On Coloring Embedded Graphs

Alexandre Nolin

CISPA Helmholtz Center for Information Security (for 8½ hours)

AMG@DISC 2025 - Berlin, 31.10.2025

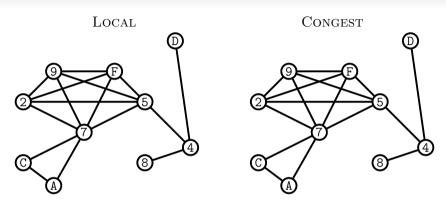
Primarily based on joint works [FHN24, FHN25] with



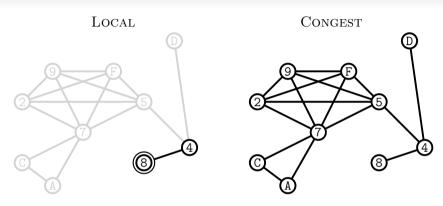
Maxime Flin



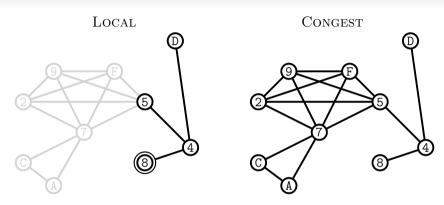
Magnús M. Halldórsson



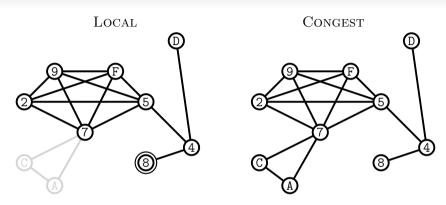
- Both: Synchronous message passing, graph models communication network.
- Local: ∞-sized messages.
- CONGEST: $O(\log n)$ -sized messages (n upper bound on number of nodes).



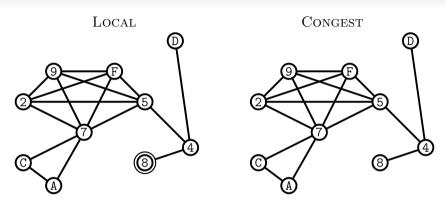
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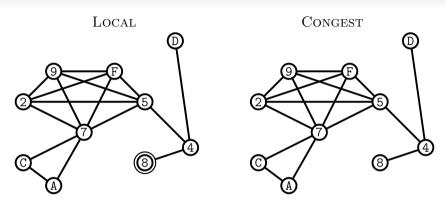
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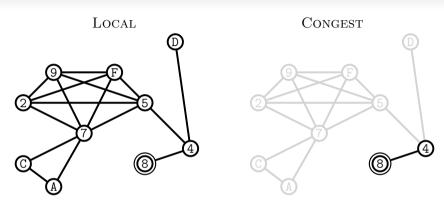
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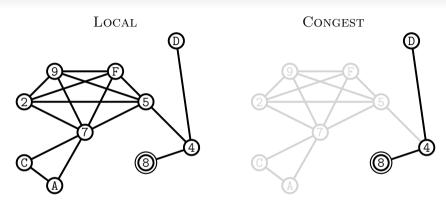
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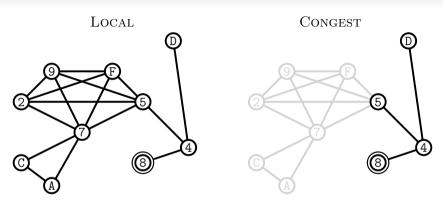
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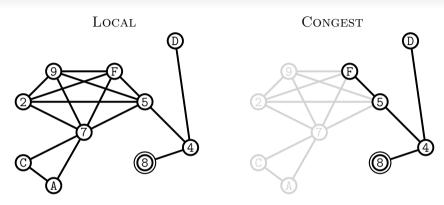
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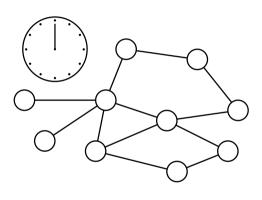


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$\Delta + 1$ -Coloring problem



Goal: starting from an initially uncolored graph G = (V, E), assign a color to each node s.t. adjacent nodes receive distinct colors.

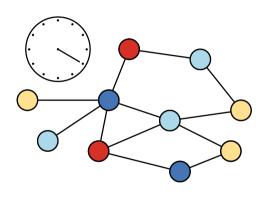
Formally: compute an assignment φ giving colors to the nodes

$$\varphi: V \to [\Delta + 1]$$

s.t. $\varphi(u) \neq \varphi(v)$ for each edge $uv \in E$.

