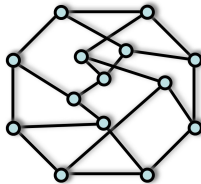


Random Regular Graphs and Differential Equations

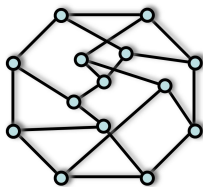
Nick Wormald
University of Waterloo

Minicourse Conference on Random Graph Processes Austin

Regular graphs - 'Uniform' model



Regular graphs - 'Uniform' model



$\mathcal{G}_{n,d}$: probability space of d -regular graphs on vertex set $\{1, \dots, n\}$ with uniform distribution:

$$\mathbf{P}(G) = \frac{1}{|\mathcal{G}_{n,d}|} \quad \text{for all } G \in \mathcal{G}_{n,d}.$$

Some properties of interest

What properties does $G \in \mathcal{G}_{n,d}$ have with respect to

- connectivity, subgraphs?
- Hamilton cycles?
- vertex and edge colourings?
- large independent sets?
- min and max bisections?

Some properties of interest

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A property Q holds **asymptotically almost surely** (a.a.s.) in a random graph model if

$$\mathbf{P}(G \text{ has } Q) \rightarrow 1 \text{ as } n \rightarrow \infty.$$

Framework of analysis of random regular graphs

Theorem [Bender, Canfield '78]

$$|\mathcal{G}_{n,d}| \sim \frac{(dn)! e^{(1-d^2)/4}}{(dn/2)! 2^{dn/2} d!^n}$$



Framework of analysis of random regular graphs

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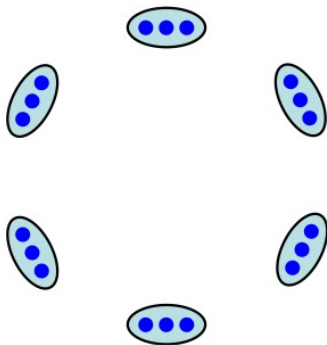
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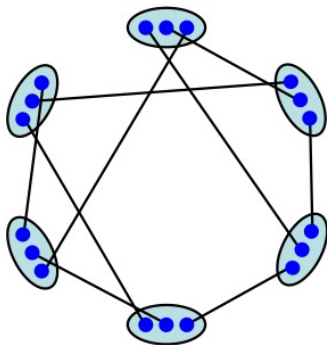
Configuration model presented by Béla Bollobás ('79) is convenient for directly showing a.a.s. results.



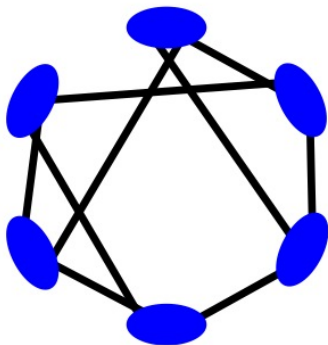
How to calculate with random regular graphs



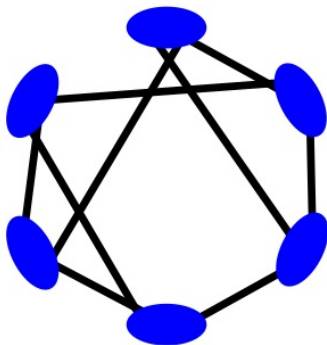
How to calculate with random regular graphs



How to calculate with random regular graphs



How to calculate with random regular graphs



... a random 3-regular graph.

By showing the probability of the graph being simple is asymptotic to $e^{(1-d^2)/4}$, we get the Bender-Canfield formula

$$|\mathcal{G}_{n,d}| \sim \frac{(dn)! e^{(1-d^2)/4}}{(dn/2)! 2^{dn/2} d!^n}$$

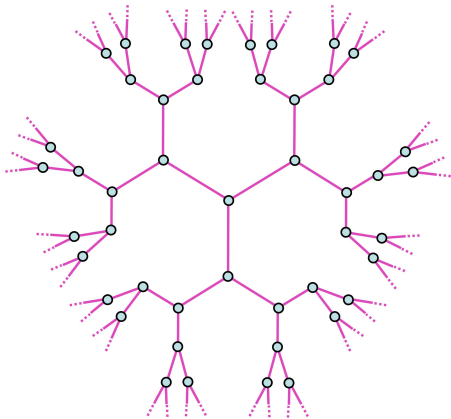
since each simple graph corresponds to $d!^n$ pairings.

