

Online Social Networks and Media

Opinion formation models

Positive and negative ties

OPINION FORMATION IN SOCIAL NETWORKS

Diffusion of items

- So far we have assumed that what is being diffused in the network is some **discrete item**:
 - E.g., a virus, a product, a video, an image, a link etc.
- For each network user a **binary decision** is being made about the item being diffused
 - Being infected by the virus, adopt the product, watch the video, save the image, retweet the link, etc.
 - This decision may happen with some probability, but the probability is over the **discrete values** $\{0,1\}$ and the decisions usually do not change

Diffusion of opinions

- The network can also diffuse **opinions**.
 - What people believe about an issue, a person, an item, is shaped by their social network
- People hold opinions that may change over time due to social influence
- Opinions may assume a **continuous range of values**, from completely negative to completely positive.
 - **Opinion diffusion** is different from item diffusion
 - It is often referred to as **opinion formation**.

Modeling opinion formation

- There is a lot of work from different perspectives:
 - **Psychologists/Sociologists**: field experiments and decades of observations
 - **Statistical Physicists**: model humans as particles and predict their behavior
 - **Mathematicians/Economists**: Use game theory to model human behavior
 - **Computer Scientists**: build algorithms on top of the models
- Questions asked:
 - How do societies reach **consensus**?
 - Not always the case, but necessary for many issues in order for society to function
 - When do we get **polarization** or **opinion clusters**?
 - More realistic in the real world where consensus tends to be local

Opinion formation models

- An **opinion** is a **real value**
 - E.g., a value in the interval $[0,1]$, or $[-1,1]$
- Opinions are shaped through our interactions with our **social network**

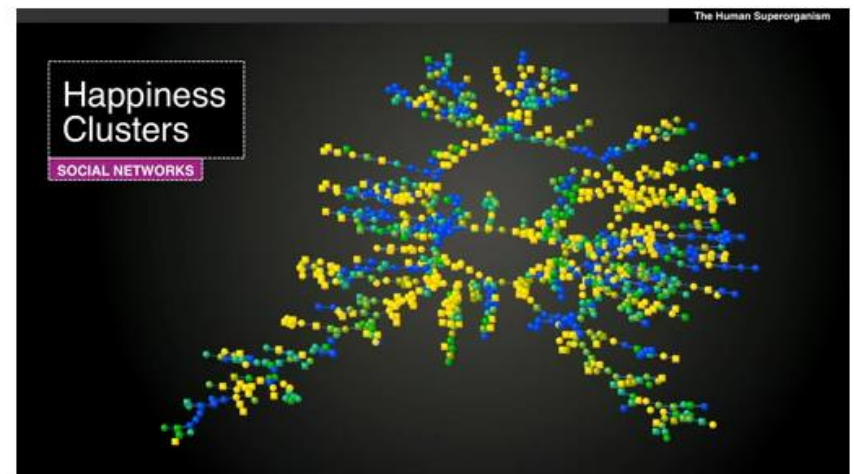
prevent global warming



reduce military spending

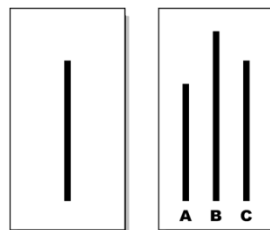


fight poverty



Social Influence

- There are two main types of social influence:
 - **Normative Influence**: Users influenced by opinion of neighbors due to social norms, conformity, group acceptance, avoiding ridicule, etc
 - **Informational Influence**: Users lacking necessary information, or not trusting their information, use opinion of neighbors to form their opinions
- Asch's conformity experiment:



Opinion formation models literature

- Long list of models
 - Ising model
 - *Claudio Castellano, Santo Fortunato, and Vittorio Loreto. 2009. Statistical physics. of social dynamics. Rev. Mod. Phys. 81 (May 2009), 591–646.*
 - Voter model
 - *Holley and Liggett. 1975. Ergodic Theorems for Weakly Interacting Infinite Systems and the Voter Model. The Annals of Probability 3, 4 (1975), 643–663.*
 - DeGroot Model
 - *DeGroot. 1974. Reaching a consensus. JASA 69, 345 (1974), 118–121*
 - Friedkin-Johnson model
 - *Friedkin and Johnsen. 1990. Social influence and opinions. Journal of Mathematical Sociology 15, 3-4 (1990), 193–206.*
 - Bounded Confidence models
 - *Deffuant, Neau, Amblard, and Weisbuch. Mixing beliefs among interacting agents. Advances in Complex Systems. 2000.*
 - *Krause. A discrete nonlinear and non-autonomous model of consensus formation. Communications in difference equations. 2000.*
 - Axelrod cultural dynamics
 - *Axelrod. The dissemination of culture: A model with local convergence and global polarization. Journal of conflict resolution. 1997.*
 - ... and multiple variants of those...

De Groot opinion formation model

- Every user i has an opinion $z_i \in [0,1]$
- The opinion of each user in the network is **iteratively** updated, each time taking the **average** of the opinions of its neighbors and herself

$$z_i^t = \frac{w_{ii}z_i^{t-1} + \sum_{j \in N(i)} w_{ij}z_j^{t-1}}{w_{ii} + \sum_{j \in N(i)} w_{ij}}$$

– where $N(i)$ is the set of neighbors of user i .

DeGroot opinion formation model

- This iterative process converges

$$z_i = \frac{w_{ii}z_i + \sum_{j \in N(i)} w_{ij}z_j}{w_{ii} + \sum_{j \in N(i)} w_{ij}}$$

- We can show that the process will converge to **consensus**
- At convergence $z_i = z^*$ for all nodes i

What about personal biases?

- People tend to cling on to their personal opinions



The Friedkin and Johnsen opinion formation model

- Every user i has an **intrinsic opinion** $s_i \in [0,1]$ and an **expressed opinion** $z_i \in [0,1]$
- The public opinion z_i of each user in the network is **iteratively** updated, each time taking the **average** of the **expressed opinions** of its neighbors and the **intrinsic opinion** of herself

$$z_i^t = \frac{w_{ii}s_i + \sum_{j \in N(i)} w_{ij}z_j^{t-1}}{w_{ii} + \sum_{j \in N(i)} w_{ij}}$$

The Friedkin and Johnsen opinion formation model

- The FJ model also converges but not to a consensus
- At convergence:

$$z_i = \frac{w_{ii}s_i + \sum_{j \in N(i)} w_{ij}z_j}{w_{ii} + \sum_{j \in N(i)} w_{ij}}$$

Opinion formation as a game

- Assume that network users are **rational** (selfish) agents
- Each user has a **personal cost** for expressing an opinion

$$c(z_i) = w_{ii}(z_i - s_i)^2 + \sum_{j \in N(i)} w_{ij}(z_i - z_j)^2$$

Inconsistency cost: The cost for **deviating** from one's intrinsic opinion

Conflict cost: The cost for **disagreeing** with the opinions in one's social network

- Each user is selfishly trying to minimize her personal cost.

D. Bindel, J. Kleinberg, S. Oren. *How Bad is Forming Your Own Opinion?* Proc. 52nd IEEE Symposium on Foundations of Computer Science, 2011.

Opinion formation as a game

- The opinion z_i that **minimizes** the personal cost of user i

$$z_i = \frac{w_{ii}s_i + \sum_{j \in N(i)} w_{ij}z_j}{w_{ii} + \sum_{j \in N(i)} w_{ij}}$$

- In linear algebra terms (assume 0/1 weights):

$$(L + I)\mathbf{z} = \mathbf{s} \Rightarrow \mathbf{z} = (L + I)^{-1}\mathbf{s}$$

where L is the **Laplacian** of the graph.

Reminder: The Laplacian is the negated adjacency matrix with the degree on the diagonal

Understanding opinion formation

- To better study the opinion formation process we will show a connection between opinion formation and **absorbing random walks**.

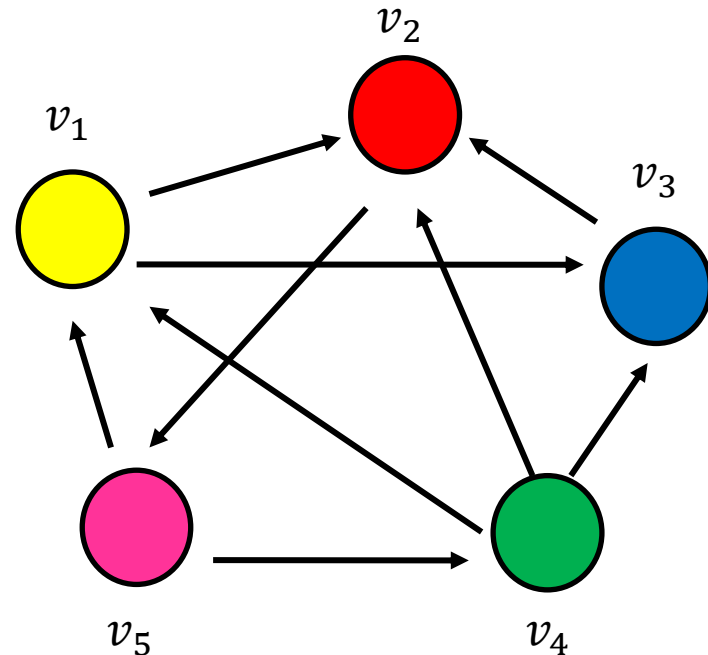
Random Walks on Graphs

- A **random walk** is a stochastic process performed on a graph
- Random walk:
 - **Start** from a node chosen **uniformly at random** with probability $\frac{1}{n}$.
 - **Pick** one of the **outgoing edges** **uniformly at random**
 - **Move** to the destination of the edge
 - Repeat.
- Made very popular with Google's **PageRank** algorithm.

