On Quantitative Testing of Samplers Presentation at Simons Institute, Satisfiability: Theory, Practice, and Beyond Reunion

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Uniform Sampling of Solutions of a CNF

CNF : Conjunctive Normal Form

- Formula consisting of boolean variables, and a set of constraints: a conjunction of disjunctions
- Ex: $(a \lor b) \land (a \lor \neg b) \land (a \lor b \lor \neg c)$
- All satisfying assignments: $a = \top$ any value for b, c.

Uniform sampling

- Provide samples uniformly at random from the solution space.
- Say, we need 1M samples from CNF above. We expect it to contain roughly 0.5M samples with $b = \top$.
- Chance of 0 samples with $b = \top$ is $2^{-500000}$, i.e. not very high. Possible, but not realistic.

Use-Cases, Previous work

Use-cases

- Configuration testing [1, 2], Constrained-random simulation [3]
- Bug synthesis [4], Function synthesis [5]

Uniform samplers

• With guarantees: SPUR [9], KUS [10], UniGen [6, 7, 8]

• Without guarantees: SearchTreeSampler (STS) [11], Quicksampler [12], CMSGen [13]

Sampler checker: Barbarik [14]

Takes SUT, a base uniform sampler (SPUR), tolerance param ϵ , intolerance param η , confidence param δ , and formula φ and returns Accept/Reject. Accept/Reject depending on whether the SUT is ϵ -additive close to a uniform sampler or whether it is η -far from the uniform sampler. Correct answer with probability at least $(1-\delta)$

Barbarik vs CMSGen and Other Uniform-Like Samplers

The paper [14] on Barbarik could clearly distinguish QuickSampler and STS from UniGen3. However, it could not distinguish UniGen3 from CMSGen.

Table: Analysis of different samplers with Barbarik over 50 benchmarks. Parameters $\epsilon : 0.3, \eta : 1.8, \delta : 0.1$. Same benchmark suite as used in [12] (QuickSampler paper)

	QuickSampler	STS	UniGen3	$CMSGen_{100}$
Accept	0	14	50	50
Reject	50	36	0	0

In other words, CMSGen could "fool" Barbarik. This showcases the power of CMSGen, however, it also highlights a weakness in Barbarik. In this paper, we sought to address this issue.

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The Initial Idea

- Let's divide the solution space into two
- Make one part **super-easy** to find solutions. Say, in this part of the solution space, there are no constraints other than $a = \top$
- Make one part **tunably hard** to find solutions. All constraints are conditioned on $a = \bot$
- For hard problem generator, we decided to use the SHA-1 preimage attack by Nossum [15]. Tunable by constraining the input/output bits and the number of rounds to have more/less solutions and to be easier/harder to reverse.

Mini-experiment with non-uniform sampler

CMSGen₁₀₀: Preimage attack with 11 rounds

<pre>soos@tiresias:build\$</pre>	./cnf_genrounds 11easy 11 > out
num hard solutions :	2048
num easy solutions :	2048
num total solutions:	4096
easy vs hard ratio :	0.5000 vs 0.5000
<pre>soos@tiresias:build\$</pre>	./sample.sh 100 1 out grep -E -o "v -?1 " sort uniq -c
53 v -1	
47 v 1	

When the SHA-1 preimage problem is easy, we get approx 50-50.

CMSGen₁₀₀: Preimage attack with 18 rounds

<pre>soos@tiresias:build\$</pre>	./cnf_genrounds 18easy 11 > out2
num hard solutions :	1925
num easy solutions :	2048
num total solutions:	3973
easy vs hard ratio :	0.5155 vs 0.4845
<pre>soos@tiresias:build\$</pre>	./sample.sh 100 1 out2 grep -E -o "v -?1 " sort uniq -c
1 v -1	
99 v 1	

When the preimage problem is hard, we get 99-1.

