On the Classification of Industrial SAT Families

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The Boolean Satisfiability Problem (SAT)

 The Boolean Satisfiability Problem (SAT) is the decision problem of determining if there exists an assignment of the Boolean variables of a propositional formulas such that the formula is evaluated as TRUE.

Notation:

- A **literal** is a Boolean variable x, or its negation $\neg x$.
- A **clause** *c* is a disjunction of *i* literals:

$$c = x_1 \lor x_2 \lor \cdots \lor x_i$$

• A CNF formula Γ is a conjunction of m clauses:

$$\Gamma = c_1 \wedge c_2 \wedge \cdots \wedge c_m$$

• A k-CNF formula is a CNF with all its clauses having size k.

Applications of SAT

- First known **NP-complete** problem [Cook71].
 - Deeply studied from a theoretical point of view.

- Extensively used to encode many other problems, which are efficiently solved by modern SAT solvers.
 - Planning, Scheduling, Formal Verification (hardware and software), cryptography, bioinformatics, ...
 - Therefore, finding good algorithms to solve SAT is of practical use in many areas of Computer Science.

SAT Instances

- Random instances:
 - Randomly generated from a well-known model: $F_k(n, m)$.

- Industrial (application) instances:
 - Problems encodings from real-world applications.
 - No precise definition/model: crypto, bmc, scheduling, planning, ...
 - Heterogeneity.
 - Usually classified into families.

SAT Solvers Performance

- Random and industrial formulas: distinct nature.
 - SAT competitions: different tracks.

 Distinct algorithms have a very different performance depending on the type of instance they are solving (i.e., random or industrial).

 Improvements on those algorithms make SAT solvers specialize.

Performance on Industrial SAT Instances

- Conflict-Driven Clause Learning (CDCL) are the dominant technique to solve industrial SAT instances.
 - Backtracking-like depth-first search, Unit Prop. (DPLL).
 - Clause Learning.
 - Conflict-driven heuristics.
 - Rapid restarts.
 - Lazy data structures, inprocessing variable elimination techniques, clause removal policies, ...
- However, why these techniques are so efficient solving this type of problems remains open.
- The common wisdom is that they exploit some hidden structure that actually exists in industrial formulas.
- What is exactly this structure of industrial SAT instances?



The Structure of Industrial SAT Instances (I)

Inspired by works on complex networks.

- We represent SAT instances as graphs:
 - Variable Incidence Graph (VIG):
 - Nodes are variables.
 - Edges between two variables appearing in the same clause.
 - Weights in the edges to represent the length of the clause.
 - Clause-Variable Incidence Graph (CVIG):
 - Nodes are either variables or clause (bi-partite graph).
 - Edges represent the existence of a variable in a clause.
 - Weights in the edges to represent the length of the clause.

The Structure of Industrial SAT Instances (II)

- The Scale-free Structure: [AnsóteguiBonetLevy.CP09].
 - A graph has scale-free structure if the degree of its nodes follows a **power-law distribution** $p(k) \sim k^{-\alpha}$.
 - The number of variable occurrences (number of neighbors of variable nodes in the CVIG) follows a power-law distribution in most industrial SAT instances: exponent α_v .
- The Community Structure: [AnsóteguiGiráldez-CruLevy.SAT12].
- The Self-Similar Structure: [AnsóteguiBonetGiráldez-CruLevy.IJCAR14].

The Structure of Industrial SAT Instances (II)

• The Scale-free Structure:

[Ans 'otegui Bonet Levy. CP09].

 The Community Structure: [AnsóteguiGiráldez-CruLevy.SAT12].

- A graph has clear community structure if there exists a partition of its nodes into communities such that most edges connect nodes of the same community.
- The **modularity** Q measures how clear this community structure is (value in [0,1]).
- Most industrial SAT instances have a clear community structure: Q (of its VIG).
- The Self-Similar Structure: [AnsóteguiBonetGiráldez-CruLevy.IJCAR14].

The Structure of Industrial SAT Instances (II)

- The Scale-free Structure: [AnsóteguiBonetLevy.CP09].
- The Community Structure: [AnsóteguiGiráldez-CruLevy.SAT12].
- The Self-Similar Structure: [AnsóteguiBonetGiráldez-CruLevy.IJCAR14].
 - A graph has self-similar structure if it keeps the same shape after rescaling (replacing groups of nodes by a single node).
 - This means that the diameter d grows as $d \sim n^{1/d}$, where n is the number of nodes, and d is its **fractal dimension**.
 - Most industrial SAT instances have fractal dimension:
 d and d^b (of its VIG and CVIG, respectively).



Algorithm Configurations

 Algorithms have configurations of their parameters that may vary their performance.

• What is the best parameter configuration to solve a particular instance?

 For instance, some industrial families are known to be easier when using strategies based on diversification (i.e., high frequency of restarts). Others prefer an intensified search (i.e., low frequency of restarts).

Portfolio Algorithms

- What is the best algorithm to solve a particular instance?
- The Algorithm Selection Problem: choose the best algorithm from a predefined set to solve a particular instance of a problem, using a prediction model.
- Portfolio SAT solvers:
 - Building the predictor:
 - Set of (core) SAT solvers: vector of *runtimes*.
 - Training set (of instances): vector of *features*.
 - Solving a particular instance:
 - Compute the features of such instance.
 - Use the predictor to choose the (expected) best algorithm.
 - How to choose these features?

