

Plurality Consensus in the Gossip Model

Emanuele Natale



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joint work with

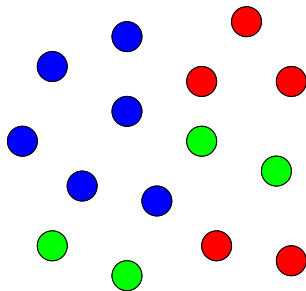
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ACM-SIAM Symposium on Discrete Algorithms
San Diego, 4-6 January 2015

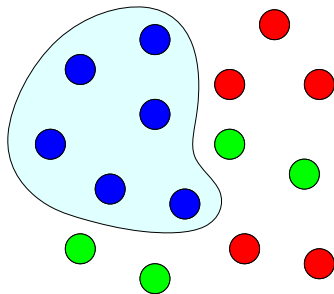
The Plurality Consensus Problem

- We have a set of nodes each having one color out of $\{1, \dots, k\}$.



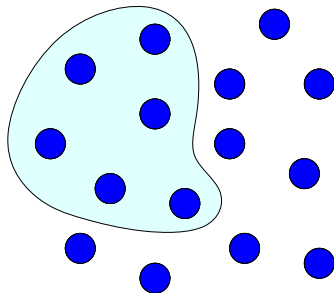
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- There is a plurality of nodes having the same color.



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- There is a plurality of nodes having the same color.
- We want to reach consensus on the plurality color.



Our Setting

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- **Local memory and message size:** $O(\log n)$.

Relationships to Other Communication Models

GOSSIP model with neighbors chosen randomly: Telephone Call, Push&Pull, Uniform Gossip. . .

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Censor-Hillel et al. (STOC '12):

Every task that can be solved in the *LOCAL* model in T rounds, can be solved in $O(T + \text{polylog}n)$ rounds in the *GOSSIP* model.

But. . .

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But. . . using the preceding theorem, message size grows dramatically!

(Main) Related Works

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|---|-------------------|-----------------|---------------------|---------------|
| Kempe <i>et al.</i> FOCS '03 | $O(k \log n)$ | any | $O(\log n)$ | <i>GOSSIP</i> |
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Our Contribution: Characterizing the Initial Bias

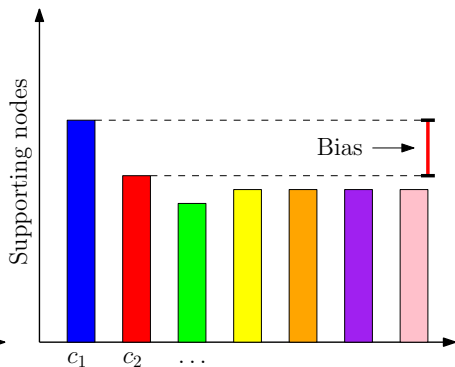
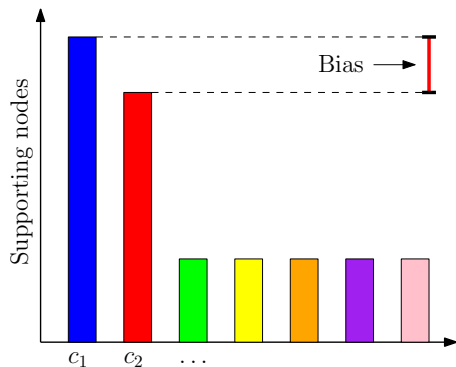
$$c_i^{(t)} := |\{i\text{-colored nodes}\}|, \quad \text{color 1 is the plurality,}$$
$$q^{(t)} := |\{\text{undecided nodes}\}|, \quad \mathbf{c}^{(t)} := (c_1^{(t)}, \dots, c_k^{(t)}, q^{(t)})$$

... wait 3 slides!

