ROMark: A Robust Watermarking System Using Adversarial Training

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Abstract

The availability and easy access to digital communication increase the risk of copyrighted material piracy. In order to detect illegal use or distribution of data, digital watermarking has been proposed as a suitable tool. It protects the copyright of digital content by embedding imperceptible information into the data in the presence of an adversary. The goal of the adversary is to remove the copyrighted content of the data. Therefore, an efficient watermarking framework must be robust to multiple image-processing operations known as attacks that can alter embedded copyright information. Another line of research adversarial machine learning also tackles with similar problems to guarantee robustness to imperceptible perturbations of the input. In this work, we propose to apply robust optimization from adversarial machine learning to improve the robustness of a CNN-based watermarking framework. Our experimental results on the COCO dataset show that the robustness of a watermarking framework can be improved by utilizing robust optimization in training.

1 Introduction

Digital watermarking as a tool for preventing copyright violation of data has been an active research field for decades [Cox et al., 2007]. Typically, a pattern of bits is embedded into a host image with no visible degradation to the original image. An ideal watermarking system should guarantee that the embedded watermarks are imperceptible and unremovable by malicious attacks. Therefore, robust watermarking systems in the presence of adversary have been developed to declare rightful ownership. In watermarking, image processing operations such as image enhancement, cropping, resizing, or compression can be regarded as attacks. As a result, the performance of watermarking systems is commonly measured by their robustness to these attacks.

Similar to the watermarking, the field of adversarial machine learning also seeks to improve the robustness of neural networks in an adversarial environment [Kurakin et al., 2016]. Adversarial examples can be defined as specifically crafted inputs by an attacker to cause the neural network models to misbehave. This phenomenon was first observed by Szegedy et al. [2013]. To mitigate this problem, the notion of adversarial training has been proposed. The basic idea is injecting adversarial examples into the training set at every step of training neural networks [Goodfellow et al., 2014].

Adversarial learning aims to minimize the adversarial risk as opposed to the traditional risk. Adversarial risk is the expected worst-case loss of each sample in some region around the sample point instead of the loss on each sample point. Hence, adversarial training can be formulated as the min-max or robust optimization problem where the task of inner maximization perturbs inputs within a region so that the loss is maximized and the outer minimization optimizes the parameters of the

Machine Learning with Guarantees Workshop (NeurIPS 2019), Vancouver, Canada.
neural network so that the worst-case loss is minimized. This provides a more accurate estimate of the performance of the neural network operating in an adversarial environment.

Most recently, [Quiring et al., 2018] attempted to bring digital watermarking and adversarial machine learning together due to the similarities in defense and attack strategies in both fields. They provided a unified notation for black-box attacks in both fields to enable transferring concepts. In this work, we formulate a robust watermarking framework ROMark by employing the concepts from the robust optimization. Watermarking schemes typically contain two components: an encoder and a decoder. The encoder takes an image as well as a watermark message and produces a watermarked image. The decoder recovers the watermark from the watermarked image. Assuming both encoder and decoder are neural networks, an adversarial attack can be simulated at the output of the encoder. In our work, we apply a set of attacks at the output of the encoder and feed the worst-case attacked image to the decoder. We then optimize the parameters of both encoder and decoder.

Related Work: Using deep networks in watermarking frameworks has become popular most recently [Zhu et al., 2018], [Mun et al., 2017], [Ahmadi et al., 2018]. Among these, CNN-based HiDDeN [Zhu et al., 2018] is the most relevant work to ours as it also uses adversarial training. HiDDeN achieves robustness in two ways: (i) by inserting a noise layer between the output of the encoder and the input of the decoder, and (ii) by adding an adversarial loss to the objective loss. However, HiDDeN does not solve the min-max optimization directly.

Our Contributions: We adopt the architecture of the HiDDeN but compute the worst-case attacked image in the noise layer whereas HiDDeN’s noise layer outputs attacked (adversarial) image by using a fixed set of parameters for the attacks. Our experiments on the COCO dataset demonstrate that our min-max formulation in training watermarking framework improves robustness to different types of image transformations.

2 Proposed approach: ROMark

Robust optimization aims to obtain solutions against the worst-case realizations of the data from a known uncertainty set. In the case of designing a robust watermarking system in an adversarial environment, the robust optimization formulation can be defined as solving two sub-problems: (i) obtaining the worst-case watermarked images that induce the largest decoding error within limits; and (ii) optimizing parameters of the watermarking model on the worst-case watermarked images so that the loss of worst-case is minimized.

