Generating and Checking DNN Verification Proofs

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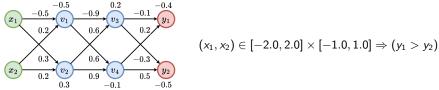


DNN Problems



DNN Verification

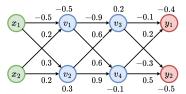
DNN Verification Example



DNN verifiers: return unsat for valid property and sat otherwise

DNN Verification

DNN Verification Example



$$(x_1, x_2) \in [-2.0, 2.0] \times [-1.0, 1.0] \Rightarrow (y_1 > y_2)$$

DNN verifiers: return unsat for valid property and sat otherwise

But. Could We Trust Verifiers?

- Currently, sat comes with counterexample; but unsat has no evidence!
- Bugs are inevitable (verification tools 20K+ lines of code)
- Multiple reports of soundness bugs in verifiers and literature
 - Claiming something is safe (unsat) when it is not

Needs Proof of "Proved" Results!

Challenges In Proof Generation and Checking

Challenge 1: Compatibility

Different verifiers use different algorithms and optimizations Need a proof generation approach compatible with many verifiers

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Proofs needs to be represented and stored efficiently Need a standard, compact, and human-readable format

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Challenge 2: Human-Readability

Proofs needs to be represented and stored efficiently Need a standard, compact, and human-readable format

Challenge 3: Efficiency

Proofs can be very large!!

Need an efficient proof checking algorithm

Challenge 1: Compatibility

Initialization

- Input: a DNN N and a property ϕ
- An ActPatterns $\leftarrow \{\emptyset\}$ to record branches (patterns)

Branch-and-Bound Loop

- Select (pop) a branch σ from ActPatterns.
- **Deduce (bound)** checks feasibility of σ wrt (N, ϕ)
 - If infeasible:
 - Prune this σ branch (verified)
 - If feasible.
 - Decide (branch) selects a neuron v
 - Splitting $\sigma \wedge (v = \text{on})$ and $\sigma \wedge (v = \text{off})$
 - Add new branches to ActPatterns

Termination

- If a counterexample is found during search, return (sat, cex)
- If no counterexample exists, return (unsat,

Challenge 1: Compatibility

Initialization

- Input: a DNN N and a property ϕ
- An ActPatterns $\leftarrow \{\emptyset\}$ to record branches (patterns)
- ullet A proof tree prooftree $\leftarrow \{\ \}$ to record conflicts

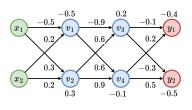
Branch-and-Bound Loop

- Select (pop) a branch σ from ActPatterns.
- **Deduce (bound)** checks feasibility of σ wrt (N, ϕ)
 - If infeasible:
 - Prune this σ branch (verified)
 - Record σ to prooftree \rightarrow prooftree $\cup \{\sigma\}$
 - If feasible.
 - Decide (branch) selects a neuron v
 - Splitting $\sigma \wedge (v = \text{on})$ and $\sigma \wedge (v = \text{off})$
 - Add new branches to ActPatterns

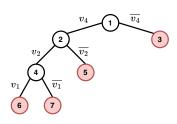
Termination

- If a counterexample is found during search, return (sat, cex)
- If no counterexample exists, return (unsat, prooftree)

Example: BaB + Proof Generation



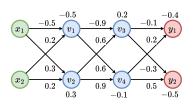
A simple DNN



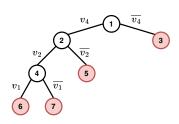
 $A \ proof \ tree$

Verifying
$$(x_1, x_2) \in [-2.0, 2.0] \times [-1.0, 1.0] \Rightarrow (y_1 > y_2)$$

Example: BaB + Proof Generation



A simple DNN



A proof tree

Verifying
$$(x_1, x_2) \in [-2.0, 2.0] \times [-1.0, 1.0] \Rightarrow (y_1 > y_2)$$

Proof Tree

- Binary tree structure
 - each neuron decision branches into two children (representing on and off cases)
- Captures unsatisfiability reasoning of BaB
 - each leaf represents an unsatisfiable branch
 - $l_3: \overline{v_4}$, $l_5: v_4 \wedge \overline{v_2}$, $l_6: v_4 \wedge v_2 \wedge v_1$, $l_7: v_4 \wedge v_2 \wedge \overline{v_1}$

Challenge 2: Human-Readability

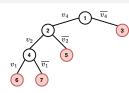
APTP Proof Language

```
⟨proof⟩ ::= ⟨declarations⟩ ⟨assertions⟩
\langle declarations \rangle ::= \langle declaration \rangle \mid \langle declaration \rangle \langle declarations \rangle
 ⟨declaration⟩ ::= (declare-const ⟨input-vars⟩ Real)
                  | (declare-const \( output-vars \) Real)
                  | (declare-pwl (hidden-vars) (activation))
 (input-vars) ::= (input-var) | (input-var) (input-vars)
(output-vars) ::= (output-var) | (output-var) (output-vars)
⟨hidden-vars⟩ ::= ⟨hidden-var⟩ | ⟨hidden-var⟩ ⟨hidden-vars⟩
  (activation) ::= ReLU | Leaky ReLU | . . .
  ⟨assertions⟩ ::= ⟨assertion⟩ | ⟨assertion⟩ ⟨assertions⟩
   ⟨assertion⟩ ::= (assert ⟨formula⟩)
    ⟨formula⟩ ::= (⟨operator⟩ ⟨term⟩ ⟨term⟩)
                  | (and \( formula \) +) | (or \( formula \) +)
       ⟨term⟩ ::= ⟨input-var⟩ | ⟨output-var⟩
                  | \langle hidden-var \rangle | \langle constant \rangle
   ⟨operator⟩ ::= < | < | > | >
  ⟨input-var⟩ ::= X_⟨constant⟩
 ⟨output-var⟩ ::= Y_⟨constant⟩
 ⟨hidden-var⟩ ::= N_⟨constant⟩
   ⟨constant⟩ ::= Int | Real
```