Basic facts on cycles

Theorem [W '80; Bollobás '80]

Let $G \in \mathcal{G}_{n,d}$. Let X_i denote the number of cycles of length i . Then X_3, X_4, \dots are asymptotically independent Poisson random variables with means $\mathbf{E}(X_i) \rightarrow \frac{(d-1)^i}{2i}$.

Closeup of a large random 3-regular graph:



Independent sets

Let $\alpha(G)$ denote the **independence number** of G , i.e.

$\alpha(G) = \max$ cardinality of an independent set of vertices in G

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Theorem [Frieze and Łuczak, '92]

Fix $d \geq 3$. Then $G \in \mathcal{G}_{n,d}$ a.a.s. satisfies

$$\alpha(G) = \frac{2 \log d}{d} n (1 + O(\xi))$$

where $\xi \rightarrow 0$ as $d \rightarrow \infty$.

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But this says nothing about $d = 3$ say.

Finding large independent sets

Greedy algorithms find large independent sets in random d -regular graphs.

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Theorem [W, '95]

Fix $d \geq 3$ and $\epsilon > 0$. Then $G \in \mathcal{G}_{n,d}$ a.a.s. satisfies

$$\alpha(G) \geq (\beta_1(d) - \epsilon)n$$

where $\beta_1(d) = \frac{1}{2}(1 - (d-1)^{-2/(d-2)})$.

Method: Build an independent set by randomly adding a vertex, deleting all its neighbours from the graph, and repeating.

Finding even larger independent sets

The **degree-greedy** algorithm for finding an independent set in a graph G :

Repeat:

Choose a random vertex v of degree $\delta(v)$.

Add v to the independent set and delete v and its neighbours from G .

Until:

G is empty.

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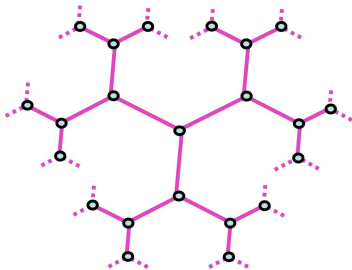
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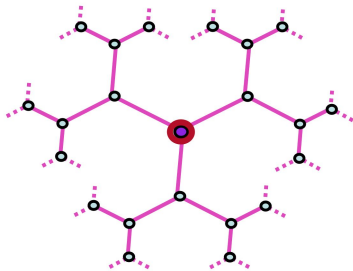
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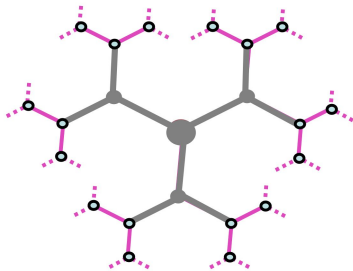
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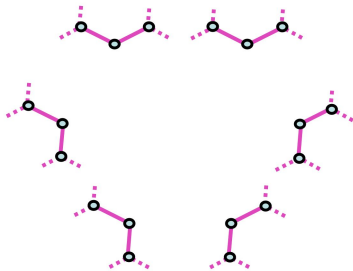
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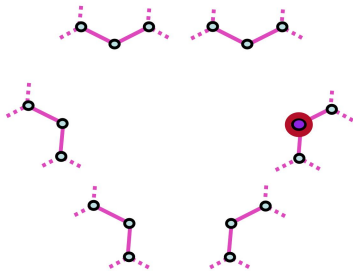
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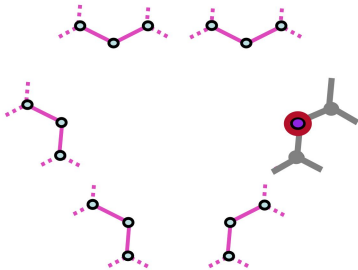
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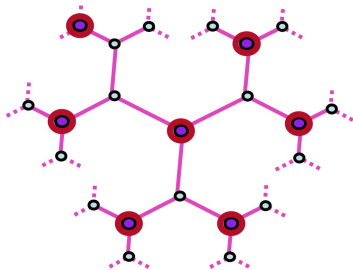
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Analysis

We actually apply the degree-greedy algorithm to the pairing model. The remaining pairing remains random (subject to its degree sequence).

