Neural Network Repair using Formal Methods

Mayank Deora Ph.D. student Indian Statistical Institute Kolkata

This presentation is based on the following research papers:

- Guy Katz et. al. Minimal Modifications of Deep Neural Networks using Verification (presented at the 23rd Int. Conf. on Logic for Programming, Artificial Intelligence and Reasoning LPAR 2020)
- Guy Katz et. al. Minimal Multi-Layer Modifications of Deep Neural Networks (https://arxiv.org/abs/2110.09929)

Minimal Repair of Deep Neural Networks (DNN)

Input

- DNN N (A faulty one)
- A set of specified input-output pairs (x_i, y_i) on which N fails

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- Modification to N is as small as possible
- For each input x_i , we get the desired output y_i

Problem statement

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- Modify DNN N such that:
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Constraints

- Cannot change the topology of N
- Cannot change activation function
- Can only alter weights

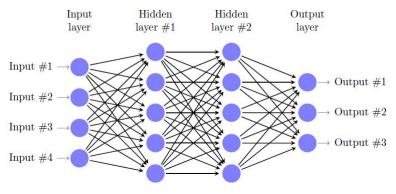
- Semantic Repair (modifying the classification rules)
- Retraining with the counter-examples
- Modifying topology / activation functions

Novelty of this work: Model edits restricted to weights only

Example

- In Machine Learning as as Service(MLaaS), clients often modify and fine-tune the DNN according to their needs.
 - Instead of modifying and retraining, minimal modification can be done.
- For low resource devices, retraining may be difficult
- Watermark analysis: For a DNN, preserve a specific set of tests for which the output classification should not change, even after retraining

Deep Neural Network: Introduction

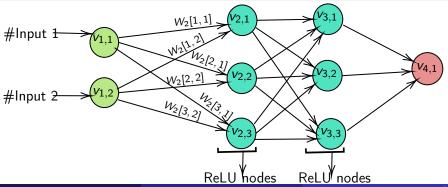


Deep Neural Network with 4 layers

Deep Neural Networks

Notations

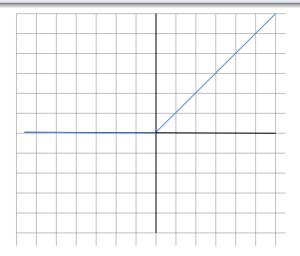
- $v_{i,j}$ represents the j^{th} neuron of the i^{th} layer.
- s_i represents the number of neurons in the i^{th} layer.
- Each layer $2 \le i \le n$ has a weight matrix W_i of size $s_i \times s_{i-1}$.
- $W_i[j, k]$ represents the weight on the edge from $v_{i-1,k}$ to $v_{i,j}$.



Deep Neural Networks

Notations

 $\operatorname{ReLU}(x) = \max\{0, x\}$

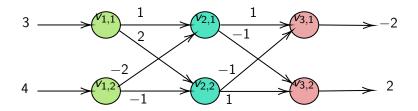


Deep Neural Networks

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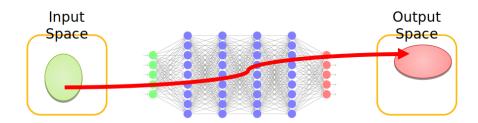
 $\operatorname{ReLU}(x) = \max\{0, x\}$

 $v_{2,1} = ReLU(3 \times 1 + 4 \times (-2)) = ReLU(-5) = 0$



 $v_{2,2} = ReLU(3 \times 2 + 4 \times (-1)) = ReLU(2) = 2$

Verification of Deep Neural Networks



For a Neural Network $\overline{N}: \overline{x} \to \overline{y}$, an input property $P(\overline{x})$ and an output property $Q(\overline{y})$, does there exist an input $\overline{x_0}$, with output $\overline{y_0} = N(\overline{x_0})$ such that $\overline{x_0}$ satisfies P and $\overline{y_0}$ satisfies Q?

Both \overline{x} and \overline{y} are vectors over reals.

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- $Q(\overline{y})$ characterizes the undesired behavior for those inputs, we are checking.
- Negative answer (UNSAT) means property Q holds.
- Positive answer (SAT) includes a counterexample, demonstrating an input x satisfying P for which Q holds.