SATzilla (2012)

- A very well-known portfolio SAT solver.
- Winner in several tracks of several SAT competitions.

• Prediction model: Random forest.

- Features: 127, divided into categories.
 - Problem size.
 - Graph: degrees and clustering coefficients in VIG and CVIG.
 - Hardness: DPLL, LP, SLS, CDCL, SP.
 - Timing.

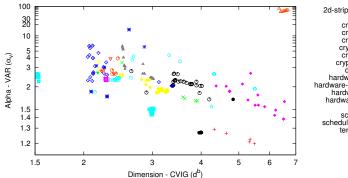
The Structure of Industrial SAT Instances

• The Scale-free Structure: α_{ν} .

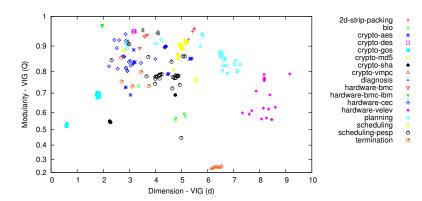
• The Community Structure: Q.

• The Self-Similar Structure: d and d^b .

Distribution of Industrial SAT Families



Distribution of Industrial SAT Families



Industrial SAT Families Classifiers (I)

• SAT Competition 2013:

- 300 instances.
- 19 industrial families.
- SAT solvers submitted to this competition.

Set of features:

- Structure (5): α_v , Q, d, d^b , m/n.
- SATzilla (115): timing features not considered.

• Evaluation:

- Classifiers: C4.5, Random Forest (RF), Naïve Bayes (NB), Multi-response Linear Regression (MLR), Logistic Regression (LR), Sequential Minimal Optimization (SMO), IBk, K*, JRip.
- 10-folds cross-validation.



Industrial SAT Families Classifiers (II)

	Structure	SATzilla		
C4.5	259 (86.33%)	263 (87.67%)		
RF	274 (91.33%)	288 (96.00%)		
NB	254 (84.67%)	256 (85.33%)		
MLR	247 (82.33%)	262 (87.33%)		
LR	251 (83.67%)	280 (93.33%)		
SMO	153 (51.00%)	241 (80.33%)		
IBk	275 (91.67%)	264 (88.00%)		
K*	273 (91.00%)	199 (66.33%)		
JRip	246 (82.00%)	251 (83.67%)		

In **bold**, classifiers with effectiveness **higher than 90%**.

Discussion

- SATzilla characterize the structure using 14 features (statistics of node degree and clustering coefficient).
- They are *local* properties of the structure.
- We use 4 global features to characterize the structure.
 - Statistics of clustering coefficient vs Modularity.
 - Statistics of node degrees vs Power-law exponent.

- **SATzilla** characterize the **hardness** using 71 features.
- We only use m/n as a simple but weak metric of such hardness.

Evaluation in a Portfolio (I)

- Portfolio solver: ISAC.
 - Prediction: *g-means* (similar to *k-means*).
- SAT instances: **SAT Competition 2013**.
- Core solvers: **SAT Competition 2013**.
- Evaluation: 10-folds cross-validation.
 - Each instance is randomly assigned to a fold.
 - 9 folds are used to build a classifier (training set). Instances
 of the remaining fold (test set) are solved using such classifier.
 - **Cross-validation**: All folds are used as test set once (repeat 10 times).
- Runtime: computing its features + the runtime of the solver selected by the classifier.

Cost of Computing the Set of Features

	Structi	SATzilla	
runtimes	VIG+CVIG	VIG	
minimum	0.07	0.04	11.71
median	4.9	3.31	49.24
average	21.65	17.70	170.43
std	36.87	34.11	362.27
maximum	287.12	275.11	3675.28

- VIG: α_v , Q, d (and m/n). VIG+CVIG: α_v , Q, d, d^b (and m/n).

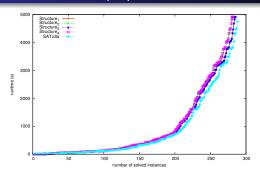
Evaluation in a Portfolio (II)

• Sets of features:

Structure ₁	$\alpha_{\it v}$	Q	d	d^b	m/n	VIG+CVIG+m/n
Structure ₂	$\alpha_{\it v}$	Q	d		m/n	VIG+m/n
Structure ₃	$\alpha_{\it v}$	Q	d	d^b		VIG+CVIG
Structure ₄	$\alpha_{\it v}$	Q	d			VIG
SATzilla	115 features			tures	no timing features	

• Timeout: 5000 seconds (timeout used in competitions).

Evaluation in a Portfolio (III)



		runtime			
	#solved	max	mean	stdev	
Structure ₁	285	4913.2	874.6	1199.6	VIG+CVIG+m/n
Structure ₂	281	4913.2	863.3	1197.7	VIG $+m/n$
Structure ₃	285	4913.2	876.8	1200.1	VIG+CVIG
Structure ₄	281	4913.2	881.2	1207.8	VIG
SATzilla	288	4745.2	831.6	1143.6	

Conclusions

 A good characterization of SAT instances requires structure and hardness.

- Computing the structure set of features is faster than computing the SATzilla set.
- However, the clause/variable ratio m/n is a **too weak** metric of the hardness.
- Therefore, the performance using SATzilla is slightly better (3 instances solved more) and faster than using any combination of structure features.

• Future work: combine the hardness features of SATzilla with the structure features of our method.



Thank you for your attention!