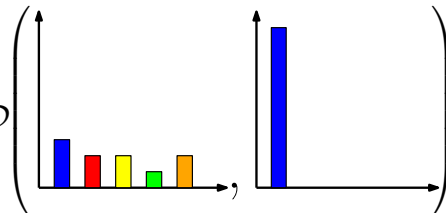
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The Monochromatic Distance

$$\text{md}(\mathbf{c}^{(0)}) := \sum_{i=1}^k \left(\frac{c_i^{(0)}}{c_1^{(0)}} \right)^2 = 1 + \mathcal{D}$$


The figure consists of two bar charts enclosed in large parentheses. The left chart has five bars of varying heights and colors: blue, red, yellow, green, and orange. The right chart has a single tall blue bar. The bars in the left chart represent the relative frequencies $\frac{c_i^{(0)}}{c_1^{(0)}}$ for $i=1, \dots, k$. The bar in the right chart represents the value 1, which is the first term in the sum.

The Monochromatic Distance

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$$1 \leq \text{md} \left(\begin{array}{c} \text{Bar chart with 7 bars of varying heights} \end{array} \right) \ll \text{md} \left(\begin{array}{c} \text{Bar chart with 7 bars of varying heights} \end{array} \right) \leq k$$

Our Results

First analysis for $k = \omega(1)$ of the Undecided-State Dynamics [Angluin et al., Perron et al., Babaee et al., Jung et al.]:

Upper Bound

If $k = O\left((n/\log n)^{1/3}\right)$ and $c_1 \geq (1 + \epsilon) \cdot c_2$ with $\epsilon > 0$, then w.h.p. the Undecided-State Dynamics reaches plurality consensus in $O\left(\text{md}(\mathbf{c}^{(0)}) \cdot \log n\right)$ rounds.

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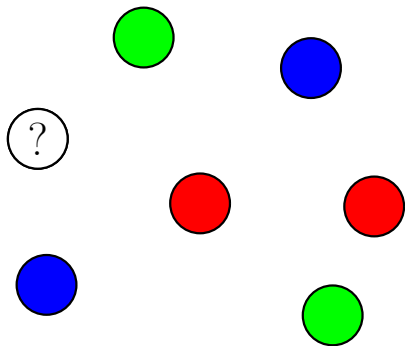
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Lower Bound

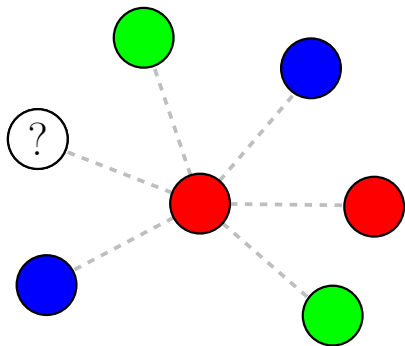
If $k = O\left((n/\log n)^{1/6}\right)$ then w.h.p. the Undecided-State Dynamics converges after at least $\Omega(\text{md}(\mathbf{c}^{(0)}))$ rounds.

The Undecided-State Dynamics



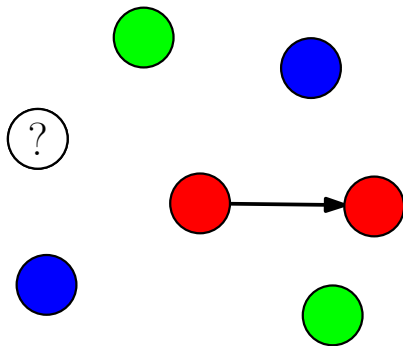
Some nodes can be “undecided”.

The Undecided-State Dynamics



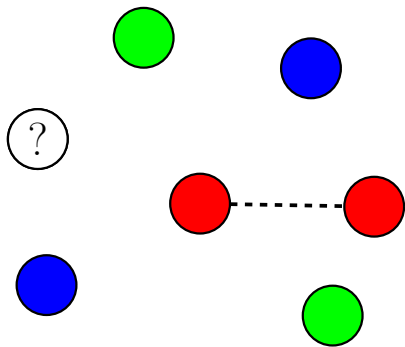
At the beginning of each round, each node observes a neighbor picked uniformly at random.