The Transition Probability matrix

$$A = \begin{bmatrix} 0 & 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ 0 & 1 & 0 & 0 & 0 \\ 1 & 1 & 1 & 0 & 0 \\ 1 & 0 & 0 & 1 & 0 \end{bmatrix}$$

$$P = \begin{bmatrix} 0 & 1/2 & 1/2 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ 0 & 1 & 0 & 0 & 0 \\ 1/3 & 1/3 & 1/3 & 0 & 0 \\ 1/2 & 0 & 0 & 1/2 & 0 \end{bmatrix}$$



$P[i, j] = 1/d_{out}(i)$: Probability of transitioning from node i to node j .

Node Probability vector

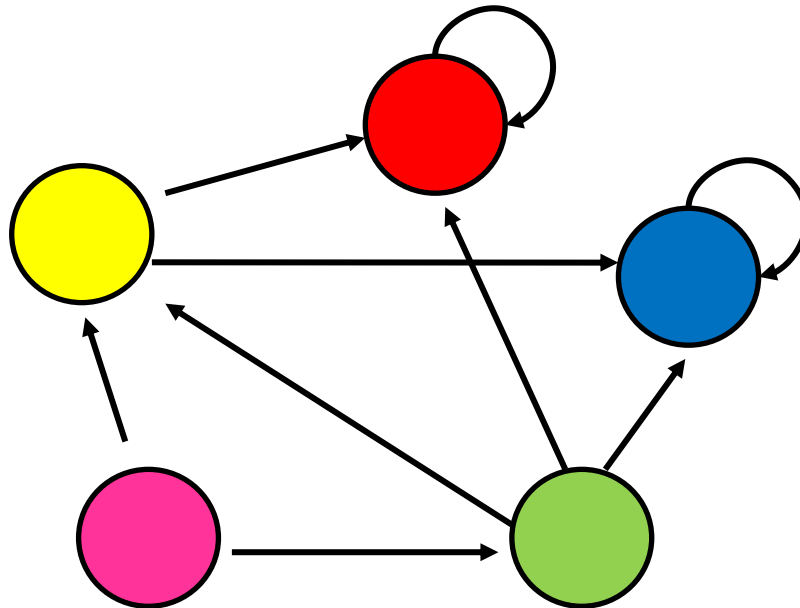
- The vector $p^t = (p_1^t, p_2^t, \dots, p_n^t)$ that stores the probability of being at node v_i at step t
 - p_i^0 = the probability of starting from state i (usually) set to **uniform**
- We can compute the vector p^t at step t using a vector-matrix multiplication
$$p^t = p^{t-1} P = p^0 P^t$$
- After many steps $p^t \rightarrow \pi$ the probability converges to the stationary distribution π

Stationary distribution

- The **stationary distribution** of a random walk with transition matrix P , is a probability distribution π , such that $\pi = \pi P$
- The **stationary distribution** is **independent of the initial vector** if the graph is **strongly connected**, and **not bipartite**.
- All the rows of the matrix P^∞ are equal to the stationary distribution π
- The stationary distribution is an **eigenvector** of matrix P
 - the **principal left eigenvector** of P – stochastic matrices have maximum eigenvalue 1
- The probability π_i is the fraction of times that we visited state i as $t \rightarrow \infty$

Random walk with absorbing nodes

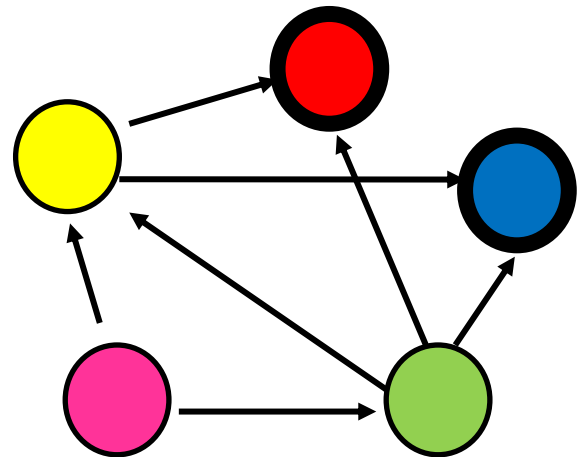
- **Absorbing nodes:** nodes from which the random walk cannot escape.



- Two absorbing nodes: the red and the blue.

Absorption probability

- In a graph with more than one **absorbing nodes** a random walk that starts from a **non-absorbing (transient)** node t will be absorbed in one of them with some probability
 - For a transient node t we can compute the **probability of absorption** at an absorbing node s



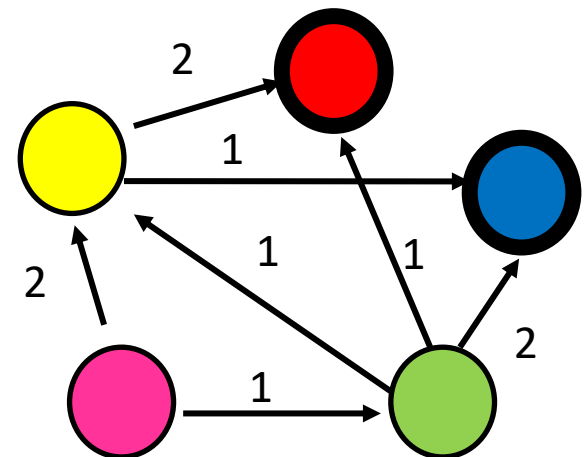
Absorption probabilities

- Computing the probability of being absorbed:
 - The **absorbing nodes** have probability 1 of being absorbed in themselves and zero of being absorbed in another node.
 - For the **non-absorbing nodes**, take the (weighted) average of the absorption probabilities of your neighbors
 - if one of the neighbors is the absorbing node, it has probability 1
 - Repeat until convergence (= very small change in probs)

$$P(\text{Red}|\text{Pink}) = \frac{2}{3}P(\text{Red}|\text{Yellow}) + \frac{1}{3}P(\text{Red}|\text{Green})$$

$$P(\text{Red}|\text{Green}) = \frac{1}{4}P(\text{Red}|\text{Yellow}) + \frac{1}{4}$$

$$P(\text{Red}|\text{Yellow}) = \frac{2}{3}$$



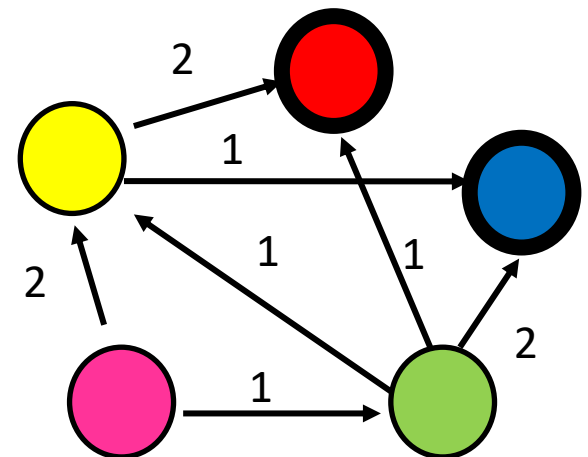
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 - if one of the neighbors is the absorbing node, it has probability 1
 - Repeat until convergence (= very small change in probs)

$$P(\text{Blue}|\text{Pink}) = \frac{2}{3}P(\text{Blue}|\text{Yellow}) + \frac{1}{3}P(\text{Blue}|\text{Green})$$

$$P(\text{Blue}|\text{Green}) = \frac{1}{4}P(\text{Blue}|\text{Yellow}) + \frac{1}{2}$$

$$P(\text{Blue}|\text{Yellow}) = \frac{1}{3}$$



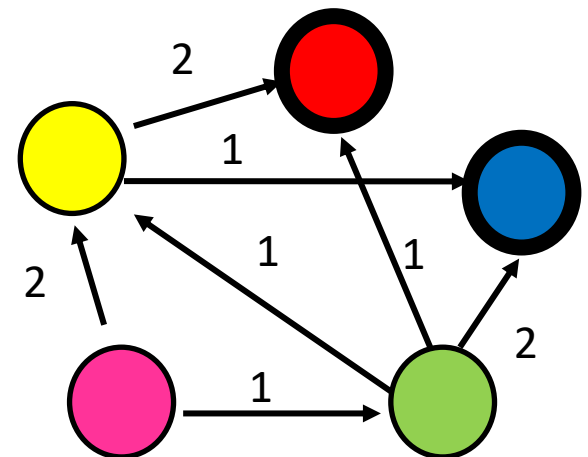
Absorption probabilities

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General equation for the probability of transient node t being absorbed at absorbing node a

