

# Applied economic networks - VII

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# Today's class

- ▶ Learning in networks
- ▶ Philippine's presentation: *How homophily affects the speed of learning and best-response dynamics*
- ▶ Philemon's presentation: *Homophily and the persistence of disagreement*

# Learning

- ▶ Individuals learn from actions of others,
- ▶ Individuals learn from talking with others,
- ▶ and they also process this information: inference on indirect information

Why is it different from diffusion?

We keep track of the information, so it's not just an issue of being infected or not.

# Main questions

- ▶ Is dispersed information aggregated efficiently?
- ▶ Whose opinions or experiences are particularly influential?
- ▶ Will choices of individuals be the same or differ? How do the networks play a role in this?

# Two main approaches

1. Individuals are rational: they observe all previous actions and a private signal.
  - ▶ Others' choices carry information about their signals,
  - ▶ **information is an externality**,
  - ▶ individuals may end up ignoring private signals and copy the crowd  $\Rightarrow$  **herding**

# Two main approaches

1. Individuals are rational: they observe all previous actions and a private signal.
  - ▶ Others' choices carry information about their signals,
  - ▶ **information is an externality**,
  - ▶ individuals may end up ignoring private signals and copy the crowd  $\Rightarrow$  **herding**
2. Individuals have bounded rationality
  - ▶ Agents start with an exogenous opinion,
  - ▶ the opinion updates over time according to an updating rule.
  - ▶ Since it is a mechanical model, we can call it *naive learning*.

# A simple Bayesian model of learning - Bala & Goyal 1998

- ▶  $n$  players in an undirected network  $g$
- ▶ Each period agents choose action  $A$  or  $B$
- ▶  $A$  gives utility 1 for sure,  $B$  gives 2 with probability  $p$  and 0 with probability  $1 - p$

# Learning

- ▶ At each point in time agents get payoff depending on their action
- ▶ Agents observe neighbors choices - the network plays a role
- ▶ The problem is to maximize the discounted stream of payoff
- ▶  $p$  is unknown



## updating beliefs

- ▶ Since agents do not know  $p$ , they make inference based on the history of choices and payoff
- ▶  $\mu_i(h_{i,t})$  is the inferred probability for an agent  $i$  that  $B$  pays 2, given a history of observations

# Result

## Proposition

If  $p \neq 1/2$ , with probability 1 there is a finite time  $t$  such that all agents play the same action from that time onward.

# Sketch of the proof

Suppose the contrary..

- ▶ Some agent plays  $B$  infinitely often, and his belief on  $p$  converges to the true  $p$ .
- ▶ If so, the belief converges to  $p > 1/2$ , or otherwise she would have stopped playing  $B$ .
- ▶ All of her neighbors see  $B$  being played infinitely often..
- ▶ Neighbors of the first agent must play  $B$ , and after some time also the neighbors of the neighbors  $\Rightarrow$  everyone plays  $B$ .

# Conclusions

The network plays little role in the end.

Agents play  $B$  if  $p > 1/2$ ,  $A$  otherwise.

Correct aggregation may fail, but under some very strict conditions:

- ▶ The complete network,
- ▶ The network where every agent has at most 1 neighbor.

# Repeated linear updating

What if agents are not rational?

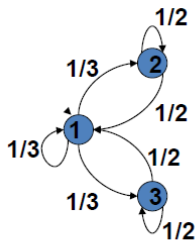
- ▶ Agents are born with some opinions.
- ▶ The network  $T$  is weighted (row-stochastic) and directed.
- ▶ The weights (and the network) do not adjust over time (different from Bayesian).

The updating rule

In every period  $t$  an agent's opinion is given by:

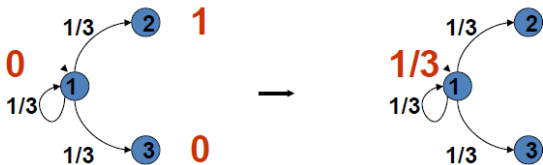
$$b_i(t) = \sum_j T_{ij} b_j(t-1)$$

## An example

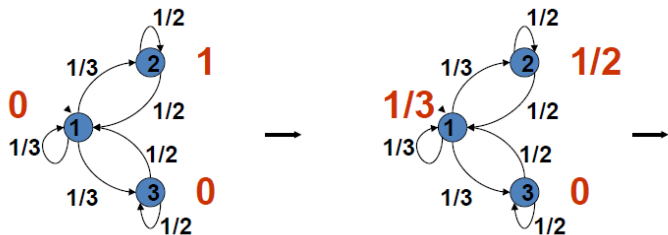


$$T = \begin{bmatrix} 1/3 & 1/3 & 1/3 \\ 1/2 & 1/2 & 0 \\ 1/2 & 0 & 1/2 \end{bmatrix}$$

## An example

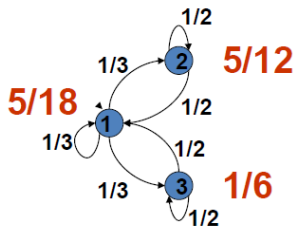
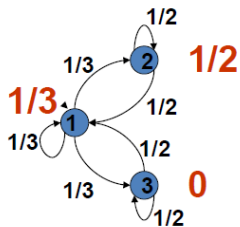
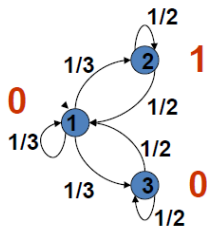