 Δ : maximum degree of the graph, given to the nodes.

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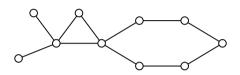
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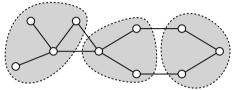
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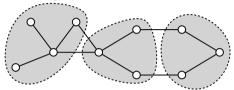
Power graphs





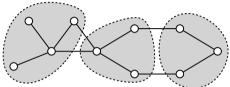
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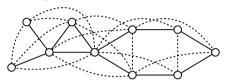


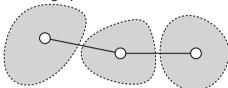
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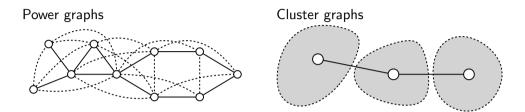




Power graphs Cluster graphs

The graph to color H is not the communication graph G, but

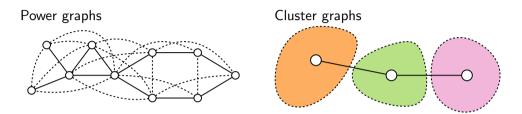
- for any node or edge of H, there is a machine in G "in charge" of that node or edge,
- the machines in charge of a node and its edges have a small depth spanning tree connecting them.



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Agenda for this talk

- 1. Explain state-of-the-art randomized coloring in LOCAL.
- 2. Wonder which parts break down in the embedded graph setting.
- 3. Talk about some nice ideas enabling almost-as-fast* randomized coloring algorithms for embedded graphs in CONGEST as in LOCAL.

Before we actually see some algorithms



Any questions at this point?

Randomized $\Delta+1$ -coloring: some milestones and the state-of-the-art Result Source

$O(\log n)$	Luby [Lub86]
3-coloring rings requires $\Omega(\log^* n)$	Naor [Nao91]
Arguably simpler $O(\log n)$	Johansson [Joh99]
$O(\log \Delta + \sqrt{\log n})$	Schneider and Wattenhofer [SW10]
$O(\log \Delta + \log \log n + T_{\mathtt{det},\mathtt{dilc}}(\operatorname{poly} \log n, O(\log n)))$	Barenboim, Elkin, Pettie, and Schneider [BEPS16]
$O(\sqrt{\log \Delta} + T_{\mathtt{rand},\mathtt{dilc}}(n, O(\log n) \cdot 2^{O(\sqrt{\log \Delta})}))$	Harris, Schneider, and Su [HSS18]
$T_{\mathtt{det},\Delta+1}(\mathit{n},\Delta) < T_{\mathtt{rand},\Delta+1}(2^{\mathit{n}^2},\Delta)$	Chang, Kopelowitz, and Pettie [CKP19]
$O(\log^* \Delta + T_{\mathtt{det},\mathtt{dilc}}(poly\log n, poly\log n))$	Chang, Li, and Pettie [CLP20]

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poly $\log \log n$, $O(\log^* n)$ if $\Delta > \log^c n$ (c a large enough universal constant)	Chang, Li, and Pettie [CLP20]

Source

Dealing with congestion

Some previously mentionned results work directly in Congest [Lub86, Joh99, BEPS16].

First poly $\log \log n$ algorithm by Halldórsson, Kuhn, Maus, and Tonoyan [HKMT21]

First $O(\log^* n)$ algorithm for $\Delta > \log^c n$ by Halldórsson, N., and Tonoyan [HNT22]

Several works on distance-2 coloring [HKM20, HKMN20, FHN23], ultimately achieving poly log log *n* complexity.

Congest with broadcast communication, complexity poly log log n by Flin, Ghaffari, Halldórsson, Kuhn, and N. [FGH $^+$ 23]

Deterministic $O(\Delta^4)$ -coloring distance-2 coloring in $O(\log \Delta + \log^* n)$, and more, by Barenboim and Goldenberg [BG24]

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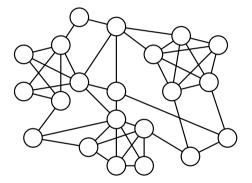
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Main works for today: [FHN24, FHN25] achieving $\Delta + 1$ -coloring of virtual graphs (notably cluster graphs) in poly log log n rounds, $O(\log^* n)$ when $\Delta > \log^c n$.