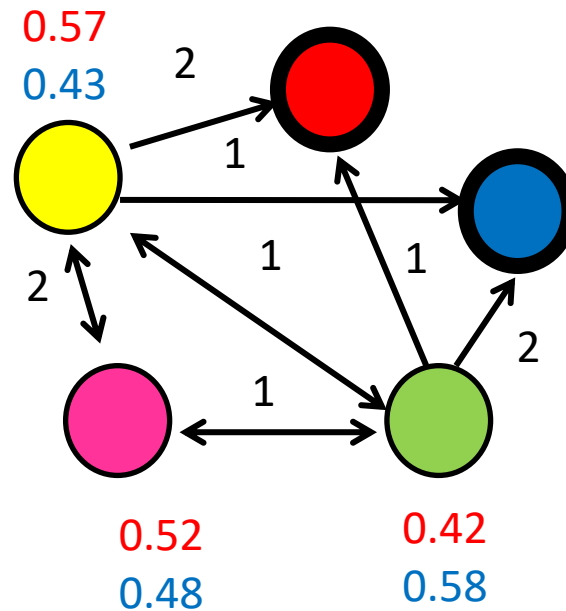
$$P(a|t) = \sum_{(t,x) \in E} P_{tx} P(a|x)$$

The weighted average of the neighbors



Absorption probabilities

- Compute the absorption probabilities for red and blue



Absorption probabilities

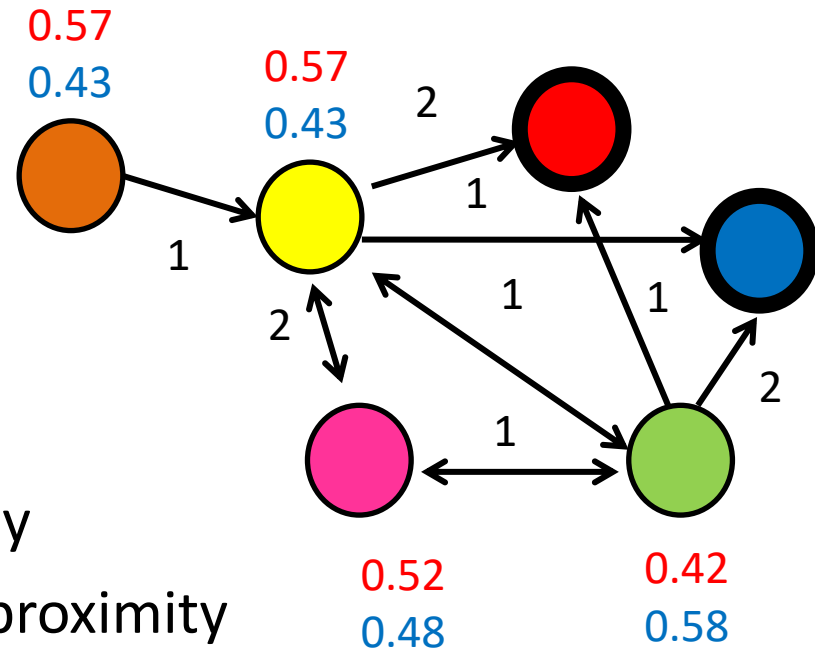
- The absorption probability has several practical uses.
- Given a graph (**directed** or **undirected**) we can choose to **make** some nodes **absorbing**.
 - Simply **direct** all edges incident on the chosen nodes towards them and create a self-loop.
- The absorbing random walk provides a measure of **proximity** of transient nodes to the chosen nodes.
 - Useful for **understanding** proximity in graphs
 - Useful for **propagation** in the graph
 - E.g, on a social network some nodes are **malicious**, while some are **certified**, to which class is a transient node closer?

Penalizing long paths

- The orange node has the same probability of reaching red and blue as the yellow one

$$P(\text{Red}|\text{Orange}) = P(\text{Red}|\text{Yellow})$$

$$P(\text{Blue}|\text{Orange}) = P(\text{Blue}|\text{Yellow})$$



- Intuitively though it is further away
- The probability does not capture proximity

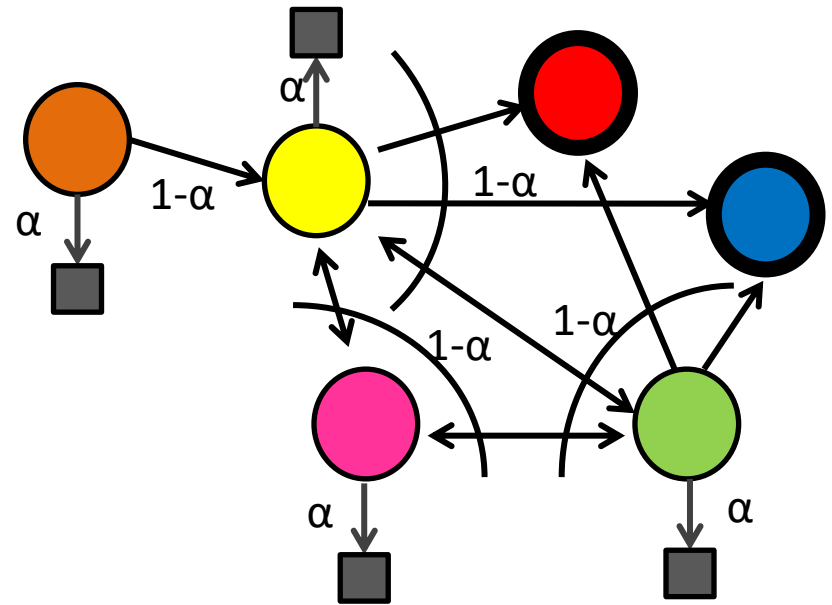
Penalizing long paths

- Add a **universal absorbing node** to which each node gets absorbed with probability α .

With probability α the random walk **dies**

With probability $(1-\alpha)$ the random walk continues as before

The longer the path from a node to an absorbing node the more likely the random walk dies along the way, the lower the absorption probability



$$P(\text{Red}|\text{Green}) = (1 - \alpha) \left(\frac{1}{4} P(\text{Red}|\text{Yellow}) + \frac{1}{4} P(\text{Red}|\text{Pink}) + \frac{1}{4} \right)$$

Linear Algebra

- The transition matrix of the absorbing random walk looks like this

$$P = \begin{array}{c|c} \text{T} & \text{A} \\ \hline \begin{bmatrix} P_{TT} \\ 0 \end{bmatrix} & \begin{bmatrix} P_{TA} \\ I \end{bmatrix} \end{array} \begin{array}{l} \text{T: transient} \\ \text{A: absorbing} \end{array}$$

- P_{TT} : transition probabilities between transient nodes
- P_{TA} : transition probabilities from transient to absorbing nodes
- Computing the absorption probabilities corresponds to iteratively multiplying matrix P with itself

Linear Algebra

- After many iterations:

$$P^{\infty} = \begin{bmatrix} 0 & Q \\ 0 & I \end{bmatrix}$$

- The matrix Q holds the absorption probabilities
 - $Q[i, k]$ = The **probability** of being **absorbed** in absorbing state a_k when starting from transient state t_i

$$Q = P_{TA} + P_{TT}P_{TA} + P_{TT}^2P_{TA} + \dots$$

Linear algebra

- The fundamental matrix

$$F = P_{TT} + P_{TT}^2 + \dots = \sum_{i=1}^{\infty} P_{TT}^i = (1 - P_{TT})^{-1}$$

