

# THE GLOBAL STRUCTURE OF LARGE LOCALLY SPARSE GRAPHS

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Bordeaux Graphs Workshop      10/2019

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\*With Cames van Batenburg, Davies, Esperet, de Joannis de Verclos, Pirot, Sereni, Thomassé.  
Research received support from Nuffic/PHC, ANR, FWB, NWO and ERC grants.

## STRUCTURE OF TRIANGLE-FREE GRAPHS

*Asymptotically, what global graph structure forms if no edge is induced in any neighbourhood?*

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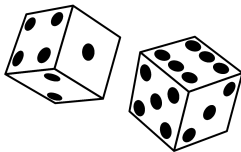
*Asymptotically, what global graph structure forms if no edge is induced in any neighbourhood?*

i.e. “local versus global”

Distinguished origins:

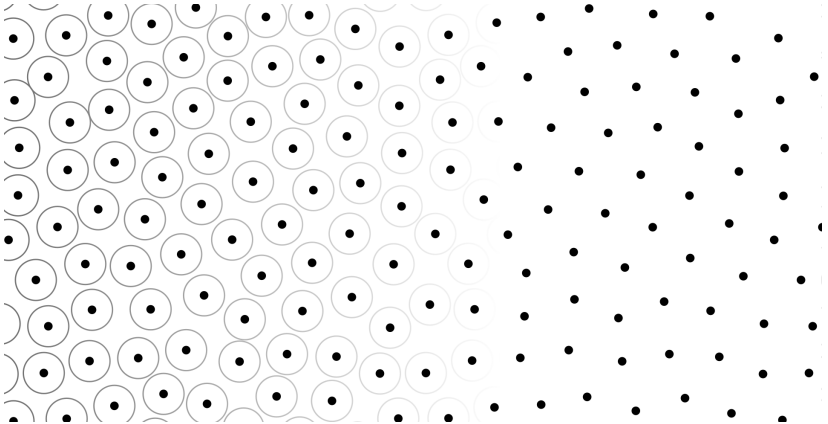
- Mantel (1907), Turán (1941)
- Ramsey (1930), Erdős & Szekeres (1935)
- Zykov (1949), Ungar & “Blanche Descartes” (1954)

## PROBABILISTIC METHOD



If a random object has desired property with positive probability,  
then there exists *at least one* object with that property

## HARD-CORE MODEL<sup>†</sup>



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<sup>†</sup> More fully, the lattice gas with hard-core self-repulsion and nearest-neighbour exclusion.  
Picture credit: Wikipedia/Grap-wh

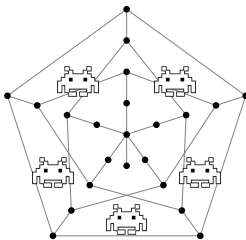


## LIST COLOURING

Given a graph  $G$ , imagine *adversaries* to you properly colouring it

- that annoyingly issue lists of permissible colours
- but must permit at least  $\ell$  colours per vertex

What is least  $\ell$  for which you can *always* win? (Necessarily  $\chi \leq \ell \leq |G|$ )

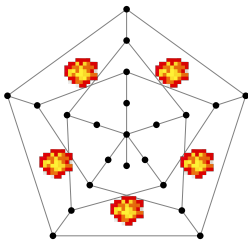


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Called **list chromatic number** or **choosability**  $\text{ch}(G)$  of  $G$



## LIST MAKES IT “HARDER”



$\text{ch}$  is not bounded by any function of chromatic number  $\chi$

Theorem (Erdős, Rubin, Taylor 1980)

$\text{ch}(K_{d,d}) \sim \log_2 d$  (and  $\text{ch}(K_{d+1}) = d + 1$ )

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More closely related to density

Theorem (Alon 2000, cf. Saxton & Thomason 2015)

$\text{ch}(G) \gtrsim \log_2 \delta$  for any  $G$  of minimum degree  $\delta$

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Still not completely well understood

Conjecture (Alon & Krivelevich 1998)

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## SEPARATION MAKES IT “EASIER”?



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Question: Does  $\text{ch}_{\text{sep}}$  grow in  $\delta$ ?

Problem: Almost-disjointness of lists is **not** monotone under edge-addition!



## RAMSEY-TYPE QUESTION/SOLUTION?



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Theorem (Kwan, Letzter, Sudakov, Tran 2018+)

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Each of  $\sim \frac{1}{2}\chi^2$  pairs of colour classes induces a bipartite graph  
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**Theorem (Esperet, Kang, Thomassé 2019)**

$\text{BID}(G) \geq \frac{\delta}{2\chi}$  for any  $G$  with minimum degree  $\delta$  and chromatic number  $\chi$



## A SEQUENCE WITH INDEPENDENCE AND COLOURING

BID( $G$ )



$$\omega(G) \leq \max_{\emptyset \neq H \subseteq G} \frac{|H|}{\alpha(H)} \leq \chi_f(G) \leq \chi(G) \leq \text{ch}(G) \leq \Delta(G) + 1$$

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We focus on triangle-free. . .

