

The Community Structure of SAT Formulas

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Introduction

- SAT is a central problem in computer science and AI with theoretical and **practical** applications.
- SAT competitions: *good* solvers for *random* SAT instances are *bad* for *industrial* instances, and vice versa.
- SAT solvers efficiency solving industrial instances has undergone a great advance, mainly motivated by the introduction of *lazy data-structures*, *learning mechanisms* and *activity-based heuristics*.
- In parallel, there have been significant advances in our understanding of *complex networks*, e.g., the notion of *small world* as first model of complex networks alternatively to the classical random graph models.

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- We propose the use of **modularity** (of graphs) for detecting the **community structure** of SAT instances.
 - The notion of *community* is more general than the notion of *connected components*.
 - It allows the existence of (a few) connections between communities.

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How does learning modify it?

SAT Formulas as Graphs

Clause-Variable Incidence Graph (CVIG):

Nodes: are variables **v** and clauses **c**

Edges: **v** — **c** if clause **c** contains variable **v**
with weight $w = \frac{1}{|c|}$

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Variable Incidence Graph (VIG):

Nodes: are variables \mathbf{v}

Edges: $\mathbf{v}_1 \text{---} \mathbf{v}_2$ if some clause \mathbf{c} contains variables \mathbf{v}_1 and \mathbf{v}_2
with weight $w = \frac{1}{\binom{|c|}{2}}$

SAT Formulas as Graphs

Clause-Variable Incidence Graph (CVIG):

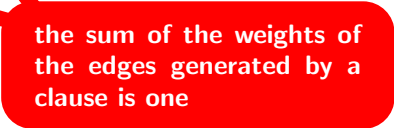
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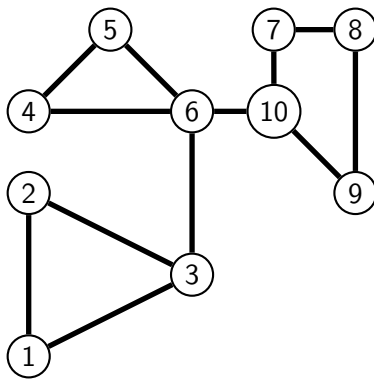
Nodes: are variables **v**

Edges: **v**₁ — **v**₂ if some clause **c** contains variables **v**₁ and **v**₂
with weight $w = \frac{1}{\binom{|c|}{2}}$



the sum of the weights of
the edges generated by a
clause is one

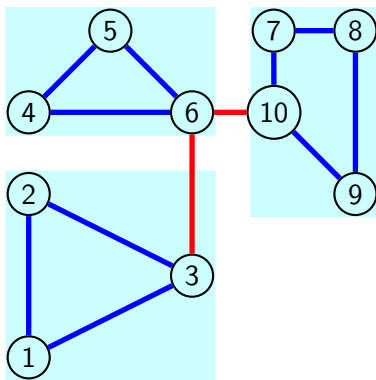
Partitions in Graphs



$$Q = \frac{\text{inner edges}}{\text{total edges}} - \frac{\text{expected inner edges}}{\text{total edges}}$$

$$Q = \frac{10}{12} - \frac{7 \cdot \frac{7}{24} + 8 \cdot \frac{8}{24} + 9 \cdot \frac{9}{24}}{12} \approx 0.8333 - 0.3368 = 0.4965$$

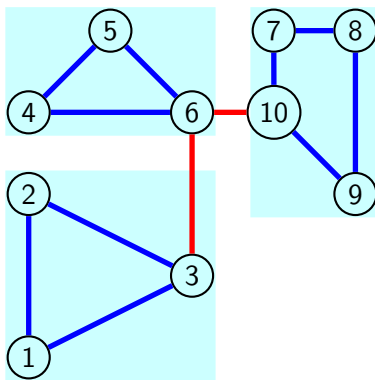
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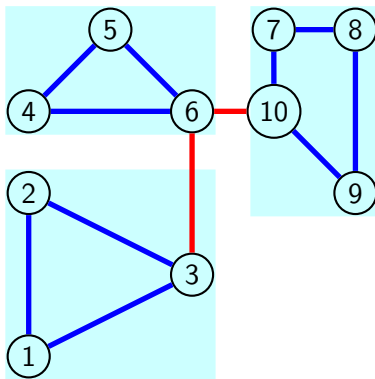
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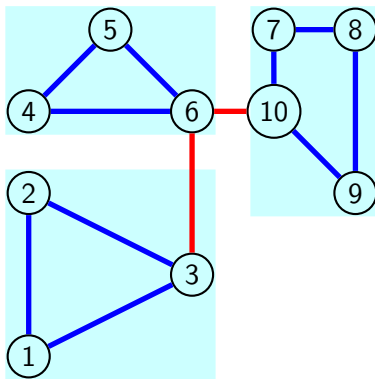
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Definition of Modularity