- $F[i, j]$ = The sum of probabilities of visiting **transient** state t_j when starting from state t_i **after any number of steps**
- **Also**: The expected number of visits to **transient** state t_j when starting from state t_i **after any number of steps**
- The transient-to-absorbing matrix Q

$$Q = F P_{TA}$$

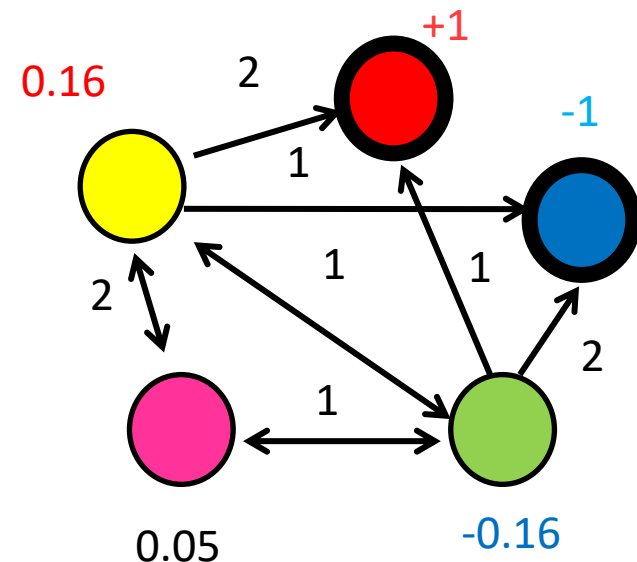
Propagating values

- Assume that **Red** has a positive value and **Blue** a negative value
- We can compute a value for all transient nodes in the same way we compute probabilities
 - This is the **expected** value at the absorbing node for the non-absorbing node

$$V(\text{Pink}) = \frac{2}{3}V(\text{Yellow}) + \frac{1}{3}V(\text{Green})$$

$$V(\text{Green}) = \frac{1}{5}V(\text{Yellow}) + \frac{1}{5}V(\text{Pink}) + \frac{1}{5} - \frac{2}{5}$$

$$V(\text{Yellow}) = \frac{1}{6}V(\text{Green}) + \frac{1}{3}V(\text{Pink}) + \frac{1}{3} - \frac{1}{6}$$



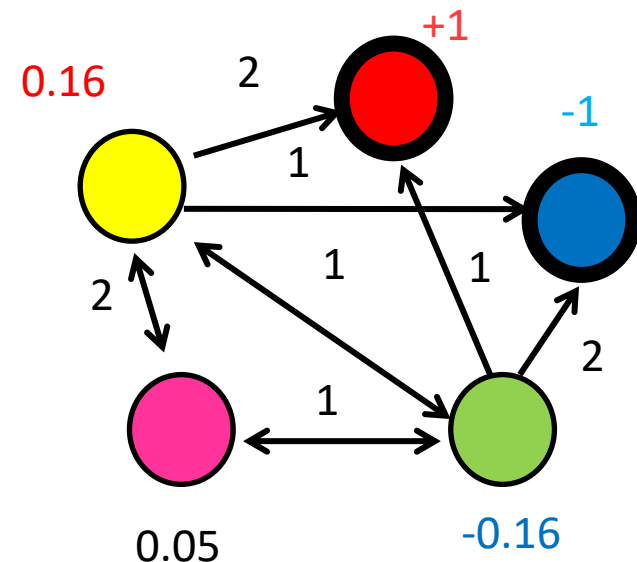
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General equation for value propagation:

$$v(i) = \sum_{(i,j) \in E} P[i,j]v(j)$$

The value of i is the weighted average of the values of its neighbors



Linear algebra

- Computation of values is essentially multiplication of the matrix Q with the vector of values of the absorbing nodes

$$\boldsymbol{v} = \boldsymbol{Q}\boldsymbol{s}$$

- \boldsymbol{s} : vector of values of the absorbing nodes
- \boldsymbol{v} : vector of values of the transient nodes

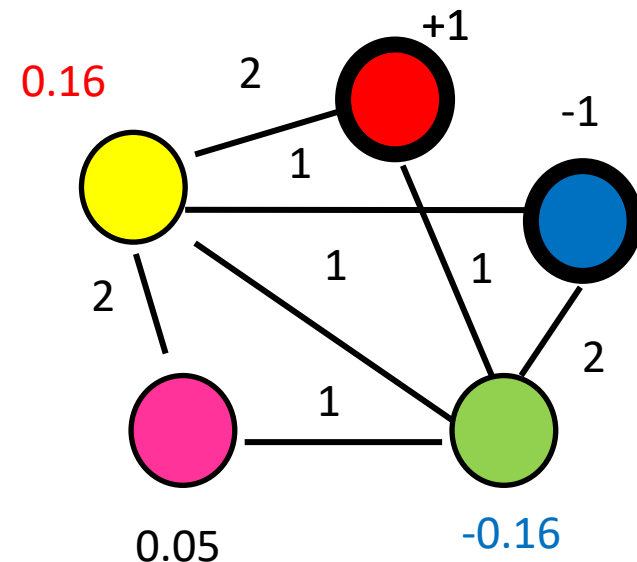
Electrical networks and random walks

- Our graph corresponds to an **electrical network**
- There is a positive **voltage** of **+1** at the Red node, and a negative voltage **-1** at the Blue node
- There are **resistances** on the edges **inversely proportional** to the weights (or **conductance proportional** to the weights)
- The computed values are the **voltages** at the nodes

$$V(\text{Pink}) = \frac{2}{3}V(\text{Yellow}) + \frac{1}{3}V(\text{Green})$$

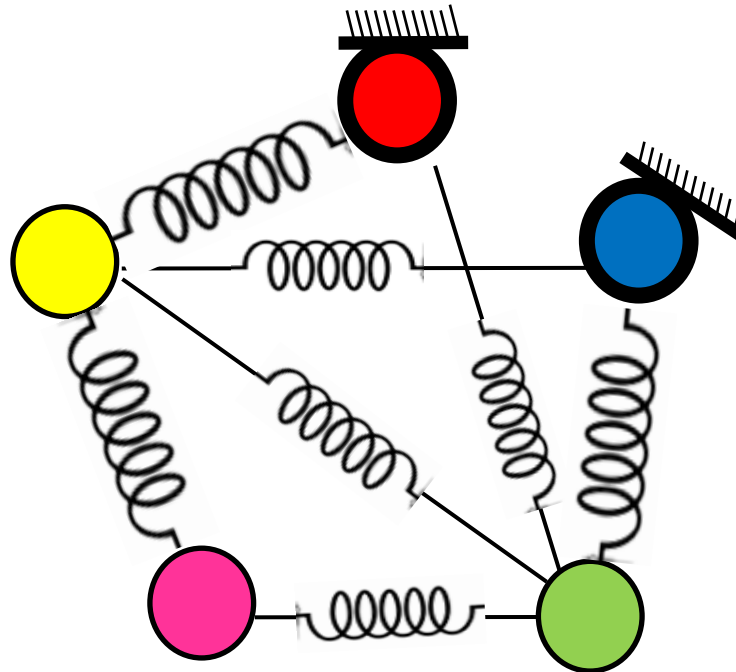
$$V(\text{Green}) = \frac{1}{5}V(\text{Yellow}) + \frac{1}{5}V(\text{Pink}) + \frac{1}{5} - \frac{2}{5}$$

$$V(\text{Yellow}) = \frac{1}{6}V(\text{Green}) + \frac{1}{3}V(\text{Pink}) + \frac{1}{3} - \frac{1}{6}$$



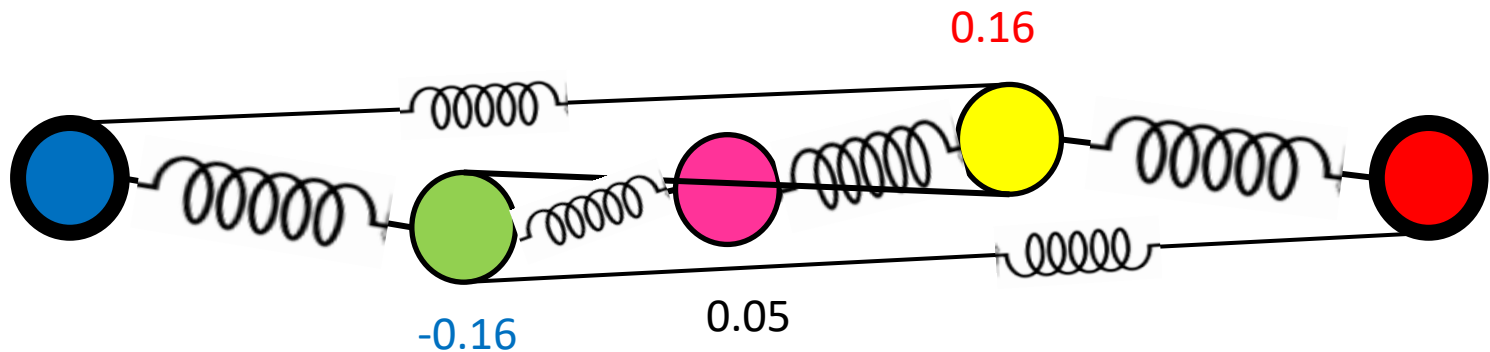
Springs and random walks

- Our graph corresponds to a **spring system**
- The Red node is pinned at position +1, while the Blue node is pinned at position -1 on a line.
- There are **springs** on the edges with hardness **proportional** to the weights
- The computed values are the **positions** of the nodes on the line