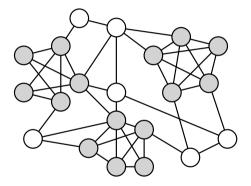
A state-of-the-art Local algorithm

- 1. Compute an Almost-Clique Decomposition
- 2. Compute Put-Aside Sets in the densest almost-cliques
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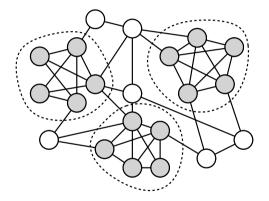
Partition nodes as **dense** or **sparse** according to the number of edges in their neighborhood.



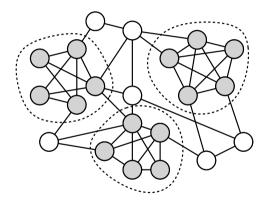
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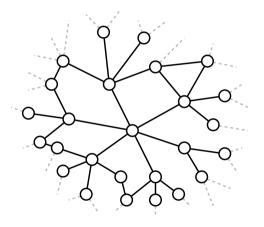
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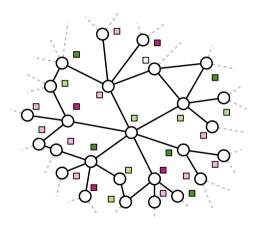


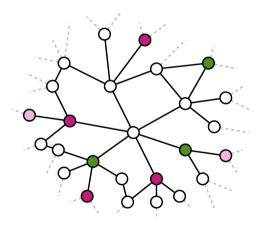
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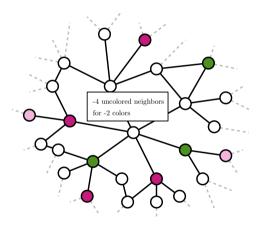


Dense nodes form low-diameter subgraphs called, **almost-cliques**, where members pairwise share $> (1 - \varepsilon)\Delta$ neighbors.

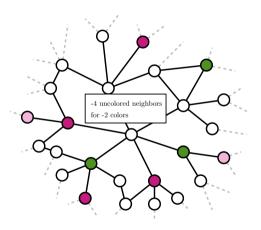








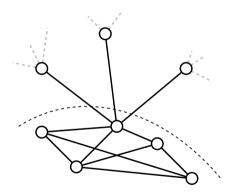
Having nodes try a color at random results in redundancies (slack) in sparse parts.



Also works for dense nodes with some neighbors outside their almost-clique.

Step 3: Generate slack

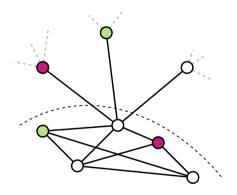
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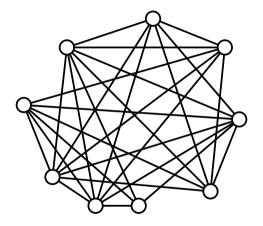
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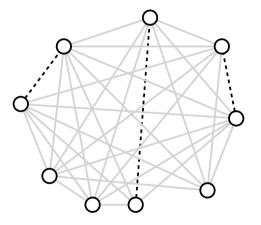
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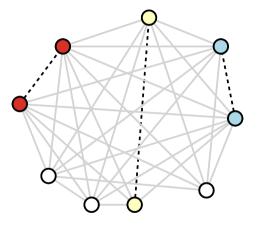
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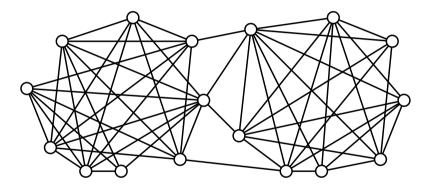
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Step 2: Put-aside sets

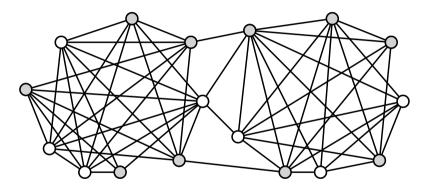
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Nodes whose coloring is delayed until the very end. Provides flexibility when color redundancies are not an option.

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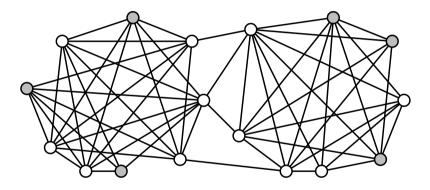
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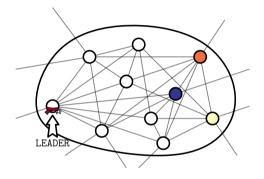
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Step 4: Synchronized Color Trials

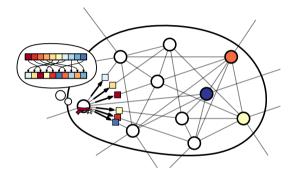
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Coordinating colors tried in almost-cliques leaves few nodes uncolored.