# An example

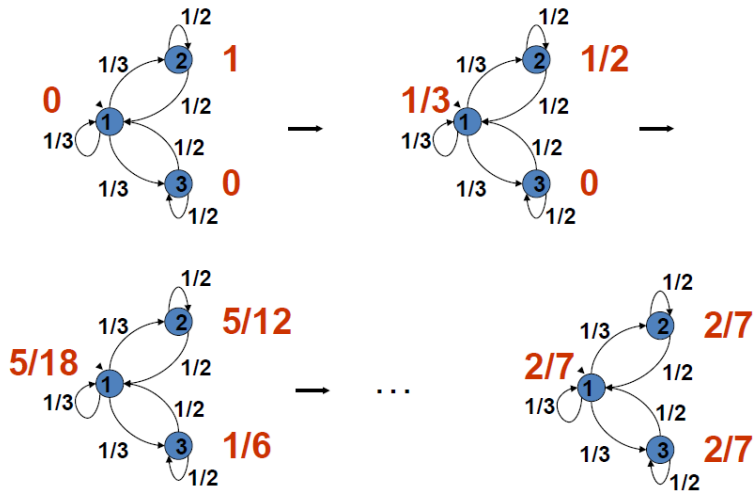




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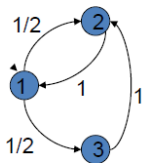


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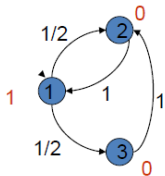
What can we say about convergence?

## An example of convergence



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

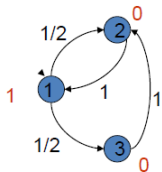
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$$T = \begin{pmatrix} 0 & \frac{1}{2} & \frac{1}{2} \\ 1 & 0 & 0 \\ 0 & 1 & 0 \end{pmatrix}$$

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

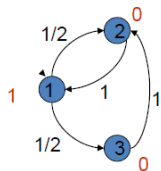
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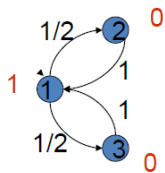
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$$b(0) = \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix} \quad b(1) = \begin{pmatrix} 0 \\ 1 \\ 0 \end{pmatrix} \rightarrow \begin{pmatrix} 1/2 \\ 0 \\ 1 \end{pmatrix} \rightarrow \begin{pmatrix} 3/4 \\ 1/2 \\ 0 \end{pmatrix} \rightarrow \begin{pmatrix}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

## An example of not-convergence

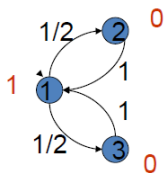


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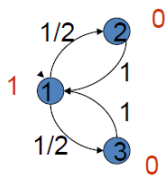
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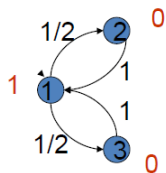
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$$b(0) = \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix} \quad b(1) = \begin{pmatrix} 0 \\ 1 \\ 1 \end{pmatrix} \rightarrow \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix}$$

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## Result

Suppose  $T$  is strongly connected (there exists a path between any two agents):  $T$  is convergent if and only if it is **aperiodic**.

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## Definition - convergence

Everyone's opinion is the same and does not change over time.

$b_i(t') = b$  for all  $i$  and for all  $t'$ .

## Definition - Aperiodicity

Greatest common divisor of cycle lengths is 1.

# Proof of the result

We need to show that if the network is strongly connected, stochastic and aperiodic, then there is convergence.

We start with an old result:

Perron-Frobenius theorem - an extrapolation

$T$  is primitive iff  $T_{ij}^t > 0$  for all  $ij$  and for all  $t > t'$ , for some  $t'$ .

If so there exists a positive eigenvalue which is strictly greater in absolute value than all the other eigenvalues. Here we use stochastic matrix.

# Proof of the result

Perkins (1961)

If  $T$  is strongly connected and stochastic then it is aperiodic iff it is primitive.

So, if  $T$  is stochastic, then it is primitive. If it is primitive it is aperiodic. The last piece:

Result

If  $T$  is strongly connected and primitive then :

$$\lim_t T^t = \mathbf{1}, \mathbf{1}, \dots, \mathbf{1}^T s \quad (1)$$

where  $s$  is the unique eigenvector associated with eigenvalue 1.

# When is the information accurate?

Assume there is some uncertainty:

- ▶ A true state of the world  $\mu$ .
- ▶ Agents see  $b_i(0) = \mu + \varepsilon_i$
- ▶ If agents are able to pool the information, they have an accurate estimate of  $\mu$ .



# The wisdom of the crowds

## Result (informal)

The crowds are wise if there are no agents “too” influential.

So wisdom depends on the social structure!

- ▶ No prominent agents (e.g. royal families)
- ▶ Reciprocal trust: attention is reciprocated (row and column stochastic matrix)

## Related questions

- ▶ How quickly a society reaches consensus? How does the *speed of learning* relate to the network structure?
- ▶ Under which conditions consensus fail to exist?

Thank you for your attention