

Vive la satisfaisabilité !

(avec le soutien de J.-P. Allouche)

N. Creignou¹ H. Daudé² E. de Panafieu³ V. Ravelomana³
R. Rossignol⁴

LIF, AMU
LATP, AMU
Paris 7
Grenoble

Paris, ANR Boole

Outline

1 Quick overview of previous results

2 Generalized Satisfiability

- Random (Quantified) Formulas in (non-)normal Form
- Sensitivity of generalized Boolean formulas

3 Variants and Robust Instances

- Related work
- 2-XOR-SAT a central problem
- Conclusion and perspectives

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A threshold phenomenon for 3-SAT

$Pr_{n,cn}(3\text{-SAT})$: probability that a 3-CNF formula over n variables with cn clauses is satisfiable

- The transition from satisfiability to unsatisfiability is sharp (Friedgut, 1998)
- The critical ratio is *estimated* at around 4.25
- Only lower and upper bounds have been established

$$Pr_{n,c \cdot n}(3\text{-SAT}) \rightarrow 1 \text{ for } c \leq 3.52$$

(Kaporis, Kirousis, Lalas, 2003) use the analysis of algorithms

$$Pr_{n,c \cdot n}(3\text{-SAT}) \rightarrow 0 \text{ for } c \geq 4.4898$$

(Diaz, Kirousis, Mitsche, Pérez, 2009)

previously 4.506 (Dubois, Boufkhad, Mandler, 2000)

A threshold phenomenon for 2-SAT

- The transition for 2-SAT is sharp and the critical ratio is 1
(Chvatal & Reed, Goerd, 1992)
They use **first and second moment methods**
- The scaling window is known (Bollobàs *et al.*, 2001)
- The probability of satisfiability of a random 2-CNF at the critical ratio $c = 1$ has been experimentally estimated to

$$Pr_{n,n}(2\text{-SAT}) \sim 0.9$$

(Deroulers, Monasson 2006)

What makes the difference (a posteriori) ?

- There is a simple combinatorial characterization of unsatisfiable 2-CNF formulas :
 - ▶ 2-SAT is in P
 - ▶ A linear time algorithm allows simulations at a very high scale
 - ▶ For the threshold, one can focus on the emergence of the most likely unsatisfiable formulas in random formulas
- Such a characterization is missing for 3-CNF formulas :
 - ▶ 3-SAT is NP-complete.
 - ▶ Simulations are therefore hard to run
 - ▶ For the threshold, no focus on typical unsatisfiable formulas is known

Nature of the transition for generalized satisfiability

Given a constraint satisfaction problem, depending on the size of the scaling window the transition SAT/UNSAT is either *sharp* or *coarse*.

Generalized satisfiability : Formulas can be seen as hypergraphs.

Theorem (Creignou, Daudé 2009)

If every tree-formula and every unicyclic formulas are satisfiable, then the satisfiability property has a sharp threshold .

Typical coarse transition : 1-SAT and 2-XOR-SAT.

What do we learn ?

How to make progress on the study of phase transition for monotone properties ?

- 1 Broaden the scope
- 2 Study variants on combinatorially robust instances

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Random Formulas Generator

Random instances are useful for

- providing the basis for theoretical investigations
- testing SAT/QSAT/non-PCNF solvers
- evaluating the performance of these solvers (hard instances are at the threshold)

[q]bfGen : a general formula generator which creates formula instances by interpreting the random model specification

<http://fmv.jku.at/qbfgen/>

(Creignou, Egly, Seidl 2012)

Constraints

$$f: \{0, 1\}^k \longrightarrow \{0, 1\}, \tau \subseteq \{1, \dots, k\}$$

$f_\tau(x) = f(x^\tau)$ where x^τ is obtained by complementing those bits in x indexed by elements of τ .

$\{x_1, \dots, x_n\}$ a set of variables

An n - $\{f\}$ -constraint is given by :

- a one-to-one function $\varphi: \{1, \dots, k\} \rightarrow \{1, \dots, n\}$ (scope),
- a subset $\tau \subseteq \{1, \dots, k\}$ (negated positions),

is denoted by

$$C = (f, \varphi, \tau)$$

and stands for

$$C = f_\tau(x_{\varphi(1)}, \dots, x_{\varphi(k)})$$

Example

- $f: \{0, 1\}^3 \longrightarrow \{0, 1\}$ such that $f^{-1}(1) = \{0, 1\}^3 \setminus \{000\}$,
 $f(x, y, z) = (x \vee y \vee z)$
- $\varphi(1) = 3, \varphi(2) = 5, \varphi(3) = 4$
- $\tau = \{1, 2\}$

$$f_{\tau}(x, y, z) = (\bar{x} \vee \bar{y} \vee z)$$

The constraint $C = (f, \varphi, \tau)$ stands for $(\bar{x}_3 \vee \bar{x}_5 \vee x_4)$.