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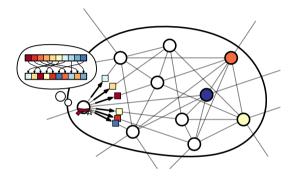
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(putting a small thing under the rug here, feel free to ask about it later)

Step 5: Coloring almost everything

Everything until now had one goal:

that uncolored nodes have $\times (1 + \Omega(1))$ more available colors than (active) uncolored neighbors.

Technique of Schneider and Wattenhofer [SW10] for coloring in $O(\log^* n)$ rounds in that situation: try increasing amounts of colors (up to $\Theta(\log n)$) as the degree of nodes goes down.

Intuition: suppose every node has $\geq C$ available colors, and $\leq d$ neighbors. Let x = C/(2d). If every node tries x colors at random, it is colored w.p. $\geq 1 - 2^{-x}$.

Step 6: Coloring put-aside sets

But we left a few nodes uncolored...

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But we left a few nodes uncolored...

...but they are organized into low-diameter sets that can be colored independently from one another. O(1) extra rounds to finish.

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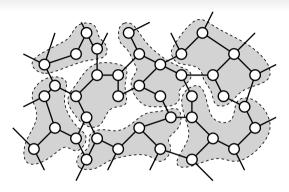
Time for CONGEST and cluster graphs!

Before adding congestion



Questions on this LOCAL algorithm?

Recalling our goal



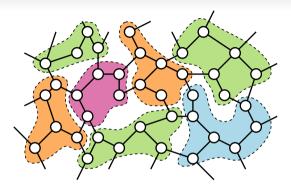
Nodes are partitioned into constant-diameter clusters.

Adjacent clusters must receive distinct colors.

Edges can only carry $O(\log n)$ bit messages

The maximum degree of the cluster graph, Δ , is given. The degree is **not** with multiplicity.

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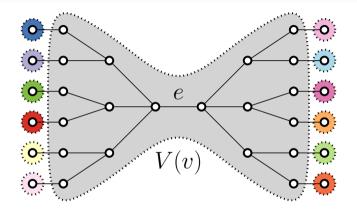
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Group exercise

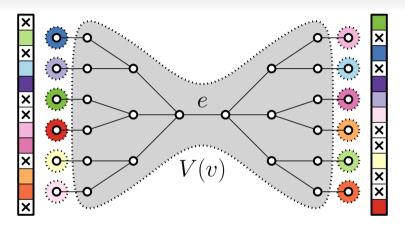
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What could go wrong in CONGEST, especially with cluster graphs?

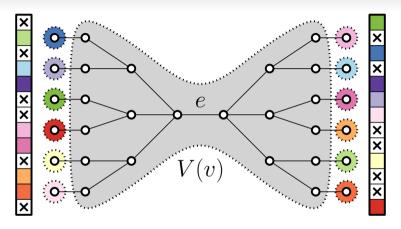
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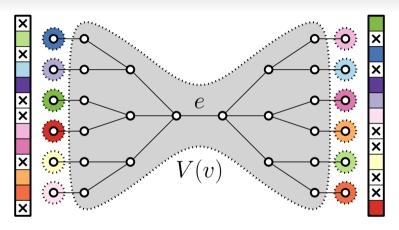


Issue 1: no access to neighbor's colors



"Trying a random available color" can be costly.

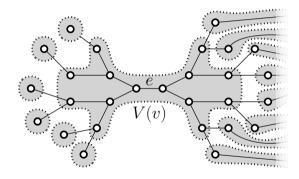
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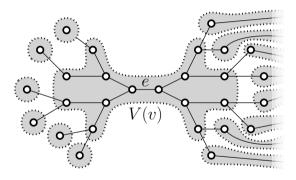
"Trying a random available color" can be costly.

Redeeming fact: "trying" a color is still fine.

Issue 2: no access to degree

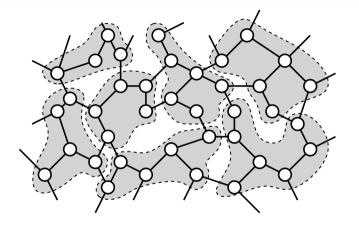


Issue 2: no access to degree

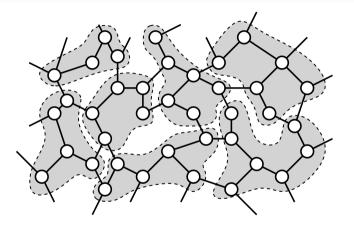


Redeeming fact: we are given Δ , and will be able to **estimate** the degree using randomness.

