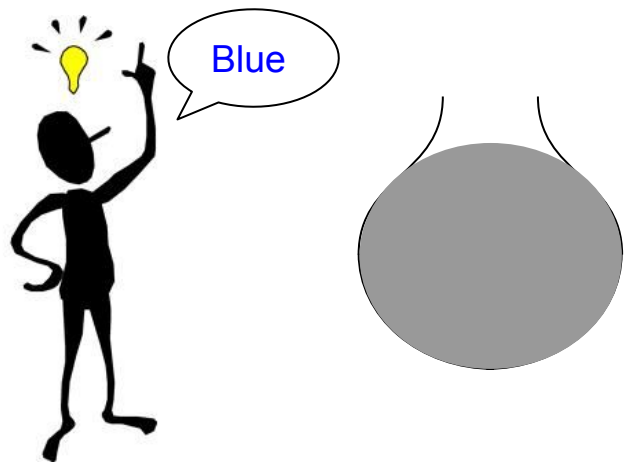
“Majority blue”

50% chance



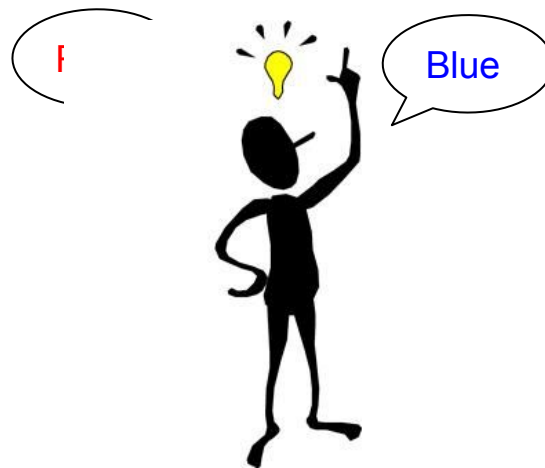
“Majority red”

The Model



1. Student

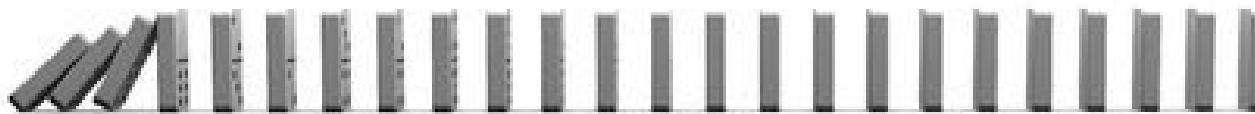
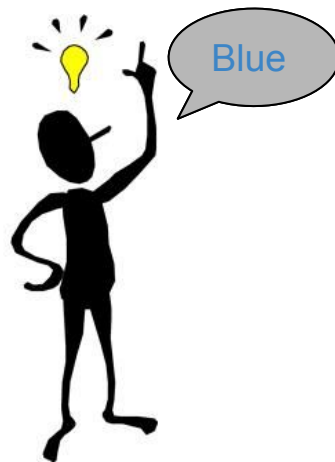
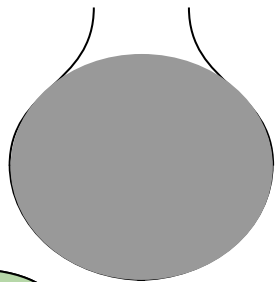
- Announces what he/she sees
- Reveals private information



2. Student

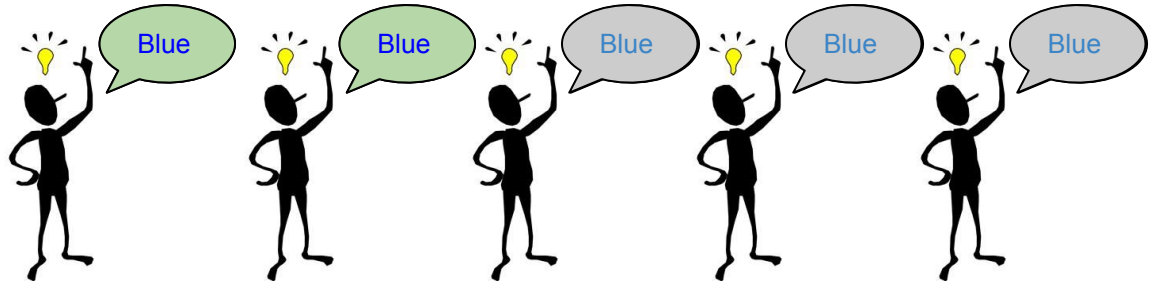
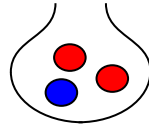
- Announces what he/she sees
- Reveals private information

