Adversarial Attack Type I: Generating False Positives

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Abstract

False positive and false negative rates are equally important for evaluating the performance of a classifier. Adversarial examples by increasing false negative rate have been studied in recent years. However, harming a classifier by increasing false positive rate is almost blank, since it is much more difficult to generate a new and meaningful positive than the negative. To generate false positives, a supervised generative framework is proposed in this paper. Experiment results show that our method is practical and effective to generate those adversarial examples on large-scale image datasets.

1 Introduction

In recent years, deep neural networks (DNN) have shown great power on image classification \[1,2\], segmentation [3] and generation \[4,5\] tasks. However, some researchers point out that many DNN models are vulnerable to adversarial examples \[6,8,25\]. \[9\] provides a theoretical framework to describe the task for obtaining adversarial examples, as shown in the left equation in (1).

\[
\begin{align*}
\text{Find } & x' \\
\text{s.t. } & f_1(x) \neq f_1(x') \\
\text{Find } & x' \\
\text{s.t. } & f_1(x) = f_1(x') \\
f_2(x) & = f_2(x') \\
f_2(x) & \neq f_2(x')
\end{align*}
\] (1)

Here, \(x, x' \in X\) with \(X\) to be image space\[1\]. \(f_1\) is the classifier to be attacked while \(f_2\) is an oracle classifier e.g. a group of human annotators. Moreover, the adversarial sample \(x'\) are regarded as the same class as the original \(x\) on the view of the oracle which is because they are close under the measurement by the pseudometric function in the latent space of the oracle.

Since the proposal by \[7\], various interesting works for obtaining adversarial examples have been put forward \[6,10,11,12\]. \[6\] proposes a fast gradient sign method (FGSM) to generate adversarial examples efficiently, where small disturbance is added directly to the input image: \(x' = x + \epsilon \text{sign} \nabla_x J_1\) with \(J_1\) to be the loss of \(f_1\). \[10\] provides an iterative and more accurate method to fool deep neural networks. \[11\] describes a practical black-box attacking method by training an alternative network through the observed labels given by the target DNN according to the inputs, where the adversarial examples for the alternative network are also effective for the target DNN.

\[1\]In this paper, we focus on Type I adversarial examples in image space.
The adversarial attack defined as the left one in (1) is only one-side of attacks. In statistics, false positives (Type I error) are as important as false negatives (Type II error). As summarized in [25], the existing methods mainly focus on increasing Type II error, but there are few practical methods for increasing Type I error. In Figure 1(a), consider a handwritten digit image which can be correctly classified by a multi layer perception (MLP). For Type II attack, an adversarial image is misclassified into another class by MLP through adding small but inconspicuous perturbation to the original image. While for Type I attack, an adversarial image belonging to a different class is generated from the original image yet still classified the same class. More formally, in this paper, we study the Type I adversarial attack defined as the right equation in (1), which means that we try to really change the input into another class while the judgement of the attacked classifier remains the same.

The Type I attack, which is to generate a totally new and meaningful sample, is much more difficult than the Type II attack, which is to generate a slightly different sample, because manipulating in the image space directly will consequently contaminates the image with noise, which cannot yield a clean image belonging to another class on the view of the oracle. As far as we know, the method for Type I attack has only been studied by [26], which however can only generate meaningless noise that might be easily defended by a discriminator.

In order to generate a new and meaningful sample for Type I attack while considering that finding adversarial examples is a generation task in essence, a supervised variational autoencoder (SVAE) model for the oracle is proposed to generate targeted adversarial examples. SVAE is the supervised extension from original variational autoencoder (VAE) [5]. Similarly, we choose the Gaussian distribution in the latent space as the prior knowledge. Moreover, when attacking, the gradients from the oracle classifier in SVAE are back propagated only to the latent space rather than image space to avoid noise. After updating the latent variables by gradient descend method, it forward propagates through a decoder to recover the revised latent variables into images. However, it is important for the oracle classifier in SVAE to provide stable gradients during attacking. Benefiting from the Gaussian restriction in the latent space and inspired by adversarial autoencoder [14], a discriminator is added to estimate the distribution of the manifold in the latent space.