Let N denote a DNN, let X denote a set of fixed input points $X = \{x_1, ..., x_n\}$

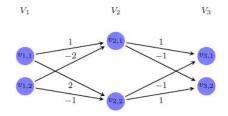
Let Q denote a predicate over the classifications $N(x_1), \ldots, N(x_n)$ of the points X.

Definition

The DNN repair problem is to find a new DNN N', such that $Q(N'(x_1), \ldots, N'(x_n))$ holds, such that the distance between N and N' is at most some $\delta > 0$.

DNN Repair Problem

• In following DNN N, for input $V_1 = \langle 3, 4 \rangle$, output will be $V_3 = \langle -2, 2 \rangle$, i.e. $v_{3,2} > v_{3,1}$



• We need $Q(N'(\langle 3,4\rangle)) = v_{3,1} \ge v_{3,2}$

Note:

Recall that hidden layer nodes are ReLU nodes

Let N^1 and N^2 denote two DNNs with identical topology i.e. the same number of layers $(n^1 = n^2)$, and the same number of neurons in every pair of matching layers $(s_i^1 = s_i^2 \text{ for all } 1 \le i \le n^1)$.

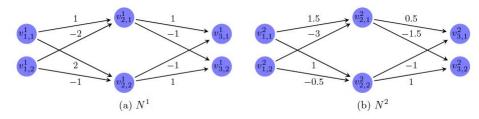
Definition

We define an *L*-distance between N^1 and N^2 denoted $||N^1 - N^2||_L$ as:

$$||N^{1} - N^{2}||_{L} = \left(\sum_{i=2}^{n^{1}} \sum_{j=1}^{s_{i}^{1}} \sum_{k=1}^{s_{i-1}^{1}} |W_{i}^{1}[j,k] - W_{i}^{2}[j,k]|^{L}\right)^{1/L}$$

for $L \neq \infty$

Distance between 2 DNNs



Distance between N^1 and N^2

$$||N^{1} - N^{2}||_{L} = \left(\sum_{i=2}^{n^{1}} \sum_{j=1}^{s_{i}^{1}} \sum_{k=1}^{s_{i-1}^{1}} |W_{i}^{1}[j,k] - W_{i}^{2}[j,k]|^{L}\right)^{1/L}$$
$$||N^{1} - N^{2}||_{1} = (|-0.5| + |1| + |1| + |-0.5| + |0.5| + |0.5| + |0| + |0|)$$

 $||N^1 - N^2||_{\infty} = max\{|-0.5|, |1|, |1|, |-0.5|, |0.5|, |0.5|, |0|, |0|\}$

Input

- DNN N (A faulty one)
- Input points $X = \{x_1, \dots, x_n\}$, and desired predicates $Q(N'(x_1), \dots, N'(x_n))$

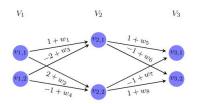
Goal

- Modify DNN N such that:
 - Distance between N and modified N' $(||N N'||_L)$ is the least.
 - As mentioned before, can only modify weights.

Minimal Repair as an Optimization Problem

 $Min ||N - N'||_L$ subject to : Q

How to generate the repaired network?





- To get N', we can only modify the weights.
- In this case, we have a single testcase to fix: input <3,4> on which the current N produces $v_{3,2} > v_{3,1}$ while Q specifies $v_{3,1} \ge v_{3,2}$.

An Optimization Problem

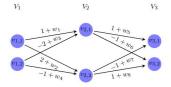
Minimal Repair as an Optimization Problem

 $Min ||N - N'||_L$

sub to :
$$v_{3,1} \ge v_{3,2}$$

 $\begin{aligned} v_{3,1} &= (1+w_5) \text{ReLU}(3(1+w_1) + 4(-2+w_3)) + (-1+w_7) \text{ReLU}(3(2+w_2) + 4(-1+w_4)) \\ v_{3,2} &= (-1+w_6) \text{ReLU}(3(1+w_1) + 4(-2+w_3)) + (1+w_8) \text{ReLU}(3(2+w_2) + 4(-1+w_4)) \end{aligned}$

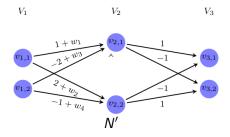
Due to ReLU functions and multiplication of w variables, it is non-linear and high-dimensional.