Modularity $Q \in [-1, 1]$ measures **how good** is partition $P = \{P_i\}$

For **weighted graphs** (Newman et al. (2004)):

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where $\deg(x) = \sum_{y \in V} w(x,y)$

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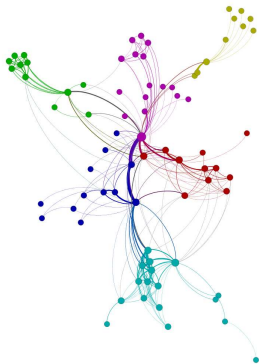
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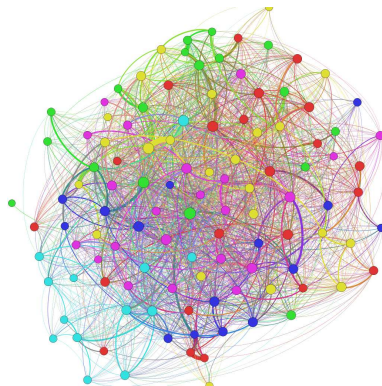
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Maximizing modularity is NP-hard

Example



$$Q = 0.560$$

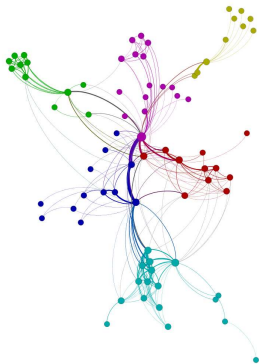


$$Q = 0.097$$

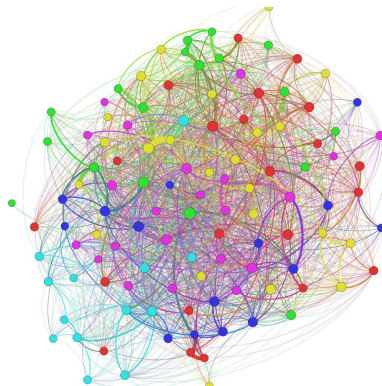
"In practice, Q values for networks showing a strong community structure range from 0.3 to 0.7, higher values are rare."

Newman et al. (2004).

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Label Propagation Algorithm (LPA)

Input: Graph $G = (X, w)$

Output: a labelling L for X

for $x \in X$ **do** $L[x] := x$; **endfor**
do

$changes := \text{FALSE}$;

for $i \in |X|$ in random order **do**

$label := \text{most_freq_label}(i, \text{neighbors}(i))$;

if $label \neq L[i]$ **then**

$changes := \text{TRUE}$;

$L[i] := label$;

endfor

while $changes$

return L

Raghavan et al. (2007).

Graph Folding Algorithm (GFA)

Input: Graph $G = (X, w)$
Output: a labelling L_1 for X
for $x \in X$ **do** $L_1[x] := x$; **endfor**
 $L_2 := \text{OneLevel}(G)$;
while $\text{Mod}(G, L_1) < \text{Mod}(G, L_2)$ **do**
 $L_1 := L_1 \circ L_2$;
 $G := \text{Fold}(G, L_2)$;
 $L_2 := \text{OneLevel}(G)$;
return L_1

```
function OneLevel(Graph  $G = (X, w)$ ): Label  $L$ 
do
    changes := FALSE;
    foreach  $i \in X$  do
        bestInc := 0;
        foreach  $c \in \{c \mid \exists j. w(i, j) \neq 0 \wedge L[j] = 0\}$  do
            inc :=  $\sum_{L[j]=c} w(i, j) - \text{arity}(i) \cdot \sum_{L[j]=c} \text{arity}(j) / \sum_{j \in X} \text{arity}(j)$ ;
            if inc > bestInc then
                 $L[i] := c$ ;
                bestInc := inc;
                changes := TRUE;
        end
    end
until  $\neg \text{changes}$ 
return  $L$ ;
```

```
function Fold(Graph  $G_1$ , Label  $L$ ): Graph  $G_2$ 
 $X_2 = \{c \mid \forall i, j \in c. L[i] = L[j]\}$ ;
 $w_2(c_1, c_2) = \sum_{i \in c_1, j \in c_2} w_1(i, j)$ ;
return  $G_2 = (X_2, w_2)$ ;
```