Constraint satisfied by an assignment

$C = (f, \varphi, \tau)$, $I: \{1, \dots, n\} \rightarrow \{0, 1\}$.

$m(I, \varphi)$ the **motif** of I pinpointed by φ :

$$m(I, \varphi) := (I(\varphi(1)), \dots, I(\varphi(k)))$$

The **status** of the constraint C with respect to I .

$$C(I) := f_{\tau}(m(I, \varphi)),$$

The n -assignment I **satisfies** C if $C(I) = 1$.

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/ the all-one assignment, $C(I) = f_{\tau}(1, 1, 1) = 1$

Schaefer's framework : \mathcal{F} -formulas

Given \mathcal{F} a finite set of Boolean functions, an \mathcal{F} -constraint is a constraint using a function f from \mathcal{F} .

A sequence of \mathcal{F} -constraints, over n variables is an (n, L) - \mathcal{F} -formula

- If $\mathcal{F} = \{f\}$ where $f(x, y, z) = (x \vee y \vee z)$
 - ▶ an \mathcal{F} -constraint is a 3-clause
 - ▶ an \mathcal{F} -formula is 3-CNF
- If $\mathcal{F} = \{g\}$ where $g(x, y) = (x \oplus y)$
 - ▶ an \mathcal{F} -constraint is a 2-XOR-clause
 - ▶ an \mathcal{F} -formula is 2-XOR-CNF

Sensitivity of Boolean functions

The **sensitivity set** of f at a particular input x , $S(f, x)$:

$$S(f, x) = \{t : 1 \leq t \leq k, f(x) \neq f(x^t)\}.$$

The **sensitivity** of f at x :

$$s(f, x) = |S(f, x)|$$

Sensitivity of constraints

Let $C = (f, \varphi, \tau)$ be an n -constraint and I be a truth assignment. The sensitivity set of C at I :

$$S(C, I) := \{t : 1 \leq t \leq n, C(I) \neq C(I^t)\}.$$

The sensitivity of C at the truth assignment I is :

$$s(C, I) := |S(C, I)|.$$

Sensitivity of formulas

$\Phi = (C_1, \dots, C_L)$ a formula, I a truth assignment

$$\Phi(I) = (C_1(I), \dots, C_L(I))$$

The **sensitivity set** of Φ at I :

$$S(\Phi, I) := \{t : 1 \leq t \leq n, \Phi(I) \neq \Phi(I^t)\}.$$

Enumeration

Let I be a truth assignment.

$$\begin{aligned} & |\{\Phi : \Phi \text{ is an } (n, L)\text{-}\mathcal{F}\text{- formula, } \Phi(I) = (1, \dots, 1) \text{ and } S(\Phi, I) = S\}| \\ & = \Gamma_{k,n,L,\mathcal{F}}^1(|S|) \end{aligned}$$

The number of formulas satisfied by I having a given sensitivity set S at I is independent from I , depends on the cardinality of S only and can be expressed according to the sensitivity of the functions in \mathcal{F} .

(Creignou, Daudé 2013)

Applications

This result allows the enumeration of \mathcal{F} -formulas

- having a given truth assignment as a sufficiently isolated solution
- having a given truth assignment as a locally maximal solution (useful for threshold upperbounds, method of [O. Dubois](#))

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Previous studies

Problem	Scale	Nature	critical ratio	complexity
2-SAT	$L = \theta(n)$	Sharp	$c_2 = 1$	P
3-XOR-SAT	$L = \theta(n)$	Sharp	$c_{XOR,3} \sim 0.918$	P
2-XOR-SAT	$L = \theta(n)$	Coarse		P

((Chvatal & Reed, Goerdt, 1992)), (Dubois, Mandler 2002)

(1,2)-QSAT

A (1,2)-QCNF-*formula* is a closed quantified formula of the following type

$$\forall X \exists Y \varphi(X, Y)$$

- X has $m = \lfloor \alpha \log n \rfloor$ variables
- Y has n variables
- each clause in φ has 1 literal from X and 2 from Y

Sharp threshold : For any value of α , we give the exact location of the associated critical ratio, $a(\alpha)$.

(Creignou, Daudé, Egly, Rossignol 2009)

The 2-XOR-SAT problem and its graphical representation

- An instance : $(\mathbf{v}_1 \vee \mathbf{v}_2) \wedge (\neg \mathbf{v}_1 \vee \mathbf{v}_3) \wedge (\neg \mathbf{v}_1 \vee \neg \mathbf{v}_2)$
- A solution : SAT with $(\mathbf{v}_1 = 1, \mathbf{v}_2 = 0, \mathbf{v}_3 = 1)$.
- Localization of the threshold : n variables, $m = c \times n$ clauses randomly picked from the set of $4 \binom{n}{2}$ clauses.
 $c < 1$ Proba SAT $\rightarrow 1$, $c > 1$ Proba SAT $\rightarrow 0$.