Let $Y_i = Y_i(t)$ denote the number of vertices of degree i (i.e. degree counts) in the graph G_t after t steps.

Deleting a vertex of degree k means that the endpoints of k pairs have to be chosen.

The probability that the other end of a pair is in a vertex of degree j is

$$\frac{\text{no. of points in cells of size } j}{\text{total number of points}} = \frac{jY_j + O(1)}{m}$$

where the total number of points is $m = \sum_i iY_i$.

Expected changes in the variables

Conditioning on the degree counts $\mathbf{Y} = (Y_0, \dots, Y_d)$,

$$\mathbf{E}\left(Y_i(t+1) - Y_i(t) \mid \mathbf{Y} \text{ s.t. } \delta(G_t) = r\right) = f_{i,r}(\mathbf{Y}/n) + o(1).$$

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Let Op_r denote the operation performed when the minimum degree is r .

For degree-greedy independent sets algorithm, Op_r is:

- choose a random vertex v of degree r
- delete v and its neighbours

Expected changes lead to a d.e.

By studying branching processes we can estimate the proportion ρ_r of steps for which Op_r is performed (i.e. $\delta(G_t) = r$) in any short segment — depending on \mathbf{Y}/n .

This suggests the differential equation

$$\frac{dy_i}{dx} = \sum_{r=0}^d \rho_r(\mathbf{y}) f_{i,r}(\mathbf{y})$$

where

$$\mathbf{y} \approx \mathbf{Y}/n, \quad x = t/n.$$

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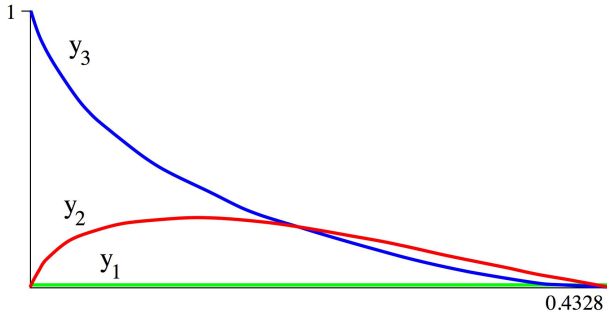
where

$$\mathbf{y} \approx \mathbf{Y}/n, \quad x = t/n.$$

Comment: $\rho_r(\mathbf{y})$ can be discontinuous, causing phases between non-smooth points, and yielding a system of right-hand derivatives only.

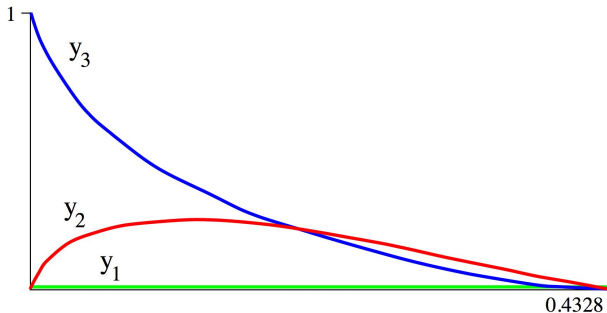
degree-greedy on 3-regular graphs: solution

Solution of the differential equations:



degree-greedy on 3-regular graphs: solution

Solution of the differential equations:



We can use a general theorem to show that the process variables a.a.s. track close to the solutions of the differential equations:

Differential equation method

Key ingredients:

- Boundedness hypothesis:

$$\|\mathbf{Y}(t+1) - \mathbf{Y}(t)\| \leq C_0$$

- Trend and Lipschitz hypotheses:

$$\|\mathbf{E}(\mathbf{Y}(t+1) - \mathbf{Y}(t) \mid H_t) - f(t/n, \mathbf{Y}(t)/n)\| = o(1)$$

where H_t is the history of the process at time t , and f is a Lipschitz function.

Conclusion: the differential equation $\frac{d\mathbf{y}}{dx} = f(x, \mathbf{y})$ has a unique solution with appropriate initial condition, and a.a.s.

$$\mathbf{Y}(t) = n\mathbf{y}(t/n) + o(n)$$

uniformly for $0 \leq t \leq Cn$.