The Model

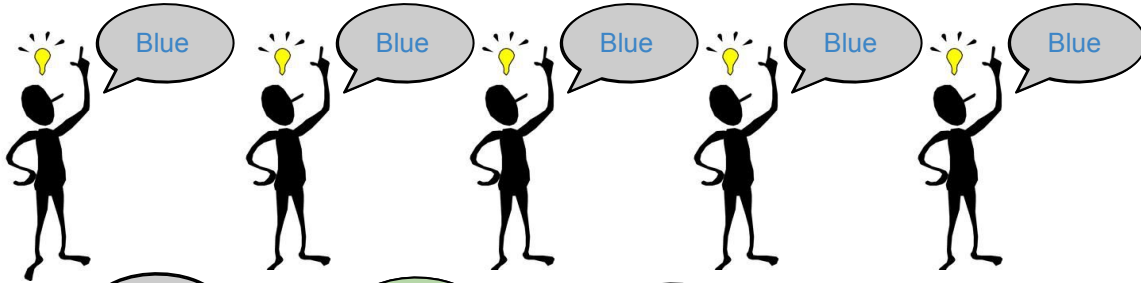


Information Cascades

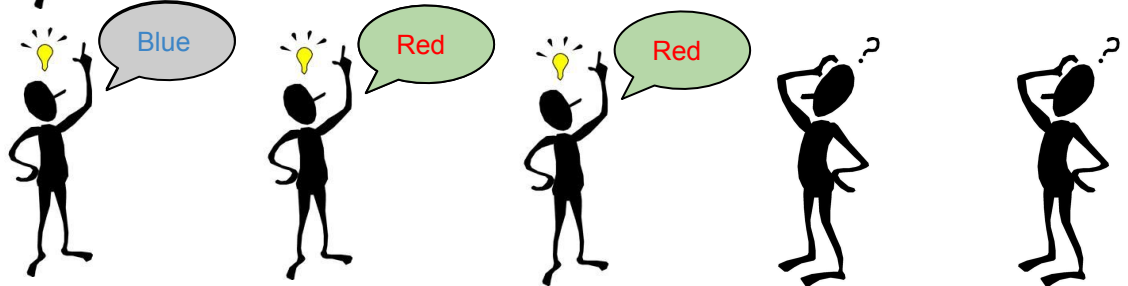
- ...can be wrong



- ...are based on little information

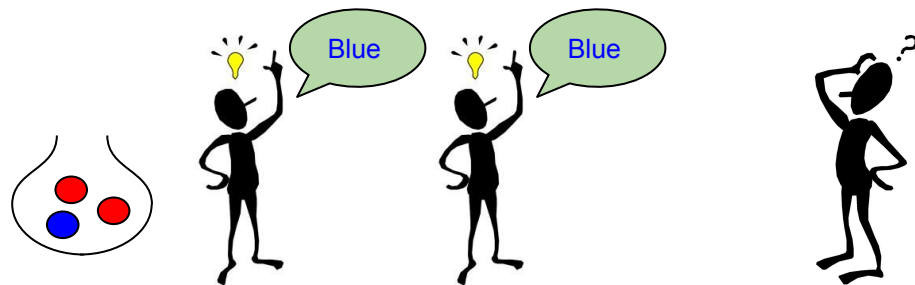


- ...are fragile



The General Model

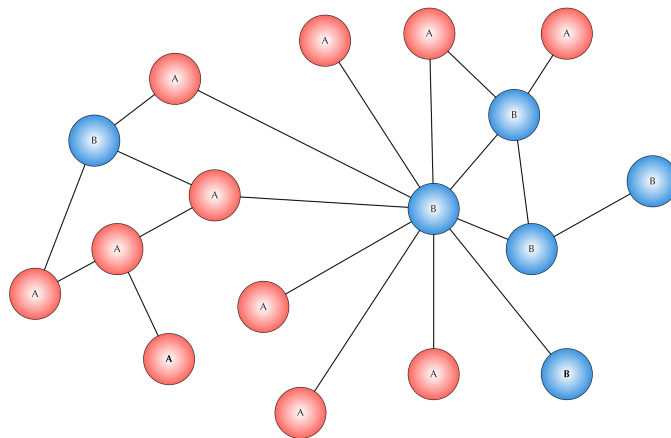
- Each agent has to accept or reject a given option
 - Limited private information
 - Public announcements of others
 - Private information is correct with probability $q > \frac{1}{2}$
- The world is in one of two states
 - Accepting is good
 - Rejecting is good



- Urne example
 - $q = \frac{2}{3}$
 - Accept “majority blue” or reject it (i.e. aim for “majority red”)

Related Work

- Sequential setting:
 - Kleinberg:¹⁾ Majority algorithm on independent signals is optimal
- Round based setting:
 - Golub and Jackson:²⁾
Convergence to truth if influence vanishes