Blondel et al. (2008).

Modularity of industrial SAT instances

- Modularity of the SAT instances used in the **2010 SAT Race Finals**.
 - 100 instances.
 - Grouped into 16 families.
 - Families classified as *cryptography*, *hardware verification*, *software verification*, and *mixed*, according to their application area.
 - All instances are *industrial* in the sense that their solubility has an industrial or practical application.
 - However, they are expected to show a **distinct nature** from random instances.

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Modularity of industrial SAT instances

Family (#instanc.)		Variable IG								Clause-Variable IG				Connect. Comp.	
		LPA				GFA				LPA				P larg.	
		Q	P	larg.	iter.	Q	P	larg.	iter.	Q	P	larg.	iter.	P	larg.
cripto.	desgen(4)	0.88	532	0.8	36	0.95	97	2	37	0.75	3639	1	25	1	100
	md5gen(3)	0.61	7176	0.1	16	0.88	38	7	40	0.78	7904	0.1	42	1	100
	mizh(8)	0.00	33	99	6	0.74	30	9	33	0.67	5189	31	43	1	100
hard. ver.	ibm(4)	0.81	3017	0.6	9	0.95	723	4	32	0.77	19743	0.2	140	70	99
	manolios(16)	0.30	66	81	9	0.89	37	9	81	0.76	6080	1	26	1	100
	velev (10)	0.47	8	68	9	0.69	12	30	24	0.30	1476	77	31	1	100
mixed	anbulagan(8)	0.55	30902	0.1	11	0.91	90	2	43	0.72	46689	0.6	26	1	100
	bioinf(6)	0.61	87	44	3	0.67	60	17	22	0.64	94027	15	10	1	100
	diagnosis(4)	0.61	20279	0.7	15	0.95	68	3	43	0.65	85928	0.1	42	1	100
	grieu(3)	0	1	100	2	0.23	9	14	11	0	1	100	14	1	100
	jarvisalo(1)	0.57	260	5	8	0.76	19	9	26	0.71	336	1	11	1	100
	palacios(3)	0.14	1864	96	58	0.93	1802	6	13	0.76	2899	0.4	35	1	100
soft. ver.	babic(2)	0.68	34033	8	54	0.90	6944	10	141	0.73	59743	4	53	41	99
	bitverif(5)	0.48	3	57	4	0.87	24	6	29	0.76	33276	0.4	8	1	100
	fuhs(4)	0.02	18	99	43	0.81	43	7	30	0.67	12617	0.8	28	1	100
	nec(17)	0.07	107	96	31	0.93	65	14	124	0.79	23826	0.8	114	1	100
	post(2)	0.36	3·10 ⁶	53	54	0.81	3·10 ⁶	9	262	0.72	3·10 ⁶	6	49	224	99

Modularity of 2010 SAT Race instances.

Modularity after preprocessing formulas

Family		Orig. Form.	Preprocessed Formula				
		Q	Modularity	Connect. Comp.			
			Q	P	larg.	P	larg.
cripto.	desgen (4)	0.951	0.929	81	3.1	1	100
	md5gen (3)	0.884	0.884	18	8.5	1	100
	mizh (8)	0.741	0.741	18	9.5	1	100
hard. ver.	ibm (4)	0.950	0.905	26	6.1	1	100
	manolios (16)	0.890	0.800	16	14.9	1	100
	velev (10)	0.689	0.687	6	30.3	1	100
mixed	anbulagan (8)	0.909	0.913	47	5.1	1	100
	bioinf (6)	0.673	0.657	25	11.1	2	99.9
	diagnosis (4)	0.952	0.950	65	3.6	1	100
	grieu (3)	0.235	0.235	9	14.3	1	100
	jarvisalo (1)	0.758	0.722	11	13.1	1	100
	palacios (3)	0.928	0.848	17	10.76	1	100
soft. ver.	babic (2)	0.901	0.875	23	9.7	1	100
	bitverif (5)	0.875	0.833	19	7.3	1	100
	fuhs (4)	0.805	0.743	32	9.6	1	100
	nec (17)	0.929	0.879	37	10.3	1	100

Modularity after preprocessing the formula with *Satellite* preprocessor.