In summary, although several methods to generate adversarial examples for Type II attack have been previously explored, the research on Type I attack and the corresponding generative method are still lacking. To fill this blank, this paper makes the following contributions:

- We describe the adversarial examples to increase Type I error of a classifier, i.e. to find a sample with different label from the original one, which will cheat the classifier to regard them as the same class.
We propose a framework based on supervised variational autoencoder to generate adversarial samples for Type I attack. In our framework, even a simple classifier as the oracle can generate cheating samples to attack a very deep network with high accuracy performance. In order to enable the oracle to provide effective supervised signal during attacking, we design a sample-based discriminator to estimate the manifold in the Gaussian latent space. Experiments verify that our framework is effective to generate the adversarial examples for Type I attack on large-scale image datasets.

2 Method

Substantially, finding an adversarial example to a vulnerable classifier $f_1$ is an image generation task. Both of the two type attacks require the generated examples to belong to the wrong classes. Traditional methods [6,10,12], as the Type II adversarial attack defined in (1), directly manipulate in the image space according to the gradients from the $f_1(x)$: $x = x + \epsilon \nabla_x f_1$. The $\epsilon \nabla_x f_1$ terms seems like meaningless and unnoticeable noise as illustrated in Figure (1a). Such small disturbance is effective for Type II attack due to the adversarial example with the disturbance remaining unchanged on the view of the oracle. However, for Type I attack, it is required to manipulate in the latent space to generate a new and clean adversarial example. Thus, an autoencoder structure is chosen to encode the input into latent space and then recover the modified latent variables into images, which is used to avoid the undesirable noise from directly modifying the input in the image space.

In Figure (1b), we show our framework for training and generating Type I adversarial examples. The attacked classifier $f_1$ is ignored during training the SVAE model. While attacking, the gradients from $f_1$ do not merely propagate to the input $x'$ of $f_1$, as the traditional methods do, but further to the latent variables $z$ through the decoder. At the same time, the gradients from the oracle $f_2$ are also used for revising the $z$ to obtain a new image $x'$ with a different label through the decoder. An equilibrium is then introduced between $f_1$ and $f_2$ to achieve the Type I attack.

In order to generate an adversarial example with a desired label, we propose to use supervised variational autoencoder (SVAE), i.e. the supervised extension of VAE. Based on the generative model of VAE for generating $x$ in the image space from latent variables $z$, which is modeled as $p(x) = \int p(x|z)p(z)dz$, the supervised VAE can be described as $p(x, y) = \int p(x, y|z)p(z)dz$, where $y$ is the label information from the oracle.

2.1 Supervised VAE model for generating targeted sample

Similar to VAE, in order to optimize the supervised variational autoencoder model, we first find a lower bound of $p(x, y)$. Assume $q(z)$ is an arbitrary distribution in the latent space, its distance to $p(z|x, y)$ can be measured by Kullback-Leibler (KL) divergence:

$$
\text{KL}[q(z)||p(z|x, y)] = E_{z \sim q} [\log(q(z)) - \log(p(z|x, y))]
$$

$$
= E_{z \sim q} [\log(q(z)) - \log(p(x, y|z)) - \log(p(z))] + \log(p(x, y)).
$$

Above can be rewritten as:

$$
\log(p(x, y)) - \text{KL}[q(z)||p(z|x, y)]
$$

$$
= -\text{KL}[q(z)||p(z)] + E_{z \sim q} [\log(p(x, y|z))]
$$

$$
= -\text{KL}[q(z)||p(z)] + E_{z \sim q} [\log(p(y|z)) + \log(p(x|y, z))].
$$

The conditional generative methods [14,15] that use label information as a prior aim to separate the style and content in the latent space. In our setting, latent variables $z$ should contain label information as in [16]. This is mainly due to two reasons: firstly, the distribution in the latent space should be constrained by the oracle according to their labels, which enables the use of gradients from oracle to modify the generated image; secondly, as described in [9], the judgement of the classifier is decided by a pseudometric measurement in the latent space. Therefore, we replace $p(x|y, z)$ by $p(x|z)$ since $z$ contains the label information $y$. Then, a lower bound of $p(x, y)$ can be given as:

$$
\log(p(x, y)) \geq -\text{KL}[q(z)||p(z)] + E_{z \sim q} [\log(p(y|z))] + E_{z \sim q} [\log(p(x|z))].
$$

(2)

To simplify the optimization, following [5] we choose $q(z)$ to be Gaussian depending on $x$ in the latent space: $q(z|x) = \mathcal{N}(\mu(x; \theta_{enc}), \sigma(x; \theta_{enc}))$. Thus, the supervised VAE model tries to maximize:

$$
J_2 = -\text{KL}[q(z|x)||p(z)] + E_{z \sim q(z|x)} [\log(p(y|z))] + E_{z \sim q(z|x)} [\log(p(x|z))]
$$

$$
\triangleq -(J_{KL} + J_2 + J_{dec}),
$$

(3)
of which the three terms are corresponding to the encoder, classifier and decoder in SVAE model respectively. The classifier in SVAE model plays a role as an oracle to impose restriction on latent variables in order to generate images with desired labels through the decoder.