Springs and random walks

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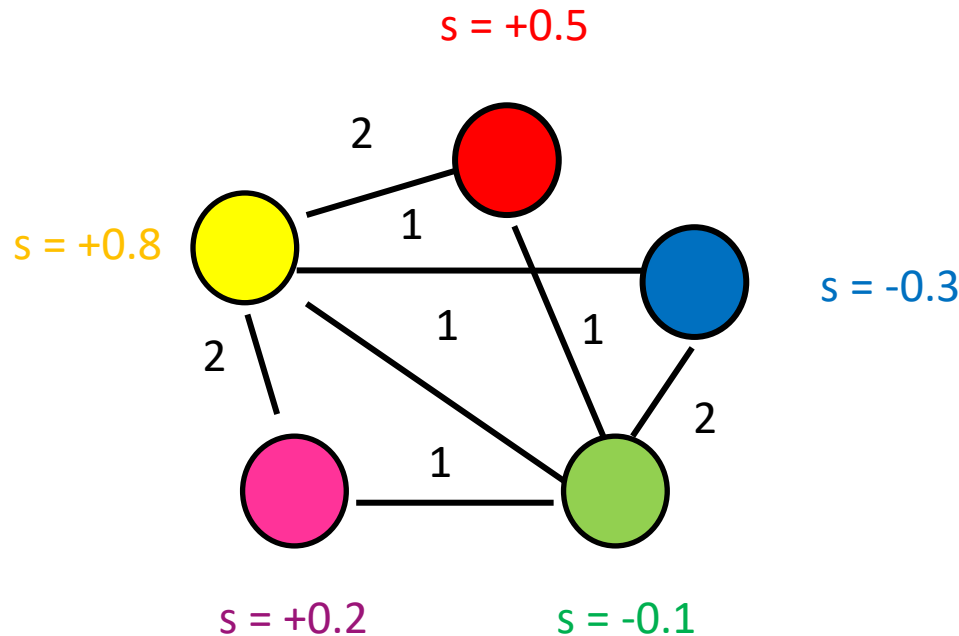


Application: Transductive learning

- If we have a graph of relationships and some **labels** on some nodes we can **propagate** them to the remaining nodes
 - Make the labeled nodes to be absorbing and compute the probability for the rest of the graph
 - E.g., a social network where some people are tagged as spammers
 - E.g., the movie-actor graph where some movies are tagged as action or comedy.
- This is a form of **semi-supervised learning/classification**
 - We make use of the unlabeled data, and the relationships
- It is also called **transductive learning** because it does not produce a model, but just labels the unlabeled data that is at hand.
 - Contrast to **inductive learning** that learns a model and can label any new example

Back to opinion formation

- The **value propagation** we described is closely related to the **opinion formation process/game** we defined.
 - Can you see how we can use absorbing random walks to model the opinion formation for the network below?



Reminder:

$$z_i = \frac{s_i + \sum_{j \in N(i)} w_{ij} z_j}{1 + \sum_{j \in N(i)} w_{ij}}$$

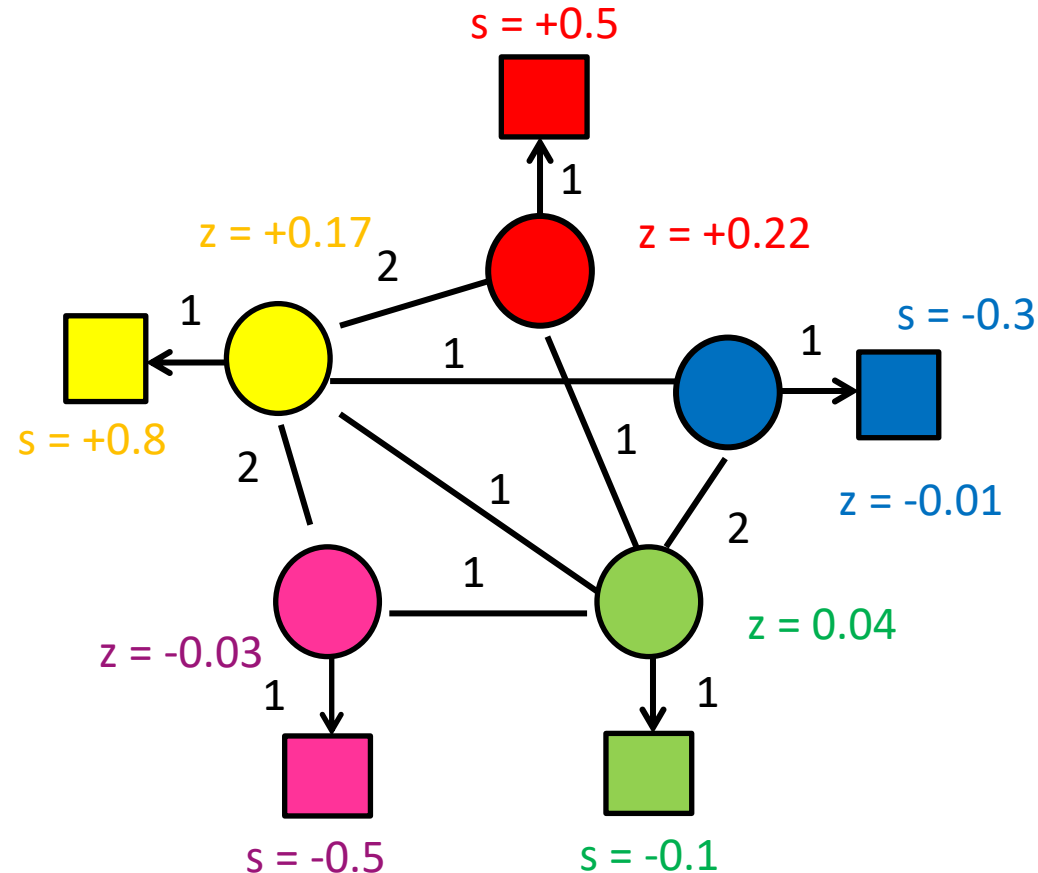
Opinion formation and absorbing random walks

Add to the network one absorbing node per user with value the **intrinsic opinion** of the user

Connect each transient node to her absorbing node with weight w_{ii}

The **expressed opinion** for each node is computed using the value propagation we described

- Repeated averaging



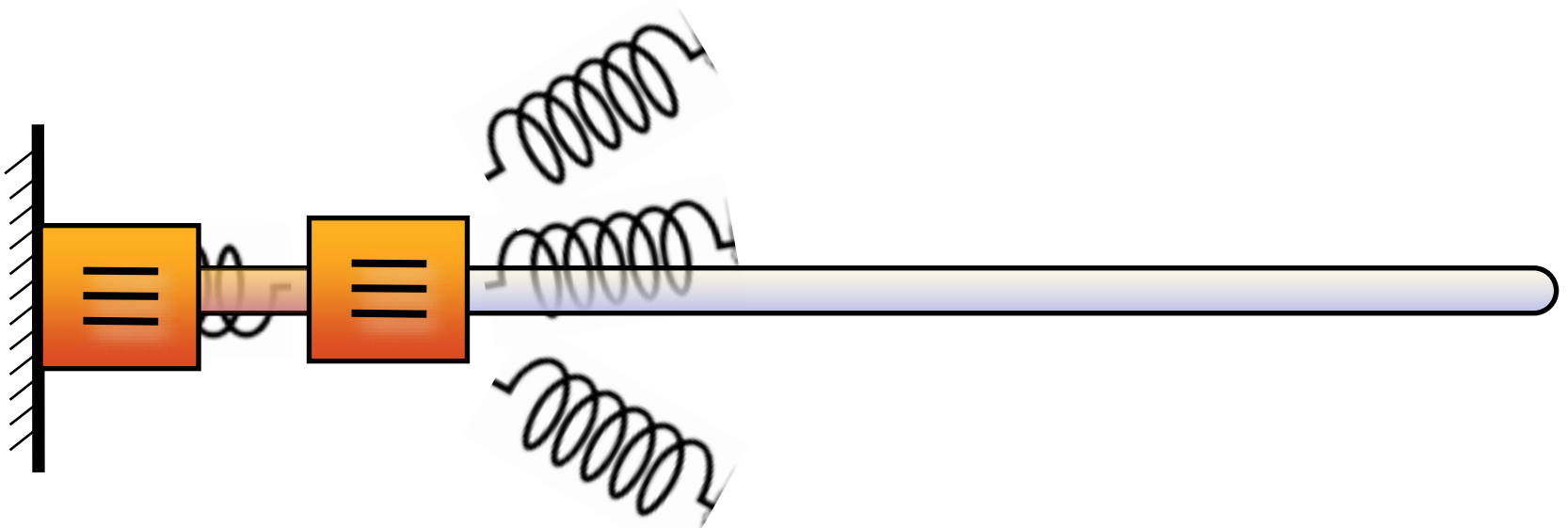
$$v(\text{red}) = \frac{0.5 + 2 \cdot v(\text{yellow}) + v(\text{green})}{4}$$