1) *Networks, crowds, and markets: Reasoning about a highly connected world.* Cambridge University Press, 2010.

2) *Naïve Learning in Social Networks and the Wisdom of Crowds.* American Economic Journal: Microeconomics 2010

How good are we doing?

Let n be the number of students

Full information

- Chance of a wrong information cascade on 3. student: $\frac{1}{3} * \frac{1}{3} = \frac{1}{9}$
- Chance of a wrong cascade in total:

$$\frac{1}{9} + \frac{1}{3} \sum_{k=1}^n \left(\frac{2}{3} \cdot \frac{1}{3} \right)^k \approx \frac{1}{5} \quad \text{for } n \rightarrow \infty$$

- Expected number of wrong guesses $\approx \frac{1}{5} n$

How good are we doing?

Let n be the number of students

No information

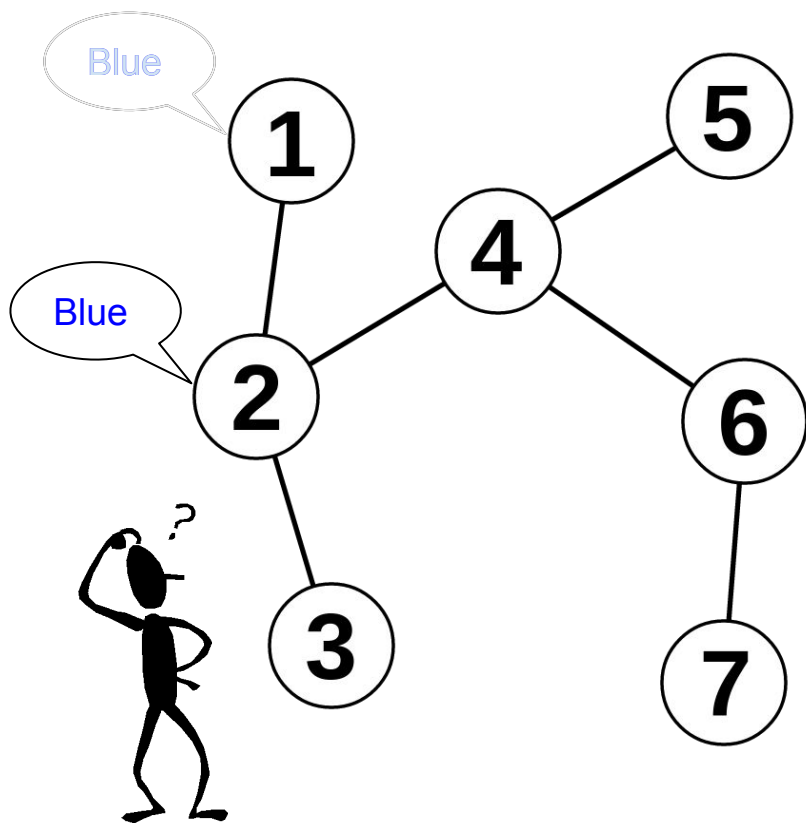
- Everybody follows private information
- Expected number of wrong guesses = $\frac{1}{3} * n$

In both cases:

→ $\Omega(n)$ expected mistakes!