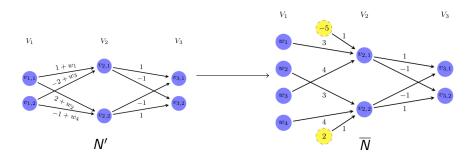
- Due to ReLU functions and multiplication of *w* variables, it is a non-linear optimization problem.
- Larger networks make the constraints more complex.

Problem!!

To overcome the problem, repair is restricted to weight modifications in only a single layer.



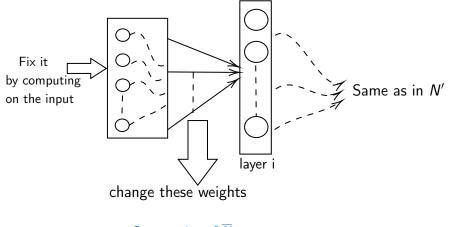
An interesting transformation



 $X = \{ \langle 3, 4 \rangle \}$ $v_{3,1} = \text{ReLU}(3w_1 + 4w_3 - 5) - \text{ReLU}(3w_2 + 4w_4 + 2)$ $v_{3,2} = -\text{ReLU}(3w_1 + 4w_3 - 5) + \text{ReLU}(3w_2 + 4w_4 + 2)$

Note: The two networks are equivalent.

Modification to single layer



Construction of \overline{N}

For some fixed point $x \in X$, for modified DNN N'

$$egin{aligned} & V_k = V_{k'} \ orall k (1 \leq k \leq i-1) \ & V_i' = \operatorname{ReLU}(W_i'V_{i-1}') = \operatorname{ReLU}((W_i+W_\epsilon)V_{i-1}') \end{aligned}$$

\Leftrightarrow

DNN \overline{N} (having input W_{ϵ} and next(second) layer computes the ReLU function in equation 1, which is fed into layers i + 1, ..., n of N').

DNN Repair reduced to DNN verification

Summary till now

- We started with the faulty network N and an input output pair (3,4)
- We chose a layer in N and added all possible edge weight modifications in that layer to get N'
- From N', we got a transformed network \overline{N}

From Repair on N to verification on \overline{N}

For $x = \langle 3, 4 \rangle$, and $\delta > 0$, consider the DNN Verification query with the following predicates on \overline{N} :

$$P = \bigwedge_{i=1}^{4} -\delta \le w_i \le \delta \qquad Q = v_{3,1} \ge v_{3,2}$$

 $x = \langle 3, 4 \rangle$, $\delta > 0$, DNN Verification query on \overline{N} :

$$P = \bigwedge_{i=1}^{4} -\delta \le w_i \le \delta \qquad Q = v_{3,1} \ge v_{3,2}$$

The above DNN Verification is SAT \Leftrightarrow DNN Modification to N' is SAT (In L_{∞} norm)

Modification to N' is SAT implies that Repair with δ is possible.

DNN Repair reduced to DNN verification

Proof.

 (\Rightarrow) Given that DNN verification problem is SAT.

$$||N - N'||_{\infty} = max\{|w_1|, |w_2|, |w_3|, |w_4|\}$$

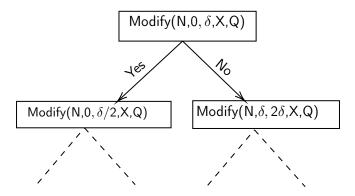
Since, $\forall \ 1 \leq i \leq 4, |w_i| \leq \delta$,

 $||\mathbf{N} - \mathbf{N}'||_{\infty} \le \delta$

(\Leftarrow) If DNN modification problem is SAT, then

$$||N - N'||_{\infty} = max\{|w_1|, |w_2|, |w_3|, |w_4|\} \le \delta$$
$$\implies \bigwedge_{i=1}^{4} -\delta \le w_i \le \delta$$

Consider the decision variant of the DNN Repair problem: given N, Q, Xand δ , does there exist any N' such that $||N' - N||_L < \delta$. We can solve the minimal repair problem using binary search on δ .



