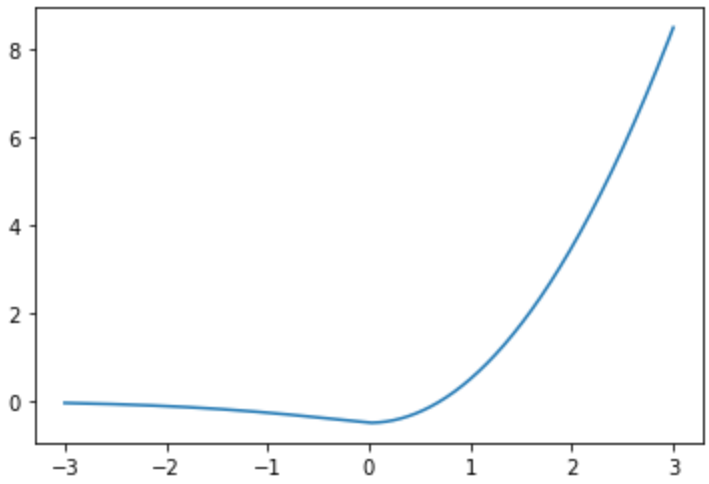
RIAI 2021 Course Project

The goal of the project is to design a precise and scalable automated verifier for proving the robustness of fully connected neural networks with Sigmoid-Parabola unit (SPU) activation against adversarial attacks. We will consider adversarial attacks based on the L_∞-norm perturbations. A network is vulnerable to this type of attack if there exists a misclassified image inside an L_∞-norm based ϵ-ball around the original image.

Sigmoid-Parabola unit

Instead of using a more standard ReLU activation function, in this project we are going to focus on the Sigmoid-Parabola unit activation function, denoted as SPU. We define SPU(x) piecewise: for $x > 0$ we set $SPU(x) = x^2 - 0.5$, and for $x \leq 0$ we set $SPU(x) = sigmoid(-x) - 1$. Here is the graph of this activation function between -3 and 3.



Your task is to design a DeepPoly transformer for SPU. At a high level, given some interval [l, u] your transformer should compute linear lower bound $w_L x + b_L$ and linear upper bound $w_U x + b_U$ so that for all x in [l, u], it holds that $w_L x + b_L \leq SPU(x) \leq w_U x + b_U$. The transformer should be as precise as possible - the goal is to verify as many images as possible.

Project Task

The input to your verifier is a neural network and a test case. The output is the result of your verification procedure (verified/not verified). Below we give more details.

Networks: We will run your verifier on 10 fully connected networks with SPU activations. The networks are trained using different training methods (standard training, PGD, DiffAI). The

architectures and weights of these networks will be provided together with the code release. The architectures are encoded as PyTorch classes in networks.py. All trained networks are provided in the folder mnist_nets.

Example Test Cases: The example test cases consist of 20 files from the MNIST test set formatted to be used by the verifier. Each file contains 785 rows. The first row of the file denotes the label of the image and the remaining rows describe the image pixel intensity in the range [0,1]. All example test cases are stored at folder mnist_specs. The epsilon value of a test case can be deduced from its name, e.g., the file img0_0.001.txt defines the 0.001-ball around image img0. We provide those example test cases for you to develop your verifier and they are **not the same** as the ones we will use for the final grading. Note that images have pixel intensities between 0 and 1, e.g. if perturbation is 0.2 and pixel has value 0.9 then you only have to verify range [0.7, 1.0] for intensities of this pixel, instead of [0.7, 1.1]. File gt.txt contains ground truth for each example (output of the master solution).

Verifier: The directory verifier contains the skeleton code of the verifier (file verifier.py). The verifier addresses the following problem:

Inputs:
- A fully connected neural network
- A test case

Output:
- verified, if the verifier *successfully* proves that network is robust for the test case
- not verified, if the verifier *fails* to prove that network is robust for the test case

Your verifier will be executed using the following command, where <network file> is replaced by a path to the network file and <test case file> is replaced by a file containing the test case:

```
$ python3 verifier.py --net <network file> --spec <test case file>
```

Your task is to implement a sound and precise verifier by modifying the "analyze" function. That is, the verifier should verify the robustness. To this end, you must build upon the DeepPoly relaxation [1] as explained before. Your verifier must be **sound**: it must never output verified when the network is not robust to a test case. It should be **precise:** it should try to verify as many test cases as possible while keeping soundness and scalability (we will use a time limit of 1 minute per test case).