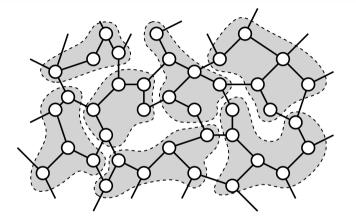
Issue 3: no access to neighborhood similarities

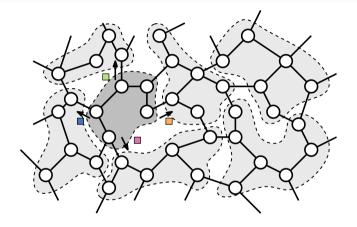


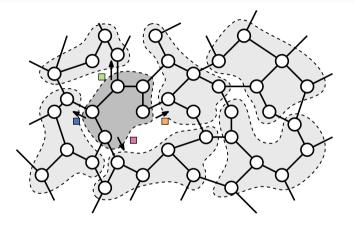
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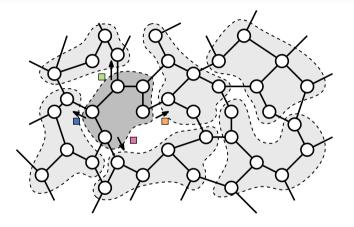
Describing a neighborhood is $\Theta(\Delta \log n)$ bits. Comparing neighborhoods might require channeling this much information through few links.







Up to $\Theta(\Delta \log \Delta)$ bits to send, which might need to go through very few links.



Up to $\Theta(\Delta \log \Delta)$ bits to send, which might need to go through very few links. Routing issue: giving color to the right recipient?

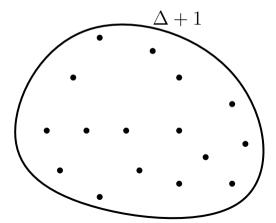
A set of $\Theta(\log n)$ colors between 1 and $\Delta + 1$ takes $\Theta(\log n \cdot \log \Delta)$ bits to represent.

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Fix known from earlier work: pseudorandom samples [HN23, HNT22]

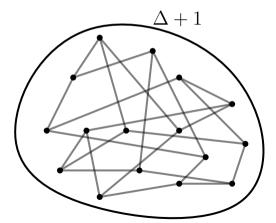
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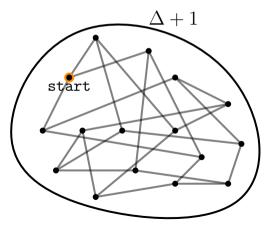
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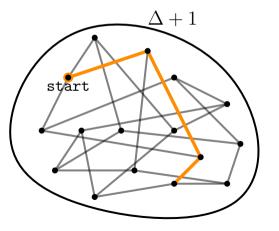
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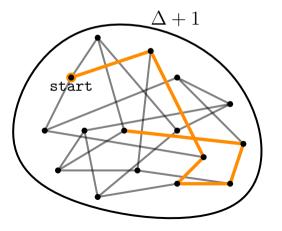
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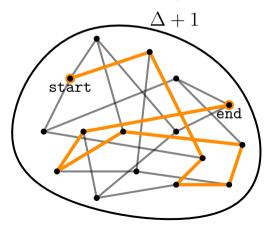
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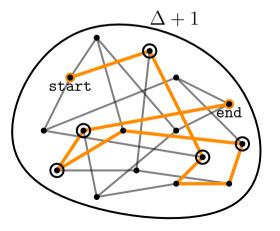
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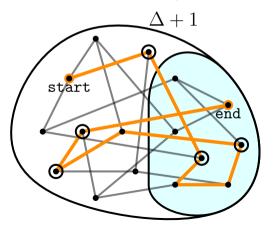
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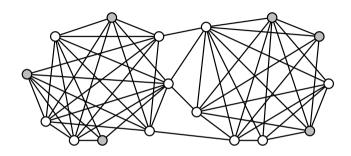
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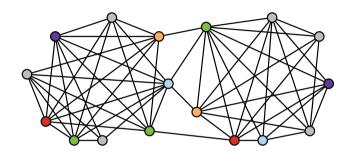
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Two reasons:

- no knowledge of the colors used by their neighbors,
- need to synchronize between themselves, and they can't learn the edges connecting them.

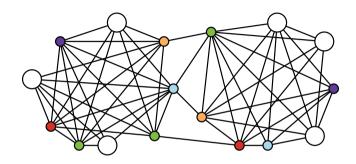
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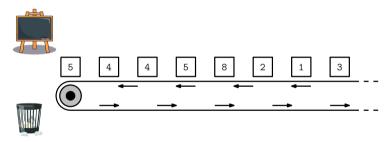
Fingerprints

Important for: computing almost-cliques, estimating their density, colorful matching

High-level idea: each cluster v computes a $\Theta(\log n)$ -bit vector f_v , combining two fingerprints f_v and f_w allows to estimate the size of $N(v) \cup N(w)$.

