

Goose: A Meta-Solver for Deep Neural Network Verification

Reporter: Chi Zhiming

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Contribution

- Goose, a meta-solver, leverages three key meta-solving techniques, namely, adaptive algorithm selection, probabilistic satisfiability inference, and time interval deepening to implement an adaptive sequential portfolio of solvers for NN verification.
- Goose improve 37.7% across benchmarks and solvers from VNN-COMP'21 and 41.4% over competition solvers on a 90 select ACAS Xu instances .

Background

VNN-COMP

- International Verification of Neural Networks Competition
- [website link](#)

Total Score

#	Tool	Score
1	α, β -CROWN	1274.9
2	MN BaB	1017.3
3	Verinet	892.5
4	Nnenum	534.0
5	Cgdtest	406.4
6	Peregrinn	399.0
7	Marabou	380.6
8	Debona	222.9
9	Fastbatllnn	100.0
10	Verapak	98.2
11	Averinn	29.1

GPU-based

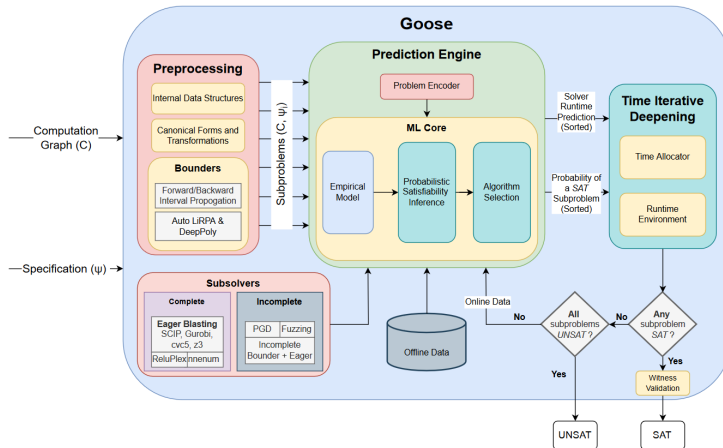
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Framework



Preliminary Study

Problem Encoder:

- Goose implements a problem encoder $\xi(C; \psi_i)$ to compute **feature vectors** - a real-valued vector representation of C, ψ_i , with 221 dimensions (features).
- Network, specification, online information and subproblem features.

Probabilistic Satisfiability Inference

- determine which subproblems to be targeted using decision NN model.

Algorithm selection:

- determine which solvers should be used decision NN model.

Pseudocode for Goose

Algorithm 1 The main execution loop of Goose

Input: A computation graph C and a linear specification ψ over C
Output: SAT/UNSAT

```

1: procedure GOOSE-MAINLOOP
2:    $t = t_{init}$ 
3:    $\mathcal{P} = \mathcal{T}(C, \psi)$   $\triangleright \mathcal{T}$  is the transform from Theorem 1
4:    $\mathcal{F} = [\perp \ \forall C, \psi_i \in \mathcal{P}]$   $\triangleright$  subproblem flag
5:   solved =  $\perp$ 
6:   while not solved do
7:      $\alpha_{\psi_i}$  = allocation of  $t$  for each unsolved  $\psi_i$  from probabilistic satisfiability
       inference.
8:     Sort  $\mathcal{P}$  in descending order by  $\alpha_{\psi_i}$ 

```

```

9:   for  $C, \psi_i$  in  $\mathcal{P}$  do
10:    if  $\mathcal{F}[C, \psi_i]$  then
11:      continue
12:    end if
13:     $\beta_{s, \psi_i}$  = allocation of  $\alpha_{\psi_i}$  for each  $s \in \mathcal{S}$  from algorithm selection.
14:    Sort  $\mathcal{S}$  in descending order by  $\beta_{s, \psi_i}$ 
15:    for  $s \in \mathcal{S}$  do
16:       $\rho = \text{run}(s, C, \psi_i, \beta_{s, \psi_i})$ 
17:      if  $\rho$  is SAT then  $\triangleright$  If any subproblem  $\psi_i$  is SAT
18:        return SAT
19:      else if  $\rho$  is UNSAT then
20:         $\mathcal{F}[C, \psi_i] = \top$ 
21:      end if
22:    end for
23:  end for
24:   $t +=$  an exponential increment
25:  solved =  $\bigwedge_{v \in \mathcal{F}} v$ 
26: end while
27: return UNSAT
28: end procedure

```

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benchmark of VNN-COMP'21

The PAR-2 score of a solver on a benchmark is the wallclock runtime if successful, otherwise twice the wallclock runtime (lower is better).

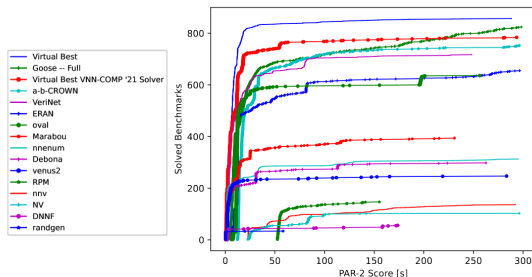


Fig. 2. Main experimental CDF plot over VNN-COMP '21 benchmarks (Section 4.2). A CDF is a visualization of a solver's performance on a benchmark suite the vertical axis represents the number of benchmarks solved (higher is better) and the horizontal axis is the benchmark wise PAR-2 (lower is better). See ablation study in

benchmark of Acasxu

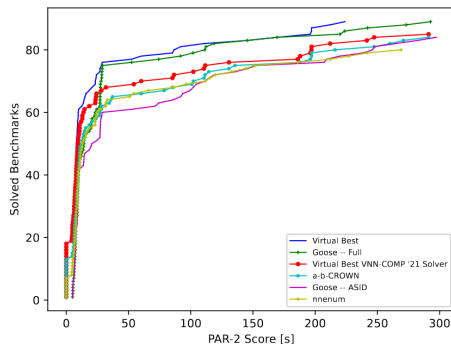


Fig. 3. CDF plot over select ACAS Xu benchmarks (Section 4.3). A CDF plot is a visualization of a solver's performance on a benchmark suite the horizontal axis represents the number of benchmarks solved (higher is better) and the vertical axis is the benchmark wise PAR-2 (lower is better).

Thank you