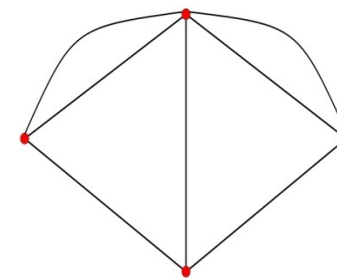


Social and Economic Networks: Models and Analysis

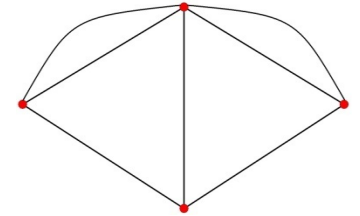


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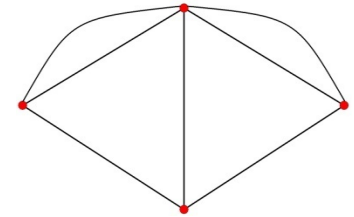
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6.1: Learning



Outline



- Part I: Background and Fundamentals
 - Definitions and Characteristics of Networks (1,2)
 - Empirical Background (3)
- Part II: Network Formation
 - Random Network Models (4,5)
 - Strategic Network Models (6, 11)
- Part III: Networks and Behavior
 - Diffusion and **Learning** (7,8)
 - Games on Networks (9)

Outline



- Bayesian learning
 - repeated actions, observe each other
- DeGroot model
 - repeated communication, ``naïve'' updating

Bayesian Learning



- Will society converge
- Will they aggregate information properly? ...

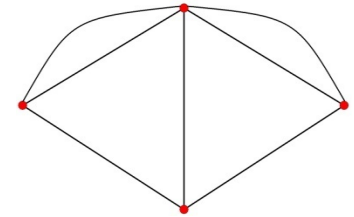
Bala Goyal 98



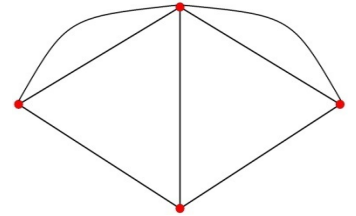
- n players in an undirected component g
- Choose action A or B each period
- A pays 1 for sure, B pays 2 with probability p and 0 with probability $1-p$

Learning

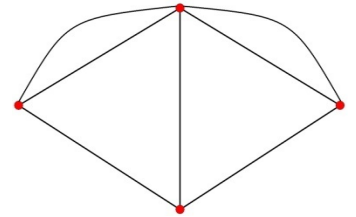
- Each period get a payoff based on choice
- Also observe neighbors' choices
- Maximize discounted stream of payoffs
 $E \left[\sum_t \delta^t \pi_{it} \right]$
- p is unknown takes on finite set of values



Challenges Bayesian Learning:

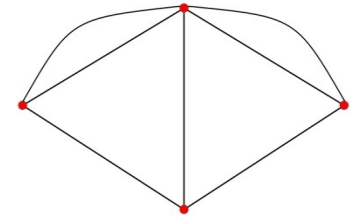


Proposition



If p is not exactly $1/2$, then with probability 1 there is a time such that all agents in a given component play just one action (and all play the same action) from that time onward

Sketch of Proof



- Suppose contrary
- Some agent in some component plays B infinitely often
- That agent will converge to true belief by the law of large numbers
- Must be that belief converges to $p > 1/2$, or that agent would stop playing B

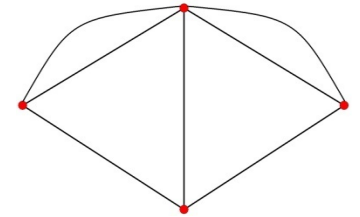
Proof continued



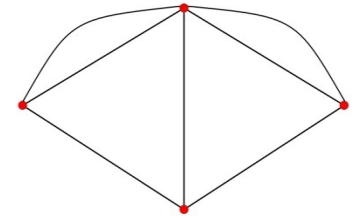
- With probability 1, all agents who see B played infinitely often converge to a belief that B pays 2 with prob $p > 1/2$
- Neighbors of agent must play B, after some time, and so forth
- All agents must play B from some time on

Play the right action?

- If B is the right action then play the right action if converge to it, but might not
- If A is the right action, then must converge to right action

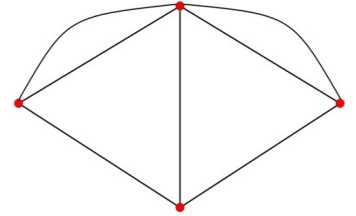


Probability of Converging to “correct” action



- Arbitrarily high if each action has some agent who initially has arbitrarily high prior that the action is the best one

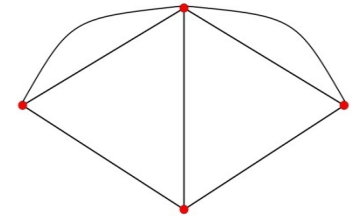
Conclusions



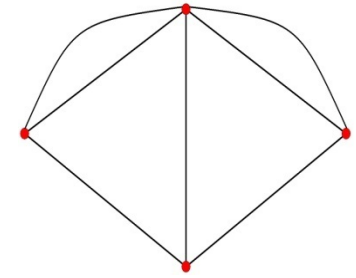
- Consensus action chosen
- Not necessarily consensus belief
- Speed of convergence?

Limitations

- Homogeneity of actions and payoffs across players
- What if heterogeneity?
- Repeated actions over time
- Stationarity
- Networks are not playing role here!



Social and Economic Networks: Models and Analysis

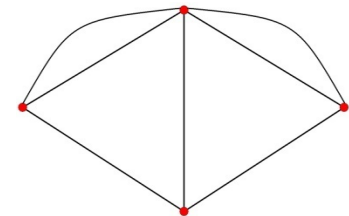


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6.2:DeGroot Model



Outline



- Bayesian learning
 - repeated actions, observe each other
- DeGroot model
 - repeated communication, “naïve” updating

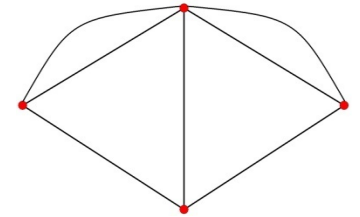
Outline: DeGroot Model



- Basic Definitions
- When is there convergence?
- When is there a consensus?
- Who has influence?
- When is the consensus accurate?

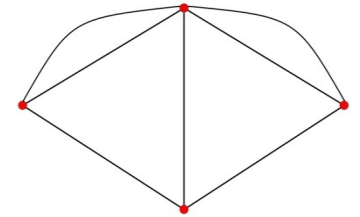
Network Structure and Learning

- Repeated communication
- Information comes only once
- See how information disseminates
- Who has influence, convergence speed, network structure impact...



Bounded Rationality Model

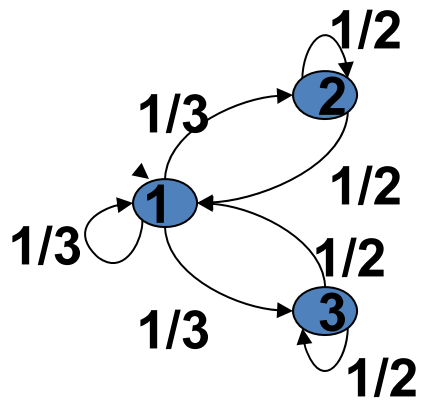
- Repeatedly average beliefs of self with neighbors
- Non-Bayesian if weights do not adjust over time
- Can under-weight neighbors (just as in experiments)



DeGroot (1974) Social Interaction Model

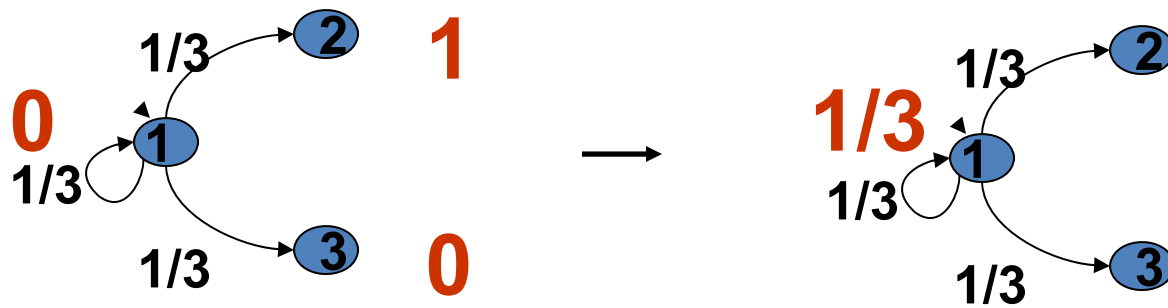
- Individuals $\{1, \dots, n\}$
- T weighted directed network, stochastic matrix
- Start with beliefs, attitude, etc. $b_i(0)$ in $[0,1]$
 - can also have these be vectors...
- Updating: $b_i(t) = \sum_j T_{ij} b_j(t-1)$

