Improved bounds for randomly colouring simple hypergraphs

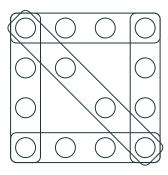
Weiming Feng Heng Guo Jiaheng Wang

University of Edinburgh

RANDOM 2022

Hypergraph (proper) colouring

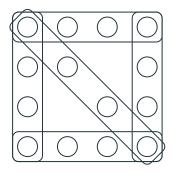
Classical combinatorial/computational problem!



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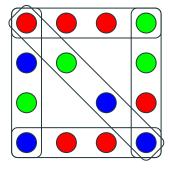
- Hypergraph (V, \mathcal{E})
 - Hyperedge $e \in \mathcal{E}: e \subseteq V$

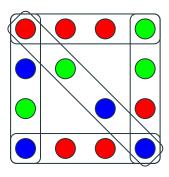


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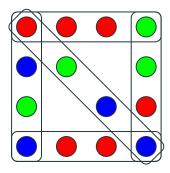
Classical combinatorial/computational problem!

- Hypergraph (V, \mathcal{E})
 - Hyperedge $e \in \mathcal{E}: e \subseteq V$
- · Proper colouring
 - · Forbidding monochromatic hyperedges

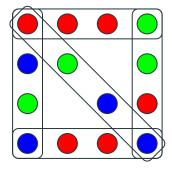




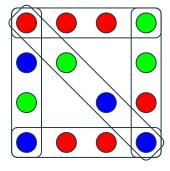
- Deciding
 - Decide if a colouring exists



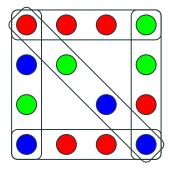
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Deciding is NP-hard in general (3-colourings on graphs).

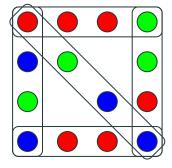
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Posing restrictions to input instances?

Treat hyperedges being monochromatic as (random) "bad" events...

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Lemma (Symmetric Lovász local lemma [Erdős-Lovász'75])

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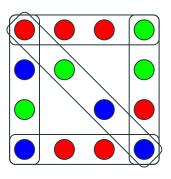
- B_i : bad events with $Pr[B_i] = p$. number of colours; size of hyperedges
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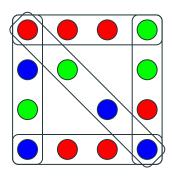
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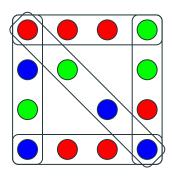


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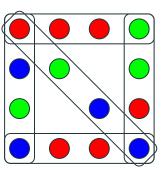
• q: Number of colours



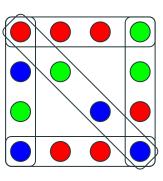
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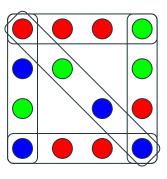


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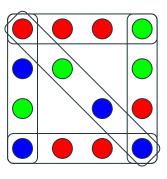


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$$\Delta \le q^{k-1}/(\mathrm{e}k)$$

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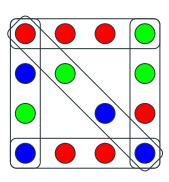
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Open problem: computational threshold for sampling problem

Simple (aka. linear) hypergraphs

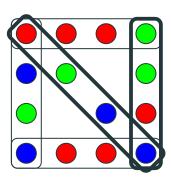
Simple hypergraph:

• Overlap of two hyperedges ≤ 1

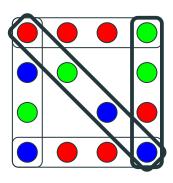


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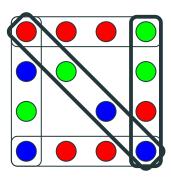
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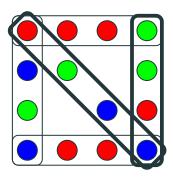
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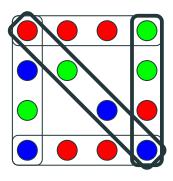
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- Refined: $\chi(H) \leq C_k \left(\frac{\Delta}{\log \Delta}\right)^{\frac{1}{k-1}}$ [Frieze-Mubayi'13]



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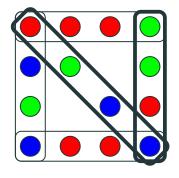


