

# Voter models and variants

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Models

# Classical voter model

- Population of  $n$  voters
- Each voter has opinion/ preference in  $\{0,1\}$
- Voters interact and update their opinions ...
- ... in either discrete or continuous time

# Classical voter model: discrete time

- Population of  $n$  voters
- Each voter has opinion/ preference in  $\{0,1\}$
- Voters update their opinions synchronously
- In each time step, each voter samples a voter uniformly at random (including itself) ...
- ... and copies the opinion of the chosen voter

# Classical voter model: continuous time

- Population of  $n$  voters
- Each voter has opinion/ preference in  $\{0,1\}$
- Voters update their opinions asynchronously
- Each voter has an alarm clock that rings after independent  $Exp(1)$  times, independent of the clocks at other voters
- When a voter's clock rings, she contacts a voter chosen uniformly at random ...
- ... and copies the opinion of that voter

# Consensus

- Voter model is a Markov process
  - All-0 and all-1 states are absorbing, reachable from all other states.
  - Hence, voters reach consensus eventually.
- 
- Q: How long does it take to reach consensus?
  - Q: What is the probability of reaching consensus on 1, for a given initial state?

# Application: Population Genetics

- Population of  $n$  alleles
- Each allele is of one of two types,  $a$  or  $A$
- Population size stays constant over time
- Composition evolves over time exactly as in voter model:
  - Discrete-time version is called Wright-Fisher model
  - Continuous-time version is called Moran model
- “Neutral” models – neither allele has a selective advantage over the other

# Moran model in population genetics

- Population of  $n$  alleles
- Each allele is of one of two types,  $a$  or  $A$
- Each allele dies after an  $Exp(1)$  lifetime, and is replaced by a copy of another allele, chosen uniformly at random from the population
- *Q: Starting with  $n - 1$  “wild-type”  $a$  alleles, and a single “mutant”  $A$  allele, what is the probability that the mutant reaches fixation?*
- *Q: How long does it take until the mutant reaches either fixation or extinction?*



# Moran model with selection

- Population of  $n$  alleles, of two types,  $a$  or  $A$
- Mutant alleles  $A$  have fitness  $1 + s$ , wild-type  $a$  have fitness 1
- Each allele dies after an  $Exp(1)$  lifetime, and is replaced by a copy of another allele, chosen at random weighted by fitness
- *Q: Starting with  $n - 1$  wild-type  $a$  alleles, and a single mutant  $A$  allele, what is the probability that the mutant reaches fixation?*
- *Q: How long does it take until the mutant reaches either fixation or extinction?*

# Infinite alleles Moran model

- Population of  $n$  alleles
- Initially, all alleles are of type 0
- Each allele dies after an  $Exp(1)$  lifetime, and:
  - with probability  $1 - \varepsilon$ , it is replaced by an allele chosen uniformly at random from the population
  - with probability  $\varepsilon$ , it is replaced by a mutant of a completely new type, i.e., no two mutations give rise to the same allele
- *Q: What is the population structure in equilibrium?*

# Voter model on a graph

- $G = (V, E)$ : connected, undirected graph
- Nodes correspond to voters
- Voters update their opinions in discrete or continuous time, sampling uniformly from among their neighbours in  $G$  ...
- ... or non-uniformly according to a given stochastic matrix  $P$  (discrete time) or rate matrix  $Q$  (continuous time)
- Remark: If  $G = K_n$ , we recover the classical model.
- *$Q$ : What can we say about consensus times and probabilities?*

# Example: Voter model on lattices

- Infinite lattice in  $d$  dimensions
- One of two initial preferences, 0 or 1, at each vertex

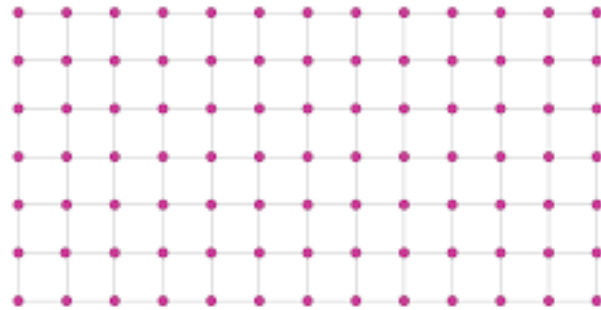


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- *Q: What happens in the long run?*

# Example: Voter model on lattices

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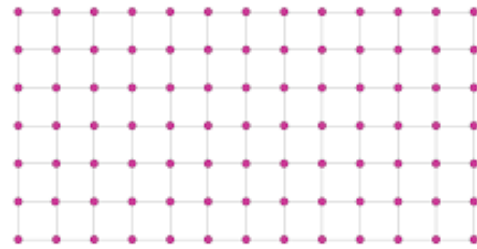