Example

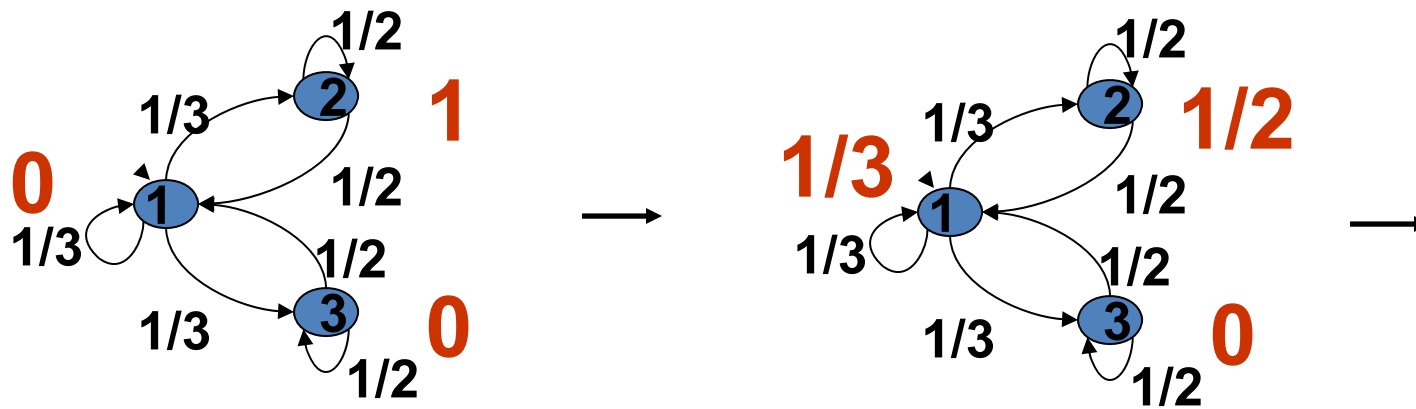


$$T = \begin{bmatrix} 1/3 & 1/3 & 1/3 \\ 1/2 & 1/2 & 0 \\ 1/2 & 0 & 1/2 \end{bmatrix}$$

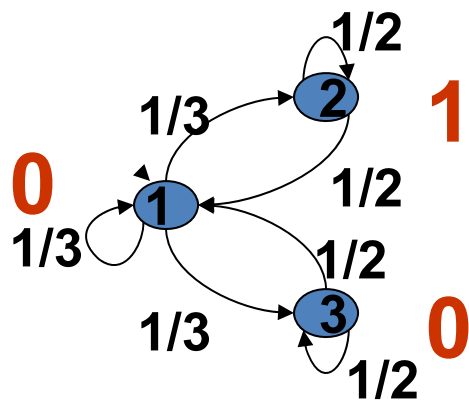
Updating



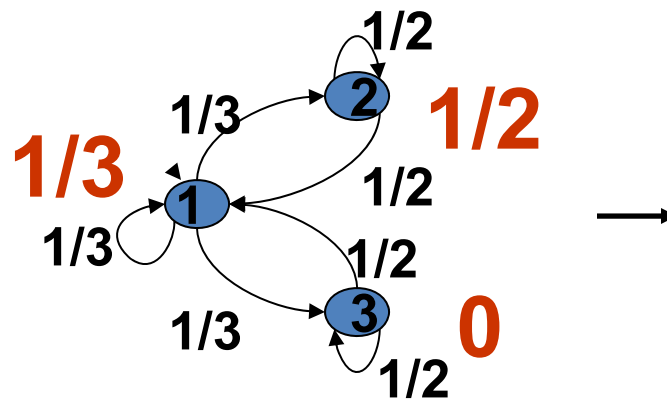
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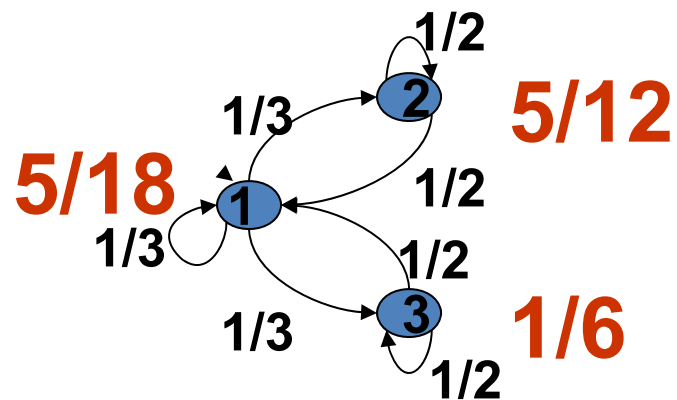
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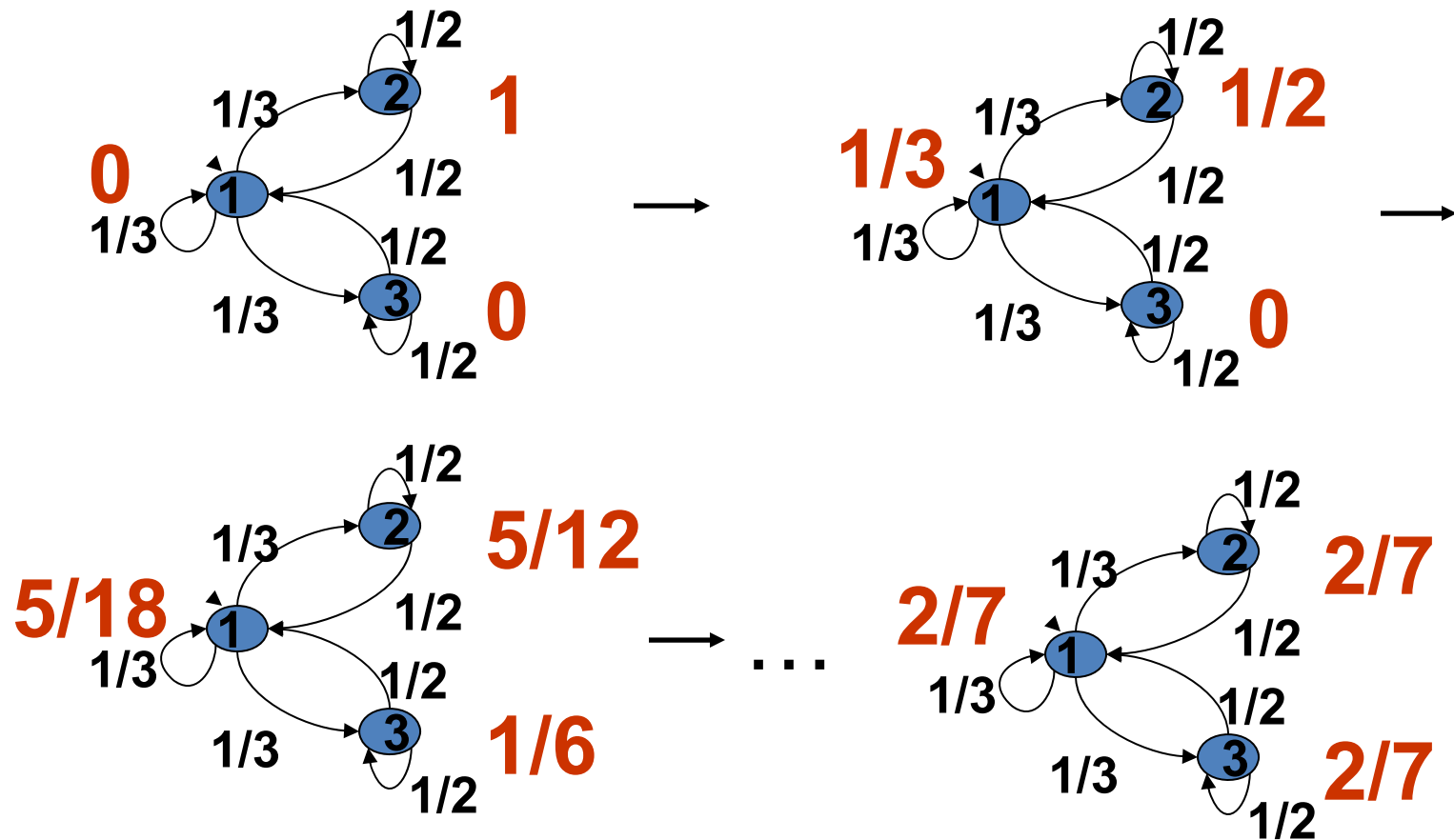
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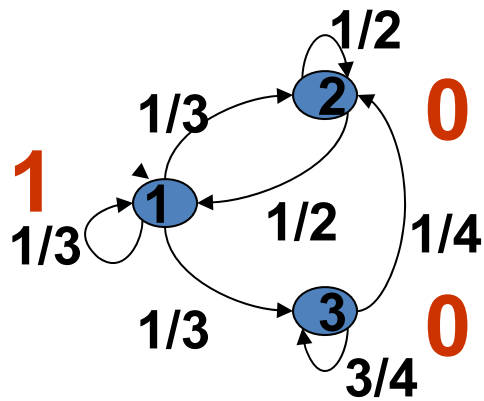
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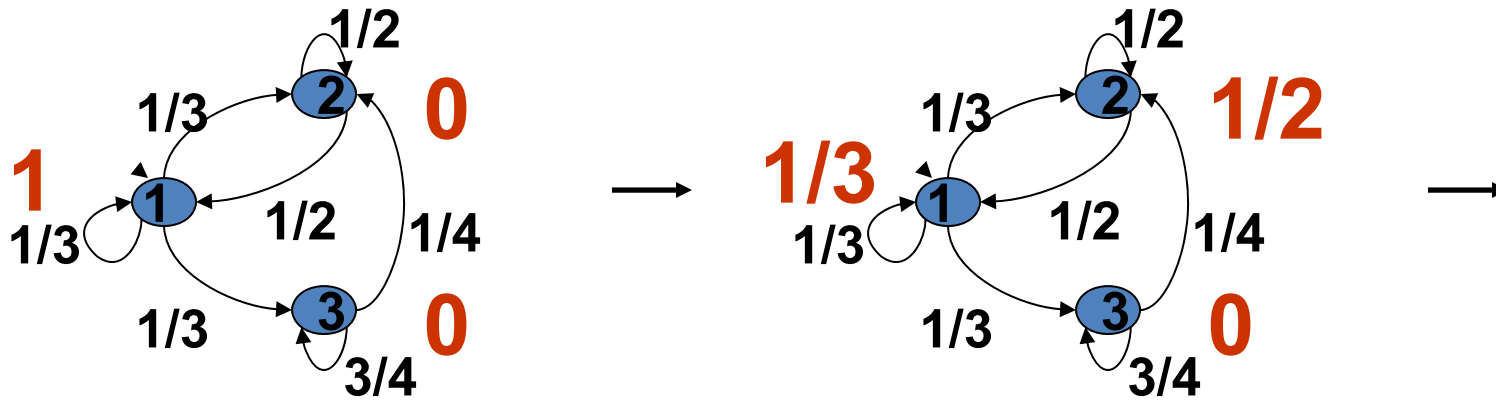