Reduction

Using Binary search on δ : DNN minimal modification problem \Rightarrow DNN modification problem \Rightarrow DNN verification problem

Modification for multiple points

For multiple points in X:

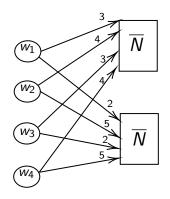
- Duplicate the construction of \overline{N} for each $x \in X$.
- Consider it as a big DNN.
- Pass it to the underlying verification engine.

DNN Minimal Repair reduced to DNN Verification

For multiple points in X:

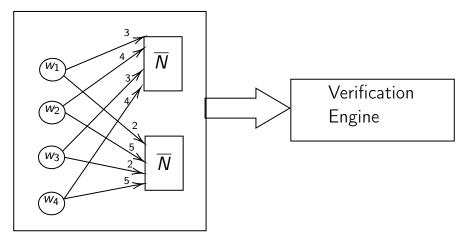
- Duplicate the construction of \overline{N} for each $x \in X$.
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Example: $X = \{\langle 3, 4 \rangle \langle 2, 5 \rangle\}$



DNN Minimal Repair reduced to DNN Verification

• Modification for multiple points example:



DNN Verification for modifying the output layer

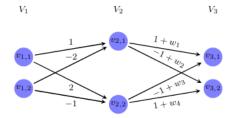
- DNN verification with RELU is NP-complete [Reference: Reluplex paper by Guy Katz et. al].
- Existence of multiple points in the set X makes the problem even more difficult.

An interesting observation that helps

Changes limited to only the weights towards output layer will render the problem easier to solve.

• No ReLU nodes at the output layer.

DNN Verification for modifying the output layer



Using the L_{∞} norm, and by changing only the output layer, the minimal modification problem can be encoded as a linear program.

DNN Verification for modifying the output layer

 $Min: \delta$ Sub to $\delta > 0$ $-\delta < w_1 < \delta$ $-\delta < w_2 < \delta$ $-\delta < W_3 < \delta$ $-\delta < W_4 < \delta$ $v_{3,1} = 0(1 + w_1) + 2(-1 + w_3)$ $v_{3,2} = 0(-1 + w_2) + 2(1 + w_4)$ $v_{3,1} \geq v_{3,2}$

But using the L_1 norm, Linear Program is not possible to due to absolute values.

Watermark Resilience

For a DNN N, a watermark x is an input point, with a specific label I.

A set of watermarks $X = \{x_1, \dots, x_n\}$ is called δ - resilient if for every DNN N' such that $||N - N'|| \le \delta$, it holds that $N(x_i) = N'(x_i)$ for all $1 \le i \le n$.

Watermark Resilience

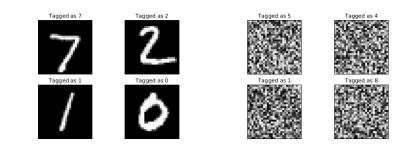
A set of watermarks $X = \{x_1, ..., x_n\}$ is called δ - resilient if for every DNN N' such that $||N - N'|| \le \delta$,

$$N(x_i) = N'(x_i) \quad \forall 1 \le i \le n$$

Solving DNN minimal modification problem serves two purposes:

- Measuring the resilience of the Watermark set X.
- Comparing different watermarking schemes (for generating the set X) for a DNN on the basis of resilience.

Evaluation: Watermark Resilience



(a) Standard MNIST inputs.

(b) Watermark inputs.

Implemented as 3M-DNN tool.

3M-DNN is comprised of two logical levels:

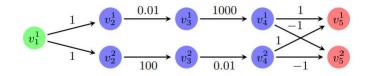
- Search level: Heuristic search through possible changes to the values computed by the separation layers.
- Single-layer modification level: modifying the sub-networks

Goal is same as that in the minimal modification problem.

- Split the original DNN into multiple subnetworks.
- On input to first subnetwork, outputs of in between subnetworks are searched (using search heuristics).
- Apply single layer modification to the subnetworks
- Best cost and corresponding best change is found

Note:

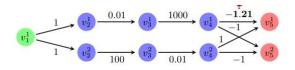
It is an Anytime algorithm (more time gives better performance).



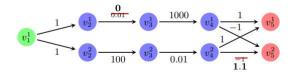
• On input 1, $v_5^1 > v_5^2$ • we want $v_5^2 \ge v_5^1$

Example

• we want $v_5^2 \ge v_5^1$



Vs



Thank You