More formally, let \( E_\theta \) parameterized by \( \theta \) and \( D_\phi \) parameterized by \( \phi \) denote the encoder and the decoder of the watermarking framework, respectively. The encoder outputs the watermarked image \( x^{wm} \) by embedding a binary secret message \( m \) into a cover image \( x \) so that \( x^{wm} = E_\theta(x,m) \). The watermarked images should perceptually look similar to the cover images. Therefore, the similarity distance between these can be characterized by the loss function \( L_E(x,x^{wm}) \) which typically measures the \( L_2 \) distance. The decoder reconstructs message \( \hat{m} \) that has the same shape as \( m \) contained in the watermarked image \( x^{wm} \): \( \hat{m} = D_\phi(x^{wm}) \). The similarity between \( m \) and \( \hat{m} \) indicates the success of the decoding process. We define a loss function \( L_D \) to measure the difference between the embedded message and the reconstructed message from the decoder. Hence the empirical objective function of our robust watermarking framework can be formulated as the min-max problem as follows:

\[
\min_{\theta,\phi} \frac{1}{n} \sum_{i=1}^{n} \max_{x^{att} \in U_i} L_D(m_i, D_\phi(x^{att}_i)) + L_E(E_\theta(x_i, m_i), x_i)
\]

where \( U_i \) is the uncertainty set corresponding to the \( i \)-th image and \( x^{att}_i \) is the corresponding simulated attacked image (or the adversarial example).

2.1 Inner maximization: Obtaining Worst-case Attacked Images

Solving outer minimization in equation [1] requires access to the worst-case attacked images \( x^{att}_i \). This maximization problem can be solved by finding the attacked image \( x^{att}_i \) within a constraint set around \( x^{wm} \) which maximizes the probability that the decoder fails to recover the watermarks. In digital watermarking, adversarial attacks are typically caused by image distortions such as crop, image compression and blurring. Therefore, we define the images distorted by these attacks with varying severity levels as our uncertainty set. Let’s assume there are \( K \) image distortion functions \( N_i \) where \( i \in \{1,\ldots,K\} \) with corresponding severity level sets \( S_i \). The worst-case attacked image can be defined as:

\[
x^{att*} = N^*(x^{wm}, s^*)
\]
where \( s^* \) and \( N^* \) are obtained by:

\[
s^*, N^* = \arg\max_{N \in \{N_1, \ldots, N_K\}, s \in \{s_1, \ldots, s_K\}} L_D (m, D_\phi (N(x_i^{w^m}, s)))
\]

(3)

### 2.2 Outer minimization: Optimizing the Model Parameters

The goal of the outer minimization problem is to optimize the model parameters that minimizes the worst-case decoding loss. Reducing the worst-case loss offers a robustness guarantee that none of the considered attacks would induce a loss of large magnitude, i.e., successfully removes watermarks. Generally, after obtaining the worst-case attacked images, the outer minimization problem can be then represented as:

\[
\min_{\theta, \phi} \frac{1}{n} \sum_{i=1}^{n} L_D (m_i, D_\phi (N^* (E_\theta (x_i, m_i), s^*))) + L_E (E_\theta (x_i, m_i), x_i)
\]

(4)

Note that, \( N^* \) in equation (4) should be differentiable to enable gradient derived from \( L_D \) to backpropogate to encoder \( E_\theta \).

#### 2.3 Overall Training

In this section, we present the details of overall training. We use the mean squared error (MSE) for the loss at the decoder: \( L_D (m_i, \hat{m}_i) = \| m_i - \hat{m}_i \|^2 \). The loss for the encoder \( L_E \) comprises the MSE loss between the watermarked and the cover image: \( L_E (x_i, x_i^{w^m}) = \| x_i - x_i^{w^m} \|^2 \) and an adversarial loss for the watermarked image: \( L_E (x_i^{w^m}) = \log (1 - C_\beta (x_i^{w^m})) \). \( C_\beta \) is a discriminator network that is parameterized by \( \beta \), which is trained by minimizing the loss \( A(x_i, x_i^{w^m}) = \log (1 - C_\beta (x_i)) + \log (C_\beta (x_i^{w^m})) \). Hence, for a set of training samples \( X \) and the secret messages \( M \), the outer minimization problem can be re-written as:

\[
\min_{\theta, \phi} \left[ J_{\theta, \phi} (X, M) = \sum_{i=0}^{n} L_D (m_i, D_\phi (x_i^{w^m*})) + \lambda_1 L_E (x_i, E_\theta (x_i, m_i)) + \lambda_A L_E (E_\theta (x_i, m_i)) \right]
\]

(5)

The Algorithm for training ROMark using combination of all attacks is given in Algorithm 1. Note that, due to computational issues we are only optimizing \( s \) for each \( N_i \) instead of optimizing both \( s \) and \( N_i \). We are investigating the latter as future work.

**Algorithm 1** Adversarial training of ROMark Combined

**Require:** Batch size: \( b \), Learning Rate: \( \gamma_\beta, \gamma_\theta, \gamma_\phi \), Attack functions: \( N_1, \ldots, N_K \)

Randomly initialize the networks: \( D_\phi, E_\theta \) and \( C_\beta \).