Underlying combinatorial structures : directed graphs.

$$\text{Write } x \vee y \quad \text{as} \quad \begin{cases} \neg x = 1 \implies y = 1 \\ \neg y = 1 \implies x = 1 \end{cases}$$

Characterization : SAT iff no directed path between x and $\neg x$ (and vice-versa).

Proof. First and second moments method [Goerdts 92, De la Vega 92, Chvátal, Reed 92].

2-XOR-SAT and the Boole Project

Main motivations and results

- What can be the contributions of **ENUMERATIVE/ANALYTIC COMBINATORICS** to SAT/CSP-like problems ?
- **MONASSON** (2007) inferred that (statistical physics) :

$$\lim_{n \rightarrow +\infty} n^{\text{critical exponent}} \times \text{Proba} \left[2\text{XORSAT}(n, \frac{n}{2}) \right] = O(1),$$

where “critical exponent” = **1/12** .

- We have **shown** that “critical exponent” is in fact = **1/12** and we made **explicit** the hidden constant behind the $O(1)$.

Remark :

This was the beginning of a whole line of research within the Boole Project cf. [Vonjy Rasendrasahasina 2012 and Elie de Panafieu's theses ~ 2014].

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Random 2-XOR-SAT

- **Ex :**
 $x_1 \oplus x_2 = 1, x_2 \oplus x_3 = 0, x_1 \oplus x_3 = 0, x_3 \oplus x_4 = 1, \dots$
- **General form :** $AX = C$ where A has m rows and 2 columns and C is a m -dimensional 0/1 vector.
- **Distribution :** uniform. We pick m clauses of the form $x_i \oplus x_j = \varepsilon \in \{0, 1\}$ from the set of $n(n-1)$ clauses.
- **Underlying structures :** **graphs with weighted edges**
 $x \oplus y = \varepsilon \iff$ edges of weight $\varepsilon \in \{0, 1\}$.

Characterisation :

SAT iff no elementary cycle of odd weight.

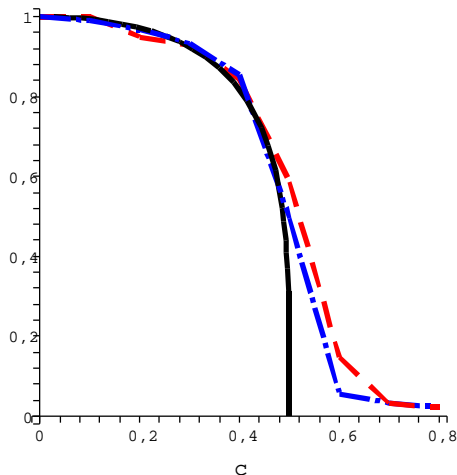
Main ideas of our approach

A basic scheme

- 1 **Enumeration** of “SAT”-graphs (graphs without cycles of odd weight) by means of generating functions.
- 2 Use the obtained results with **analytic combinatorics** to compute :

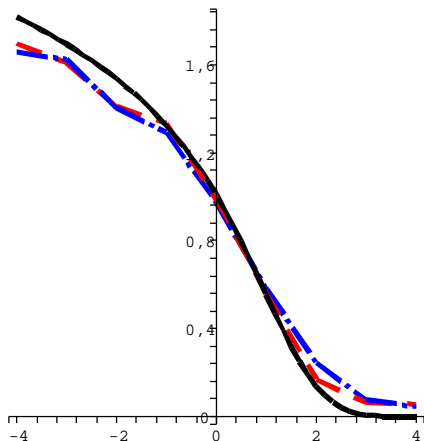
$$\text{Prob. SAT} = \frac{\text{Nbr of configurations without cycles of odd weight}}{\text{Nbr total of configurations}} .$$

Taste of our results : the whole window



$p(n, cn) \stackrel{\text{def}}{=} \text{Proba} [2\text{-XOR with } n \text{ variables, } cn \text{ clauses}] \text{ is SAT}$
for $n = 1000$, $n = 2000$ and the **theoretical** function : $e^{c/2}(1 - 2c)^{1/4}$.

Taste of our results : rescaling the critical window



Rescaling at the point “zero”, i.e $c = 1/2$: $n = 1000$, $n = 2000$ and $\lim_{n \rightarrow \infty} \underbrace{n^{1/12}}_{\times} p(n, n/2 + \mu n^{2/3})$ as a **function of μ** .

Enumerating graphs of 2-XORSAT.