Can we do better?

Information Sharing Based on Graphs



How much connectivity is needed?

Random Graph $G(n,p)$

- n is the number of nodes
- Each pair of nodes is connected with probability p



$p = 0.1$



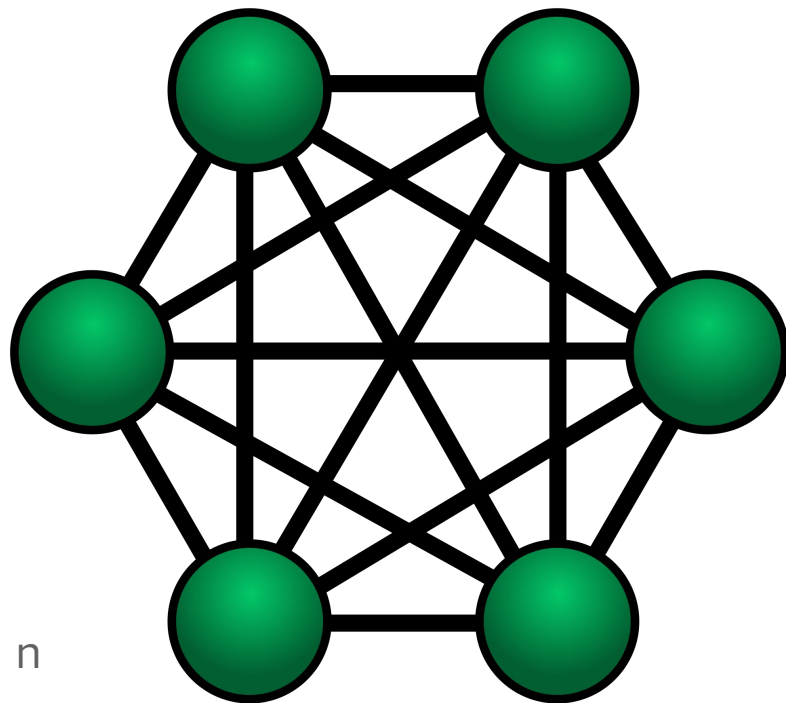
$p = 0.25$



$p = 0.5$

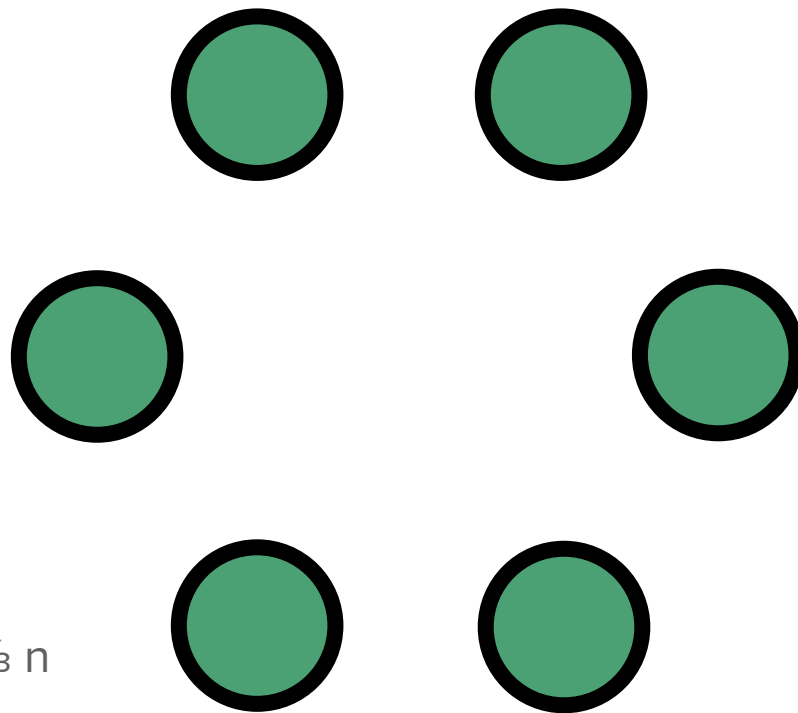
Random Graph $G(n,p)$

- $p = 1 \rightarrow$ fully connected graph
- All nodes get information of all other nodes
- Chance of a wrong cascade $\approx \frac{1}{5}$
- Expected number of wrong guesses $\approx \frac{1}{5} n$