Example

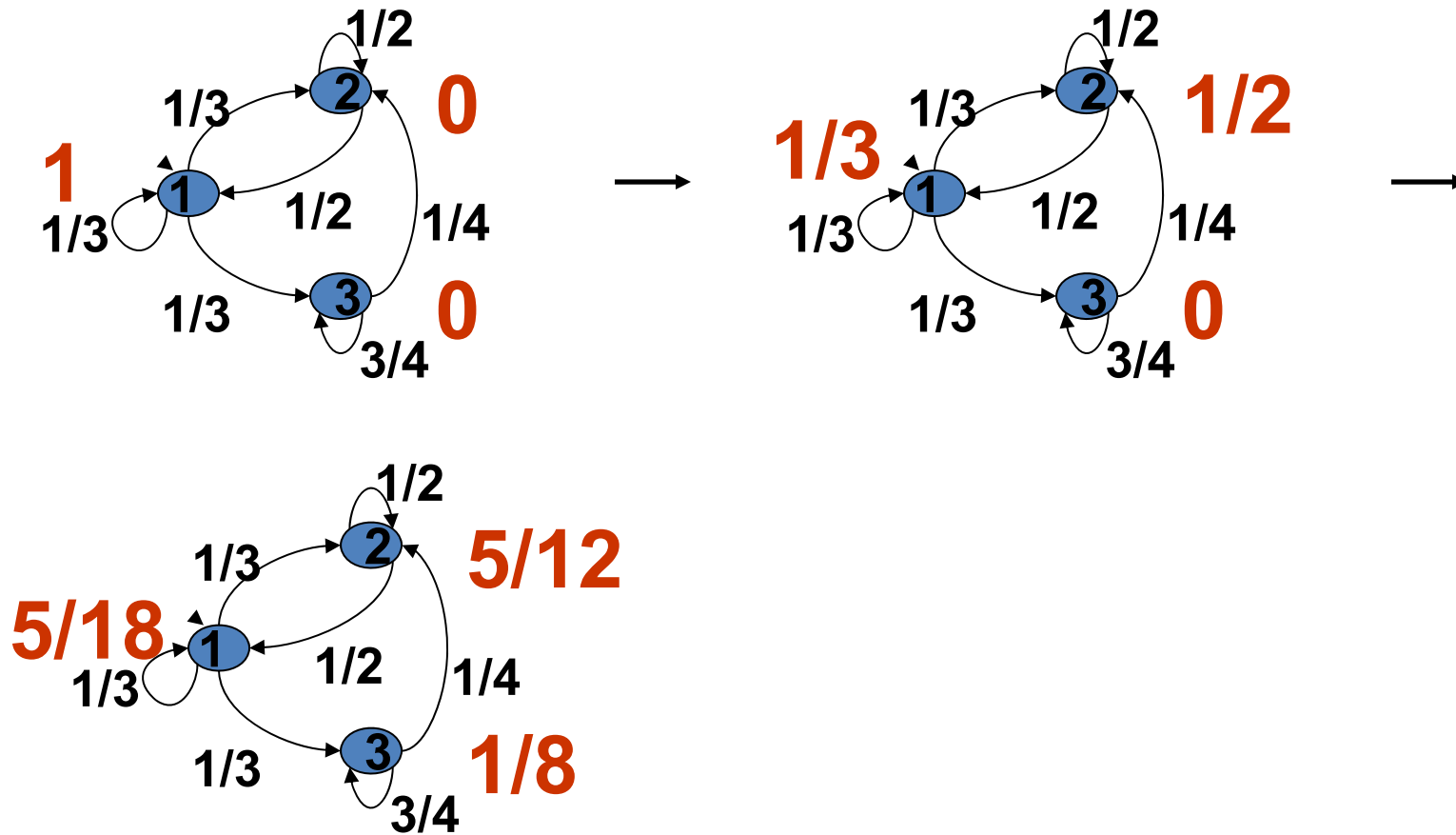


$$T = \begin{pmatrix} 1/3 & 1/3 & 1/3 \\ 1/2 & 1/2 & 0 \\ 0 & 1/4 & 3/4 \end{pmatrix}$$