Lower bounds on independent set ratio

β_0 : earlier known (from Shearer)

β_1 : simple greedy

β_2 : degree greedy

d	$\beta_0(d)$	$\beta_1(d)$	$\beta_2(d)$
3	0.4139	0.3750	0.4328
4	0.3510	0.3333	0.3901
5	0.3085	0.3016	0.3566
10	0.2032	0.2113	0.2573
20	0.1297	0.1395	0.1738
50	0.0682	0.0748	0.0951
100	0.0406	0.0447	0.0572
$\rightarrow \infty$	$\rightarrow \log d/d$	$\rightarrow \log d/d$?

More general issues

Bayati, Gamarnik and Tetali ['13] showed existence of a limiting value for the proportion of vertices in a max independent set (d -regular in general, d fixed).

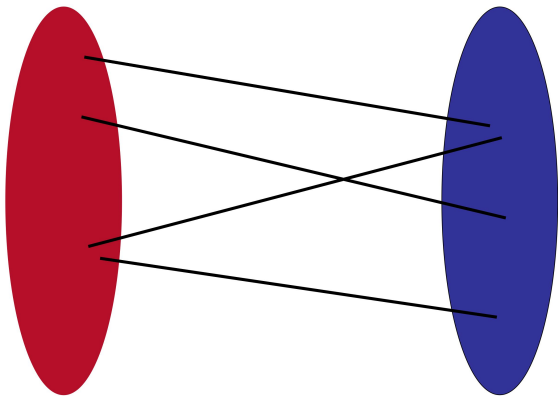
Ding, Sly and Sun recently confirmed the predictions of one-step replica symmetry breaking heuristics to find this limit for d sufficiently large.

Max bisection of random regular graphs

Max number of edges crossing a balanced partition of the vertex set.