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## OFF-DIAGONAL RAMSEY NUMBERS<sup>§</sup>



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<sup>§</sup>Picture credit: Soifer 2009

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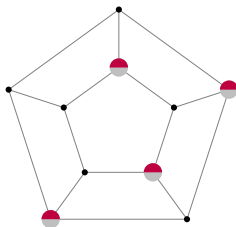
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¶ Yes, cf. Davies, Jenssen, Perkins, Roberts 2018...

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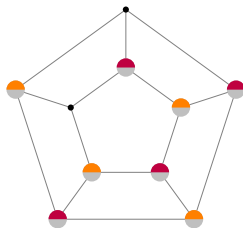
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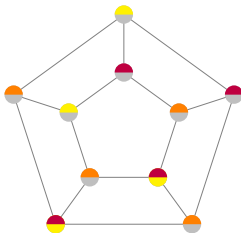
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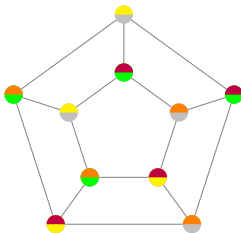
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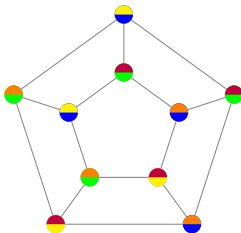
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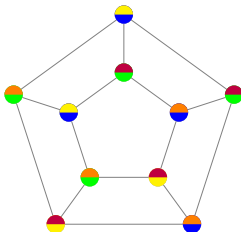
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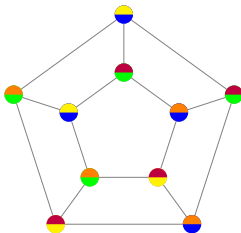
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$$\chi_f \geq n/\alpha = 5/2$$

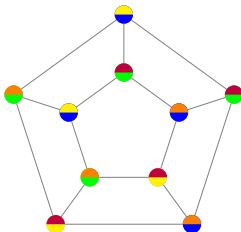
**fractional vertex-colouring** : allow “fractions” of independent sets

**fractional chromatic number**  $\chi_f$  : least “amount” needed

$\chi_f(G) \leq k$  if there is probability distribution over  $\mathcal{I}(G)$  such that for random  $I$

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$$\xRightarrow{\text{linearity}} \mathbb{E} |\mathbf{I}| \geq n/k$$



## CHROMATIC NUMBER OF TRIANGLE-FREE GRAPHS

$$\omega(G) \leq \max_{\emptyset \neq H \subseteq G} \frac{|H|}{\alpha(H)} \leq \chi_f(G) \leq \chi(G) \leq \text{ch}(G) \leq \Delta(G) + 1$$

Theorem (Shearer 1983, cf. Ajtai, Komlós, Szemerédi 1980/1)

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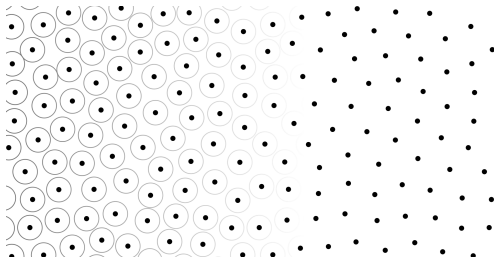
Why?

Simple, conceptual, versatile, and more. . .



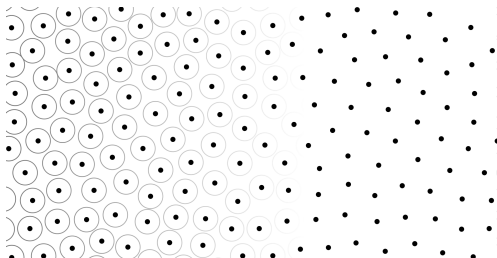
## HARD-CORE MODEL

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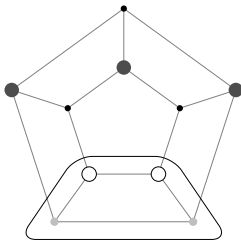


Hard-core model on  $G$  at fugacity  $\lambda > 0$  is probability distribution over  $\mathcal{I}(G)$  such that random  $\mathbf{I}$  satisfies for all  $S \in \mathcal{I}(G)$

$$\mathbb{P}(\mathbf{I} = S) = \frac{\lambda^{|S|}}{Z_G(\lambda)}, \quad \text{where } Z_G(\lambda) = \sum_{S \in \mathcal{I}(G)} \lambda^{|S|}$$