Random Graph $G(n,p)$

- $p = 0 \rightarrow$ empty graph
- All nodes get only their private information
- Chance of being wrong = $\frac{1}{3}$
- Expected number of wrong guesses = $\frac{1}{3} n$



Random Graph $G(n,p)$

- $p = 1 \rightarrow$ fully connected graph \rightarrow full information $\rightarrow \Omega(n)$ mistakes
- $p = 0 \rightarrow$ empty graph \rightarrow no information sharing $\rightarrow \Omega(n)$ mistakes
- What happens in between?

Majority algorithm on random graphs with optimal connection probability p results in $\Theta(\log n)$ mistakes in expectation

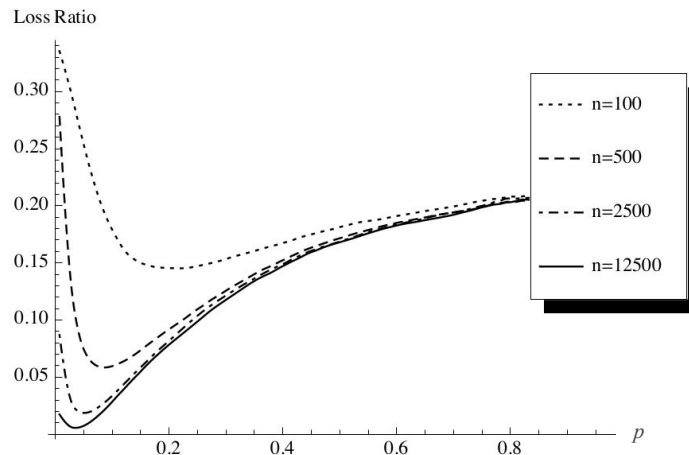
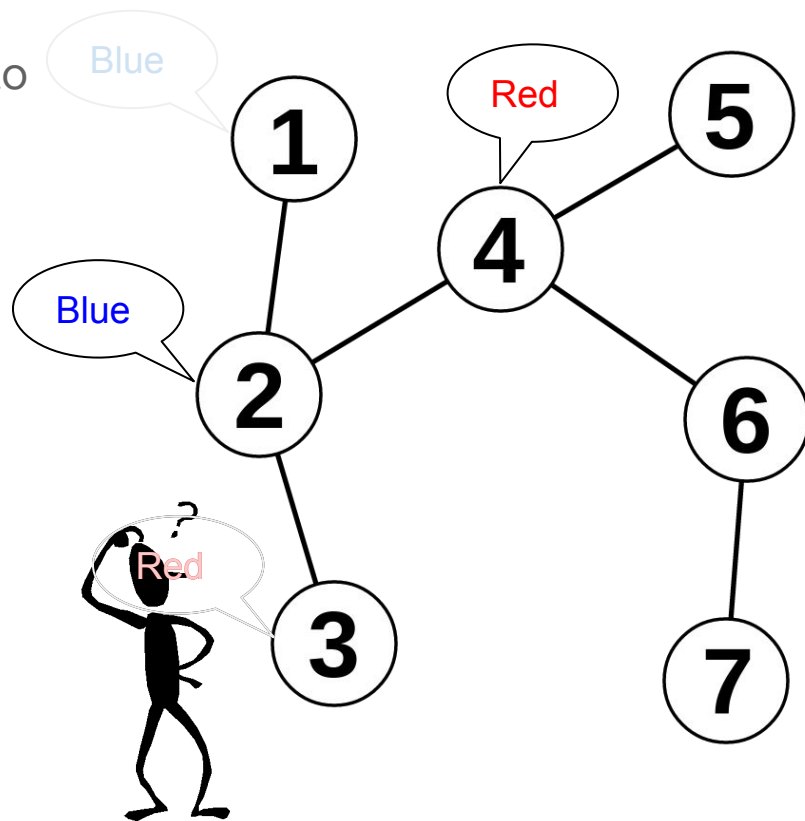


Figure 1 Performance of random graphs for different p and n .

