## Diffusion models on social networks

Mark C. Wilson (with Patrick Girard, Alex Raichev) www.cs.auckland.ac.nz/ ${ }^{\text {mcw/blog/ }}$

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## References

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- Girard, Seligman, Liu developed a model of belief change in a social network.
- This talk sets out a broader research programme.


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- strong influence: if all neighbours are green, node turns green;
- weak influence: if no neighbours are red and at least one is green, red node turns yellow.
- By symmetry, each rule also holds when the roles of red and green are reversed. Note that a yellow node can only change colour under strong influence.



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－We have a 3－colour model，with lack of symmetry，as yellow is more resistant to changing colour than the others．
－A related interpretation：green means＂break the law＂，red means＂report offenders＂，yellow means＂stay neutral＂．三 $\ddagger$ ミの

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- Abstractly, each node has a certain state (colour), and each node updates its colour based on some local rule. Updates can be simultaneous, sequential (fixed order of agents), or asynchronous (anyone can move).
- There are two main methodologies: analytic results for specific network models, and agent-based simulation.


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－Most common setup is 2 colours．Can use a monotone voting rule（simple game）among neighbours＇colours，and switch my colour to the winning colour．
－In linear threshold models，each node $v$ has a threshold $\theta_{v} \in[0,1]$ ，and a weight $b_{v w}$ for each neighbour $w$ ．If $\sum_{w} b_{v w}>\theta_{v}$ ，then $v$ changes its colour in some way．

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－Majority dynamics falls into both classes－each node has weight 1 for all others，and $\theta_{v}=\operatorname{deg}(v) / 2$ ．
－Higher thresholds correspond to a bias in favour of the status quo．

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- GSL model is in this class, for $m=3$. The voting rule is unnatural, and depends on the node. If I vote green, then green wins, unless everyone else votes yellow (yellow wins), or someone else votes red and no one votes green (red wins). Same with red and green reversed. If I vote yellow, then yellow wins unless everyone else votes green (green wins) or red (red wins).


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- The class of local voting rules that do not depend on the node, and are anonymous and neutral (that is, ordinary voting rules + polling neighbours) is worth studying.


## Example: Petersen, step 0



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## Example: Petersen, step 1



## Example: Petersen, step 2



## Example: Petersen, step 3



## Example: Petersen, step 4



## Example: $K_{10}$, converges immediately



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－（homophily）Describe the effect on the process of assuming that nodes of same colour are more likely to be connected．
－（cascades）When do arbitrary changes to some nodes propagate to a large fraction of the network？

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- Validation of models is not very advanced.
- Proving anything rigorous about dynamics, even for the above models, is technically hard.
- Simulations may be sensitive to small changes in initial conditions.


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－A pendant vertex whose neighbour is not yellow will change colour immediately．
－A star graph converges in 2 steps to unanimity if the centre is not yellow，otherwise converges immediately．

## Special case: complete graph

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- Simultaneous majority dynamics converge in one step to unanimity if $|V|$ is odd. The crowd is wise (related to Condorcet jury theorem).
- With high probability, random initial colourings will converge immediately under GSL dynamics with high threshold. This happens whenever there are at least two nodes of each colour, for example.


## Some related models and work

- Kempe, Kleinberg, Tardos (2003). Update rule:
(generalization of) linear threshold model with $m=2$. Aim: find optimal initial set of green nodes of given size $k$ to maximize number of green nodes in equilibrium (influence maximization). Result: the problem is NP-complete, but a greedy algorithm gives a ( $1-1 / e$ )-approximation ratio.


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－Mossel，Neeman，Tamuz（2012）．Update rule：local plurality． Results：for $m=2$ ，crowds are not wise in general，but they are when no orbit of the automorphism group on the graph is small．

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- See Sage worksheet!


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- Consider polling over distance- $k$ neighbourhoods for increasing $k$, and quantify how phenomena depend on $k$.
- Strategic behaviour - when does an agent have incentive to vote untruthfully? to break edges?
- Instead of threshold dynamics, consider best reply voting, where we poll our neighbours and act as though only our 1-neighbourhood is taking part in the election. For completeunasy dAcuanem graphs, some results are known.