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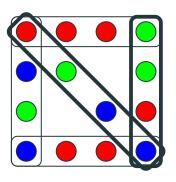
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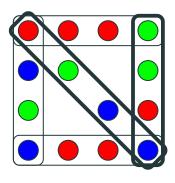


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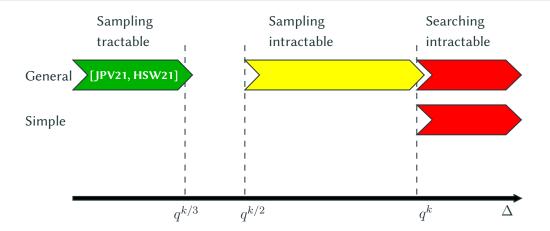
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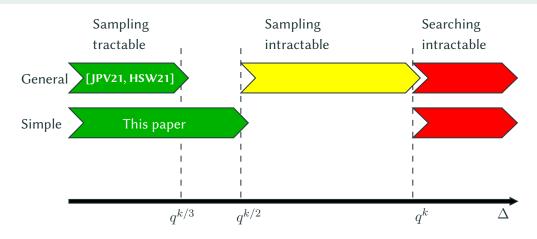
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Our result

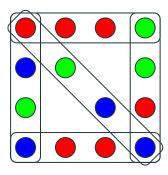


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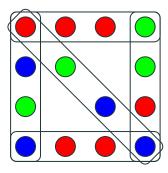


Theorem

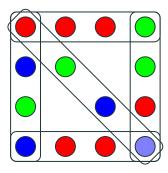
There exists an algorithm such that, for any $\delta>0$, given a k-uniform Δ -degree hypergraph as an input, the algorithm outputs an almost uniform random q-colouring, if $k\geq 20\left(1+\frac{1}{\delta}\right)$ and $\Delta\leq 0.1^kq^{k/2-(k\delta+1/\delta)}$. The running time is $\tilde{O}(\operatorname{poly}(\Delta k)\cdot n^{1.01})$.



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- · Update its value according to its marginal

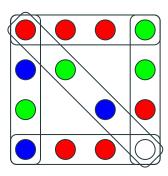


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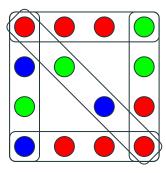


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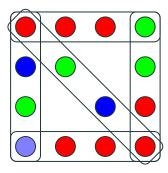
$$\Pr[\bullet] = \frac{1}{3}, \Pr[\bullet] = \frac{1}{3}, \Pr[\bullet] = \frac{1}{3}$$



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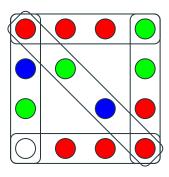


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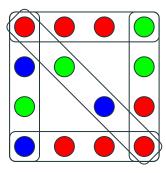


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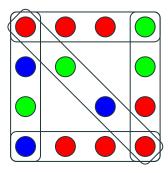
$$\Pr[\bullet] = 0, \Pr[\bullet] = \frac{1}{2}, \Pr[\bullet] = \frac{1}{2}$$



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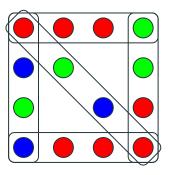


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Natural approach: Glauber dynamics

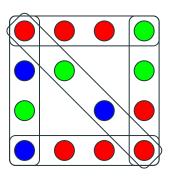
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Stationary distribution is uniform (the correct distribution).

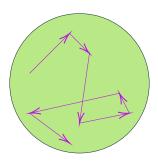
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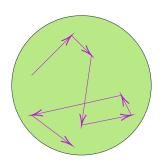


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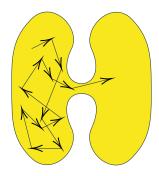
Does this chain *mix rapidly* (i.e., converge to stationary distribution quickly)?