How come?

- Basic idea: less neighbors \rightarrow more likely to reveal private information
 - \rightarrow Increased chance of correct information cascade
- If $p \in \Theta(1/\log n)$, w.h.p. each of the first $\Theta(\log n)$ nodes has at most one neighbor
- Nodes with at most one neighbor reveal private information

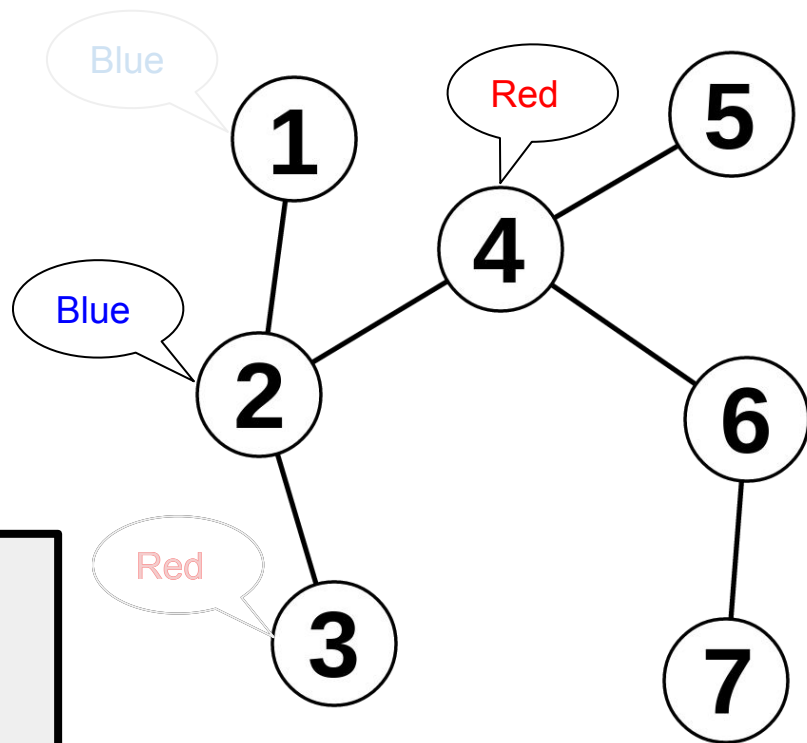


How come?

- If $p \in \Theta(1/\log n)$, w.h.p. each of the first $\Theta(\log n)$ nodes has at most one neighbor
 - Nodes with at most one neighbor reveal private information
- The first $\Theta(\log n / p)$ nodes mostly correct
- The remaining $n - \Theta(\log n / p)$ nodes have expected number of mistakes in $O(1)$

$\Theta(\log n)$ expected mistakes for correct p

→ Fraction of mistakes goes to 0 as $n \rightarrow \infty$



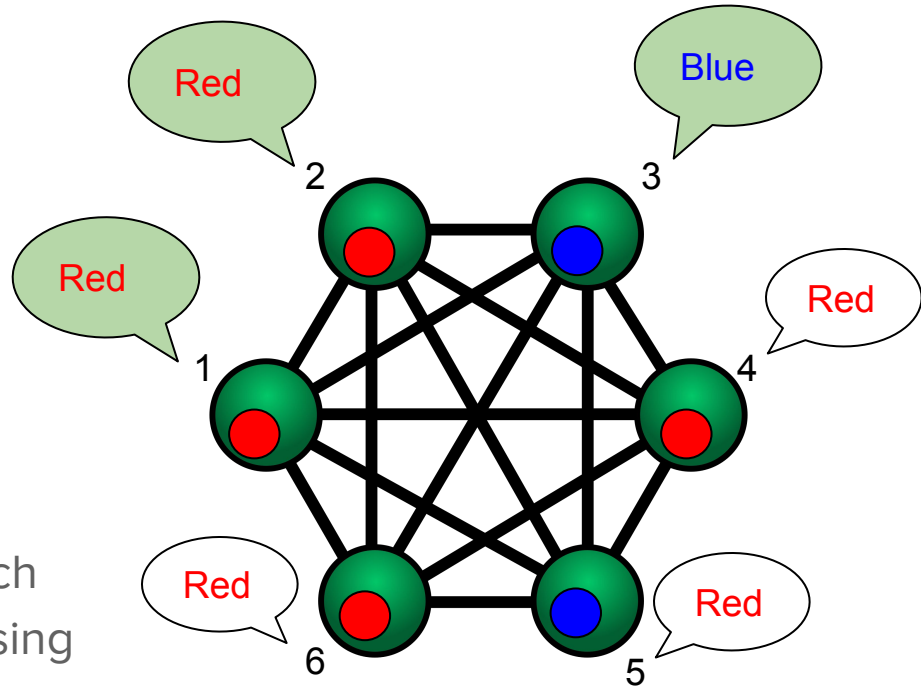
Can we do better?