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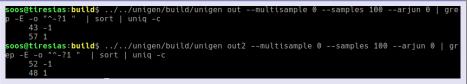
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Mini-experiment with uniform sampler

UniGen3: Preimage attack with 11 and 18 rounds



Using an probabilistically approximate uniform sampler, UniGen3, we get approx 50-50 in both cases.

Barbarik – Main Idea

- Take a satisfying assignment σ_1 from the SUT, and a σ_2 from the base uniform sampler. $T = \{\sigma_1, \sigma_2\}$
- If the distribution D_{φ} from which SUT is sampling is close to uniform distribution, then the conditional distribution $D_{\varphi|T}$ is also close to uniform distribution.
- If the distribution D_{φ} is far from uniform distribution, then the conditional distribution $D_{\varphi|T}$ is also far from uniform distribution.

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Barbarik – The Code

Algorithm 1: Barbarik($\mathcal{G}, \mathcal{U}, \varepsilon, \eta, \delta, \varphi$) 1 $S \leftarrow Supp(\varphi)$ 2 for $j \leftarrow 1$ to $\left\lceil \log(\frac{4}{2\varepsilon+n}) \right\rceil$ do $t_i \leftarrow f(\eta, \epsilon, \delta), N_i \leftarrow g(\eta, \epsilon, \delta)$ 3 for $i \leftarrow 1$ to t_i do 4 while $L_1 = L_2$ do 5 $L_1 \leftarrow \mathcal{G}(\varphi, S, 1); \sigma_1 \leftarrow L_1[0] /* \mathcal{G} \text{ samples } \sigma_1 \in \text{Sol}(\varphi)$ 6 $L_2 \leftarrow \mathcal{U}(\varphi, S, 1); \sigma_2 \leftarrow L_2[0] /* \mathcal{U} \text{ samples } \sigma_2 \in \text{Sol}(\varphi)$ 7 end 8 $\hat{\varphi} \leftarrow Kernel(\varphi, \sigma_1, \sigma_2, N_i)$ 9 $L_3 \leftarrow \mathcal{G}(\hat{\varphi}, S, N_i)$ /* \mathcal{G} samples N_j solutions from Sol $(\hat{\varphi})$ */ 10 $b \leftarrow Bias(\sigma_1, L_3, S)$ 11 if $b < \frac{1}{2}(1-c_i)$ or $b > \frac{1}{2}(1+c_i)$ then 12 return REJECT 13 end 14 end 15 return ACCEPT 16 17 end

*/

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Kernel

- To generate distribution $D_{\varphi|T}$, Barbarik constructs formula $\hat{\varphi}$ from φ using subroutine Kernel.
- Kernel takes $\varphi, \sigma_1, \sigma_2, N$, where N is number of assignments needed, and returns $\hat{\varphi}$. It restricts φ to these T, and extend each using *Chain* Formulas to required no. of solutions.

Algorithm 2: Kernel($\varphi, \sigma_1, \sigma_2, N$)

- 1 lit $\leftarrow (\sigma_1 \setminus \sigma_2)[0]$ /* Choose first literal lit s.t. lit $\in \sigma_1$, and lit $\notin \sigma_2 * /$
- 2 $\varphi' = \varphi \wedge (\sigma_1 \vee \sigma_2)$
- 3 $\hat{\varphi} \leftarrow \varphi' \land (\mathsf{lit} \to \mathsf{ConstructChain}(N, Supp(\psi)))$
- 4 $\hat{\varphi} \leftarrow \hat{\varphi} \land (\neg \mathsf{lit} \rightarrow \mathsf{ConstructChain}(N, Supp(\psi)))$
- 5 return $\hat{\varphi}$.

ScalBarbarik: new kernel

Essentially, we replace Kernel in Barbarik with a new Kernel that generates an asymmetrical problem. We call this Kernel Shakuni. This new Kernel uses chain formulas as per Barbarik for the "easy" side of the problem, and the new, GenHard algorithm for the "hard" side of the problem.