Testing Conditions and Grading

Your verifier will be tested on the following conditions:
- Inputs to the networks are images from the MNIST dataset.
- ϵ values range between 0.001 and 0.3.

- Configuration of the machine used for testing: Intel Xeon E5-2690 v4 CPUs and 512GB RAM. We will use 14 threads and memory limit 64GB to verify each test case.
- Your verifier will be executed using Python 3.7

The verifier will be graded based on the precision and soundness of your verifier:

- You start with 0 points.
- **You receive 1 point** for any verification task for which your verifier correctly outputs `verified` within the time limit.
- **You will be deducted 2 points** if your verifier outputs `verified` when the network is not robust for the provided test case.
- If your verifier outputs `not verified` you receive 0 points. This means that the maximum number of points that can be achieved by any solution may be less than 100.
- If there is a timeout or memory limit exceeded on a verification task, then the result will be considered as `not verified`.

We do not require your verifier to be floating-point sound and we guarantee that full points can be obtained using torch.float32. If you have questions about the grading, please send an email to mislav.balunovic@inf.ethz.ch.

Requirements

You should obey the following rules otherwise you may get **0 points** for the project:

1. The implementation must be in Python 3.7.
2. You must use the DeepPoly relaxation. No other relaxations are allowed.
3. You are not allowed to check for counter-examples using any kind of adversarial attack.
4. The only allowed libraries are PyTorch 1.10.0, Torchvision 0.11.1, Numpy 1.19.5 and Python Standard Library. Other libraries are not allowed and will not be installed on the evaluation machine.

Deadlines

Event	Deadline
Project announcement	November 3, 2021
Skeleton code release	11:59 PM CET, November 3, 2021
Preliminary submission (optional)	5:59 PM CET, December 1, 2021
Preliminary feedback	5:59 PM CET, December 3, 2021
Final submission	**5:59 PM CET, December 20, 2021**

Groups can submit their project by the preliminary submission deadline to receive feedback. We will run your verifier on 25 out of 100 test cases which will be used for the final grading and report to you, for each test, the ground truth, output and the runtime of your verifier. The feedback will be sent by 5:59 PM CET, December 3, 2021. Your preliminary submission results do not affect your final project score.

Submission

Each group is going to receive an invitation to the GitLab repository of name **ddd-riai-project-2021** where **ddd** here is the group number that will be assigned to you. This repository will contain template code, networks and test cases (content is the same as the zip file released on the course website on November 3).

You should commit your solutions to the assigned repository. After the final submission deadline, we will treat the assigned repository as your submission and evaluate your solution in the repository on the final test cases. Note that we are **not going to accept** any submission by email. Below are detailed instructions for final submission. You should follow the rules in the instructions, otherwise you may be **deducted points**:

1. Before the final submission deadline, you should prepare your code in the **master** branch of the assigned repository. The code should:
    a. only print `verified` or `not verified`. If additional messages are printed, we will take the last line as your output.
    b. follow the **Requirements** section of this document. Especially, you should only use the allowed libraries. In the final evaluation, importing libraries not allowed will crash the verifier as they are not installed in the evaluation environment, resulting in **0 points**.
2. At the deadline time, we will pull your solution and put it into the **final_submission** branch. You **should not commit** to the final_submission branch. After the final evaluation, we will put the evaluation result into the **final_submission** branch.

References

[1] Singh, Gagandeep, Timon Gehr, Markus Püschel, and Martin Vechev. "An abstract domain for certifying neural networks." *Proceedings of the ACM on Programming Languages* 3, no. POPL (2019)
https://www.sri.inf.ethz.ch/publications/singh2019domain