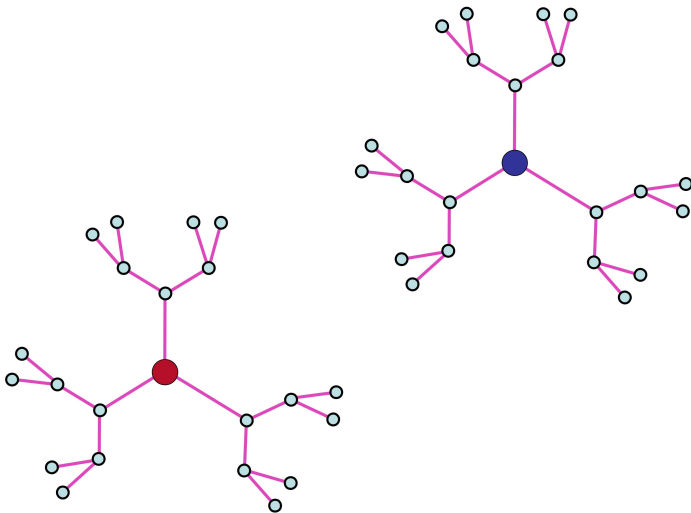
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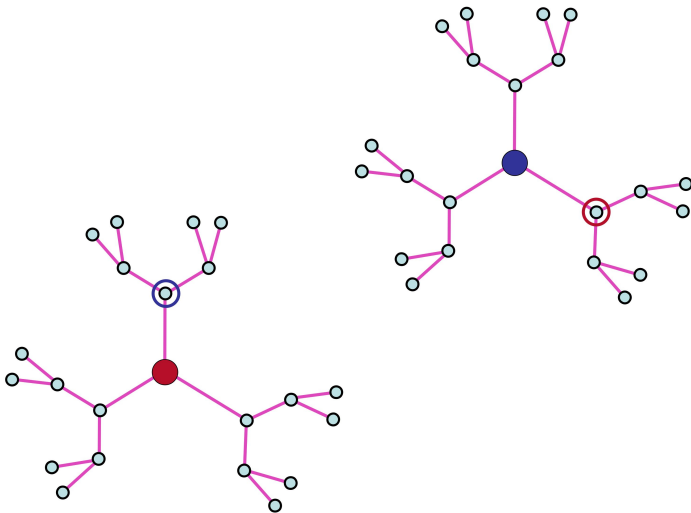
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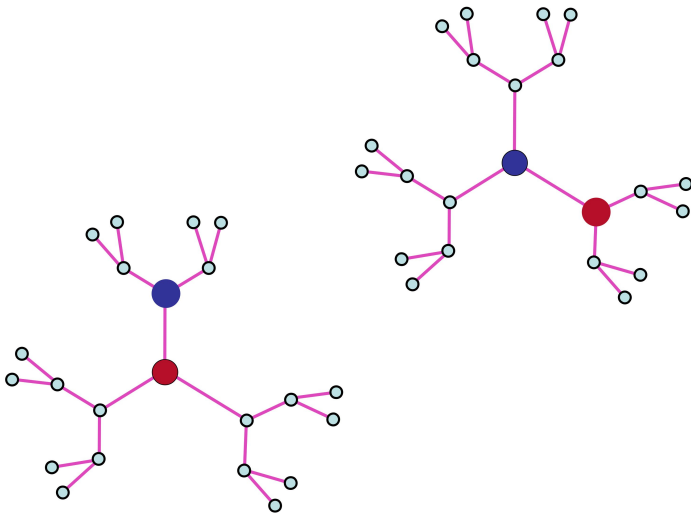
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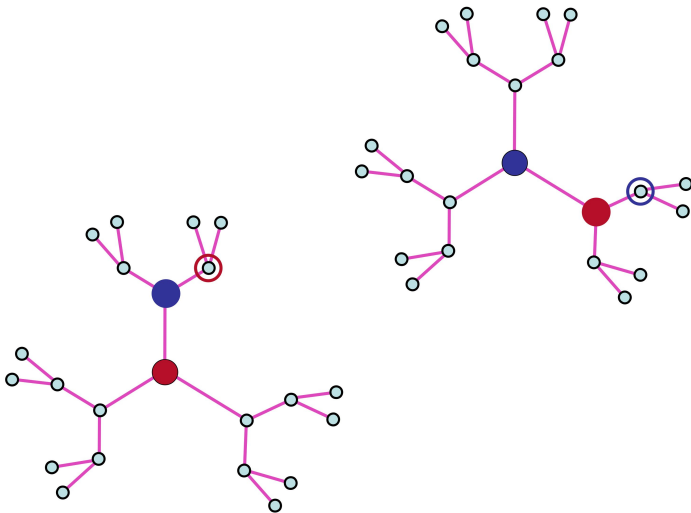
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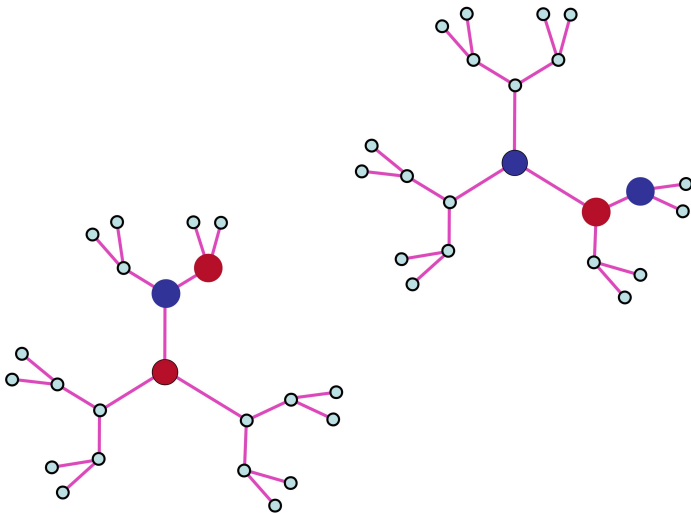
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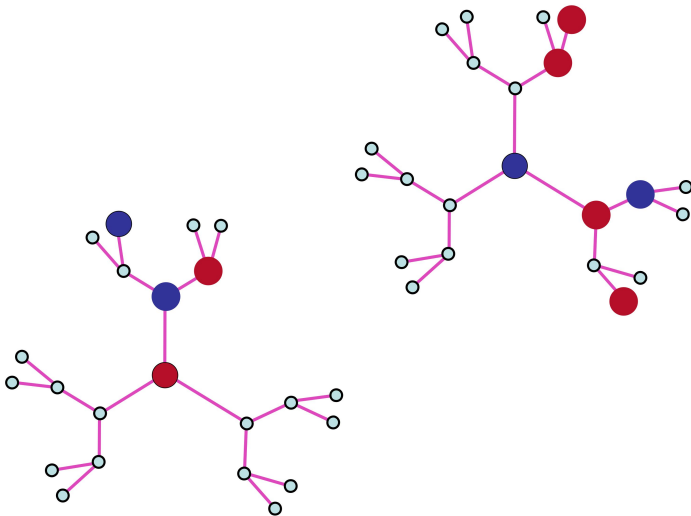
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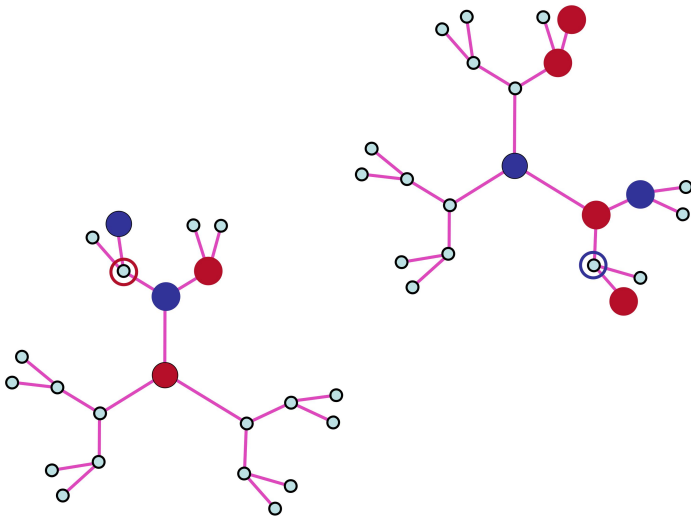
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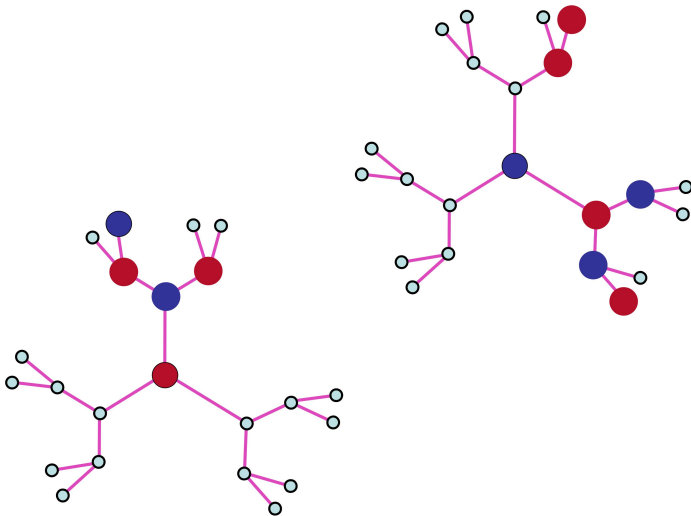
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Lower bounds for max bisection (or max cut) a.a.s. ([Díaz, Do, Serna, W., 2003–2007](#)):