The *GenHard* algorithm

- Takes κ as hardness parameter, and τ as number of solutions
- Uses SHA-1 preimage attack as hard problem. $\mathcal{H}_{\mathsf{SHA-1}} := \{h : \{0,1\}^{512} \mapsto \{0,1\}^{160}\}.$
- Encodes the problem h^{-1} with varying number of rounds, and varying number of input/output bits set.
- To know the exact number of solutions, it uses a fast implementation of SHA-1.

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Shakuni

Algorithm 3: Shakuni $(\varphi, S, \sigma_1, \sigma_2, \tau, \kappa)$

- $\begin{array}{ll} 1 \mbox{ lit} \leftarrow (\sigma_1 \setminus \sigma_2)[0] & \ \ /* \mbox{ Choose first literal lit s.t. } \mbox{ lit} \in \sigma_1 \, , \\ \mbox{ and lit} \notin \sigma_2 \ */ & \end{array}$
- $\mathbf{2} \ \varphi' = \varphi \land (\sigma_1 \lor \sigma_2)$
- $\mathbf{3} \ (\psi, \hat{\tau}) \leftarrow \mathsf{GenHard}(\tau, \kappa)$
- 4 $\hat{\varphi} \leftarrow \varphi' \land (\mathsf{lit} \rightarrow \psi)$
- $\mathbf{5} \ \hat{\varphi} \leftarrow \hat{\varphi} \land (\neg\mathsf{lit} \rightarrow \mathsf{ConstructChain}(\hat{\tau}, Supp(\psi)))$
- 6 $\hat{S} \leftarrow S \cup Supp(\hat{\varphi})$
- 7 return $(\hat{\varphi}, \hat{S})$.

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Analysis of Various Samplers by ScalBarbarik

Table: Analysis of different samplers with ScalBarbarik. Total of 50 benchmarks. Parameters used: $\epsilon=0.2, \eta=1.6, \delta=0.1$

ScalBarbarik	QuickSampler		STS			$CMSGen_{100}$	
(κ)	Accept	Reject	Accept	Reject		Accept	Reject
10	0	50	0	50		50	0
11	0	50	0	50		41	9
12	0	50	0	50		19	31
13	0	50	0	50		0	50

ScalBarbarik	UniGen3				
(κ)	Accept	Reject			
10	50	0			
11	50	0			
12	50	0			
13	50	0			

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Analysis of CMSGen by ScalBarbarik

Table: Analysis of CMSGen_{100}, CMSGen_{300}, CMSGen_{500} by ScalBarbarik. Total of 50 benchmarks. Parameters used: $\epsilon=0.2, \eta=1.6, \delta=0.1$,

ScalBarbarik	$CMSGen_{100}$		CMSGen ₃₀₀			CMSGen ₅₀₀		
(κ)	Accept	Reject	Accept	Reject		Accept	Reject	
11	41	9	47	3		47	3	
15	0	50	37	13		42	8	
18	0	50	0	50		36	14	
22	0	50	0	50		0	50	

ScalBarbarik	UniGen3				
(κ)	Accept	Reject			
11	50	0			
15	50	0			
18	50	0			
22	50	0			

Conclusions & Future Work

- ScalBarbarik is a much improved testing tool based on Barbarik, that can help spur a new generation of scalable uniform-like samplers.
- ScalBarbarik came about as a response to the CMSGen, a uniform-like sampler without guarantees, that Barbarik could not distinguish from a true uniform sampler.
- We envisage this cycle to continue: with better samplers come better testers and vice versa.
- Improved uniform-like samplers can help with the scalability of tools: e.g. the Manthan [5] function synthesis tool significantly benefits from CMSGen.





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Thank you for your time

Any questions?

Priyanka, Sourav, and Kuldeep are on-site to answer questions if you have ideas/questions after the talk!

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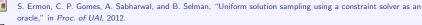
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