Out-of-Distribution (OOD) Learning via Generative Adversarial Networks (GANs)

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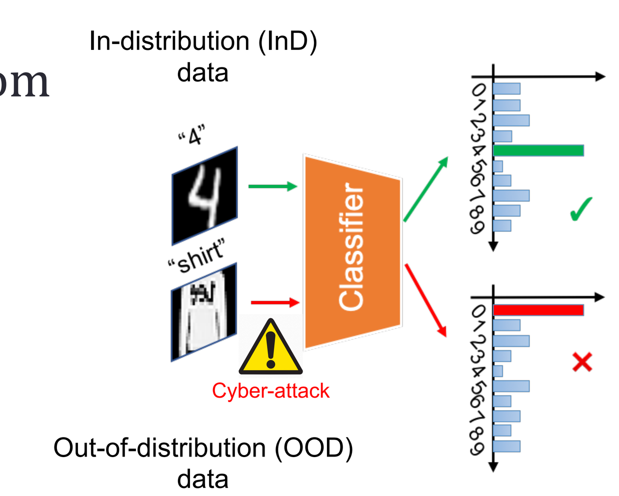
Introduction

- In deep neural networks (DNNs), the training and test data are possibly from different distributions
- Classifier tends to overconfidently predict OOD data with class labels of InD data
- OOD data threatens the reliability of classifier in practice
- OOD data is rarely observed and should be augmented via generative models



Objectives

- Goal: Strengthen the classifier with the ability to detect OOD samples.
- Task 1: Train an OOD **detector** such that:

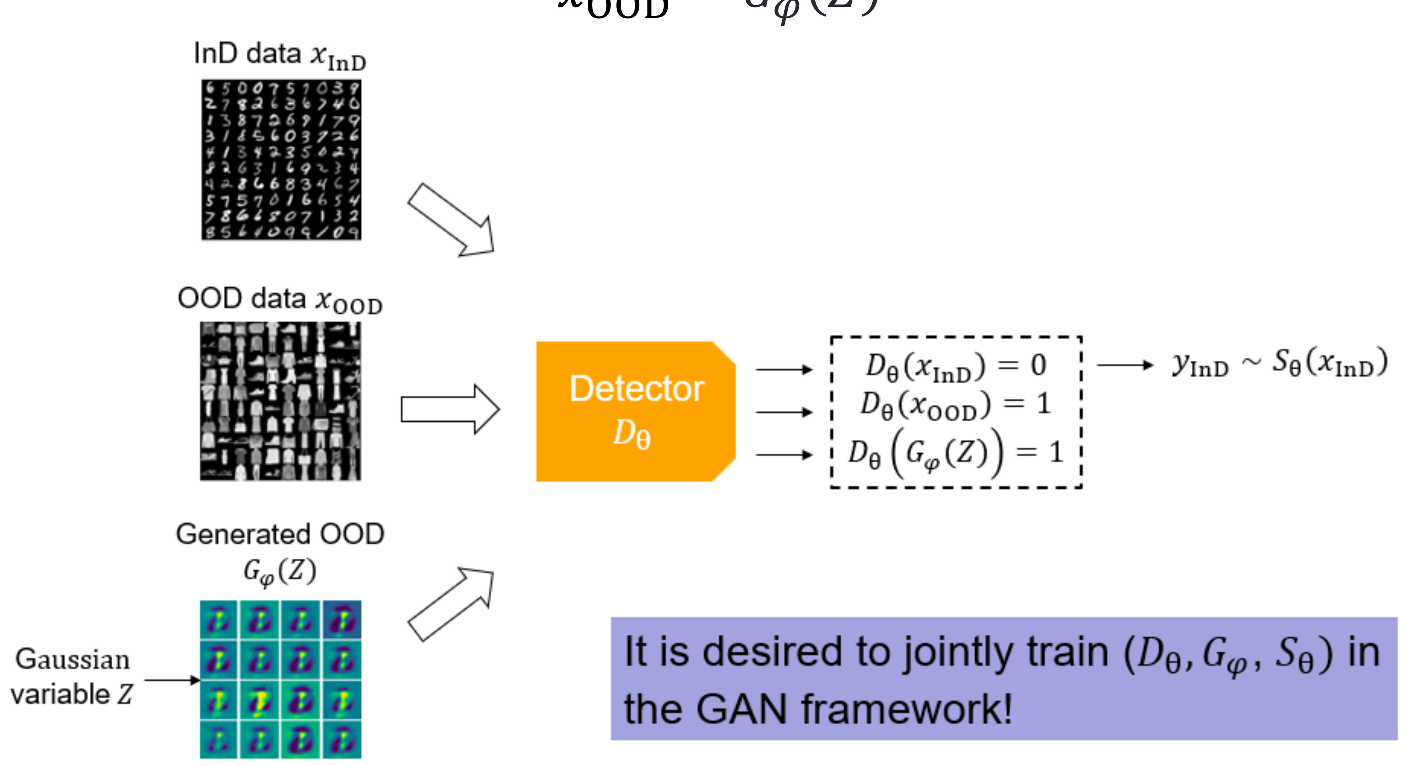
$$D_\theta(x) = \begin{cases} 1, \text{if } x \in \mathcal{X}_{\text{OOD}} \\ 0, \text{if } x \in \mathcal{X}_{\text{InD}} \end{cases}$$