3-regular: $1.326n$

4-regular: $5n/3$

5-regular: $1.997n$

etc.

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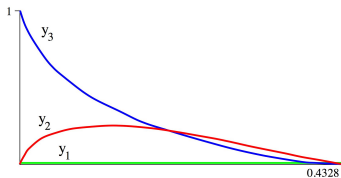
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* there are more recent improvements on max cut in the 3-regular case

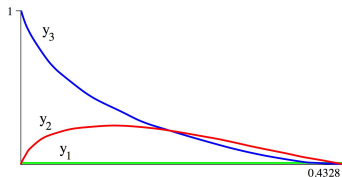
Deprioritisation for smoother algorithms

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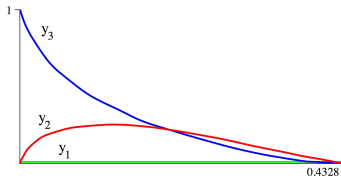
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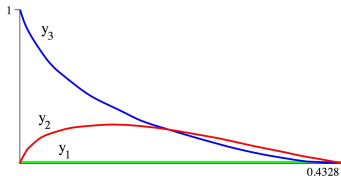


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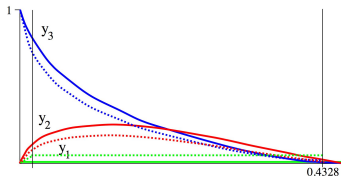
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So include an initial period creating vertices of all degrees.