We will enumerate the connected graphs without cycles of odd weight according to two parameters : **number of vertices** n and **number of edges** $n + l$. $l \stackrel{\text{def}}{=} \mathbf{excess}$.

Let

$$C_\ell(z) = \sum_{n>0} c_{n,n+l} \frac{z^n}{n!} .$$

What are the series C_ℓ ?

Th.

$$C_\ell(z) = \frac{1}{2} W_\ell(2z)$$

with $W_\ell =$ Exponential generating functions of connected graphs
WRIGHT (1977).

Enumerating graphs of 2-XORSAT.

We will **enumerate** the connected graphs without cycles of odd weight according to two parameters : **number of vertices** n and **number of edges** $n + \ell$. $\ell \stackrel{\text{def}}{=} \mathbf{excess}$.

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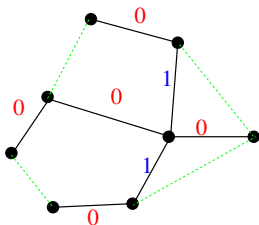
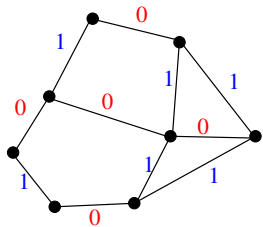
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Main ideas behind the enumerations

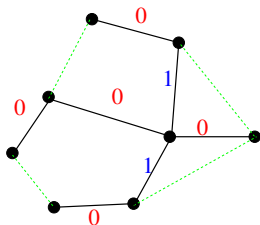
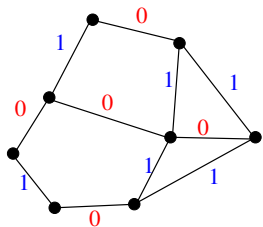


On a connected “SAT”-graph with n vertices and $n + \ell$ edges, the edges of a spanning tree can be colored in 2^{n-1} ways. The colors of the other edges are “determined”.

Remark :

As we obtained the generating functions, the whole machinery to study random graphs apply to random 2-XOR-SAT to get the results.

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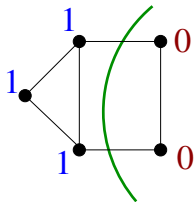
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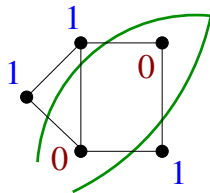
Random MAX-2-XOR-SAT

- **MAX-2-XORSAT** is an NP-optimization problem (NPO). The corresponding decision problem is in NP (deciding if the size of the MAX is k ...).
- **MAX/MIN** problems are interesting (and difficult) in randomness context.
- **PREVIOUS WORKS** : [Coppersmith, Gamarnik, Hajiaghayi, Sorkin 04] **Expectations** of the **Maximum** number of satisfiable clauses in MAX-2-SAT and MAX-CUT for the subcritical phases. **Bounds** of these expectations for some cases (namely for the critical and supercritical phases of random graphs) !
- **OUR WORK** : Quantification of the **Minimum** number of clauses to remove in order to get satisfiable formula.

MAX-CUT \sim MAX-2-XORSAT (i)



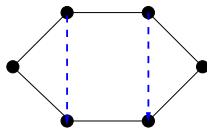
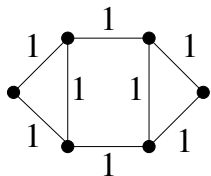
CUT



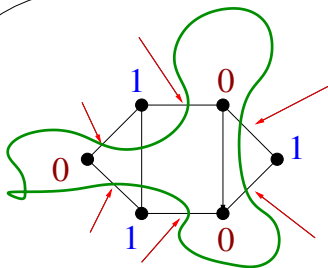
MAX-CUT

MAX-CUT \sim MAX-2-XORSAT (ii)

Graph \longrightarrow MAX-2-XORSAT



MAX-CUT



Our results on MAX-2-XOR-SAT

(Daudé, Martinez, Rasendrasahasina, R. 2012)

- Precise results such as convergence in distribution to Poisson r.v and then to Gaussian r.v. if the random graph is **very sparse**
- “Only” bounds of the size of the MAX-CUT as soon as the giant component of the random graph is born (**truly disappointing**!).
- We have a conjecture about the size of the MAX-CUT in the latter case (confirmed by colleagues empirical data).

Conclusion and perspectives

The **enumerative/analytic approaches** and the random 2-XOR-SAT problem has lead to several directions.

Similar **methods** worked on other problems such as

- 1 bipartiteness (or 2-COL).
- 2 2-QXORSAT (quantified formula) and generalizations (cf. [\[Elie's talk\]](#)).
- 3 planarity

but not completely on MAX-2-COL, MAX-CUT, MIN-VERTEX-COVER, MIN-BISECTION, MAX-PLANAR

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