## SPATIAL MARKOV PROPERTY

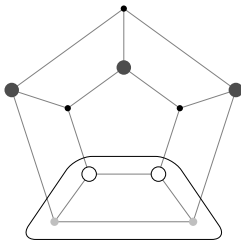
For  $S \in \mathcal{I}(G)$ , call  $u$  **occupied** if  $u \in S$  and call  $u$  **uncovered** if  $N(u) \cap S = \emptyset$





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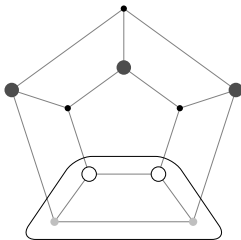


Take  $\mathbf{I}$  from hard-core model on  $G$  at fugacity  $\lambda$  and let  $X \subseteq V(G)$

Reveal  $I \setminus X$  and let  $U_X := X \setminus N(I \setminus X)$  (the **externally uncovered** part)

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Then  $\mathbf{I} \cap X$  is hard-core on  $G[\mathbf{U}_X]$  at fugacity  $\lambda$

## LOCAL OCCUPANCY METHOD

Distribution  $\mathbf{I}$  on  $\mathcal{I}(G)$  has **local  $(a, b)$ -occupancy** if for every vertex  $v$

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$$\leadsto \text{analysis to minimise } a + b \cdot \Delta \leadsto \chi_f(G) \lesssim \frac{\Delta}{\log \Delta} \quad \text{🎲}$$

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Originally used by Molloy & Reed (2002) to prove fractional Reed's Conjecture

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Idea: greedily add weight/colour to independent sets according to probability distribution induced by  $\mathbf{I}$  on vertices not yet completely coloured, and iterate

One can think of it as “evening out” the distribution

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$$\Rightarrow a \cdot \mathbb{P}(v \in \mathbf{I}) + b \cdot \mathbb{E}|N(v) \cap \mathbf{I}| \geq \frac{\lambda}{1 + \lambda} \left( a \cdot (1 + \lambda)^{-\mathbb{E}J} + b \cdot \mathbb{E}J \right)$$

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**Fact 1**  $\mathbb{P}(v \in \mathbf{I} \mid v \text{ uncovered}) = \frac{\lambda}{1 + \lambda}$

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- A** Hard-core model on any triangle-free  $G$  has local  $(a, b)$ -occupancy, for specific  $a, b$  depending on fugacity  $\lambda$  and maximum degree  $\Delta$
- B** If there is probability distribution  $\mathbf{I}$  on  $\mathcal{I}(G)$  with local  $(a, b)$ -occupancy, then  $\chi_f(G) \leq a + b \cdot \Delta$

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and so from **B** it suffices to show

$$a + b \cdot \Delta \lesssim \frac{\Delta}{\log \Delta} \quad \text{subject to} \quad \frac{b\lambda(\log((ea/b) \log(1 + \lambda)))}{(1 + \lambda) \log(1 + \lambda)} \geq 1 \rightsquigarrow$$





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Hard-core model on  $G$  has **local  $(a, b)$ -occupancy** if for every vertex  $v$  and every induced subgraph  $F$  of the neighbourhood subgraph  $G[N(v)]$ .

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- C** If hard-core model has local  $(a, b)$ -occupancy (+ mild conditions), then  $\text{ch}(G) \leq a \cdot O(\log \Delta) + (1 + \varepsilon)b \cdot \Delta$

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C relies crucially on seminal proofs of Molloy (2019) and Bernshteyn (2019) combined with properties of the hard-core model

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## GRAPHS WITH COLOURABLE NEIGHBOURHOODS

Theorem (Johansson 1996+, cf. Alon 1996, Molloy 2019, Bonamy, Kelly, Nelson, Postle 2018+)

$\text{ch}(G) = O\left(\log(r+1)\frac{\Delta}{\log \Delta}\right)$  for any  $G$  of maximum degree  $\Delta$   
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Theorem (Davies, Kang, Pirot, Sereni, in progress)

$\text{ch}(G) \lesssim K(r) \cdot \frac{\Delta}{\log \Delta}$  for any  $G$  of maximum degree  $\Delta$   
in which every neighbourhood is  $r$ -colourable,  
where  $K(1) = 1$  and  $K(r) \sim \log r$  as  $r \rightarrow \infty$



## GRAPHS WITH SPARSE NEIGHBOURHOODS

Theorem (Alon, Krivelevich, Sudakov 1999, cf. Vu 2002 and Achlioptas, Iliopoulos, Sinclair 2019)

$$\text{ch}(G) = O\left(\frac{\Delta}{\log \Delta - \log \sqrt{T+1}}\right) \text{ for any } G \text{ of maximum degree } \Delta$$

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Conjecture (Cames van Batenburg, de Joannis de Verclos, Kang, Pirot)

$$\chi_f(G) \lesssim \sqrt{\frac{2n}{\log n}} \text{ and } \text{ch}(G) = O\left(\sqrt{\frac{n}{\log n}}\right) \text{ for any } n\text{-vertex triangle-free } G$$

Merci!