- Task 2: Train a **classifier** such that:

$$y_{\text{InD}} \sim S_\theta(x_{\text{InD}})$$

- Task 3: Train a **generator** for OOD data augmentation:

$$x_{\text{OOD}} \sim G_\varphi(Z)$$



Methods

Overall minimax objective function for GAN:

$$\min_\theta \max_\varphi \; \lambda_{CE} E_{X_{InD}}[CE(S_\theta(X_{InD}), Y_{InD})] + \lambda_d E_{Z, X_{InD}}[d(G_\varphi(Z), X_{InD})] + \lambda_W E_{X_{OOD}}[-\log W(S_\theta(X_{OOD}))] + \lambda_W E_Z[-\log W(D_\theta(G_\varphi(Z)))]$$

Methods

Objective function interpretation:

- $CE = E_{X_{InD}}[CE(S_\theta(X_{InD}), Y_{InD})]$ classification accuracy
- $W_{OOD} = E_{X_{OOD}}[-\log W(S_\theta(X_{OOD}))]$ detection of OOD samples
- $W_Z = E_Z[-\log W(D_\theta(G_\varphi(Z)))]$ detection of generated samples
- $d_{InD} = E_{Z, X_{InD}}[d(G_\varphi(Z), X_{InD})]$ forcing $G_\varphi(Z)$ away from $\mathcal{X}_{\text{InD}}$

Network architecture:

- Traditional CNN architecture for D_θ
- CNN with transposed convolutional layers for G_φ
- In each iteration, update generator twice and discriminator once for a more balanced training.

Wasserstein loss: Joint distribution Distance matrix

$$W(r, c) = \inf_{P \in \Pi(r,c)} \langle P, M \rangle \longrightarrow \text{Kronecker product}$$

$$\Pi(r, c) = \{P \in \mathbb{R}_+^{K \times K} | P\mathbf{1}_K = c, P^\top \mathbf{1}_K = r\}$$

Minimax optimization solution:

During the training stage, we use alternating gradient descent. The objective function for discriminator D_θ and classifier S_θ is the following:

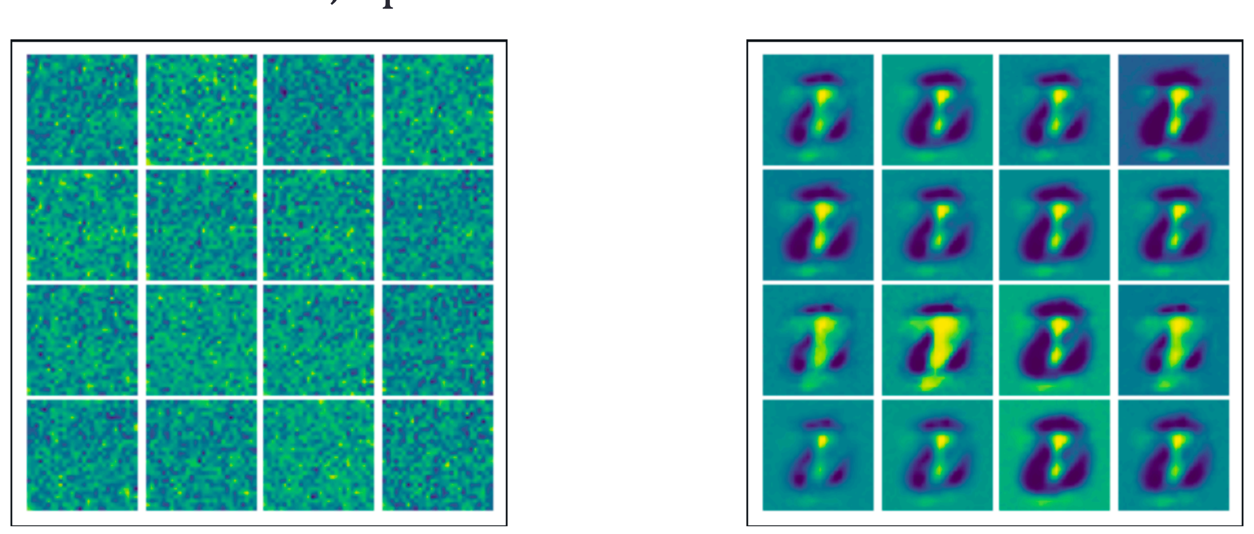
$$\min_\theta \lambda_{CE}\, CE + \lambda_W W_{OOD} + \lambda_W W_Z$$