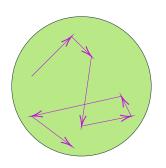
Well connected Fast mixing



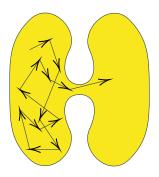
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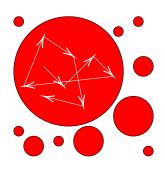
Poorly connected Slow mixing



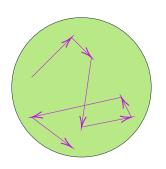
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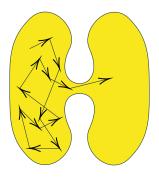
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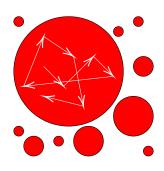
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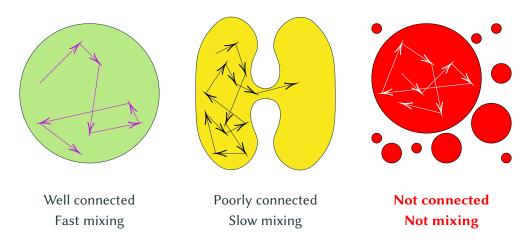
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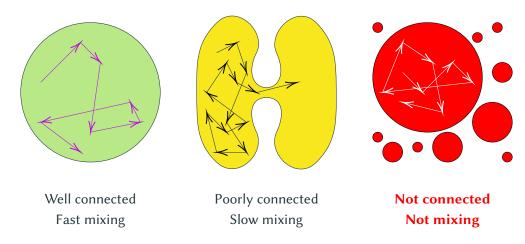
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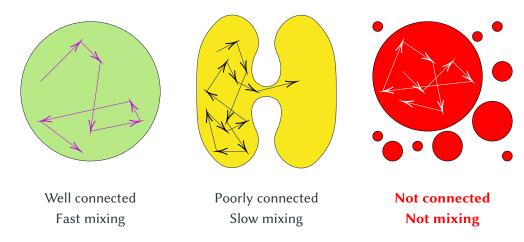


Not that bad if there is a giant component — start from a random configuration



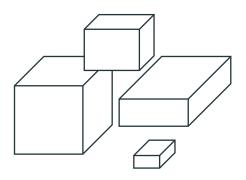
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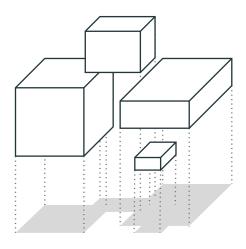
• Simple hypergraph with $q \ge \max\{\Theta_k(\log n), \Theta_k(\Delta^{\frac{1}{k-1}})\}$ [Frieze-Anastos'17]

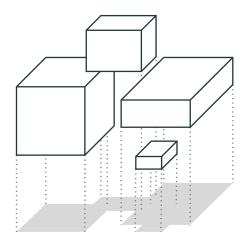


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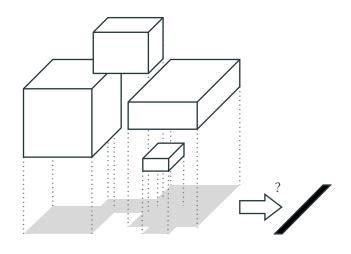
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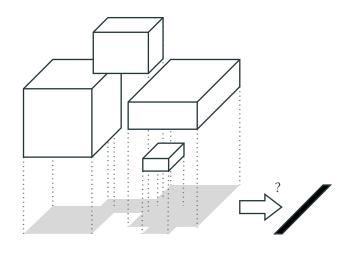




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- Harder to simulate transition / recover a sample

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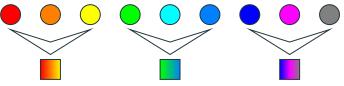
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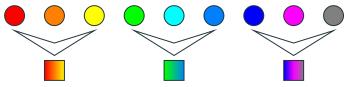
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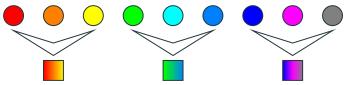
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Improve both to get $\Delta \lesssim q^{k/2}$ on simple hypergraphs.

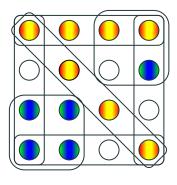
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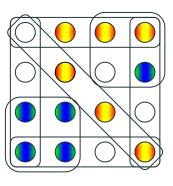
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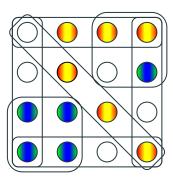
• We focus on implementation in this talk.



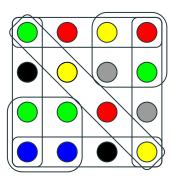
• How can we know the correct projected distribution?