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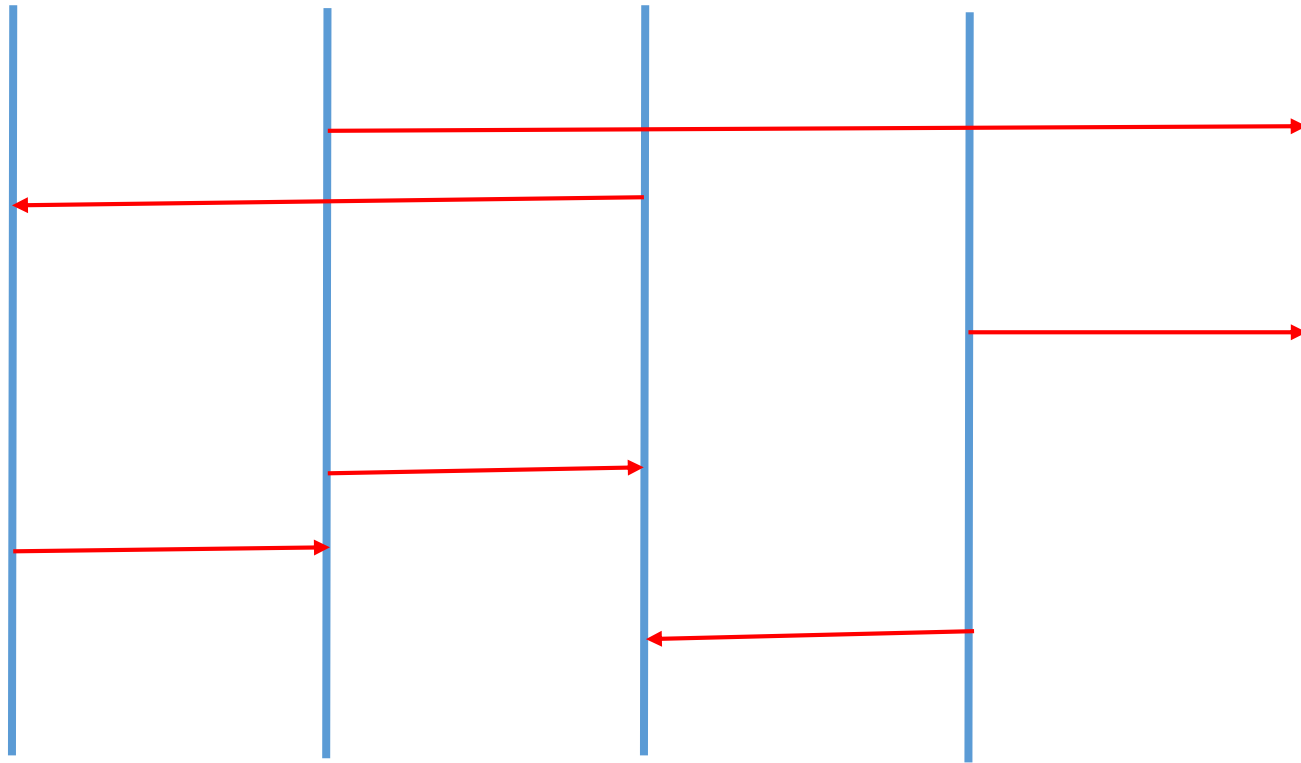
- Answer: In the long run, there is
  - consensus in dimension 1 or 2
  - co-existence in 3 or more dimensions

# Applications

- Spin glasses
  - voter preference represents spin
- Evolutionary biology / population genetics
- Ecology
  - behaviour of social insects, bioluminescent bacteria (quorum sensing), flocking of fish and birds
- Economics and social science
  - competition between products and technologies, adoption of customs and behaviours, fads and fashions, movement of crowds
- Computer science
  - decentralised algorithms for averaging, consensus, information fusion

Analysis

# Graphical representation and duality





# Coalescing random walks

- Start with a single particle at each vertex  $v \in V$
- Particles perform independent random walks with rates  $q(v, w)$
- If a particle moves to an occupied site, it immediately merges with the particle there – the new particle continues to perform a random walk with the same rate
- Voter model in reversed time corresponds to a coalescing random walk

# Implications

- Time to consensus in voter model is bounded by the time to have a single particle in the coalescing random walk
  - in particular, for  $G = K_n$ , we have  $E[T] \leq n$
- Voter model in 1 and 2 dimensions achieves consensus, but in 3 or more dimensions, there is co-existence