Modularity of Learnt Clauses

- Formulas are transformed during the proof or the satisfying assignment search.
 - Even if the original formula shows a community structure, could it be the case that **this structure is quickly destroyed during the search process?**
 - How **new learnt clauses affect the community structure** of the formula?
 - Even if the value of the modularity is not altered, could it be the case that **communities are changed?**

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Modularity of resulting Formulas adding Learnt Clauses

Family		Orig. Form. Q	Orig. + Learnt Formula Modularity		
			Q	$ P $	larg.
cripto.	desgen (2)	0.951	0.561	53	13.0
	md5gen (3)	0.884	0.838	19	8.0
	mizh (1)	0.741	0.705	28	11.4
hard. ver.	ibm (3)	0.950	0.912	752	6.7
	manolios (14)	0.890	0.776	31	11.2
	velev (1)	0.689	0.558	6	30.1
mixed	anbulagan (4)	0.909	0.876	84	2.6
	bioinf (5)	0.673	0.287	32	58.7
	grieu (3)	0.235	0.085	6	35.0
	palacios (2)	0.928	0.851	2289	7.4
soft. ver.	babic (2)	0.901	0.904	6942	10.7
	fuhs (1)	0.805	0.670	24	7.6
	nec (15)	0.929	0.936	62	7.3

Modularity of the formula with learnt clauses included
(using *PicoSAT*).

Modularity of Learnt Clauses using Original Partitions

Family	VIG			CVIG		
	orig.	first 100	all	orig	first 100	all
desgen (1)	0.89	0.74	0.08	0.77	0.28	0.09
md5gen (1)	0.61	0.74	0.02	0.78	0.96	0.02
ibm (2)	0.84	0.60	0.47	0.81	0.58	0.29
manolios (10)	0.21	0.04	0.10	0.76	0.11	0.09
anbulagan (2)	0.56	0.16	0.01	0.87	0.10	0.04
bioinf (4)	0.62	0.46	0.06	0.68	0.69	0.15
grieu (1)	0.00	0.00	0.00	0.00	0.00	0.00
babic (2)	0.68	0.36	0.36	0.71	0.33	0.33
fuhs (1)	0.66	0.59	0.14	0.71	0.78	0.07
nec (10)	0.12	0.01	0.12	0.78	0.49	0.24

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	orig.	first 100	all	orig.	first 100	all
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ibm (2)	0.84	0.50	0.43	0.81	0.58	0.42
anbulagan (1)	0.55	0.03	0.00	0.87	0.13	0.05
manolios (9)	0.20	0.07	0.10	0.76	0.27	0.15
nec (10)	0.12	0.05	0.05	0.78	0.30	0.22

Modularity of (only) learnt clauses, computed using original partition, for all the instances that were solved (top), and only for unsatisfiable ones (bottom).

Modularity of Random Formulas

- **Random formulas** have a clear community structure?
Obviously NO!!
- **Modularity** can be used as a reference value to compare how *modular* other kind of instances are:
 - Is it as high in random formulas as in industrial ones?
 - Is it dependent on the clause-variable ratio α ?
 - Is it dependent on the number of variables?
 - How modularity is affected by the effects of:
 - Preprocessing the formula?
 - Learning new clauses?