Challenge 2: Human-Readability

APTP Proof Language

```
⟨proof⟩ ::= ⟨declarations⟩ ⟨assertions⟩
⟨declarations⟩ ::= ⟨declaration⟩ | ⟨declaration⟩ ⟨declarations⟩
 ⟨declaration⟩ ::= (declare-const ⟨input-vars⟩ Real)
                 | (declare-const (output-vars) Real)
                 | (declare-pwl (hidden-vars) (activation))
 (input-vars) ::= (input-var) | (input-var) (input-vars)
(output-vars) ::= (output-var) | (output-var) (output-vars)
⟨hidden-vars⟩ ::= ⟨hidden-var⟩ | ⟨hidden-var⟩ ⟨hidden-vars⟩
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  ⟨assertions⟩ ::= ⟨assertion⟩ | ⟨assertion⟩ ⟨assertions⟩
   ⟨assertion⟩ ::= (assert ⟨formula⟩)
    ⟨formula⟩ ::= (⟨operator⟩ ⟨term⟩ ⟨term⟩)
                 | (and \( formula \) +) | (or \( formula \) +)
      ⟨term⟩ ::= ⟨input-var⟩ | ⟨output-var⟩
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 ⟨hidden-var⟩ ::= N_⟨constant⟩
   ⟨constant⟩ ::= Int | Real
```



Example

```
· Declare variables
   (declare-const X 0 Real)
   (declare-const X 1 Real)
  (declare-const Y O Real)
5 (declare-const Y_1 Real)
  (declare-pwl N 1 ReLU)
7 (declare-pwl N 2 ReLU)
8 (declare-pwl N_3 ReLU)
  (declare-pwl N_4 ReLU)
   : Input constraints
   (assert (>= X 0 -2.0))
   (assert (<= X 0 2.0))
  (assert (>= X 1 -1.0))
   (assert (<= X_1 1.0))
   : Output constraints
   (assert (<= Y 0 Y 1))
   : Hidden constraints
   (assert (or
19
       (and (< N_4 0))
                                               ; 1_3
20
       (and (< N_2 0) (>= N_4 0))
       (and (>= N_2 0) (>= N_1 0) (>= N_4 0)); 1_6
22
       (and (>= N_2 0) (< N_1 0) (>= N_4 0)); 1_7
23 ))
```

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Challenge 3: Efficiency

APTP Checker Algorithm

Challenge 3: Efficiency

APTP Checker Algorithm

```
input : DNN \mathcal{N}, property \phi_{in} \Rightarrow \phi_{out}, proof output : certified if proof is valid, otherwise uncertified

1 if \neg RepOK (proof) then RaiseError(Invalid proof tree);

2 model \leftarrow CreateMILP(\mathcal{N}, \phi_{in}, \phi_{out}) // initialize MILP model with inputs

3 while proof do

4 | node \leftarrow Select(proof) // get node to check

5 | model \leftarrow AddConstrs(model, node) // add corresponding constraints

6 | if CheckFeasibility(model) then

7 | return uncertified // cannot certify
```

Optimizations

- **1** Stabilization: fix stable ReLUs to reduce MILP constraints
- 2 Pruning: check parent nodes and if unsat then skip children
- Parallelization: check multiple leaves in parallel

Evaluation

Name		Instances			
	Num.	Layers	Neurons	Param.	Num.
CNN	8	1-2C;1F	320-3920	41K-180K	200
FNN	8	2-6F	64-3072	27K-1.7M	200

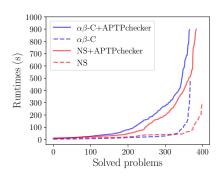
Benchmarks

8 CNNs, 8 FNNs; 25 properties; total 400 problem instances

Verifiers

Add APTP proof generation to $\alpha\beta$ -CROWN, NeuralSAT, and Marabou

APTP Checker Performance



- Performance of verifiers (dashed) differ across configurations
 - They are able to verify between 337 and 400 problems
- APTP checker (solid) certified 93.7% and 99.4% of generated proofs
- This demonstrates that:
 - APTP proof format can encode proofs generated by different DNN verifiers
 - APTP checker can check them efficiently

Trade-offs Between Verifiers

Verifier	Num. Mean	Sub-Proofs Median	MILP Mean	Complexity Median
NeuralSAT	95	36	601	545
$\alpha\beta$ -CROWN	230	180	414	179

- NeuralSAT: smaller proof trees, but with more complex MILP problems.
- $\alpha\beta$ -CROWN: significantly larger proof trees, but with simpler MILP problems
- Strategies(?):
 - Generate larger proof trees with simpler MILPs for better parallelization
 - Adopting fast verification during development
 - Switching to proof-friendly strategies

APTP Checker vs. Marabou Checker

Checker	Proof checking time (seconds)			
Checker	Mean	Median	Max	
Marabou checker	4	204	785	
APTP checker	3	9	38	

- Extract APTP proofs from 54 problems that Marabou verified
- For simple problems, both checkers handle quickly (similar mean times)
- ullet For challenging problems, APTP checker is over 20imes speedup

Key Takeaways

- Verifiers producing unsound results: UNACCEPTABLE!
- Proof generation technique applicable to a wide-range of verifiers
- 3 Standard, compact, and human-readable proof format
- Efficient, lightweight, and verifier-independent proof checker

Try APTP Checker:

https://github.com/dynaroars/aptpchecker

Thank You!