On Polynomial Approximations for Privacy-Preserving and Verifiable ReLU Networks

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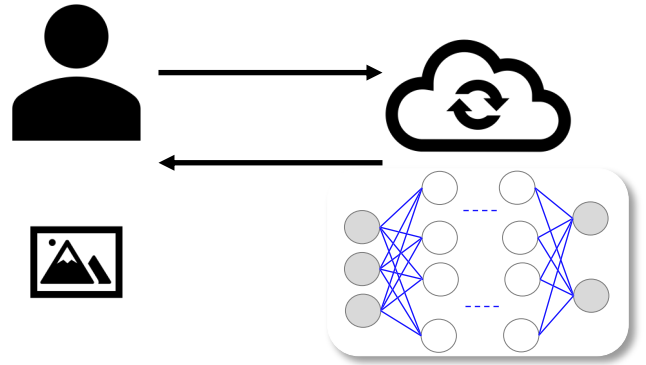
Introduction

- Outsourcing inference tasks raises several privacy and integrity concerns.
  - The users must verify the correctness of the computations.
  - The users may want to keep their data private.
  - The cloud also may want to keep its model private.



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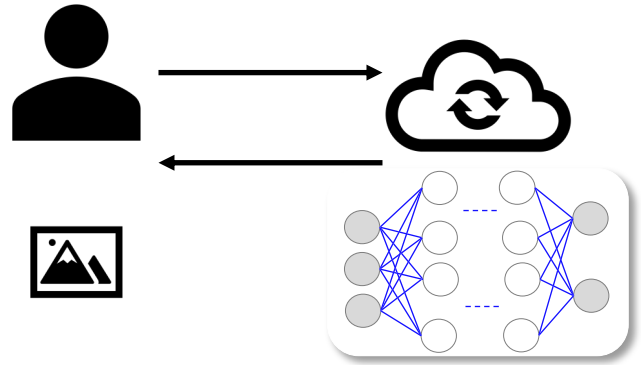

- While there are many efficient privacy-preserving and verifiable techniques for polynomial-based computations [1-4], neural networks involve non-polynomial computations.

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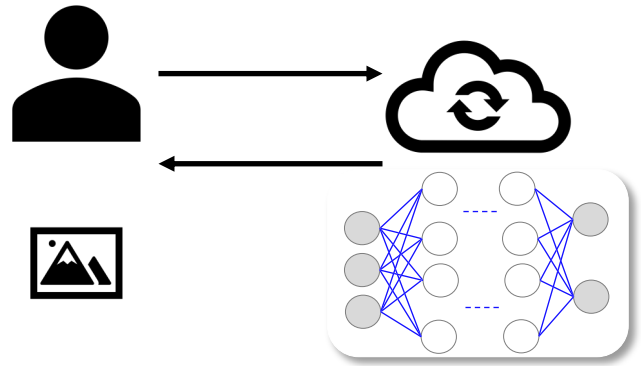

- While there are many efficient privacy-preserving and verifiable techniques for polynomial-based computations [1-4], neural networks involve non-polynomial computations.

- Hence, several frameworks as CryptoNets [5] and SafetyNets [6] replace or approximate the non-polynomial functions with polynomial functions.

Previous Work

- Much previous works as [5, 6] replace the ReLU function

  $$\sigma_r(x) = \max(x, 0)$$

  with the square function

  $$\sigma_{square}(x) = x^2.$$

- Max-pooling layers also are replaced with sum-pooling layers.
- This was shown empirically to work well for networks with small number of activation layers (3 or 4 layers).