The Undecided-State Dynamics



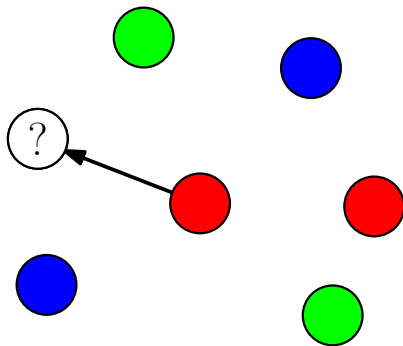
If the observed node shares the same color. . .

The Undecided-State Dynamics



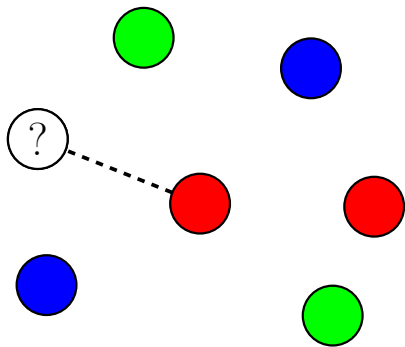
... nothing happens;

The Undecided-State Dynamics



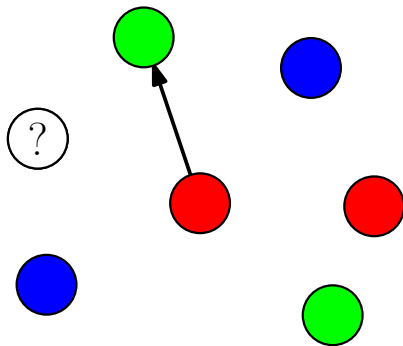
if the node observes an undecided one. . .

The Undecided-State Dynamics



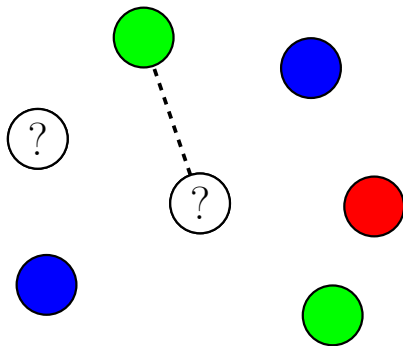
... nothing happens too;

The Undecided-State Dynamics



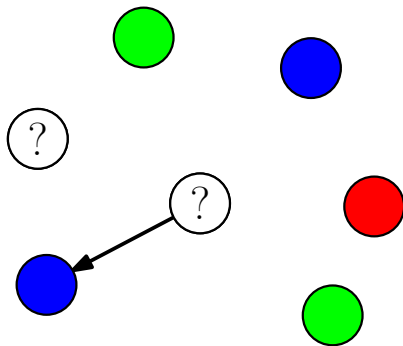
but, if the observed node has a different color...

The Undecided-State Dynamics



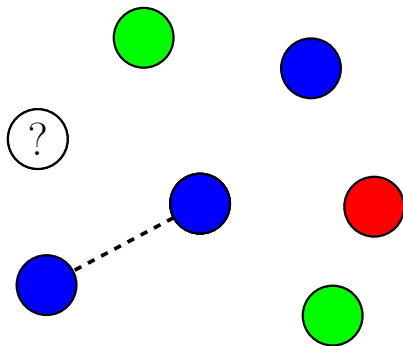
... then the node becomes undecided.

The Undecided-State Dynamics



Once undecided...

The Undecided-State Dynamics



... the node copies the first color it sees.

Overview of the Process

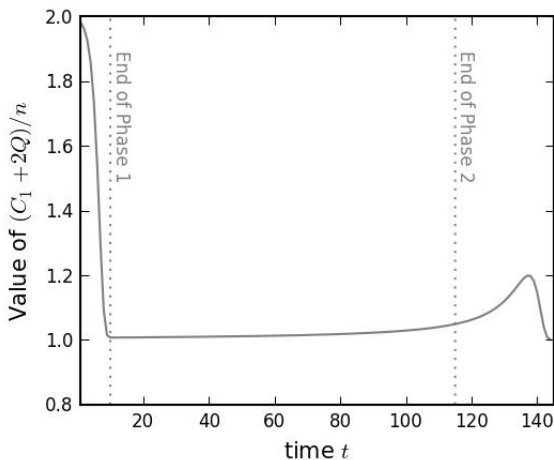
$$\begin{aligned} \mathbf{E} \left[c_i^{(t+1)} \mid \mathbf{c}^{(t)} \right] &= \\ &= c_i^{(t)} \cdot \underbrace{\frac{c_i^{(t)} + 2q^{(t)}}{n}}_{\text{Growth factor}} \end{aligned}$$