# Consensus value

- Assumption: the matrix  $Q$  or  $P$  governing the random walk admits a unique invariant distribution  $\pi$
- $X(t)$  : configuration of the voter model at time  $t$
- Then,  $M(t) = \langle \pi | X(t) \rangle$  is a bounded martingale
- Optional stopping theorem yields:  
$$P(\text{consensus value} = 1) = \langle \pi | X(0) \rangle$$

# Bounds on the coalescence time: continuous time model

- Random walks on  $n$ -vertex graph with  $q(v, w) = 1/\deg(v)$

Theorem (Hassin & Peleg, 2001): On any connected graph,  
$$E[T] = O(n^3 \log n)$$

- Close to best possible:  $\Theta(n^3)$  in general
  - e.g., dumbbell graph: two cliques of  $n/4$  vertices, joined by a path of  $n/2$  vertices
- Better results available for specific types of graphs

# Bound on the coalescence time: discrete time model

- Definitions and notation:
  - $\lambda_2$ : second eigenvalue of random walk transition probability matrix
  - $\nu = \frac{\sum_{v \in V} \deg(v)^2}{nd^2}$ , where  $d$  = average degree,

Theorem(Cooper, Elsassser, Ono & Radzik, 2016)

$$E[T] \leq \frac{\text{const.}}{1 - \lambda_2} \left( \log^4 n + \frac{n}{\nu} \right)$$

# Corollaries

- Coalescence time is linear in  $n$  for expanders
- Coalescence time is sublinear in  $n$  for power-law (scale-free) random graphs

# Key ideas behind proof

- Fix  $k^* = k^*(n)$
- Split coalescence time into time to go from  $n$  particles to  $k^*$  and then from  $k^*$  to 1, and bound each of them separately
- First part: Bound probability that there are  $k^*$  particles that avoid meeting each other for a given time
- Second part: Instead of  $k$  independent random walks on  $G$ , consider one random walk on tensor product graph  $G^k$
- Meeting time of two walks on  $G$  is equivalent to hitting time of a specific subset on  $G^k$

# Product graph and hitting times

- Vertices of  $G^k$  are  $k$ -tuples  $(v_1, v_2, \dots, v_k)$
- Edge  $(\mathbf{v}, \mathbf{w})$  exists if  $(v_i, w_i)$  exists for all  $i$
- $S_k = \{\mathbf{v} : v_i = v_j \text{ for some } i \neq j\}$  : set of diagonal vertices
- $\Gamma$  : graph obtained by contracting  $S_k$  to single vertex,  $\gamma$
- Want to bound hitting time of  $\gamma$  from arbitrary initial condition
- Bound it by sum of mixing time, and hitting time started from stationarity
- Key fact:  $\lambda_2(G) = \lambda_2(G^k) \geq \lambda_2(\Gamma)$



# Moran model with selection

- $N(t)$ : number of  $A$  alleles at time  $t$
- Define  $M(t) = (1 + s)^{-N(t)}$
- $M(t)$  is a martingale
- Optional Stopping Theorem implies fixation probability is given by

$$P(N(T) = n | N(0) = 1) \rightarrow \frac{s}{1+s} \text{ as } n \rightarrow \infty$$

- Expected time to fixation is  $E[T] \approx \log n$

# Moran model with selection on a graph

- Very little known in general
- No good tools – neither duality nor martingales

Lieberman, Hauert & Nowak (2005):

- Fixation probability is exactly the same for *regular* graphs/digraphs as for the complete graph
- It is approximately the same if the graph is close to regular, i.e., ratio of maximum to minimum degree is close to 1

Majority consensus

# Problem Statement

- Given a population of  $n$  voters, with opinions in  $\{0,1\}$
- Objective: determine the majority vote
  - quickly, i.e., in  $\text{polylog}(n)$  time
  - reliably, i.e., with high probability, but not necessarily equal to 1
  - using decentralised algorithms
- Motivation: consensus in large distributed systems

# Voters with internal states

- Each voter in one of 3 possible states, 0, 1 or undecided
- Contacts between voters as in classical voter model
- But update rule on opinions is different
  - if a voter contacts someone with the same opinion, or an undecided voter, his opinion stays unchanged
  - if a 0 contacts a 1 (or vice versa), he becomes undecided
  - an undecided voter copies the opinion of whoever he contacts
- *Q: What is the probability of reaching consensus on 0/1?*
- *Q: How long does it take?*