This Work

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- We instead propose

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- This is motivated by the Minimax polynomial approximation

$$p_2(x) = \frac{1}{2}x^2 + \frac{1}{2}x + \frac{1}{16}.$$

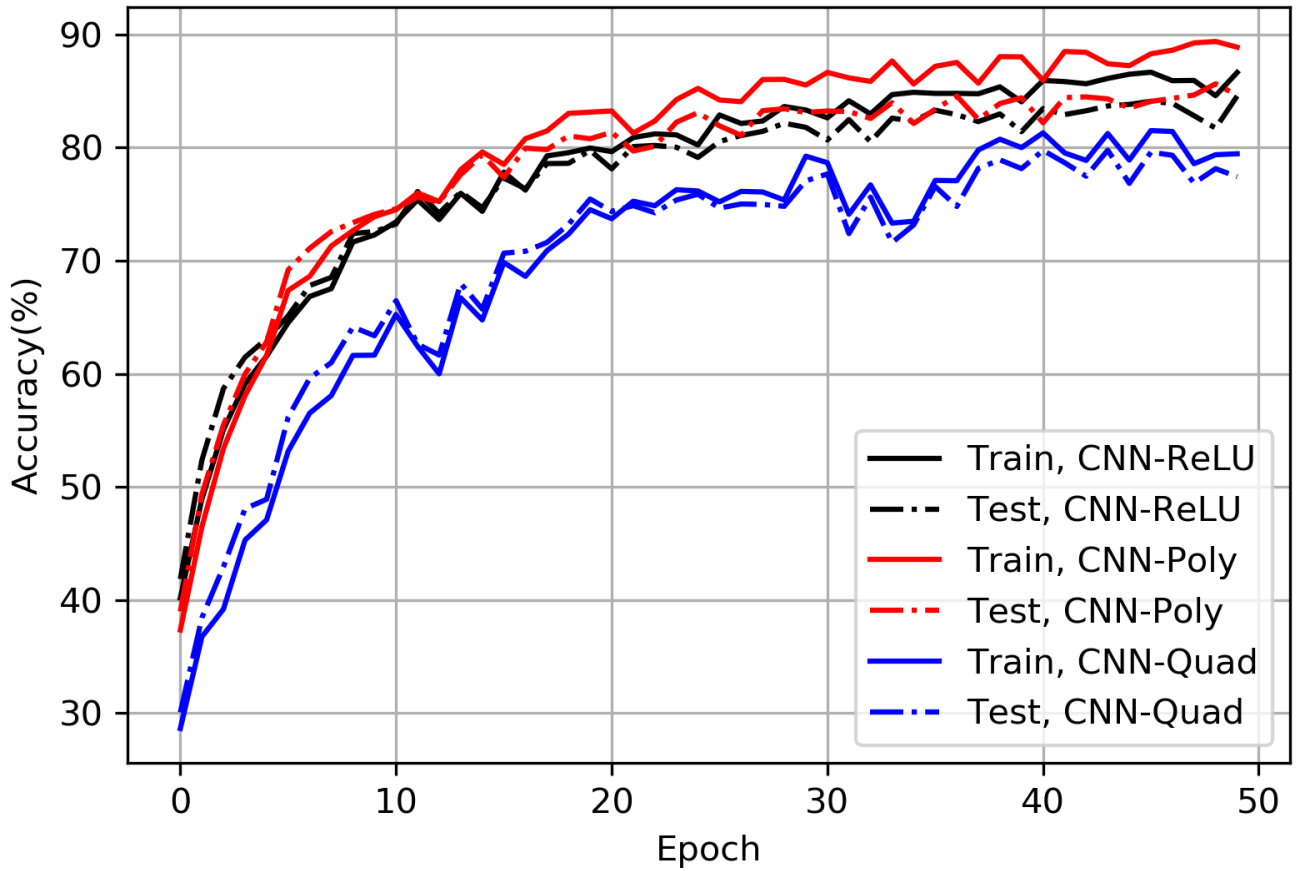
- Scaling this polynomial and ignoring the bias term lead to our activation function.

Evaluation

1. We consider the convolutional network of [7] with the CIFAR-10 dataset.

The network has

- 7 convolutional layers
- 7 ReLU activation layers
- 2 max-pooling layers
- a fully connected layer and
- a Softmax activation layer.