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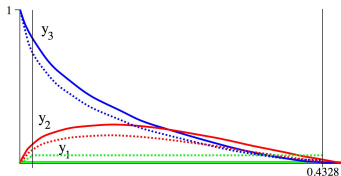
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The result is a **deprioritised** algorithm.

Deprioritised algorithms are convenient

Theorem [W, '04]

Provided the functions $f_{i,r}$ governing the prioritised algorithm satisfy certain simple conditions, there is a deprioritised algorithm with behaviour governed by the same differential equation.

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This has been convenient to use for a number of algorithms, particularly the ones exhibiting phases.

Results on other problems

A.a.s. upper bound on minimum **independent** dominating sets [Duckworth and W., '06]. (Easiest to analyse using a deprioritised algorithm.)

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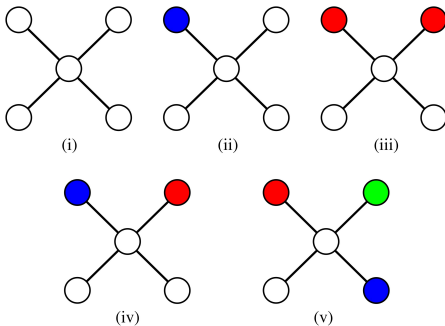
Other results: k -independent sets, maximum induced matchings, ...

Chromatic number of random 4-regular graphs

Greedy colouring algorithm analysed by differential equations.

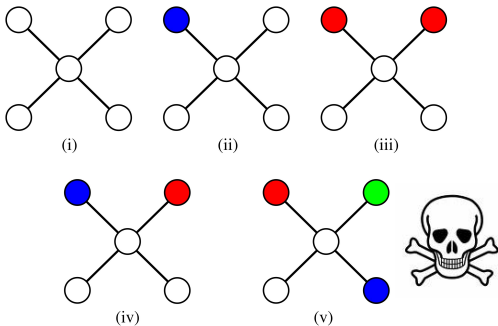
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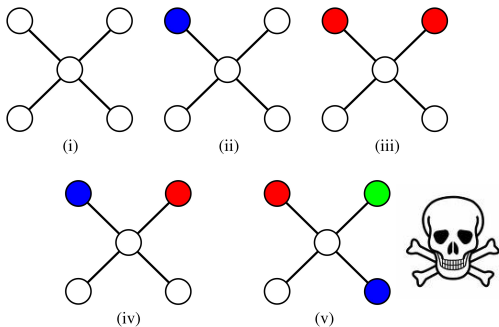
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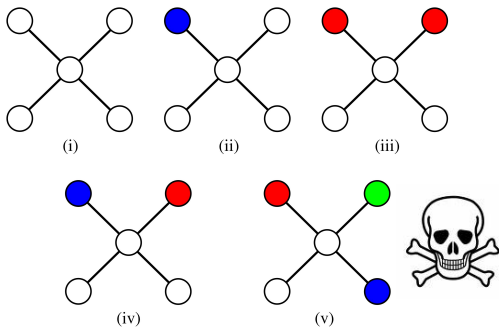
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BUT colour the short odd cycles first, THEN be greedy.

Chromatic number of random 4-regular graphs

Greedy colouring algorithm analysed by differential equations.



BUT colour the short odd cycles first, THEN be greedy.
AND stop with cn vertices uncoloured.

Theorem [Shi and W, '07]

$$\chi(\mathcal{G}_{n,4}) = 3 \text{ a.a.s.}$$

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Similarly,

5-regular: 3 or 4

6-regular: 4

7-regular: 4 or 5

Just a few unsolved problems

What is the (limiting) size of the

- largest independent set
- max cut
- min bisection

in a random 3-regular graph?

Is there a limiting size (scaled by n) in the d -regular case for max cut and max/min bisection?