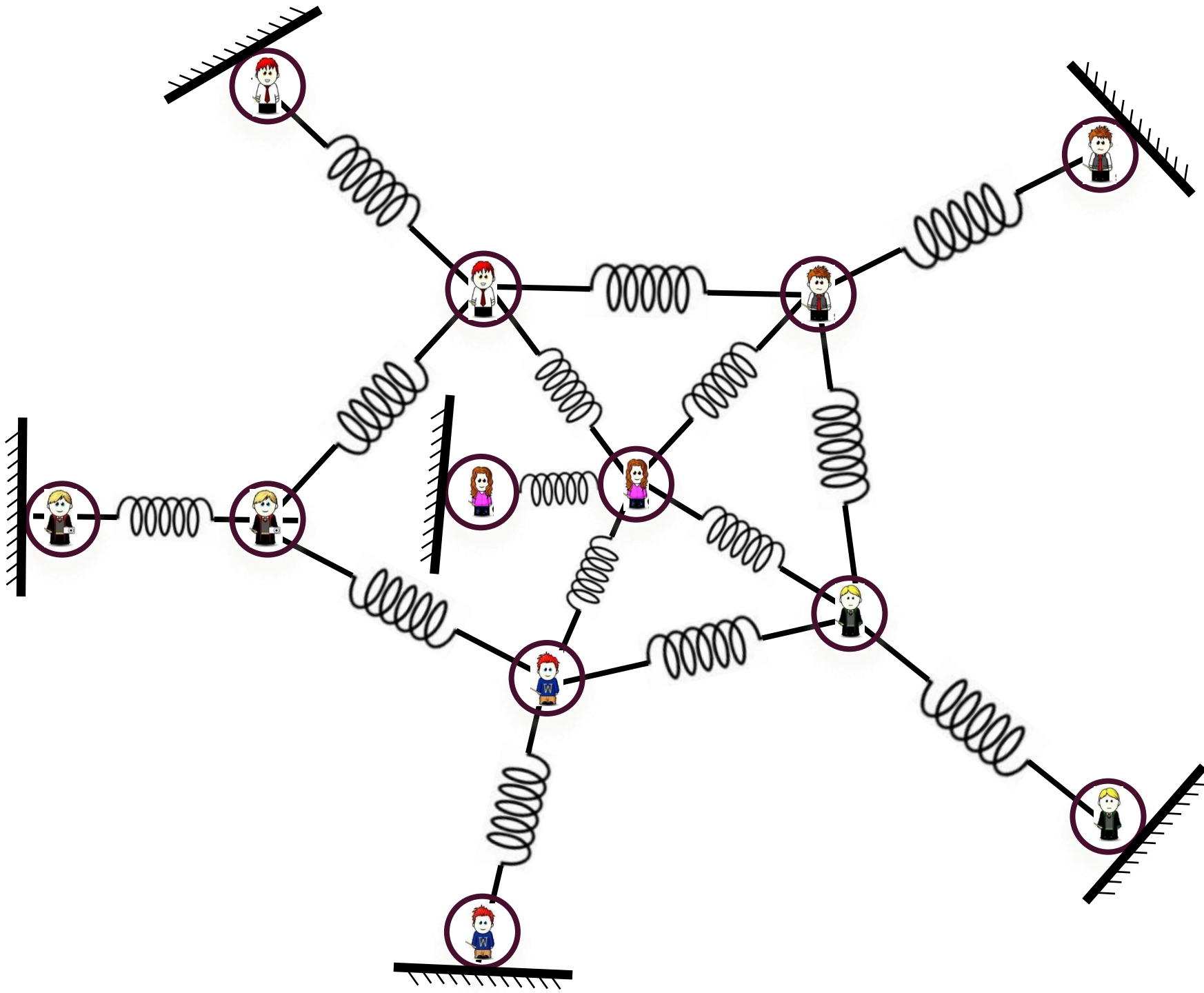
$$z_{\text{red}} = \frac{0.5 + 2 \cdot z_{\text{yellow}} + z_{\text{green}}}{4}$$

It is equal to the **expected intrinsic opinion** at the place of absorption

Opinion of a user

- For an individual user u
 - u 's absorbing node is a stationary point
 - u 's transient node is connected to the absorbing node with a spring.
 - The neighbors of u pull with their own springs.





Opinion maximization problem

- Public opinion:

$$g(z) = \sum_{i \in V} z_i$$

- **Problem:** Given a graph **G**, the given opinion formation model, the intrinsic opinions of the users, and a budget **k**, perform **k interventions** such that the **public opinion is maximized**.
- Useful for image control campaign.
- What kind of interventions should we do?

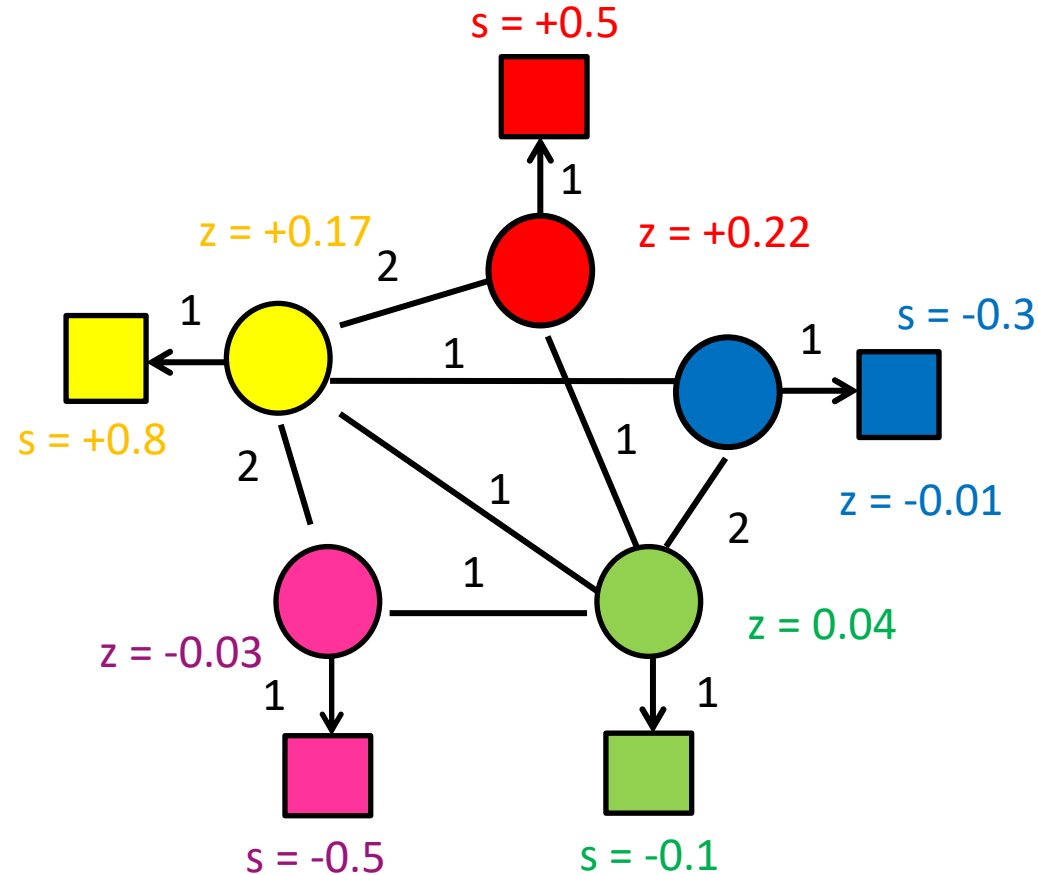
Possible interventions

1. Fix the **expressed opinion** of k nodes to the maximum value 1.
 - Essentially, **make these nodes absorbing**, and give them value 1.
2. Fix the **intrinsic opinion** of k nodes to the maximum value 1.
 - Easy to solve, we know exactly the contribution of each node to the overall public opinion.
3. Change the **underlying network** to facilitate the propagation of positive opinions.
 - For undirected graphs this is not possible