- Each node i should try to minimize the expected number of wrong guesses
- Optimal algorithm:
 - Node n tries to minimize its own failure probability
 - Node $n-1$ tries to minimize the failure probability of itself and node n
 - ...
 - Node 1 tries to minimize the overall failure probability
 - Given how node 1 decides, node 2 can determine how it will decide in each case
 - ...
 - Given how nodes 1 to $n-1$ will decide in each case, node n can determine how it will decide

More concrete

Given full information

- Up to a given point, nodes reveal their private information
 - From that point on, all nodes will choose the majority of previous outputs
- At a given switching point m , nodes switch from revealing private information to choosing the majority of previous outputs
- $m > \Omega(\log n)$ or the expected number of mistakes is $> \sqrt{n} / 2$



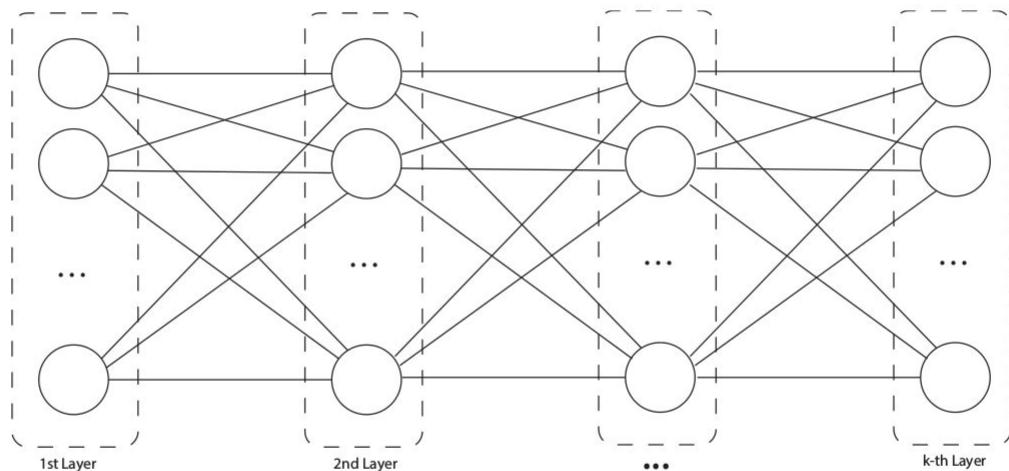
What we have seen so far...

- Random graphs achieve $\Theta(\log n)$ expected mistakes
- $\Theta(\log n)$ expected mistakes is asymptotically optimal
- Can we achieve it without randomness?

Layer Graphs

Idea:

Choose the number and sizes of the layers such that the expected number of mistakes is minimal, i.e. in $\Theta(\log n)$



- Let $s = 1/(4q(1 - q))$, $q > 1/2$ is the probability of a private information being correct
- The optimal layer topology has $k = n / \log_s(n) + o(n / \log_s(n))$ many layers
- The first layer has $\log_s(n)$ many nodes
- All following layers decrease in size as a staircase

Conclusion

- Too much information is (asymptotically) as bad as no shared information
- Just enough information can lead to less mistakes
- This can be achieved through:
 - Connectivity regulation
 - Algorithmic regulation
 - Structural regulation