Similarly, the objective function for generator G_φ is given below:

$$\max_\varphi \lambda_W W_Z + \lambda_d d_{InD}$$

Results

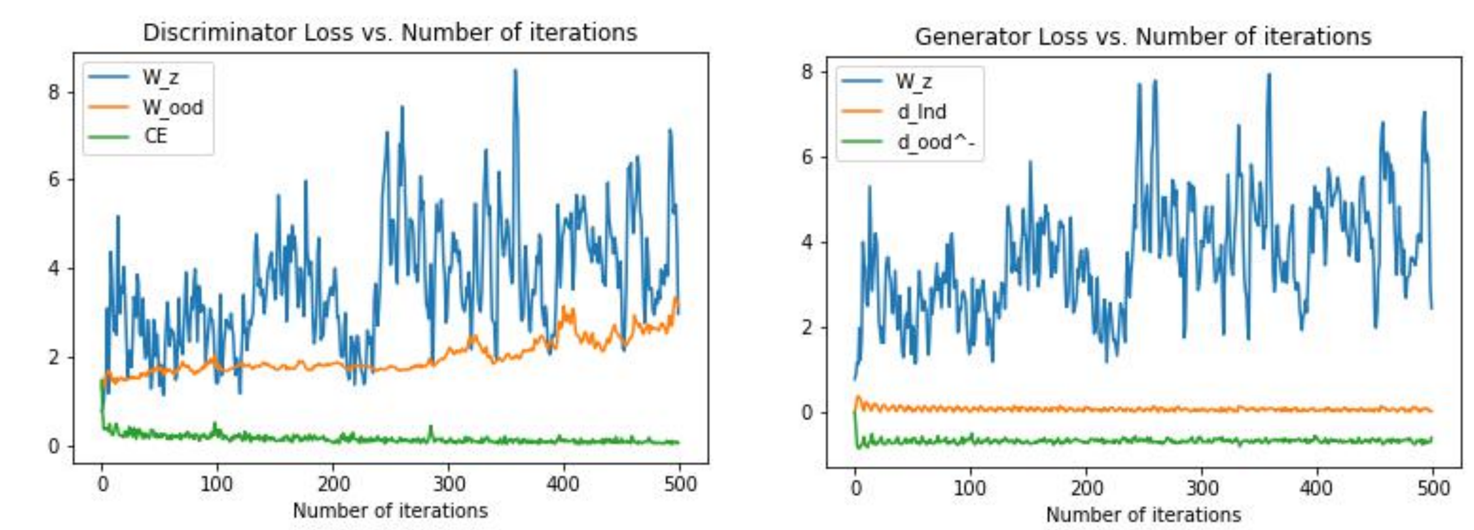
- Dataset: MNIST, InD labels: {2, 3, 6, 8, 9}, OOD labels: {1, 7}
- Distance metric in d_{InD}: image correlation coefficient
- Batch size: 256, Epochs: 15



- Left: generated OOD images before training
- Right: generated OOD images after training for 500 iterations
- The generator generated the horizontal and vertical structures in the OOD samples, while staying away from InD samples

Results

The training loss curve for discriminator (D_θ) and generator (G_φ) are shown below:



Analysis of loss curve.

- CE: Decreasing CE → Better InD sample classification accuracy.
- d_{InD}: Oscillating between [0, 0.1] → Generated images are not similar to InD images.
- d_{OoD}^-: Oscillating between [−1, −0.8] → Generated images are highly correlated (i.e. close to) OoD distributions.
- W_Z: Oscillating with decreasing magnitude → Oscillation illustrates the adversarial process of GANs.
- W_{OoD}: Reached a value of 2.5 after 15 epochs → Based on the definition of Wasserstein distance, a value of 2.5 implies that the model is likely to output uniform Softmax for OoD data.

- The discriminator achieved a prediction accuracy of 98% for InD data classification.
- The discriminator returned Softmax close to uniform for OoD data.

Conclusions

- The proposed OOD GAN discriminator returns low confidence scores for OOD samples and classifies InD data correctly
- The trained generative model recovers the OOD spaces
- With proper tuning and selection of distance metrics, the joint training scheme for OOD GAN shows its effectiveness

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