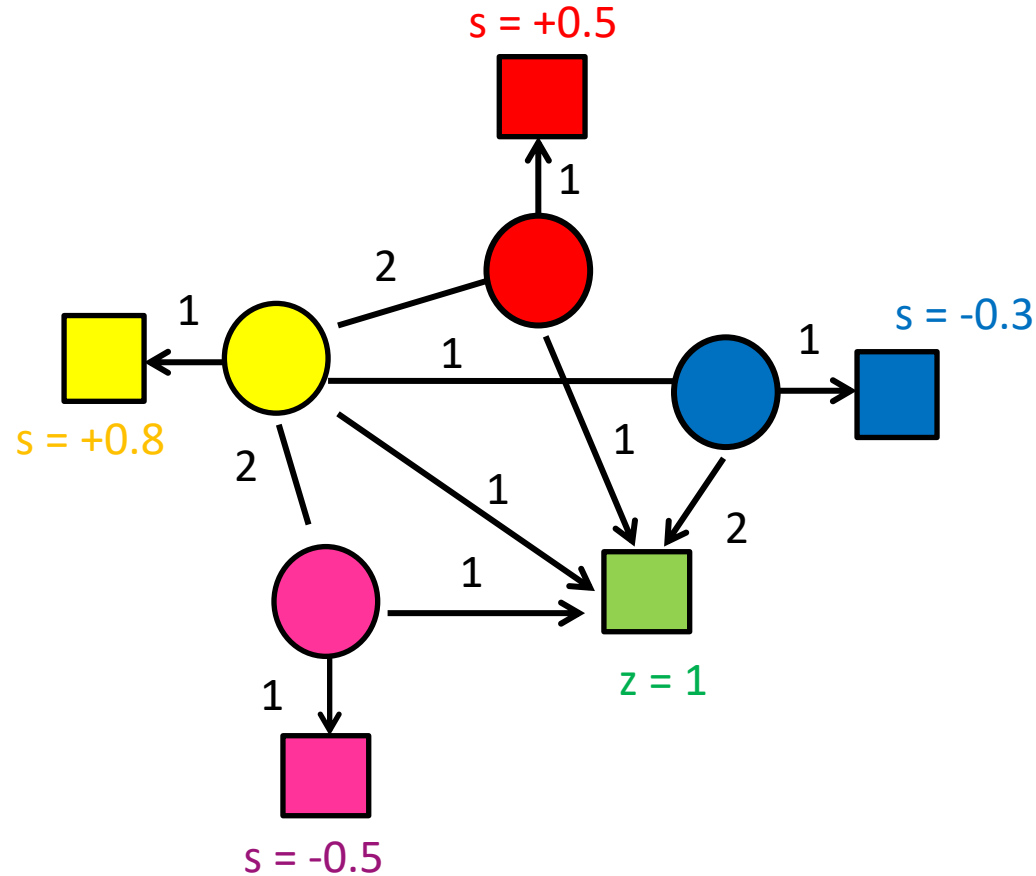
$$g(z) = \sum_i z_i = \sum_i s_i$$

- The overall public opinion **does not depend** on the **graph structure**!
- What does this mean for the wisdom of crowds?

Fixing the expressed opinion



Fixing the expressed opinion



Opinion maximization problem

- The opinion maximization problem is **NP-hard**.
- The public opinion function is **monotone** and **submodular**
 - The Greedy algorithm gives a $\left(1 - \frac{1}{e}\right)$ -approximate solution
- In practice Greedy is slow. Heuristics that use random walks perform well.

Additional models

- Ising model
- Voter model
- Bounded confidence models
- Axelrod cultural dynamics model

A Physics-based model

- The Ising ferromagnet model:
 - A user i is a “spin” s_i that can assume two values: ± 1
 - The total energy of the system is

$$H = -\frac{1}{2} \sum_{\langle i,j \rangle} s_i s_j$$

Defined over the neighboring pairs

- A spin is flipped with probability $\exp(-\frac{\Delta E}{T})$ where ΔE is the change in energy, and T is the “temperature” of the system.
- The model assumes no topology
 - Complete graph (all-with-all), or regular lattice.
- For low temperatures, the system converges to a single opinion

The Voter model

- Each user has an **opinion** that is an **integer** value
 - Usually opinions are in $\{0,1\}$ but multiple opinion values are also possible.
- Opinion formation process:
 - At each step we select a user at random
 - The user selects one of its neighbors at random (including herself) and adopts their opinion
- The model can be proven to converge for certain topologies.

Bounded confidence model

- **Confirmation bias**: People tend to accept opinions that agree with them
 - “Why facts don’t change our minds” (New Yorker)
- **Bounded Confidence** model: A user i is influenced by a neighbor j only if
$$|z_i - z_j| \leq \epsilon$$

for some parameter ϵ

Bounded Confidence models

- **Defuant** model: Given a parameter μ at time t , a randomly selected user i selects a neighbor j at random, and if $|z_i^t - z_j^t| \leq \epsilon$ their opinions are updated as:

$$z_i^{t+1} = z_i^t + \mu(z_j^t - z_i^t)$$

$$z_j^{t+1} = z_j^t + \mu(z_i^t - z_j^t)$$

Similar to Voter model

- **Hegselmann-Krause** (HK) model: Each node i updates their opinions as the average of the opinions of the neighbors that agree with them

$$z_i^t = \frac{w_{ii}z_i^{t-1} + \sum_{j \in N(i): |z_i^{t-1} - z_j^{t-1}| \leq \epsilon} w_{ij}z_j^{t-1}}{w_{ii} + \sum_{j \in N(i): |z_i^{t-1} - z_j^{t-1}| \leq \epsilon} w_{ij}}$$

Similar to DeGroot model

Bounded Confidence models

- Depending on the parameter ϵ and the initial opinions, bounded confidence models can lead to **plurality** (multiple opinions), **polarization** (two competing opinions), or **consensus** (single opinion)

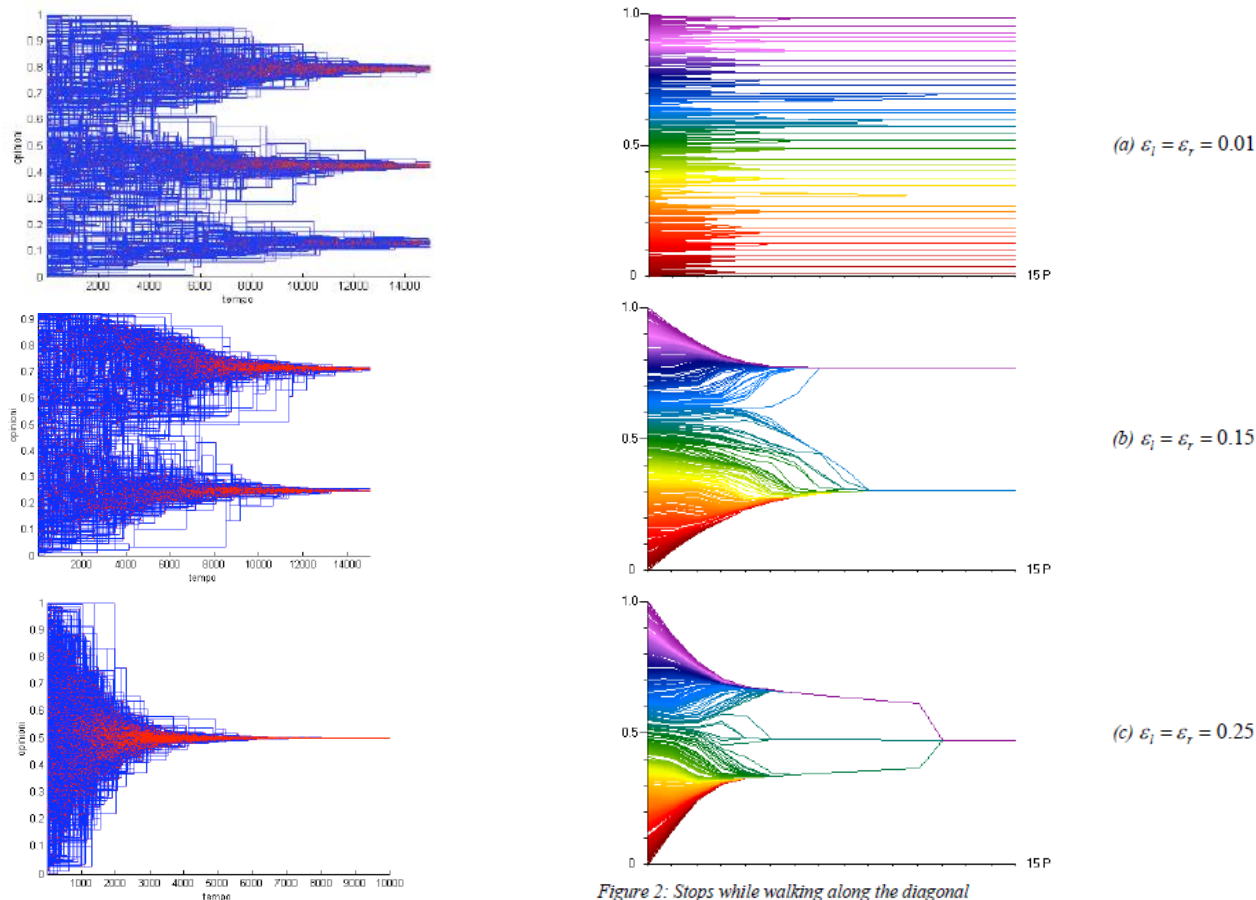


Figure 2: Stops while walking along the diagonal

Axelrod model

- **Cultural dynamics**: Goes beyond single opinions, and looks at different features/habits/traits
 - Tries to model the effects of **social influence** and **homophily**.
- **Model**:
 - Each user i has **a vector σ_i of F features**
 - A user i decides to interact with user j with probability

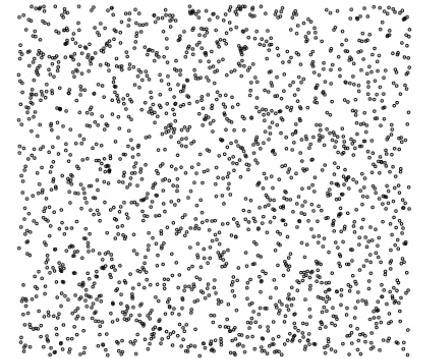
$$\omega_{ij} = \frac{1}{F} \sum_{f=1}^F \delta(\sigma_i(f), \sigma_j(f))$$

