Satisfiability and the Giant Component in Online Variants of the Classical Random Models

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- For any k ≥ 1, a random k-set is chosen uniformly at random from (^[n]_k).
- Random edges in graphs are k-sets when k = 2.
- Duplications within *k*-sets won't change any of our results so we ignore them.

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A component of size $\Omega(n)$ is called a giant component .

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If $i \neq j$ then

$$X(G+e) - X(G) = \frac{1}{n} \left(|C_i| + |C_j| \right)^2 - \frac{1}{n} |C_i|^2 - \frac{1}{n} |C_j|^2$$

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• Offline Algorithms - All *cn* pairs are presented and then the *cn* choices are made.

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- Online Algorithms Pairs appear sequentially.
 - The choice between e_i , f_i is made upon presentation, without knowledge of future edges.
 - This is called an Achlioptas Process, named after Dimitris Achlioptas who first posed the question of online avoidance of a giant component.

The interesting case for online avoidance is $c > \frac{1}{2}$.

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- A bounded size algorithm is a size algorithm that makes no distinction between components larger than some fixed constant *m*.
- A bounded first-edge algorithm is a bounded size algorithm that chooses between e_{i+1} and f_{i+1} only by looking at the sizes of the components in $G_A(i)$ connected by e_i .

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- If $c = t_0 + \epsilon$ then whp the largest component of $G_A(cn)$ has $\Omega(n)$ vertices, and all other components are of size $O(\log n)$.

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- The main tool in our proof is the differential equations method.
- The critical value c_A is the given by the blow-up point in the differential equation for the susceptibility.

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Theorem 2: If c > 0.385 then whp this algorithm will create a graph with a component of size $\Omega(n)$.

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Theorem 3: If c < 0.2544 then for any Achlioptas process, whp all of the components of the graph created in cn steps will be of size $O(\log n)$.

Theorem 4: If c > 0.25 then whp there is a way to choose one edge from each pair and create a graph with a component of size $\Omega(n)$.

Theorem 4b: If $c > \frac{1}{2k}$ then whp there is a way to choose one edge from each k - tuple and create a graph with a component of size $\Omega(n)$.

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An assignment must exist to the Boolean variables which satisfies every clause.

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- If c < 1 then $\Pr[F_2(cn) \text{ is satisfiable }] \rightarrow 1$.
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c = 1 is called the threshold density for k = 2.

Threshold Density

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Satisfiability Threshold Conjecture

For each k > 2 there exists a threshold density c_k such that:

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- These thresholds may not converge to a limit as $n \to \infty$.
- Friedgut used Fourier Analysis in his proof of this theorem.

Theorem: (Achlioptas, Naor, Peres, 2003) For $k \ge 1$, there exist constants α and β such that

- If $c < 2^k \ln 2 \alpha k$ then $F_k(cn)$ is satisfiable whp.
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Theorem: (Dubois, Boufkhad, Mandler, 2000) $F_3(4.6n)$ is not satisfiable with high probability.

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(either c is fixed or $c \to \infty$)

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There is an online algorithm which accepts an expected $(1 - \frac{1}{2^k})cn$ clauses.

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So, if k = 2 then accept $\{\bullet, \bullet\}$, $\{\bullet, \bullet\}$, $\{\bullet, \bullet\}$, and reject $\{\bullet, \bullet\}$. This accepts an expected $\frac{3}{4}cn$ clauses.

Given: ($k=2$)	Accept?	Set to:
$\{\bullet,\bullet\}$, $\{\bullet,\bullet\}$, $\{\bullet,\bullet\}$	Yes	$\{ullet,ullet\},\{ullet,ullet\}$, $\{ullet,ullet\}$, $\{ullet,ullet\}$
$\{\bullet,\bullet\}$	No	
$[\{\bullet, \bullet\}, \{\bullet, \bullet\}, \{\bullet, \bullet\}, \{\bullet, \bullet\}, \{\bullet, \bullet\}]$	Yes	

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This accepts an expected $\frac{3}{4}cn + \frac{3}{8}n$ clauses as $c \to \infty$.

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This accepts an expected $(1 - \frac{1}{2^k})cn + a_k n$ clauses as $c \to \infty$.

k	1	2	3	4	5	10
a_k	0.5	0.375	$0.2842\ldots$	0.2209	$0.1765\ldots$	0.0809

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Therefore, an optimal online algorithm is somewhere between $(1 - \frac{1}{2^k})cn + a_k n$ and $(1 - \frac{1}{2^k})cn + \Theta(\sqrt{c})n$.

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Theorem: (K,05) Any online algorithm accepts less than $(1 - \frac{1}{2^k})cn + \ln 2n$ clauses with high probability.

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Corollary: The naive algorithm is asymptotically optimal.

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Need to show $B_{cn} \leq n \ln 2 + o(n)$ with high probability.

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This means $Y_{cn} \leq Y_0 + o(n)$ is true whp.

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More about offline

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Question: Is there a correlation?

• Let G be any simple graph with 2n vertices and cn edges.

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- Make a family of clauses S(G) by randomly assigning $\{x_1, \overline{x}_1, x_2, \overline{x}_2, \dots, x_n, \overline{x}_n\}$ to the 2n vertices, so each edge in *G* corresponds to one clause.

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- This question is equivalent to Random 2 SAT with n variables and cn clauses if G is a random graph, but we allow G to be *anything*, provided $\Delta(G)$ isn't too large.

- Let G be any simple graph with 2n vertices and cn edges.
- Make a family of clauses S(G) by randomly assigning $\{x_1, \overline{x}_1, x_2, \overline{x}_2, \dots, x_n, \overline{x}_n\}$ to the 2n vertices, so each edge in G corresponds to one clause.
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Notation: For any graph G, $\Delta(G)$ is the maximum degree and $d_i(G)$ is the number of vertices of degree i ($i \ge 0$).

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Conjecture: If G has more than $(1 + \epsilon)n$ edges then there exists ϕ such that if $\Delta(G) = o(n^{\phi})$ then S(G) is not satisfiable whp.

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- Solve the conjecture!

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Are there any questions?