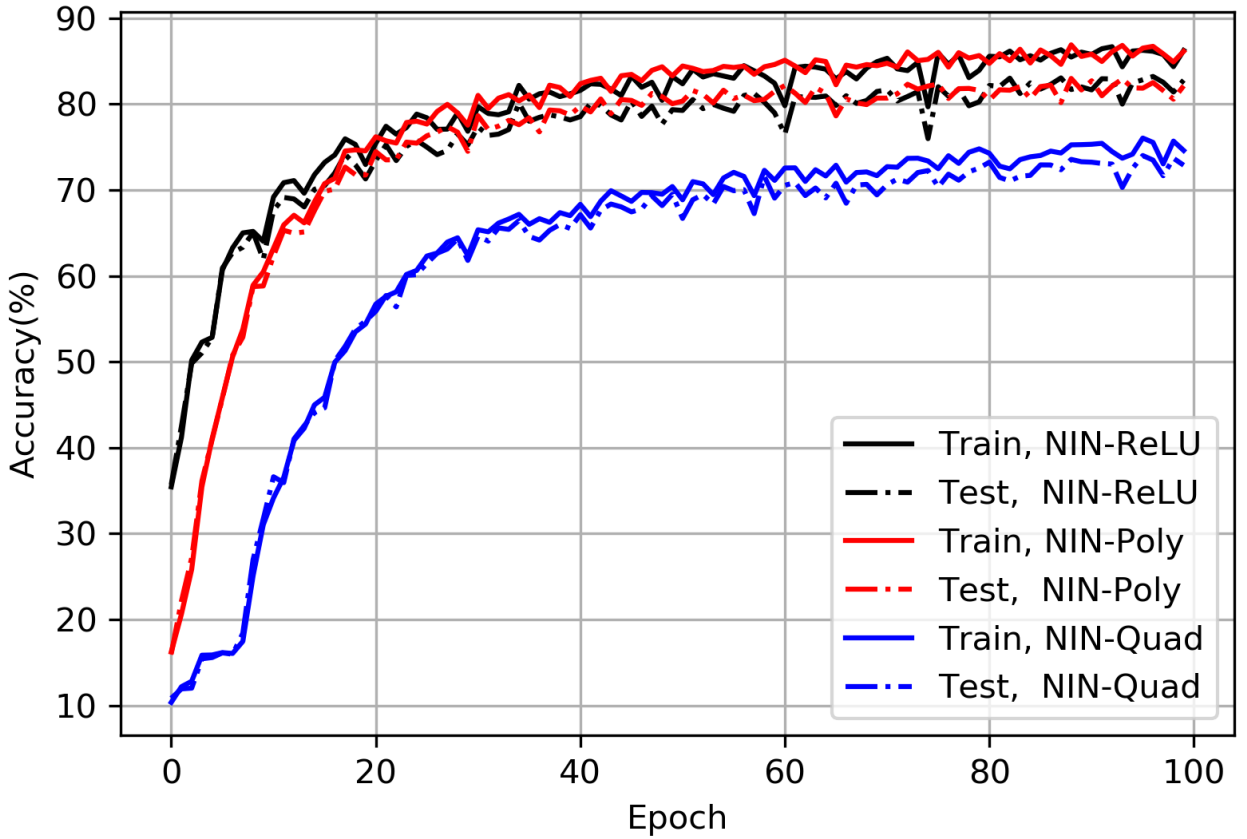


Evaluation

2. We consider the “Network In Network” architecture of [8] with the CIFAR-10 dataset.

The network has

- 9 convolutional layers
- 9 ReLU activation layers
- 2 max-pooling layers, Global pooling layer and
- a Softmax activation layer.



Discussion

- We have that empirically show that $\sigma_{poly}(x) = x^2 + x$ significantly outperforms $\sigma_{square}(x) = x^2$.

- Our future work aims to test our activation function on deeper networks and other datasets and to investigate its optimality.

Questions?

Thank you

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