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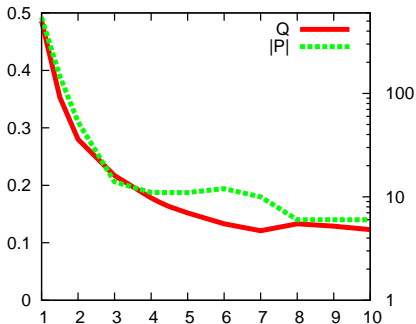
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- **Random formulas** have a clear community structure?
Obviously NO!!
- **Modularity** can be used as a reference value to compare how *modular* other kind of instances are:
 - Is it as high in random formulas as in industrial ones?
 - Is it dependent on the clause-variable ratio α ?
 - Is it dependent on the number of variables?
 - How modularity is affected by the effects of:
 - **Preprocessing** the formula?
 - **Learning** new clauses?

Modularity of Random Formulas

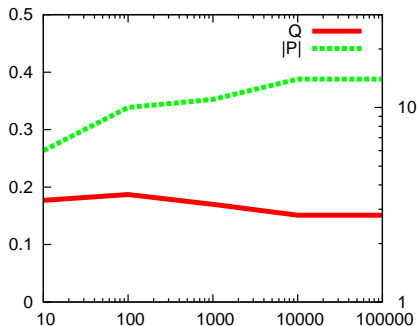
n	α	Q	P	larg.	iter
10^4	1	0.486	545	3.8	54
10^4	1.5	0.353	146	5.1	52
10^4	2	0.280	53	6.8	51
10^4	3	0.217	14	15.5	64
10^4	4	0.178	11	14.8	54
10^4	4.25	0.170	11	14.6	53
10^4	4.5	0.163	11	14.7	53
10^4	5	0.152	11	14.3	51
10^4	6	0.133	12	13.9	53
10^4	7	0.120	10	15.0	56
10^4	8	0.138	6	25.0	50
10^4	9	0.130	6	24.3	49
10^4	10	0.123	6	24.4	47



Modularity of random formulas varying the clause variable ratio α .

Modularity of Random Forms. at the peak transition region

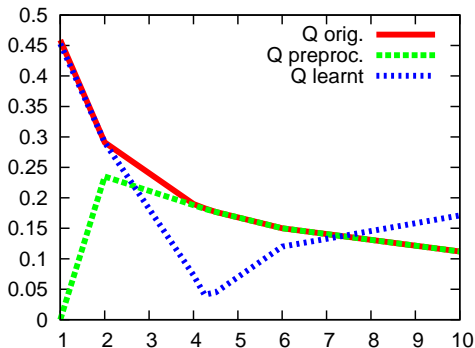
n	α	Q	P	larg.	iter
10^2	4.25	0.177	6	14.5	11
10^3	4.25	0.187	10.5	11.4	35
10^4	4.25	0.170	11	12.2	53
10^5	4.25	0.151	14	6.8	102
10^6	4.25	0.151	14	5.7	167



Modularity of random formulas at the peak transition region (clause-var. ratio $\alpha = 4.25$) varying the number of variables (n).

Modularity of Random Forms: Preprocessing and Learning

n	α	Orig.	Prep.	Learnt	C.C.
300	1	0.459	0	0.453	1
300	2	0.291	0.235	0.291	1
300	4	0.190	0.188	0.073	1
300	4.25	0.183	0.182	0.041	1
300	4.5	0.177	0.177	0.045	1
300	6	0.150	0.150	0.120	1
300	10	0.112	0.112	0.171	1



Modularity of random formulas (varying the clause variable ratio) after preprocessing, and including all learnt clauses.

Conclusions

- Industrial SAT instances have a **clear community structure**.
- Preprocessing these instances has **almost no impact** in this structure. However, it eliminates almost all the small unconnected components.
- Modularity weakly decreases with the learnt clauses. Therefore, learning does **not completely destroy the organization of the formula**. Nevertheless, it does **change the partitions structure**.
- Modularity of random instances is **only significant** for very low clause-variable ratios (α). Even for them, the modularity is **not as high as for industrial instances**. No abrupt change in the phase transition point is observed. This modularity does **not depend on the number of variables** (it seems to tend to a particular value).
- Preprocessing has almost **no impact** on the modularity of the formula. However, learning process **totally changes** this modularity. So, it totally changes the structure of the formula.

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- To understand better how to **exploit** the community structure in SAT solvers (heuristics, learning, restarts, ...).
- **Generate** industrial-like random SAT instances with similar modularity to industrial instances.
- Study **other measures** of complex networks (such as the fractal dimension).

**Thank you for your
attention!!**