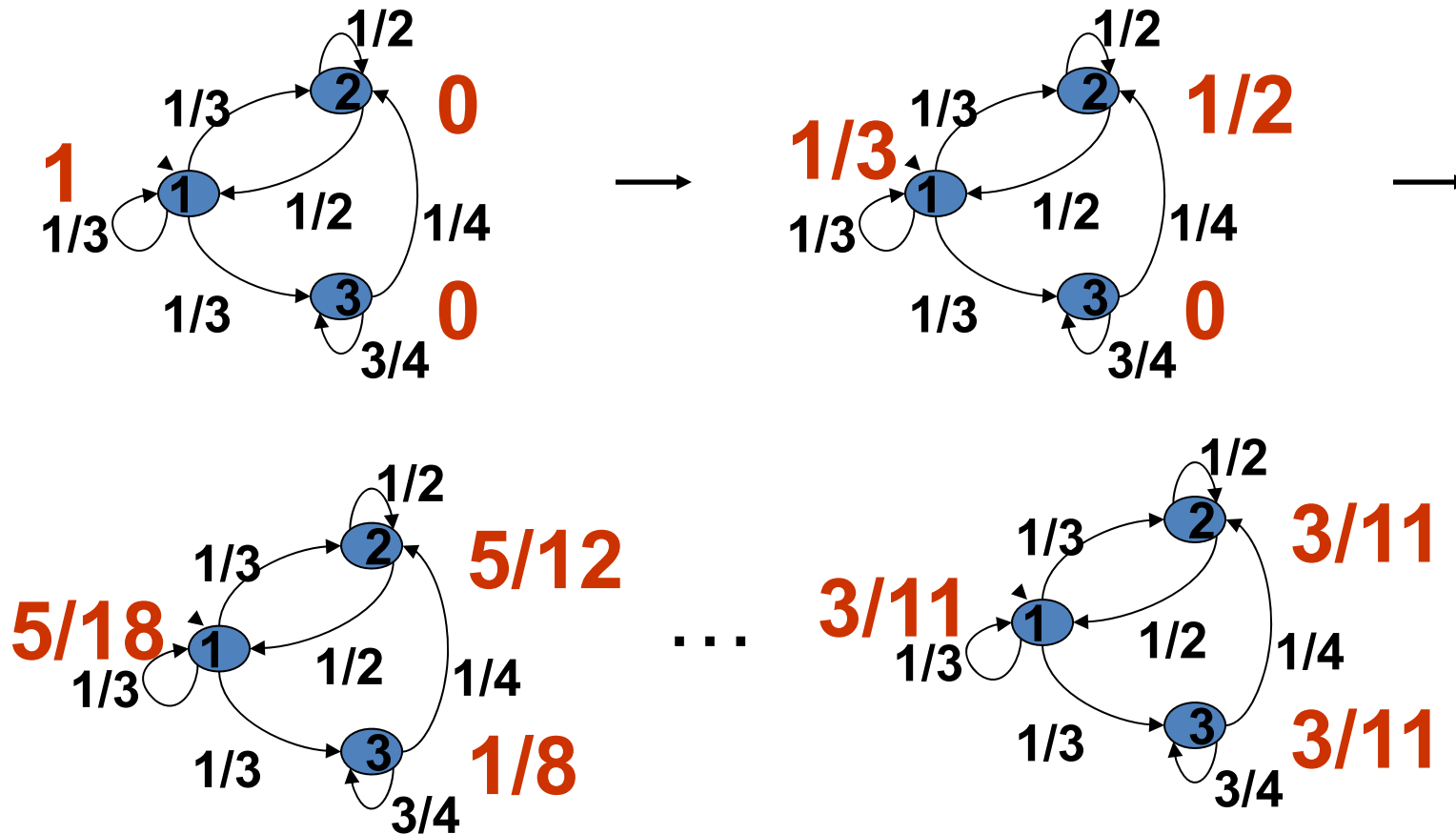
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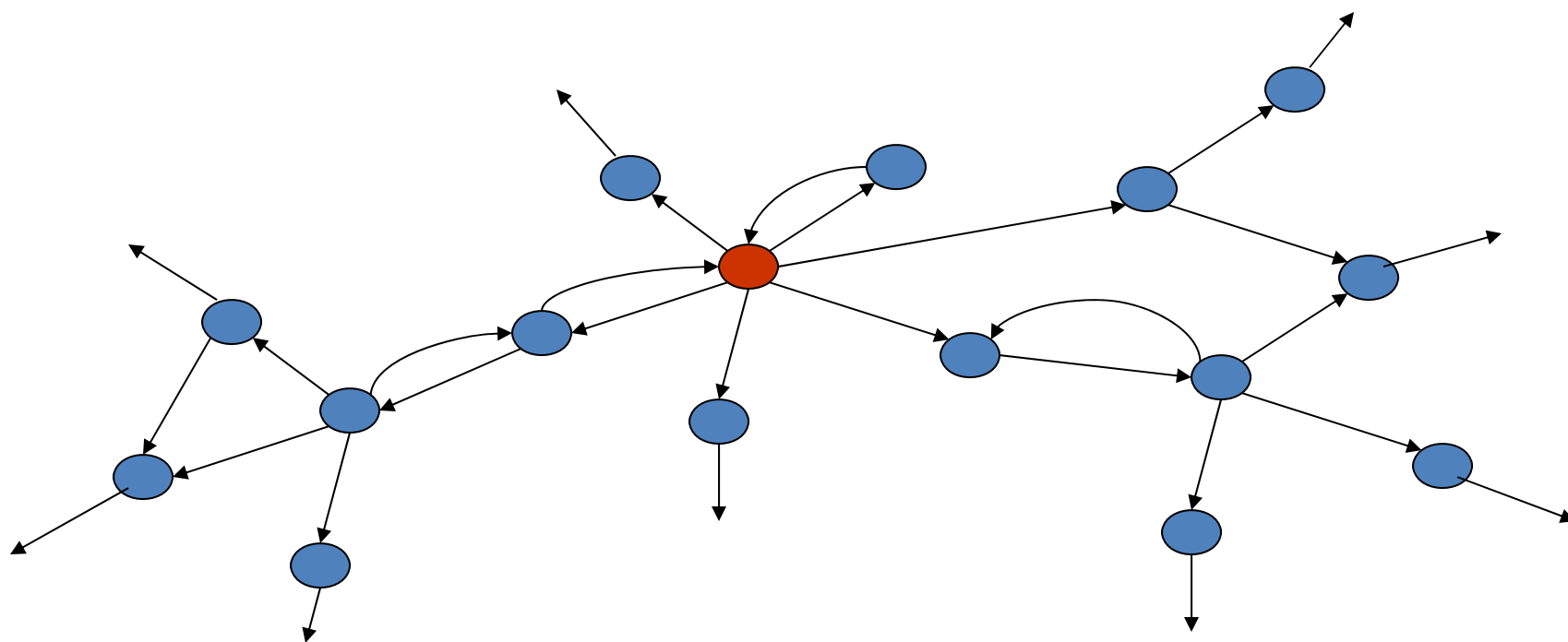


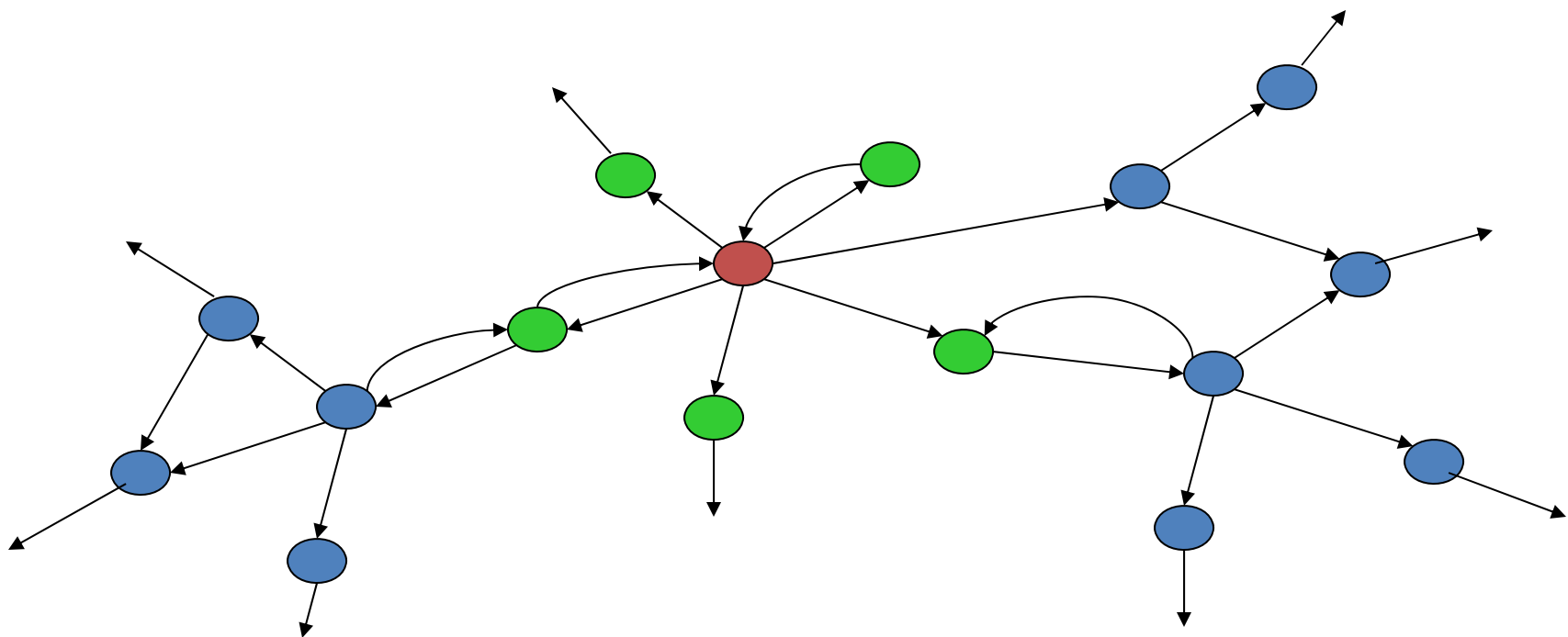
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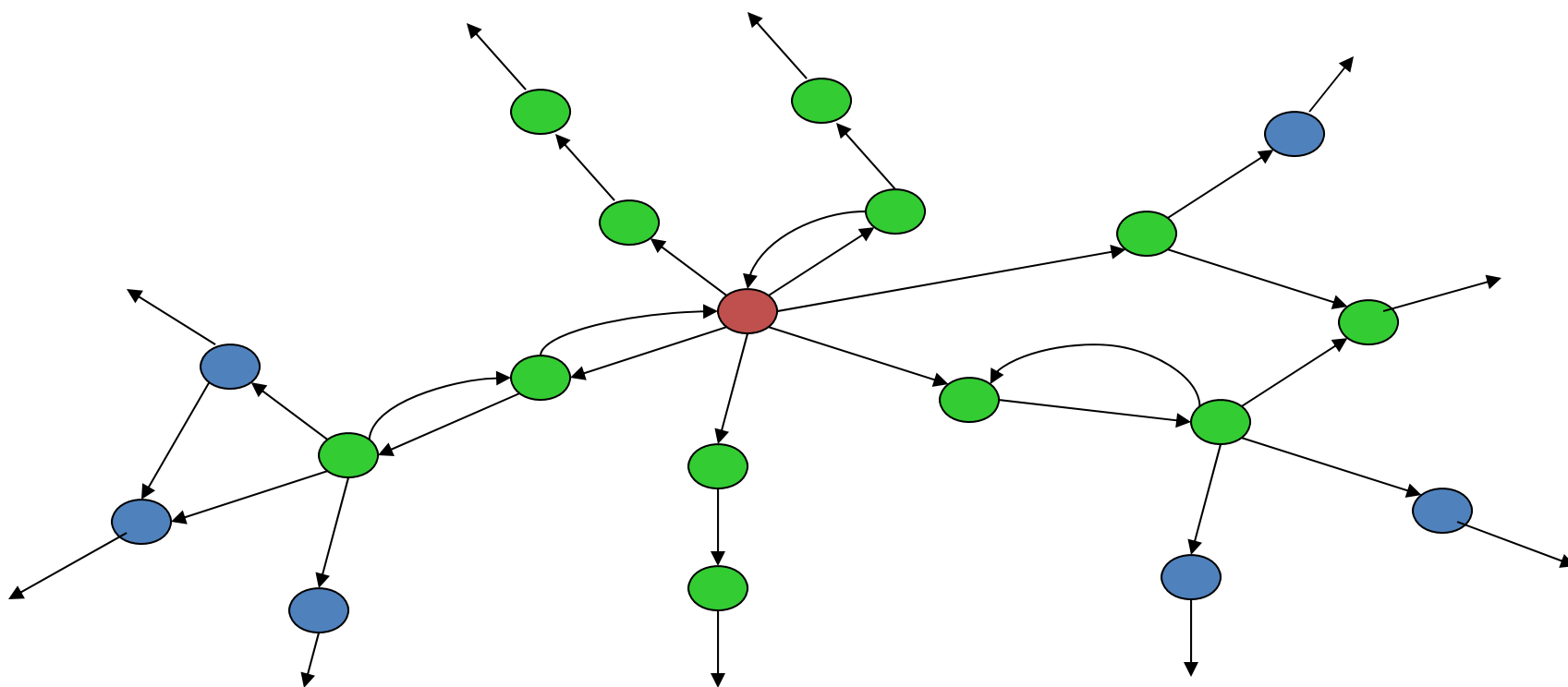