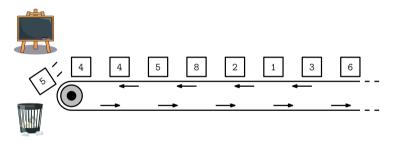
Consider a stream of n numbers between 1 and m.

Goal: estimate F_0 , the number of seen distinct elements, using as little memory as possible. (0-th frequency moment)



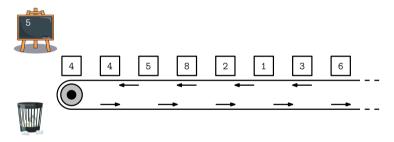
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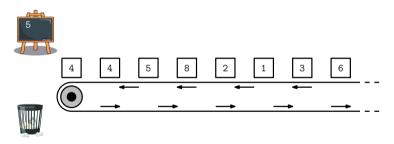
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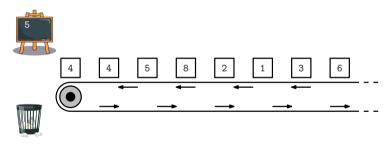
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Claim: given access to a large source of randomness, can estimate $(1 \pm \varepsilon)F_0$ using $O(\varepsilon^{-2} \log n)$ bits w.p. $1 - 1/\operatorname{poly}(n)$.

$$Pr[Y < x] =$$

$$\Pr[Y \ge x] \le$$

$$\Pr[Y < x] = (1 - 2^{-x})^k \le \exp(-k \cdot 2^{-x})$$
.
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$$Pr[Y \ge x] \le \sum_i Pr[X_i \ge x] \le k \cdot 2^{-x}$$
.

Consider k independent geometric random variables X_1, \ldots, X_k : for each $i \in [k], x \in \mathbb{N}$, $\Pr[X_i \ge x] = 2^{-x}$. Let $Y = \max_i X_i$.

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Conclusion: $Pr[|Y - \log k| > 4] < 1/10$.

Fingerprints: construction

For each element $e \in [m]$, use the randomness to build $T \in \Theta(\log n/\varepsilon^2)$ geometric random variables $X_{e,1}, \ldots, X_{e,t}$.

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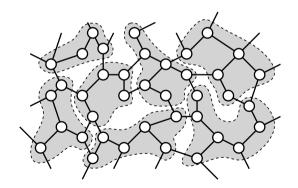
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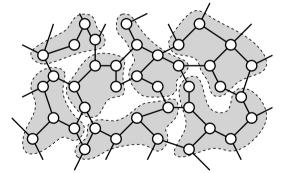
With high probability, the Y_i 's are concentrated around $\log |S|$. This gives an estimation of |S|, and makes them easy to store.

In streaming, this is not enough: still need to replace the large randomness by a hash function [Bla20].



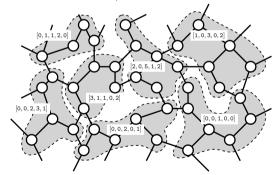
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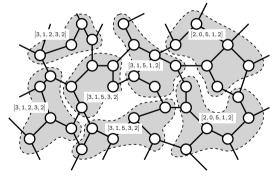
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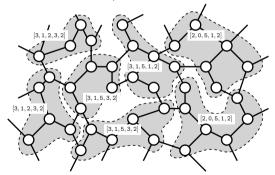
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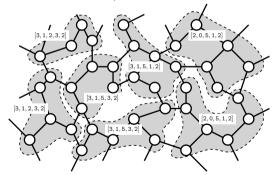


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 $|N(u) \cup N(v)| \gg \min(|N(u)|, |N(v)|)$ will be detected using fingerprints at links connecting the clusters u and v.

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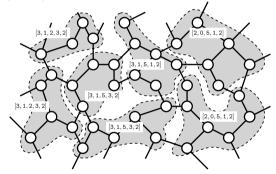


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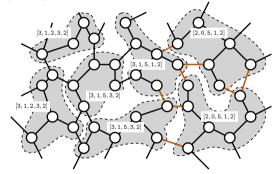
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Unlocks almost-clique decomposition, estimating number of missing edges in almost-cliques, number of external neighbors...