Remarks

W.h.p.:

- Plurality does not change.
- Growth factor of plurality is > 1 .

Simulation of the growth factor:



Expected Behaviour of the Process

$$\left\{ \begin{array}{l} \mathbf{E} [q^{(t+1)} \mid \mathbf{c}^{(t)}] = \frac{1}{n} \left[(q^{(t)})^2 + (n - q^{(t)})^2 - \sum_i (c_i^{(t)})^2 \right] \\ \mathbf{E} [c_1^{(t+1)} \mid \mathbf{c}^{(t)}] = c_1^{(t)} \cdot \frac{c_1^{(t)} + 2q^{(t)}}{n} \\ \quad \vdots \\ \mathbf{E} [c_k^{(t+1)} \mid \mathbf{c}^{(t)}] = c_k^{(t)} \cdot \frac{c_k^{(t)} + 2q^{(t)}}{n} \end{array} \right.$$

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Our Key Idea

Tip: Look for $md(\mathbf{c}^{(t)})$ and $R(\mathbf{c}^{(t)}) := \sum_{i=1}^k \frac{c_i^{(t)}}{c_1^{(t)}}$.

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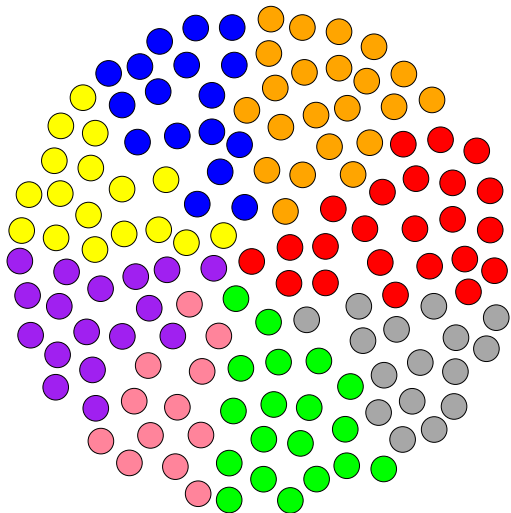
Tip: Look for $md(\mathbf{c}^{(t)})$ and $R(\mathbf{c}^{(t)}) := \sum_{i=1}^k \frac{c_i^{(t)}}{c_1^{(t)}}$.

Lemma

$$\begin{aligned} \mathbf{E} \left[\frac{c_1^{(t+1)} + 2q^{(t+1)}}{n} \mid \mathbf{c}^{(t)} \right] &= \\ &= 1 + \frac{(n - 2q^{(t)} - c_1^{(t)})^2}{n^2} + \frac{2(R(\mathbf{c}^{(t)}) - md(\mathbf{c}^{(t)})) \cdot (c_1)^2}{n^2} \end{aligned}$$

First Round

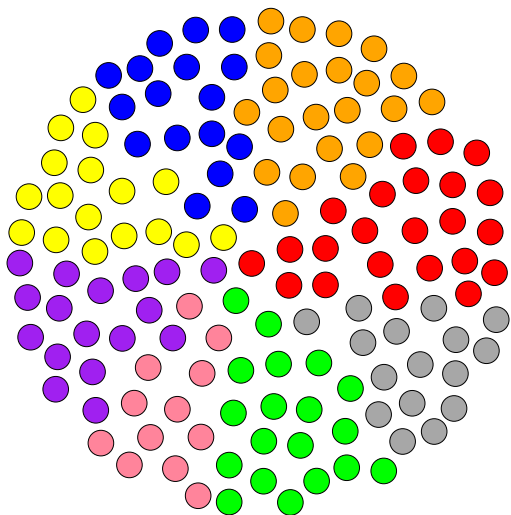
Round 1: Each node observes another random one.