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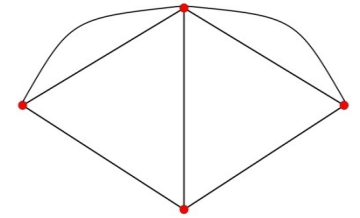






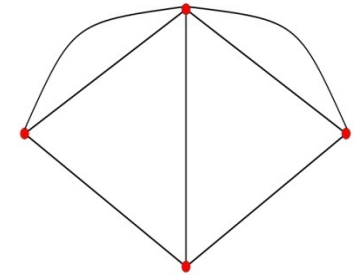


Other interpretations



- Social influence on actions
- Random actions (Markov process...)
- Page ranks...

Social and Economic Networks: Models and Analysis

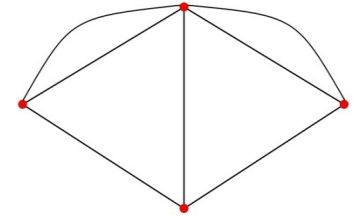


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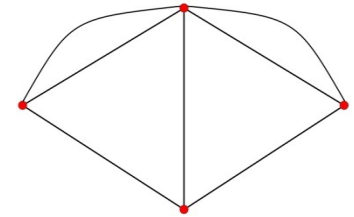
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6.3: Convergence in DeGroot Model

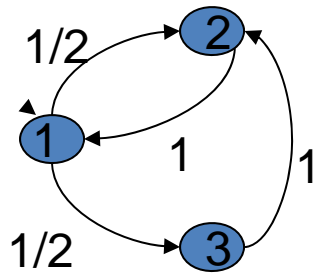


Outline: DeGroot Model

- Basic Definitions
- When is there convergence?
- When is there a consensus?
- Who has influence?
- When is the consensus accurate?

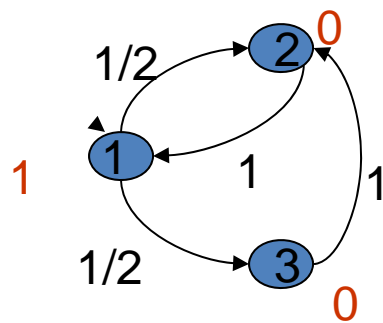


Example - Convergence:



$$T = \begin{pmatrix} 0 & \frac{1}{2} & \frac{1}{2} \\ 1 & 0 & 0 \\ 0 & 1 & 0 \end{pmatrix}$$

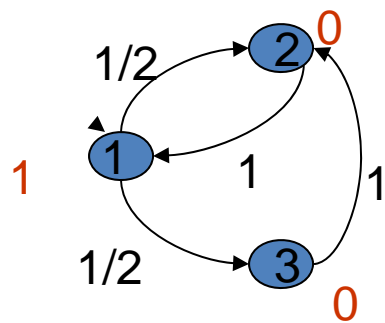
Example - Convergence:



$$T = \begin{pmatrix} 0 & \frac{1}{2} & \frac{1}{2} \\ 1 & 0 & 0 \\ 0 & 1 & 0 \end{pmatrix}$$

$$b(0) = \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix}$$

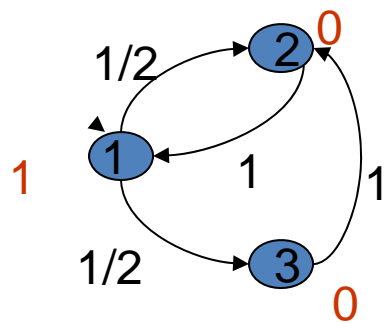
Example - Convergence:



$$T = \begin{pmatrix} 0 & \frac{1}{2} & \frac{1}{2} \\ 1 & 0 & 0 \\ 0 & 1 & 0 \end{pmatrix}$$

$$b(0) = \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix} \quad b(1) = \begin{pmatrix} 0 \\ 1 \\ 0 \end{pmatrix}$$

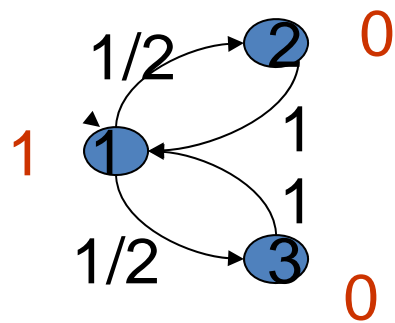
Example - Convergence:



$$T = \begin{pmatrix} 0 & \frac{1}{2} & \frac{1}{2} \\ 1 & 0 & 0 \\ 0 & 1 & 0 \end{pmatrix}$$

$$b(0) = \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix} \quad b(1) = \begin{pmatrix} 0 \\ 1 \\ 0 \end{pmatrix} \rightarrow \begin{pmatrix} 1/2 \\ 0 \\ 1 \end{pmatrix} \rightarrow \begin{pmatrix} 3/4 \\ 1/2 \\ 0 \end{pmatrix} \rightarrow \begin{pmatrix} 1/4 \\ 3/4 \\ 1/2 \end{pmatrix} \dots \rightarrow \begin{pmatrix} 2/5 \\ 2/5 \\ 2/5 \end{pmatrix}$$

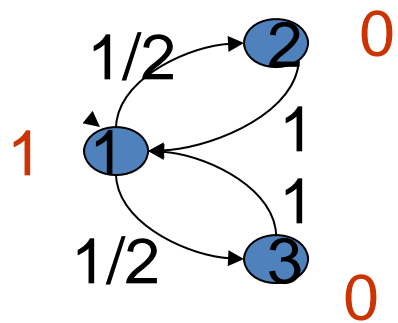
Example – No Convergence:



$$T = \begin{pmatrix} 0 & \frac{1}{2} & \frac{1}{2} \\ 1 & 0 & 0 \\ 1 & 0 & 0 \end{pmatrix}$$

$$b(0) = \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix}$$

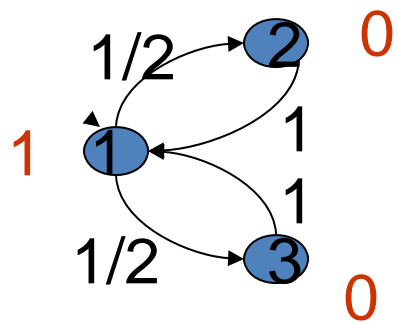
Example – No Convergence:



$$T = \begin{pmatrix} 0 & \frac{1}{2} & \frac{1}{2} \\ 1 & 0 & 0 \\ 1 & 0 & 0 \end{pmatrix}$$

$$b(0) = \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix} \quad b(1) = \begin{pmatrix} 0 \\ 1 \\ 1 \end{pmatrix}$$

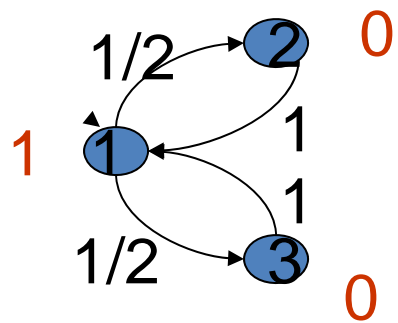
Example – No Convergence:



$$T = \begin{pmatrix} 0 & \frac{1}{2} & \frac{1}{2} \\ 1 & 0 & 0 \\ 1 & 0 & 0 \end{pmatrix}$$

$$b(0) = \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix} \quad b(1) = \begin{pmatrix} 0 \\ 1 \\ 1 \end{pmatrix} \rightarrow \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix}$$

Example – No Convergence:

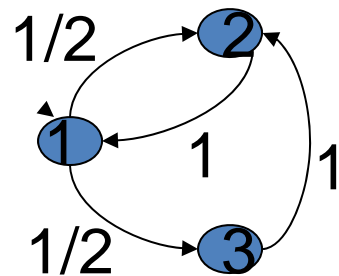


$$T = \begin{pmatrix} 0 & \frac{1}{2} & \frac{1}{2} \\ 1 & 0 & 0 \\ 1 & 0 & 0 \end{pmatrix}$$

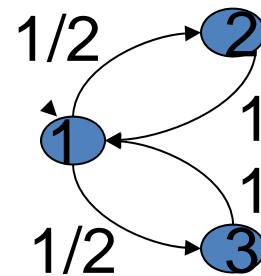
$$b(0) = \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix} \quad b(1) = \begin{pmatrix} 0 \\ 1 \\ 1 \end{pmatrix} \rightarrow \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix} \rightarrow \begin{pmatrix} 0 \\ 1 \\ 1 \end{pmatrix} \rightarrow \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix} \rightarrow \dots \rightarrow$$

Convergence

- T *converges* if $\lim T^t b$ exists for all b
- T is *aperiodic* if the greatest common divisor of its cycle lengths is one



aperiodic



periodic

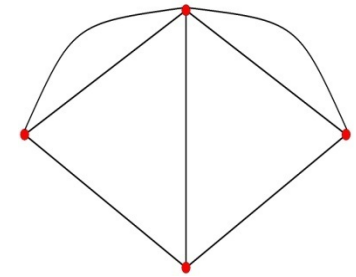
Theorem

Suppose T is strongly connected.