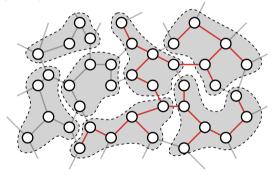
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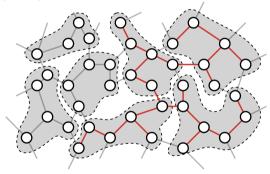


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BFS in an almost-clique: allows to count its exact size, number of colored nodes, sum values...

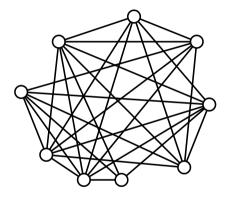
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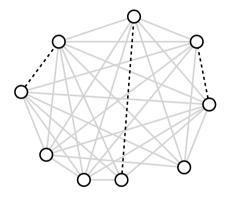
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Can partition almost-cliques into $\Theta(\Delta/\log n)$ random groups, each able to broadcast/aggregate $\Theta(\log n)$ bits in O(1) rounds.

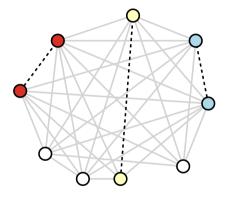
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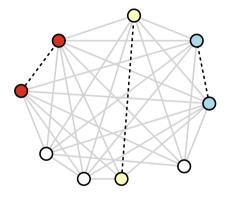


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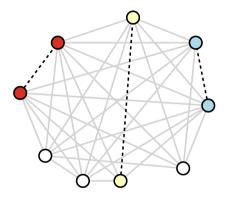


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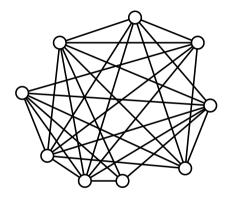




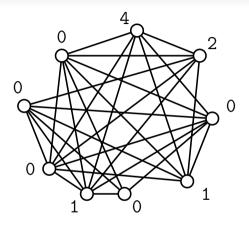
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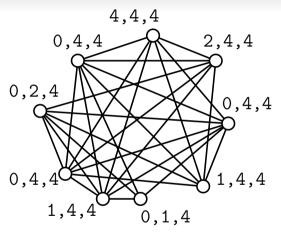
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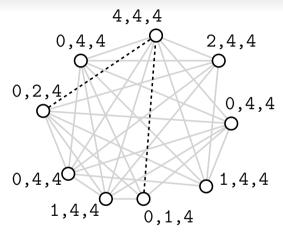
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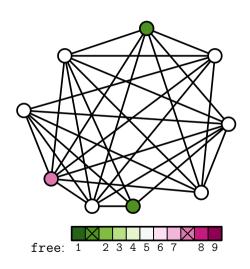
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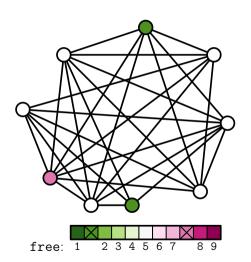
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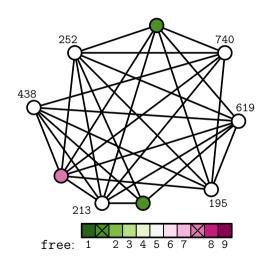
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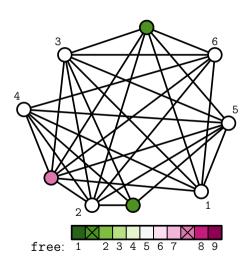
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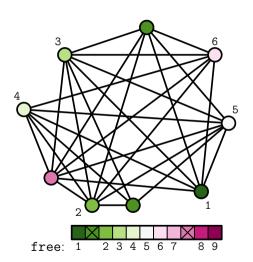
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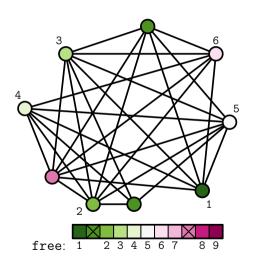
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Uncolored nodes randomly permute themselves, node number i tries free color number i.

+ bunch of routing, etc...

What next...



Coloring put-aside sets:

Routing colors to neighbors, finding anti-edges:

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Intuition: every node in an almost-clique has $\approx \Delta$ neighbors in the almost-clique. If every node picks one of $\Theta(\Delta/\log n)$ random groups, every node has $\Theta(\log n)$ neighbors in each group w.h.p. Divide the work between the groups.

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Pseudorandom color samples: Pseudorandom samples are much simpler when everyone agrees on the overall sampling space. We enforce this by reserving some colors for late in the algorithm.

Concluding



What have we learned?

- 1. Can perform distance-2 coloring in $O(\log^* n)$ rounds when $\Delta > \log^c n$.
- 2. In general, we can perform distributed coloring as a series of "broadcast/aggregate" operations.