Randomly sample message batch \( M \) of batch size \( b \).

Select \( K \) integers: \( k_1, \ldots, k_i, \ldots, k_K \), where \( K \) is the number of types of attacks and \( \sum_{i=1}^{K} k_i = b \)

repeat

Read minibatch \( B = \{x_1, \ldots, x_b\} \) from training set.

Generate the watermarked minibatch \( B_{wm} = \{E_\theta (x_i, m_i) : x_i \in B, m_i \in M\} \)

Separate the minibatch \( B_{wm} \) into \( K \) subsets \( B_{wm}^{1}, \ldots, B_{wm}^{K} \) where each contains \( k_i \) images

Load severity ranges of attacks: \( S_1, \ldots, S_K \)

for \( i = 1, 2, \ldots, K \) do

Search the worst-case \( s_i^* \) by: \( s_i^* = \arg\max_{s \in S_i} \sum_{x_i^{w^m} \in B_i} L (m, \phi_i (x_i^{w^m}, s)) \)

Calculate the worst-case attacked image batch \( B_{att}^{i} = \{N_i (x_i^{w^m}, s_i^*) : x_i^{w^m} \in B_{wm}^{i}\} \)

end for

Generate attacked minibatch \( B_{att} = \{B_{att}^{1}, \ldots, B_{att}^{K}\} \)

Feed \( B_{att} \) into decoder, and then do one step training step:

Updating discriminator \( C \):

\[
\beta_{t+1} = \beta_t - \gamma_\beta \sum_{x_i \in B, x_i^{w^m} \in B_{wm}} \nabla_\beta A(x_i, x_i^{w^m})
\]

Updating \( D_\phi \) and \( E_\theta \):

\[
\theta_{t+1} = \theta_t - \gamma_\theta \nabla_\theta J (B, M) \quad \text{and} \quad \phi_{t+1} = \phi_t - \gamma_\phi \nabla_\phi J (B, M)
\]

until Training losses converged
Table 1: Parameter settings of noise layers used in training HiDeN and ROMark models.

| Model   | Attack Type | Identity (no attack) | Crop | Cropout | Dropout | Gaussian Blur | JPEG Compression | Combined |
|---------|-------------|----------------------|------|---------|---------|---------------|------------------|---------|
| ROMark | Range       | -                    | (0, 1, 0.8) | (0.3, 0.9) | (0, 1) | (1, 3) | (50, 100) | Combination of all |
| HiDeN  | Intensity   | -                    | 0.1  | 0.1     | 0.1     | 1              | 2                | Combination of all |

3 Implementation Details

We apply our ROMark and HiDeN to the COCO dataset [Lin et al., 2014] (10, 000 for training and 1000 for testing) and evaluate the robustness to image processing attacks. We use peak signal-to-noise ratio (PSNR) and the bit accuracy to measure the performance. PSNR measures the amount of distortion in the encoded images so that high value of PSNR indicates better quality of the images. Bit accuracy is the ratio of correctly recovered bits to the total number of bits in the decoded watermarks. The embedded watermarks are randomly sampled binary vectors with length of 30. We use crop, cropout, dropout, Gaussian Blur and JPEG compression with various severity levels as attacks. Both ROMark and HiDeN are trained with these specialized attacks and also combination of all. For a fair comparison, we use the same network architecture and hyperparameters for both ROMark and HiDeN. The parameters of the attacks used in training are shown in Table 1.

4 Experimental Results

In Figure 1, we show the bit accuracy rates for both models under different attacks with different severity levels. When trained with the combination of all attacks, our ROMark Combined is more robust than HiDeN Combined to all attacks at all severity levels. Using only the specialized attacks in training, our ROMark Specialized is more robust than the HiDeN specialized for all attacks. Furthermore, HiDeN Specialized yields higher accuracy under the attacks which were also used in training, i.e. overfits. Our ROMark, on the other hand, does not have the overfitting problem.

Figure 1: Bit accuracy of ROMark models and HiDeN models for various attacks and intensities. X-axis represents severity levels which increases from left to right.

| Model Type | Crop | Cropout | Dropout | Gaussian Blur | JPEG | Combined |
|------------|------|---------|---------|----------------|------|----------|
| HiDeN      | 24.32| 24.20   | 24.20   | 24.81          | 23.57| 24.56    |
| ROMark     | 26.78| 23.98   | 26.58   | 23.67          | 27.70| 27.80    |

Table 2: Average watermarking PSNR over 1000 testing images.

5 Conclusion

We proposed a novel way to train a watermarking framework using the min-max formulation from robust optimization. The idea of minimizing the worst-case loss across several attacks makes the watermarking framework more robust to malicious attacks. Our experiments on the COCO dataset demonstrate that our min-max formulation in training watermarking framework improves robustness to different types of watermarking attacks.
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