First Round

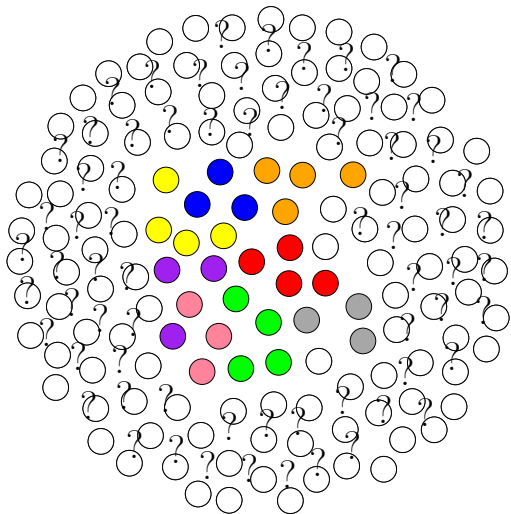
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The larger the number of colors and the more uniform the initial distribution, the higher the expected number of undecided nodes.



First Round

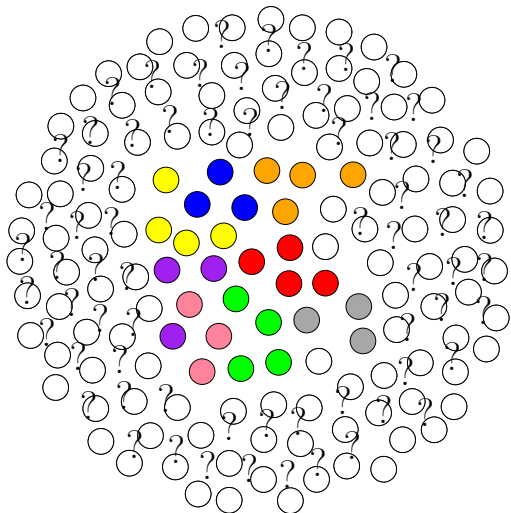
The size of each color is reduced to $\frac{(c_i^{(0)})^2}{n}$.



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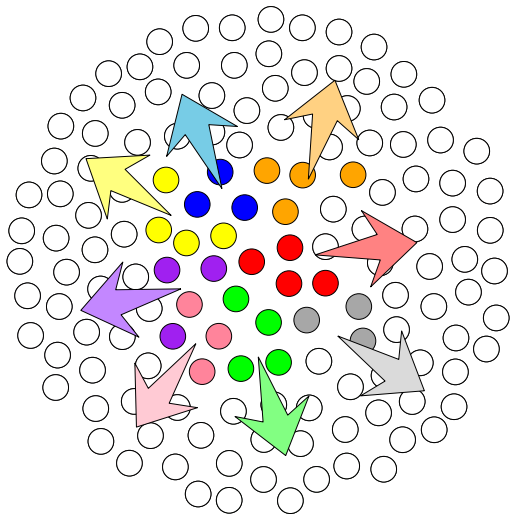
Colors with $c_i^{(0)} = O(\sqrt{n})$ nodes are likely to disappear.



Phase 1

If the initial distribution is quite uniform there are $\Omega(n)$ undecided nodes.

Undecided nodes take the first color they pull, causing colors to spread very fast.