Fraction of common features

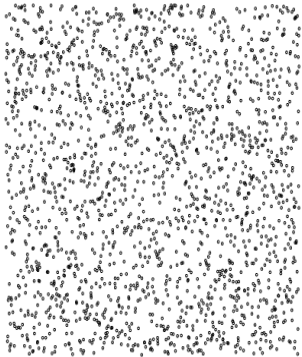
- If there is interaction, the user changes **one of the disagreeing features** to the value of the neighbor
- The state where all users have the same features is an equilibrium, but it is not always reached (**cultural pockets**)

Empirical measurements

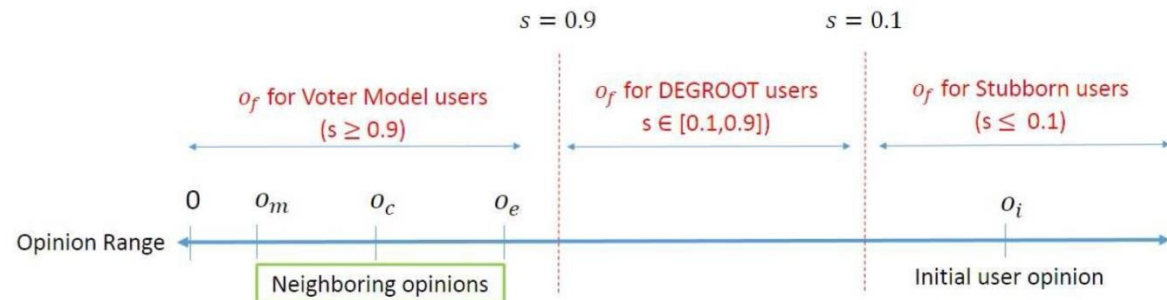
- There have been various experiments for validating the different models in practice
- Das, Gollapudi, Munagala (WSDM 2014)
 - User surveys:
 - estimate number of dots in images
 - Estimate annual sales of various brands.
 - For each survey:
 - Users asked to provide initial answers on all questions in the survey
 - Then, each user shown varying number of (**synthetic**) neighboring answers.
 - Users given opportunity to update their answers



Online User Studies

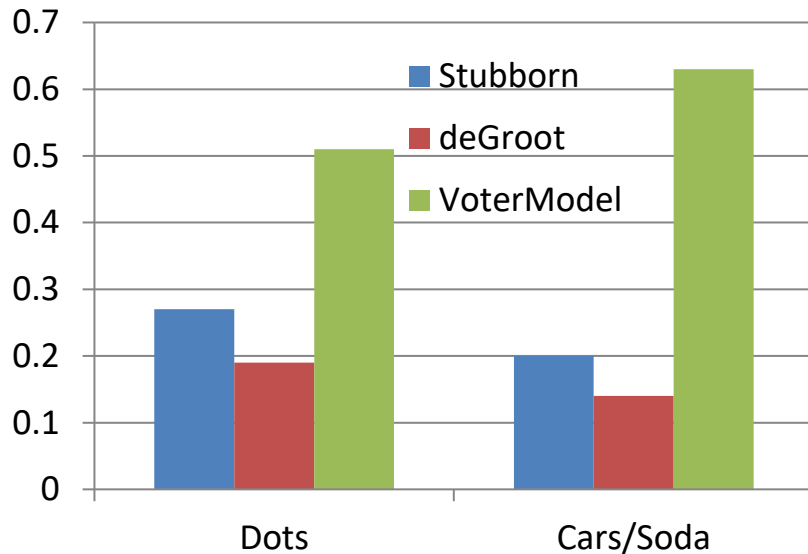


?

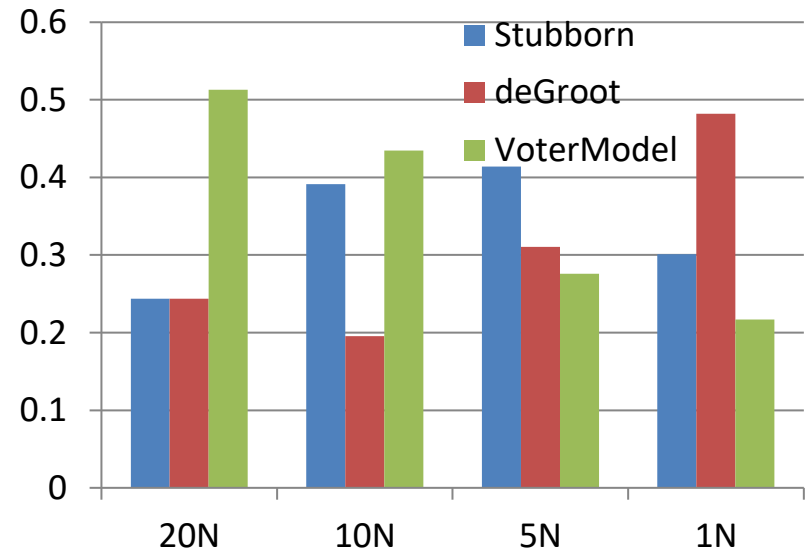


- Define $s = \frac{|o_i - o_f|}{|o_i - o_e|}$
 - (o_i : original opinion, o_f : final opinion, o_e : closest neighboring opinion)
- User behavior categorized as:
 - Stubborn ($s < 0.1$)
 - DeGroot ($0.1 < s < 0.9$)
 - Voter ($s > 0.9$)

Voter vs DeGroot



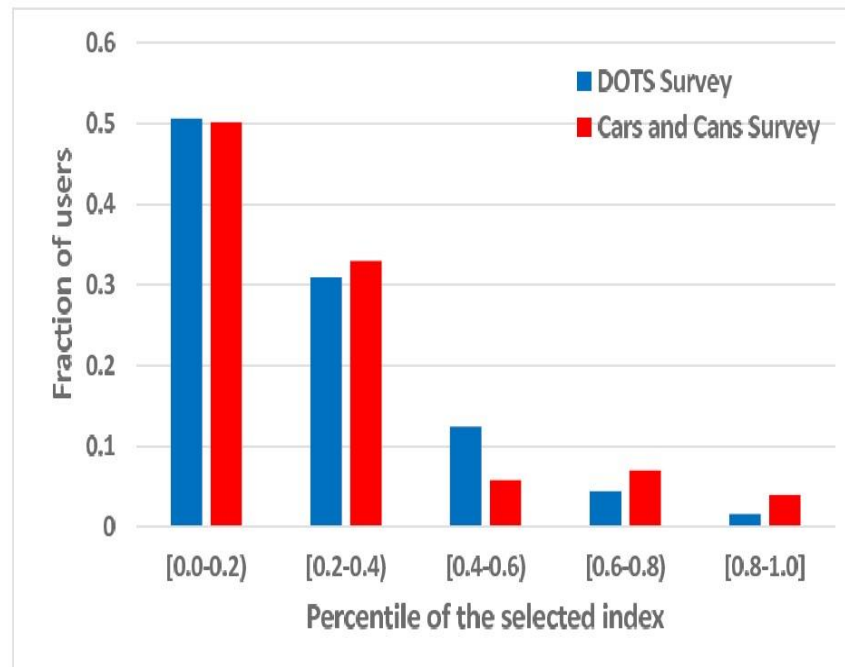
Distribution over stubborn, deGroot and voter



Effect of number of neighboring opinions

- Voter model is prevalent for large number of neighbors,
- DeGroot becomes more prevalent for smaller number of neighbors

Biased Conforming Behavior



- Adoption of neighboring opinions not uniform random (unlike Voter Model)
- Users give higher weights to “close by” opinions

Biased Voter Model

- Users update their opinions iteratively
- At each iteration, a user sorts the opinions of her neighbors in increasing order of distance from her own opinion
- With probability p she adopts the 1st closest, else with probability p she adopts the 2nd closest, else ...
- If no opinion has been adopted, with probability α she keeps her own opinion
- With probability $1 - \alpha$ she adopts an opinion chosen uniformly at random between her own opinion and the closest neighboring opinion

Other problems related to opinion formation

- Modeling **polarization**
 - Understand why extreme opinions are formed and people cluster around them
- Modeling **herding/flocking**
 - Understand under what conditions people tend to follow the crowd
- Modeling the **backfire effect**
 - Understand when opposite opinions lead to strengthening your opinion, rather than moderating it
- **Computational Sociology**
 - Use big data for studying and modeling human social behavior.

R. Hegselmann, U. Krause. *Opinion Dynamics and Bounded Confidence. Models, Analysis, and Simulation*. Journal of Artificial Societies and Social Simulation (JASSS) vol.5, no. 3, 2002

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