T is convergent if and only if it is aperiodic.

**T is convergent if and only if: $\lim T^t = (1,1,\dots,1)^T s$
where s is the unique lhs eigenvector with
eigenvalue 1**

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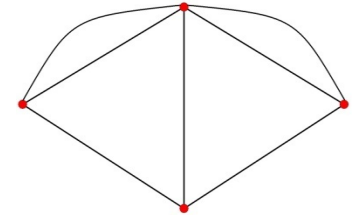


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6.4: Proof of Convergence Theorem



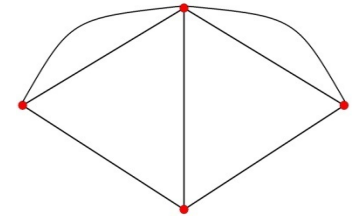
Theorem

Suppose T is strongly connected.

T is convergent if and only if it is aperiodic.

**T is convergent if and only if: $\lim T^t = (1,1,\dots,1)^T s$
where s is the unique lhs eigenvector with
eigenvalue 1**

Proof :



Defn: T is *primitive* if $T^t_{ij} > 0$ for all ij after some t

- If T is strongly connected and stochastic then it is aperiodic if and only if it is primitive. (Perkins (1961))
- If T is strongly connected and primitive then
$$\lim T^t = (1, 1, \dots, 1)^T s$$

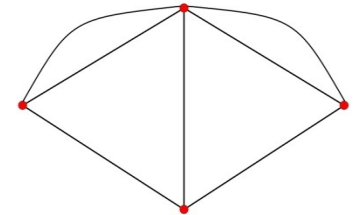
where s is the unique lhs eigenvector with eigenvalue 1 (e.g., see Meyer (2000))

Proof Cont'd



- So, strongly connected and aperiodic implies convergence.
- Converse comes from showing:
If T is strongly connected, stochastic and convergent, then it is primitive.

Proof Cont'd



- Show:

If T is strongly connected, stochastic and convergent, then it is primitive.

Let $S = \lim T^t$ by convergence

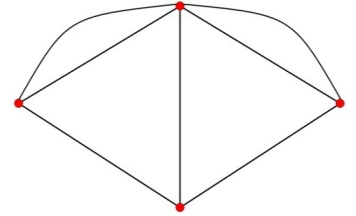
Then $ST = \lim T^t T = S$

So each row is a lhs eigenvector with eigenvalue 1: it is a positive vector by Perron-Frobenius theorem (An eigenvector of an irreducible non-negative matrix is strictly positive *if* (and only if) it is associated with its largest eigenvalue. This vector is unique if the matrix is primitive)

So since S is all positive, T is primitive.

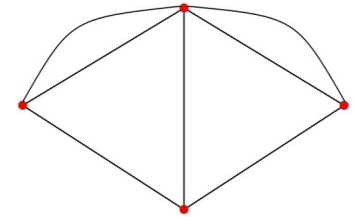
Since, T is primitive then Perron-Frobenius implies the eigenvector is unique, and all rows of S are the same s

Aperiodicity Easy



- Aperiodicity is easy to satisfy:
 - Have some agent weight him or herself
 - Or have at least one communicating dyad and a transitive triple...

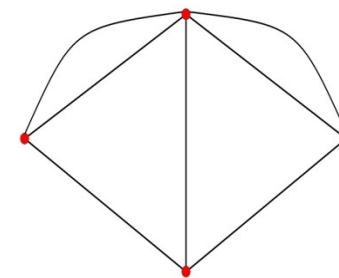
Outline: DeGroot Model



- Basic Definitions
- When is there convergence?
- When is there a consensus? - Just answered: convergence is sufficient, aperiodicity (see G&J11 for details more generally)
- Who has influence?
- When is the consensus accurate?

Social and Economic Networks: Models and Analysis

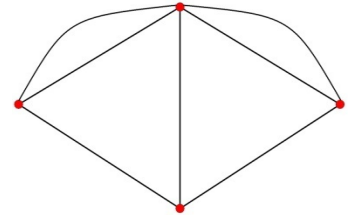
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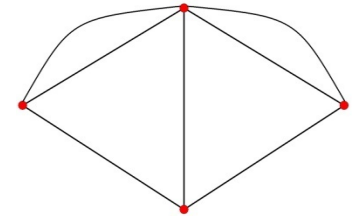
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6.5: Influence



Outline: DeGroot Model

- Basic Definitions
- When is there convergence?
- When is there a consensus?
- Who has influence?
- When is the consensus accurate?



Consensus



- Converge to (normalized) eigenvector weighted sum of original beliefs.

Consensus

$$T = \begin{pmatrix} 0 & 1/2 & 1/2 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \end{pmatrix}$$

$$T^2 = \begin{pmatrix} 1/2 & 1/2 & 0 \\ 0 & 1/2 & 1/2 \\ 1 & 0 & 0 \end{pmatrix}$$

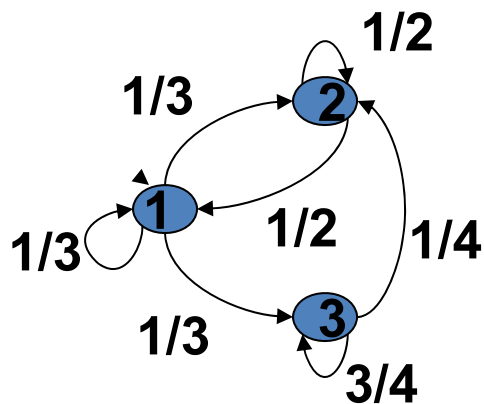
$$T^3 = \begin{pmatrix} 1/2 & 1/4 & 1/4 \\ 1/2 & 1/2 & 0 \\ 0 & 1/2 & 1/2 \end{pmatrix}$$

$$T^4 = \begin{pmatrix} 1/4 & 1/2 & 1/4 \\ 1/2 & 1/4 & 1/4 \\ 1/2 & 1/2 & 0 \end{pmatrix}$$

$$T^5 = \begin{pmatrix} 1/2 & 3/8 & 1/8 \\ 1/4 & 1/2 & 1/4 \\ 1/2 & 1/4 & 1/4 \end{pmatrix}$$

$$T^\infty = \begin{pmatrix} 2/5 & 2/5 & 1/5 \\ 2/5 & 2/5 & 1/5 \\ 2/5 & 2/5 & 1/5 \end{pmatrix}$$

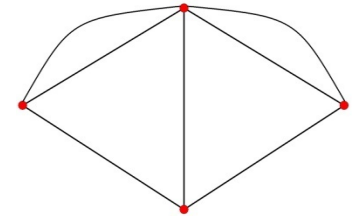
Consensus



$$\lim_t \left(\begin{matrix} 1/3 & 1/3 & 1/3 \\ 1/2 & 1/2 & 0 \\ 0 & 1/4 & 3/4 \end{matrix} \right)^t \mathbf{b}(0)$$

$$\lim_t \left(\begin{matrix} 1/3 & 1/3 & 1/3 \\ 1/2 & 1/2 & 0 \\ 0 & 1/4 & 3/4 \end{matrix} \right)^t = \left(\begin{matrix} 3/11 & 4/11 & 4/11 \\ 3/11 & 4/11 & 4/11 \\ 3/11 & 4/11 & 4/11 \end{matrix} \right)$$

What are Limiting beliefs?