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Thank you for attending!

- Leonid Barenboim, Michael Elkin, Seth Pettie, and Johannes Schneider. The locality of distributed symmetry breaking. *Journal of the ACM*, 63(3):20:1–20:45, 2016.
- Leonid Barenboim and Uri Goldenberg.

 Speedup of distributed algorithms for power graphs in the CONGEST model.

 In the Proceedings of the International Symposium on Distributed Computing (DISC), volume 319 of LIPIcs, pages 6:1–6:23. Schloss Dagstuhl Leibniz-Zentrum für Informatik. 2024.
- Jaroslaw Blasiok.

 Optimal streaming and tracking distinct elements with high probability.

 ACM Trans. Algorithms, 16(1):3:1–3:28, 2020.
- Yi-Jun Chang, Tsvi Kopelowitz, and Seth Pettie.

 An exponential separation between randomized and deterministic complexity in the LOCAL model.

SIAM J. Comput., 48(1):122-143, 2019.

- Yi-Jun Chang, Wenzheng Li, and Seth Pettie. Distributed ($\Delta+1$)-coloring via ultrafast graph shattering. SIAM Journal of Computing, 49(3):497–539, 2020.
- Maxime Flin, Mohsen Ghaffari, Magnús M. Halldórsson, Fabian Kuhn, and Alexandre Nolin.

 Coloring fast with broadcasts.

 In the Proceedings of the ACM Symposium on Parallelism in Algorithms and Architectures (SPAA), pages 455–465. ACM, 2023.
- Maxime Flin, Magnús M. Halldórsson, and Alexandre Nolin.
 Fast coloring despite congested relays.
 In the Proceedings of the International Symposium on Distributed Computing (DISC), 2023.
- Maxime Flin, Magnús M. Halldórsson, and Alexandre Nolin.

 Decentralized Distributed Graph Coloring II: Degree+1-Coloring Virtual Graphs.

- In the Proceedings of the International Symposium on Distributed Computing (DISC), volume 319, pages 24:1–24:22, 2024.
- Maxime Flin, Magnús M. Halldórsson, and Alexandre Nolin.

 Decentralized distributed graph coloring: Cluster graphs.

 In the Proceedings of the ACM Symposium on Principles of Distributed Computing (PODC), pages 394–405. ACM, 2025.
- Magnús M. Halldórsson, Fabian Kuhn, and Yannic Maus. Distance-2 coloring in the CONGEST model. In PODC '20: ACM Symposium on Principles of Distributed Computing, Virtual Event, Italy, August 3-7, 2020, pages 233–242, 2020.
- Magnús M. Halldórsson, Fabian Kuhn, Yannic Maus, and Alexandre Nolin. Coloring fast without learning your neighbors' colors.
 In 34th International Symposium on Distributed Computing, DISC 2020, October 12-16, 2020, Virtual Conference, pages 39:1–39:17, 2020.
- Magnús M. Halldórsson, Fabian Kuhn, Yannic Maus, and Tigran Tonoyan.

Efficient randomized distributed coloring in CONGEST.

In the Proceedings of the ACM Symposium on Theory of Computing (STOC), pages 1180–1193. ACM, 2021.

Full version at CoRR abs/2105.04700.

- Magnús M. Halldórsson and Alexandre Nolin.
 Superfast coloring in CONGEST via efficient color sampling.

 Theor. Comput. Sci., 948:113711, 2023.
- Magnús M. Halldórsson, Alexandre Nolin, and Tigran Tonoyan. Overcoming congestion in distributed coloring. In the Proceedings of the ACM Symposium on Principles of Distributed Computing (PODC), pages 26–36. ACM, 2022.
- David G. Harris, Johannes Schneider, and Hsin-Hao Su. Distributed ($\Delta + 1$)-coloring in sublogarithmic rounds. Journal of the ACM, 65:19:1–19:21, 2018.
- 🔋 Öjvind Johansson.

Simple distributed $\Delta + 1$ -coloring of graphs. *Inf. Process. Lett.*, 70(5):229–232, 1999.

M. Luby.

A simple parallel algorithm for the maximal independent set problem. *SIAM Journal on Computing*, 15:1036–1053, 1986.

Moni Naor.

A lower bound on probabilistic algorithms for distributive ring coloring. *SIAM J. Discret. Math.*, 4(3):409–412, 1991.

Johannes Schneider and Roger Wattenhofer.

A new technique for distributed symmetry breaking.

In the Proceedings of the ACM Symposium on Principles of Distributed Computing (PODC), pages 257–266. ACM, 2010.