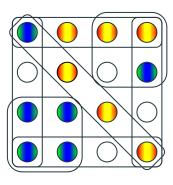
- How can we know the correct projected distribution?
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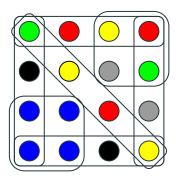
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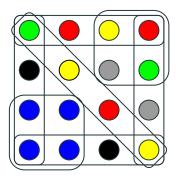
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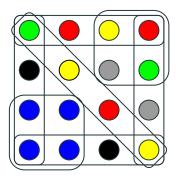
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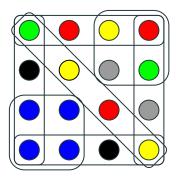
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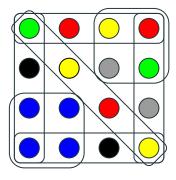
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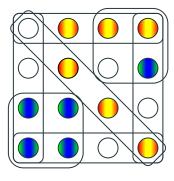
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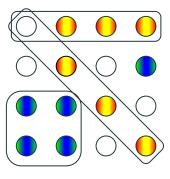
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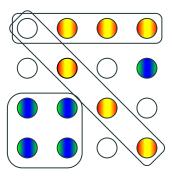
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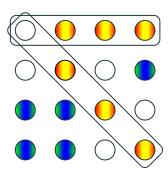
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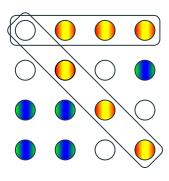
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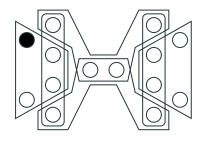


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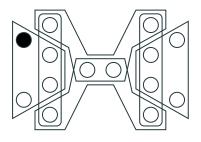
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- We are done if number of hyperedges is $O(\log n)$ w.h.p.



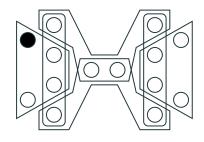


Union bound over all possible size- α (#edges) components:

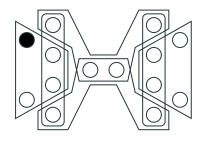
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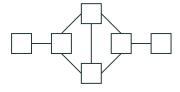
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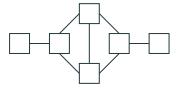
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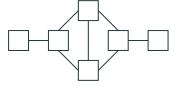
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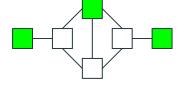
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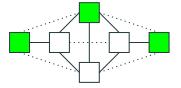
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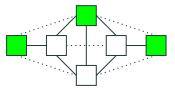
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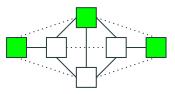
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Assuming bucketing into \sqrt{q} buckets.

$$\sum_{\ell} \Pr[\mathsf{size}\text{-}\ell \; \mathsf{2}\text{-tree exists}] < 1.$$

Assuming bucketing into \sqrt{q} buckets.

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Let G be a graph with maximum degree D and v is a vertex. Then the number of 2-trees in G of size ℓ containing v is at most $(eD^2)^{\ell-1}/2$.

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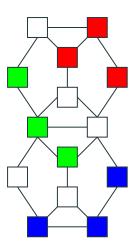
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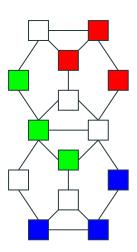
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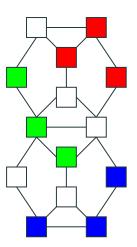
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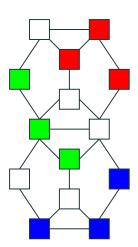
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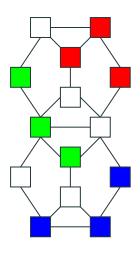
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Requires:

$$\Delta \lesssim q^{\frac{k}{2 + O(1/\theta)}}$$



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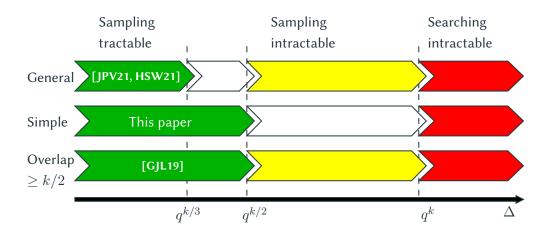
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 - Better condition?
- Utilising overlap information?
 - Partial rejection sampling [Guo-Jerrum-Liu'19] gives transition at $\Delta \approx q^{k/2}$ when overlaps are large.



Thank you! arXiv: 2202.05554