- When group reaches a consensus, what is it?
- Who are the influential agents in terms of steering the limiting belief?
- Must be that the rows of \mathbf{T}^t converge to same thing since beliefs converge to same thing for all initial vectors

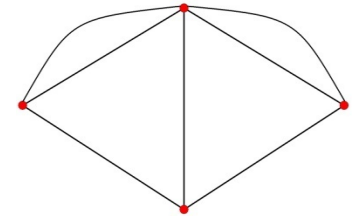
Influence:

$$\text{Limit} \begin{pmatrix} 1/3 & 1/3 & 1/3 \\ 1/2 & 1/2 & 0 \\ 0 & 1/4 & 3/4 \end{pmatrix}^t \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix} = \begin{pmatrix} 3/11 \\ 3/11 \\ 3/11 \end{pmatrix}$$

$$\text{Limit} \begin{pmatrix} 1/3 & 1/3 & 1/3 \\ 1/2 & 1/2 & 0 \\ 0 & 1/4 & 3/4 \end{pmatrix}^t \begin{pmatrix} 0 \\ 1 \\ 0 \end{pmatrix} = \begin{pmatrix} 4/11 \\ 4/11 \\ 4/11 \end{pmatrix}$$

$$\text{Limit} \begin{pmatrix} 1/3 & 1/3 & 1/3 \\ 1/2 & 1/2 & 0 \\ 0 & 1/4 & 3/4 \end{pmatrix}^t \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix} = \begin{pmatrix} 4/11 \\ 4/11 \\ 4/11 \end{pmatrix}$$

Influence Measure



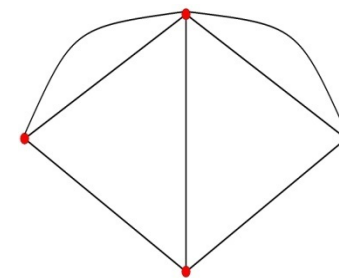
- What do rows of \mathbf{T}^t converge to?
- Look for a row vector \mathbf{s} indicating the *relative influence* each agent has – *limit belief* is $\mathbf{s} \mathbf{b}$
- Note that $\mathbf{s} \mathbf{b} = \mathbf{s} \mathbf{T} \mathbf{b}$
- So, $\mathbf{s} = \mathbf{s} \mathbf{T}$: \mathbf{s} is the **left unit eigenvector**

Who has Influence



- $s_i = \sum_j T_{ji} s_j$
- High influence from being paid attention to by people with high influence...
- Power measures, Google Page Ranks
- Related to eigenvector centrality...

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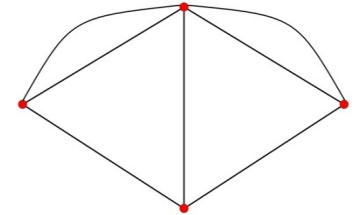


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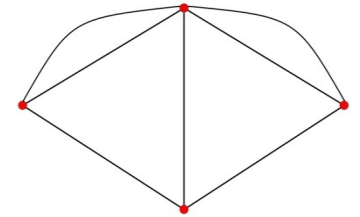
6.6: Examples of Influence



▶

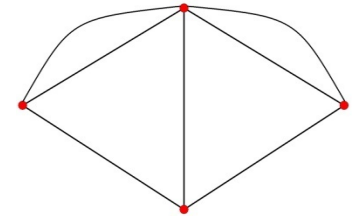
Outline: DeGroot Model

- Basic Definitions
- When is there convergence?
- When is there a consensus?
- Who has influence?
- When is the consensus accurate?



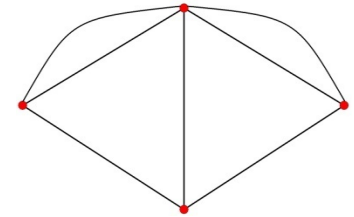
Stubborn Agents

- An agent who places high weight on self will maintain belief while others converge to that agent's belief
- Groups that are highly introspective will have substantial influence.

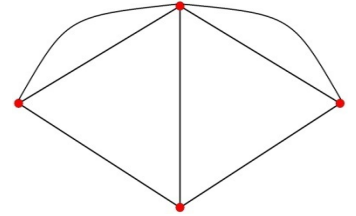


Another Example: Influence

- Suppose equally weight connections
- Suppose also that $T_{ij} > 0$ if and only if $T_{ji} > 0$
- d_i is i 's out degree
- So, $T_{ij} = 1/d_i$ for each i and j that i has a (directed) link to: so weight friends and weight them all equally



Example: Influence

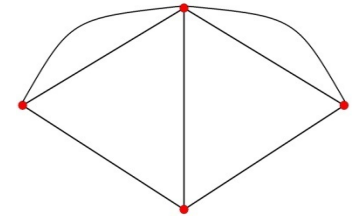


Let $D = \sum_k d_k$

Claim: $s_i = d_i / D$ for each i

- Recall s is unit eigenvector: $s_i = \sum_j T_{ji} s_j$
- Verify that $s_i = \sum_j T_{ji} s_j$

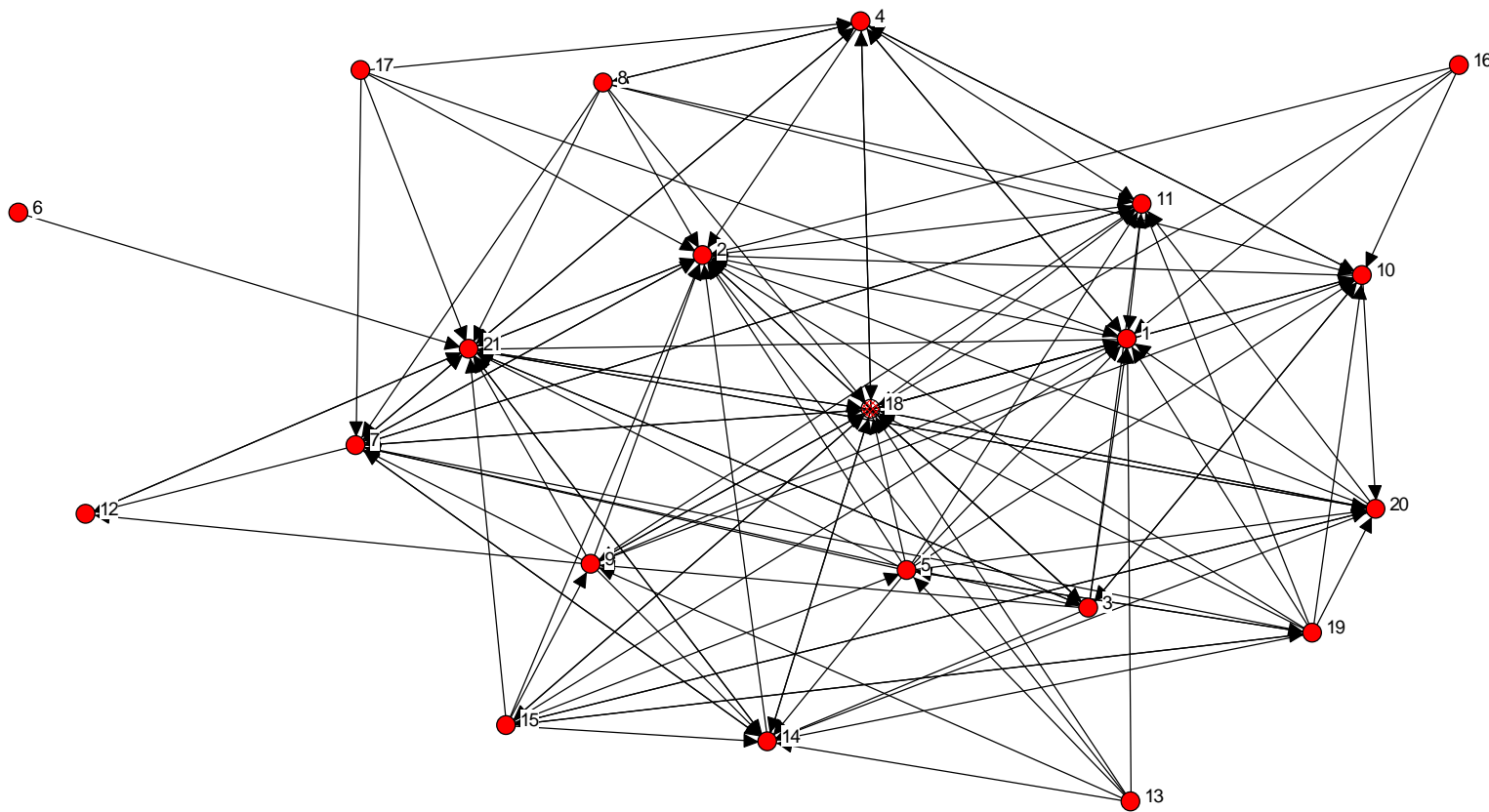
Example: Influence



Claim: $s_i = d_i / D$ for each i

- Recall s is unit eigenvector: $s_i = \sum_j T_{ji} s_j$
- Verify that $s_i = \sum_j T_{ji} s_j$
- $s_i = \sum_j T_{ji} s_j = \sum_{j: T_{ij}>0} (1/d_j) d_j / D = d_i / D$

Krackardt's (1987) advice network:



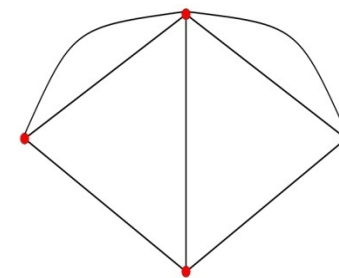
label	s	level	dept.	age	tenure
1	0.048	3	4	33	9.3
2	0.132	2	4	42	19.6
3	0.039	3	2	40	12.8
4	0.052	3	4	33	7.5
5	0.002	3	2	32	3.3
6	0.000	3	1	59	28
7	0.143	1	0	55	30
8	0.007	3	1	34	11.3
9	0.015	3	2	62	5.4
10	0.024	3	3	37	9.3
11	0.053	3	3	46	27
12	0.051	3	1	34	8.9
13	0.000	3	2	48	0.3
14	0.071	2	2	43	10.4
15	0.015	3	2	40	8.4
16	0.000	3	4	27	4.7
17	0.000	3	1	30	12.4
18	0.106	2	3	33	9.1
19	0.002	3	2	32	4.8
20	0.041	3	2	38	11.7
21	0.201	2	1	36	12.5

Influence



- Provides foundation for eigenvector-based centrality or power measures
- Saw relation of eigenvector to walks - g^t gives measure of all walks of length t ...