Phase 1

Lemma

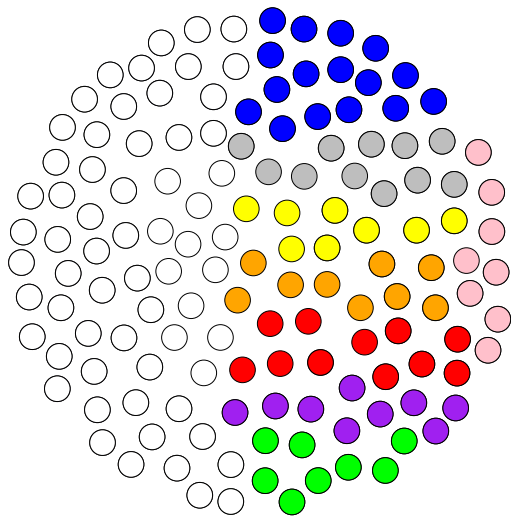
Within $T = O\left(\log \frac{R(\mathbf{c})^2}{\text{md}(\mathbf{c})}\right)$ rounds the system reaches a configuration such that w.h.p.

$$c_1^{(T)} = \Theta\left(\frac{n}{\text{md}(\mathbf{c})}\right)$$
$$q^{(T)} = \frac{n}{2} \left(1 \pm \Theta\left(\frac{1}{\text{md}(\mathbf{c})}\right)\right)$$

and, for every i , $c_1^{(0)}/c_i^{(0)}$ is approximately preserved.

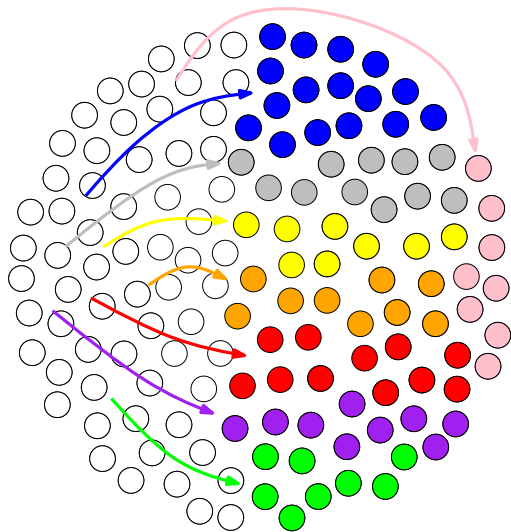
Phase 2

new colored
 \approx
new undecided.



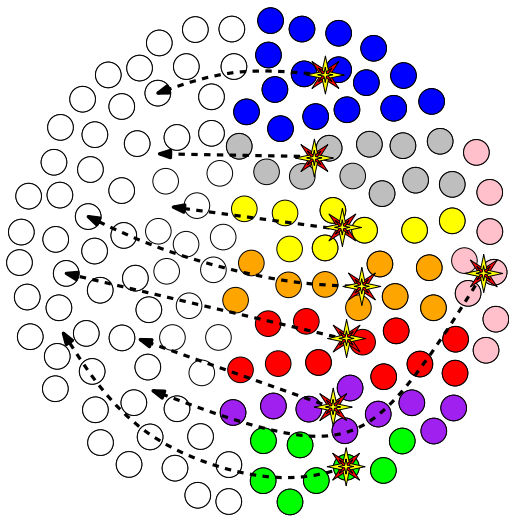
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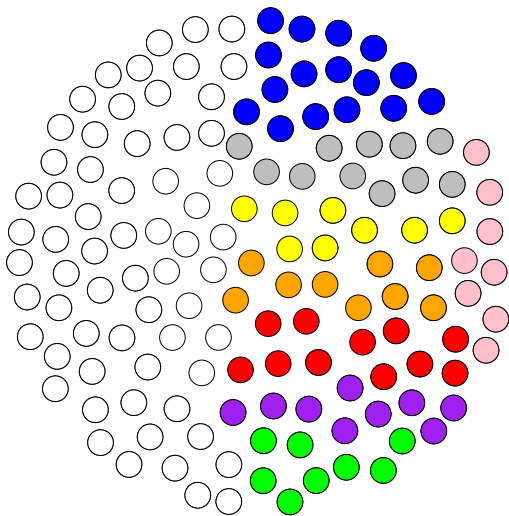
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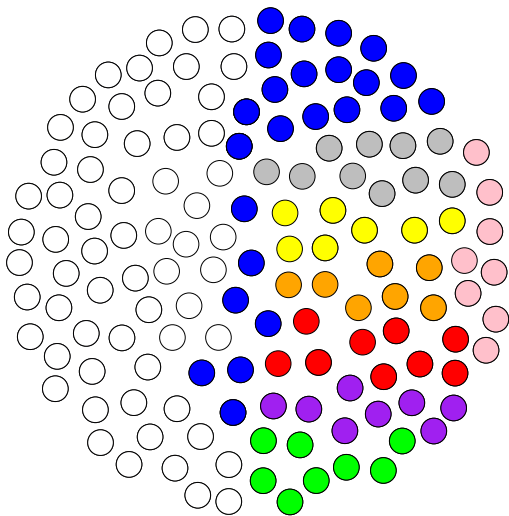
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The plurality has a
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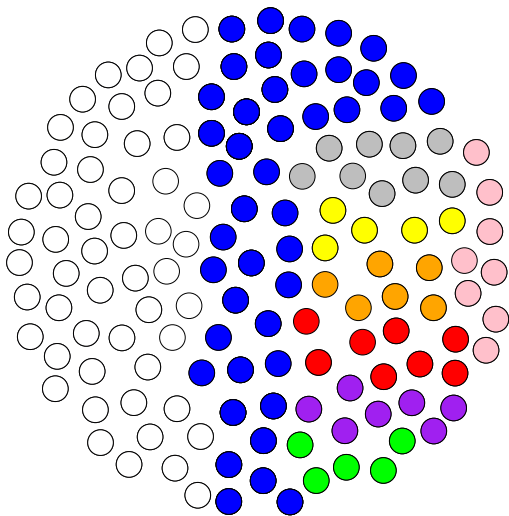
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$$\text{Plateau around } \begin{cases} c_1^{(T)} & = \Theta\left(\frac{n}{\text{md}(\mathbf{c})}\right) \\ q^{(T)} & = \frac{n}{2} \left(1 \pm \Theta\left(\frac{1}{\text{md}(\mathbf{c})}\right)\right) \end{cases}$$