# Results for 3-state model

- Definitions and notation:
  - $\alpha, 1-\alpha$ : initial fraction of voters in state 0, 1
  - $p_\alpha$ : probability of reaching consensus on 1
  - $H(\alpha) = -\alpha \log \alpha - (1 - \alpha) \log(1 - \alpha)$ : entropy of  $\text{Bern}(\alpha)$  random variable
  - $D(\alpha; 1/2) = \log 2 - H(\alpha)$ : relative entropy of  $\text{Bern}(\alpha)$  wrt  $\text{Bern}(1/2)$

Theorem (Perron, Vasudevan and Vojnovic, 2008): If  $\alpha > 1/2$ , then

$$p_\alpha \approx \exp\left(-nD(\alpha; 1/2)\right)$$

Expected time to reach consensus is  $O(\log n)$

# Remarks about 3-state model

- Probability of reaching consensus on minority value is small
  - decays exponentially in population size, rather than being constant, as in classical voter model
- Consensus is reached quickly
  - in time logarithmic in population size, as opposed to linear in population size for the classical voter model
- Algorithm is fully decentralised

# Open Questions

- Is there an advantage to having even more internal states?
- What happens if voters aren't identical and only some have internal states?



# Alternative model: Polling and majority rule

- No internal states
- Voter activity is as in classical model, but ...
- ... each voter, on becoming active, polls two other voters, and only changes opinion if both have opposite opinion
- More generally, polls  $m$  other voters, and only changes state if at least  $k$  have opposite opinion
- Yields a family of models parametrised by  $(m, k)$
- Vector  $(m, k)$  can be random, to model individual differences

# Results for polling model: $k = m$

- Definitions and notation:
  - $\alpha, 1-\alpha$ : initial fraction of voters in state 0, 1
  - $p_\alpha$ : probability of reaching consensus on 1

Theorem (Cruise and G., 2014): If  $\alpha > 1/2$ , then

$$p_\alpha \approx \exp\left(-n(m-1)D(\alpha; 1/2)\right)$$

Expected time to reach consensus is  $O(\log n)$  for fixed  $m$ , but grows exponentially in  $m$

# Results for polling model: $k < m$

- Definitions

- $Z_x$ : Binomial random variable
- $g(x) = \frac{xP(Z_x \leq m-k)}{(1-x)P(Z_x \geq k)}$

Theorem (Cruise and G., 2014):

$$\frac{1}{n} \log p_\alpha \rightarrow \int_{1-\alpha}^{1/2} \log g(x) dx \text{ as } n \rightarrow \infty$$

Time to consensus is  $O(\log n)$  for fixed  $m$  and  $k$

# Results for polling model: random $(m, k)$

- Define  $g(x)$  as before, but now taking expectations over the joint distribution of  $(m, k)$
- Then, theorem still holds, with this modified  $g$
- Implication:
  - Have exponential decay of error probabilities, and fast convergence to majority, even if only a fraction of voters use the majority rule, and the rest behave as in the classical voter model

# Main ingredients of proof

- Number of 1 votes follows a biased random walk
- Bias is towards the closer boundary, 0 or  $n$ , and gets stronger as you get closer to the boundary
- Want to compute probability of hitting boundary at  $n$  before boundary at 0
- Exploit well-known connection between random walks and electrical networks to compute hitting probabilities
- Hitting times bounded in terms of number of visits to each state before hitting the boundary

# Two-sampling on general graphs

- Cooper, Elsasser, Radzik, Rivera, Shiraga (2015):
- Time is discrete
- In each time step, each node samples two neighbours independently, with replacement – if both have same opinion, adopts that opinion
- Sampling can be uniform, or weighted by given edge weights:

$$P(u, v) = \frac{w(u, v)}{w(u)}$$

# Definitions and notation

- $A, B$  : subsets of vertices with initial opinion 0, 1

$$\lambda = \max\{\lambda_2(P), |\lambda_n(P)|\}$$

$$\nu = \frac{n \sum w^2(v)}{w(G)^2}$$

$$\epsilon_0 = \frac{|w(A) - w(B)|}{w(G)}$$

- $\delta, \xi$  : arbitrary small constants;  $K$  : arbitrary large constant

# Main result

- Theorem (Cooper et al., 2015)
- If  $\lambda < \frac{1}{\sqrt{2}} - \delta$  and  $\epsilon_0 > 2\lambda^2$  and  $\epsilon_0^2 > \frac{vK \log n}{n}$ , then whp voting is completed in  $O(\log n)$  rounds, and the winner is the opinion with larger initial weight.
- If  $\lambda = o(1)$  and  $\lambda^\xi > \frac{vK \log n}{n}$ , then whp voting is completed in  $O(\log \frac{1}{\epsilon_0}) + O(\log \log \frac{1}{\lambda}) + O(\log_{1/\lambda} n)$  rounds and the winner is the opinion with larger initial weight