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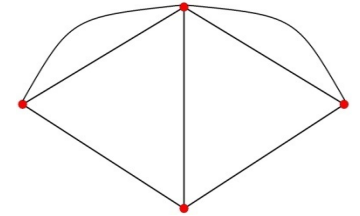


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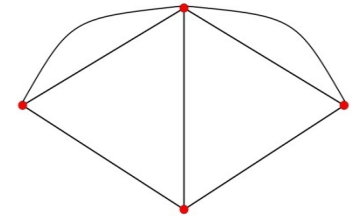
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6.7: Information Aggregation

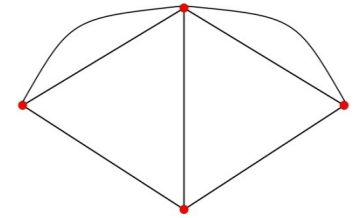


Outline: DeGroot Model

- Basic Definitions
- When is there convergence?
- When is there a consensus?
- Who has influence?
- When is the consensus accurate?



When is Information Aggregation Accurate:



- How does this depend on network structure?
- How does it depend on influence?
- How does it relate to speed of convergence

Uncertainty Structure



- Suppose true state is μ
- Agent i sees $b_i(0) = \mu + \varepsilon_i$
- ε_i has 0 mean and finite variance, bounded below and above,
- signal distributions may differ across agents, but are independent conditional on μ

Wise Crowds



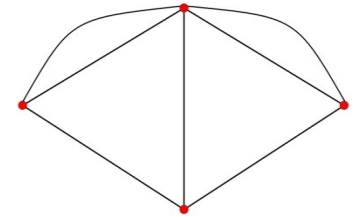
- Consider large societies
- If they pooled their information, they would have an accurate estimate of μ
- For what sequences of societies indexed by n does

$$\text{Prob} \lim_t [| b_j^n(t) - \mu | > \delta] \rightarrow_n 0 \text{ for all } \delta, j?$$

A Weak Law of Large Numbers:

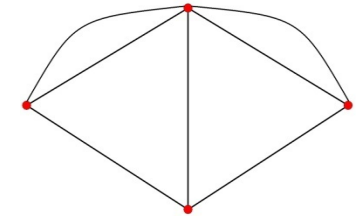
Let ε_i 's be independent, zero mean, and each have finite variance (bounded below). Then:

$$\text{plim } \sum s_i^n \varepsilon_i = 0 \quad \text{iff} \quad \max_i s_i^n \rightarrow 0$$



Wise crowds iff max influence vanishes

A Weak Law of Large Numbers:



Let ε_i 's be independent, zero mean, and each have finite variance (bounded below). Then:

$$\text{plim } \sum s_i^n \varepsilon_i = 0 \quad \text{iff} \quad \max_i s_i^n \rightarrow 0$$

Wise crowds iff max influence vanishes: recall that

$$\begin{aligned} \lim_t b_j^n(t) &= \sum s_i^n b_i^n(0) \\ &= \sum s_i^n (\mu + \varepsilon_i) \\ &= \mu + \sum s_j^n \varepsilon_j \end{aligned}$$

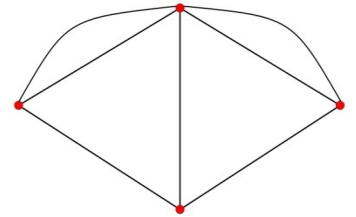
So: $\text{plim } (\lim_t b_j^n(t)) = \mu$ iff $\text{plim}(\sum s_j^n \varepsilon_j) = 0$, iff $\max_i s_i^n \rightarrow 0$

Reciprocal Attention:

Suppose that T is column stochastic (so each agent receives weight one). Then $s=(1/n, \dots, 1/n)$ is a unit lhs eigenvector, and so T is wise.

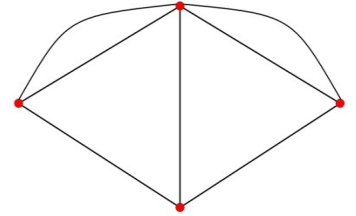
So, **reciprocal trust** implies wisdom.

But that is a very strong condition...

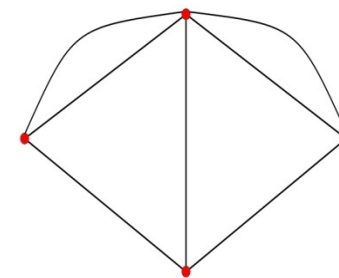


No Opinion Leaders

- $s_i = \sum_j T_{ji} s_j$
- If there is some i with $T_{ji} > a > 0$ for all j , then $s_i > a$
- So clearly cannot have too strong an “opinion leader”



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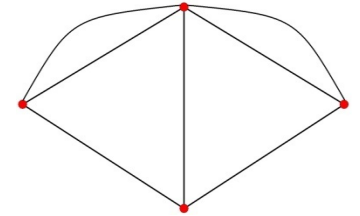


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6.8: Learning Summary



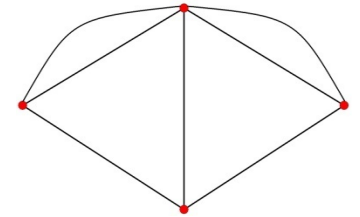
Summary



- **Convergence/Consensus** if and only if **aperiodicity**
- **Limiting influence** related to eigenvectors and weights from **influential neighbors**
- **Wise crowds**: nobody retains too much influence

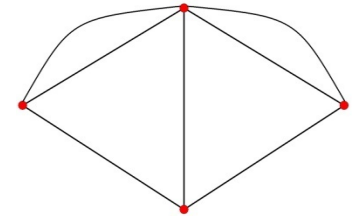
Learning Models

- Bayesian is computationally demanding in network settings
- Restricted Bayesian gives consensus network not much of a role
- DeGroot and other myopic models bring network into play
- Can reach consensus, can be wise
- Influence and speed are tractable...

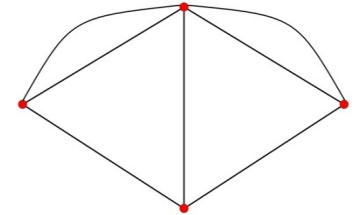


To do list:

- Between myopic and rational?
- Richer settings with strategic considerations (political...)
- Translate social structure to learning conclusions: homophily, etc.

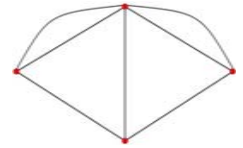


Week 6 Wrap



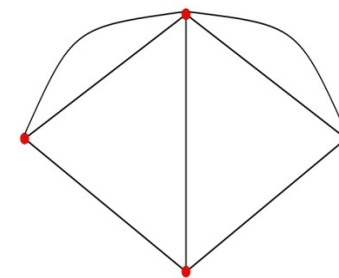
- Rational/Bayesian learning: complex but leads to consensus actions if: homogeneous, repeated observations, stationary
- Network Structure: DeGroot model
 - tractable repeated discussions
 - eventual consensus for many structures (speed depends on homophily)
 - influence depends on how much listened to – rationalizes eigenvector-style centrality measures
 - accurate beliefs depend on balance

Week 6: References in order mentioned



- Bala, V., and S. Goyal (1998) "Learning from Neighbors," *Review of Economic Studies* 65:595–621.
- Acemoglu D, Dahleh M, Lobel I, Ozdaglar A. 2011. Bayesian learning in social networks., *Review of Economic Studies*, 78:4, 1201-1236.
- DeGroot, M.H. (1974) "Reaching a Consensus," *Journal of the American Statistical Association* 69:118–121.
- French, J. (1956): A Formal Theory of Social Power, *Psychological Review*, 63: 181 -194.
- Harary▲F. 1959. "Status and Contrastatus." *Sociometry*, 22(1): 23–43.
- Friedkin, Noah E., and Eugene C. Johnsen. 1997. "Social Positions in Influence Networks." *Social Networks*, 19(3): 209–22
- DeMarzo, Peter M., Dimitri Vayanos, and Jeffrey Zwiebel. 2003. "Persuasion Bias, Social Influence, and Unidimensional Opinions." *Quarterly Journal of Economics*, 118(3): 909–68.
- Golub B, Jackson MO. 2010. "Naive learning and influence in social networks: convergence and wise crowds," *the American Economic Journal: Microeconomics*, 2(1): 112-49,
- Golub B, Jackson MO. 2012 ``How Homophily affects the Speed of Learning and Best Response Dynamics, *Quarterly Journal of Economics* Vol. 127, Iss. 3, pp 1287—1338
- Jackson, M.O. (2008) *Social and Economic Networks*, Princeton University Press, Princeton NJ.
- Krackhardt, D. (1987) "Cognitive Social Structures," *Social Networks* 9:109–134.

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