Average Growth:

$$\mathbf{E} \left[c_1^{(t+1)} \mid \mathbf{c}^{(t)} \right] \approx c_1^{(t)} \left(1 + \Theta\left(\frac{1}{\text{md}(\mathbf{c})}\right) \right)$$

$$\mathbf{E} \left[q^{(t+1)} \mid \mathbf{c}^{(t)} \right] \approx \frac{n}{2} \left(1 - \Theta\left(\frac{1}{\text{md}(\mathbf{c})}\right) \right)$$

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\implies Lower bound of $\Omega(\text{md}(\mathbf{c}))$.

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Average Growth:

$$\mathbf{E} \left[c_1^{(t+\text{md}(\mathbf{c}))} \mid \mathbf{c}^{(t)} \right] \approx c_1^{(t)} \left(1 + \Theta\left(\frac{1}{\text{md}(\mathbf{c})}\right) \right)^{\text{md}(\mathbf{c})}$$

$$\mathbf{E} \left[q^{(t+\text{md}(\mathbf{c}))} \mid \mathbf{c}^{(t)} \right] \approx \frac{n}{2} \left(1 - \Theta\left(\frac{1}{\text{md}(\mathbf{c})}\right) \right)^{\text{md}(\mathbf{c})}$$

\implies After $O(\text{md}(\mathbf{c}) \log n)$ rounds, $R(\mathbf{c}^{(t)}) = 1 + o(1)$.

Phase 3

$$R(\mathbf{c}^{(t)}) = 1 + o(1) \implies c_1^{(t)} = \frac{n - q^{(t)}}{R(\mathbf{c}^{(t)})}$$

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Given a d -regular expander graph, $k = O\left((n/\log n)^{1/3}\right)$ and $c_1 \geq (1 + \epsilon) \cdot c_2$ with $\epsilon > 0$, using polylogarithmic memory and message size the plurality consensus problem can be solved in w.h.p. $O(\text{md}(\mathbf{c})\text{polylog}(n))$ rounds.

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