Table 1: Two stage learning algorithm for training the parameters in the autoencoder, oracle classifier $f_2$, and discriminator networks.

| Algorithm 1 Two stage learning in SVAE |
|----------------------------------------|
| **while** stage1Training() **do** |
| $x, y \leftarrow$ getMiniTrainingBatch() |
| $z \sim \mathcal{N}(\mu(x; \theta_{\text{enc}}), \sigma(x; \theta_{\text{enc}}))$ |
| $(\theta_{\text{enc}}, \theta_{\text{dec}}, \theta_{\text{ora}}) \leftarrow (\theta_{\text{enc}}, \theta_{\text{dec}}, \theta_{\text{ora}}) + \nabla_{\theta} J_{\text{enc}}$ |
| end while |
| **while** stage2Training() **do** |
| $x, y \leftarrow$ getMiniTrainingBatch() |
| $z_{\text{true}} \sim \mathcal{N}(\mu(x; \theta_{\text{enc}}), \sigma(x; \theta_{\text{enc}}))$ |
| $z_{\text{fake}} \sim \mathcal{N}(0, I)$ |
| $\theta_{\text{dis}} \leftarrow \theta_{\text{dis}} + \nabla_{\theta} J_{\text{dis}}$ |
| end while |

Table 2: Iterative generating algorithm for finding Type I adversarial example by revising $z$ in the latent space.

| Algorithm 2 Generating for Type I attack |
|-----------------------------------------|
| **given** input $x$ |
| $z_{0} \leftarrow \mu(x; \theta_{\text{enc}}), k_{0} \leftarrow 0, t \leftarrow 0$ |
| **while** not converging() **do** |
| $z_{t+1} \leftarrow z_{t} + \nabla_{z} J_{\text{dis}}(z_{t})$ |
| $x'_{t+1} \leftarrow f_{\text{dec}}(z_{t+1})$ |
| $k_{t+1} \leftarrow k_{t} + \eta(\beta J_{1}(x'_{t+1}, y_{t+1}) - J_{2}(z_{t}, y_{t}) + \max\{J_{1}(f_{\text{dec}}(z_{t}, y_{t}), z_{t}) - J_{1}(0, 0)\})$ |
| $k_{t+1} \leftarrow \max(0, \min\{k_{t+1}, 0.005\})$ |
| end while |
| $x' = f_{\text{enc}}(z_{T}), T$ is the final time step |
| **return** $x'$ |

2.2 Sample-based discriminator in the latent space

It is well-known that the classifier only fits well on the manifold in the latent space of the images but might have bad behaviour outside [13]. Since we directly manipulate the latent variables iteratively according to the gradients from the oracle and the attacked classifier, a discriminator is necessary to prevent the latent variables from lying outside the manifold in the latent space while attacking. Consequently, the oracle can provide stable and effective direction for updating the latent variables under the restraint of the discriminator. In SVAE, the distribution of latent variables is standard Gaussian, which makes a sample-based discriminator applicable. Specifically, a binary classification discriminator with a sigmoid activation function on the output layer is designed to distinguish the real latent values encoded from input images by the decoder and the fake latent values sampled randomly from the Gaussian distribution:

$$J_{\text{dis}} = E_{z_{\text{true}} \sim q(z|x)}[f_{\text{dis}}(z_{\text{true}})] + E_{z_{\text{fake}} \sim \mathcal{N}(0, I)}[1 - f_{\text{dis}}(z_{\text{fake}})].$$

(4)

2.3 Optimization of SVAE networks

A two-stage optimization method is utilized in this paper to train SVAE networks. In the first stage, we simultaneously train the encoder, decoder and classifier to maximize the objective function in [5]. The encoder function $f_{\text{enc}}$ maps the input to a Gaussian distribution with its mean and variance to be $\mu(x; \theta_{\text{enc}})$ and $\sigma(x; \theta_{\text{enc}})$. By the reparameterization trick [5], a latent variable $z$ is sampled in such a Gaussian distribution, which is then used for classification and recovery as $f_{\text{dec}}$ and $f_{\text{ora}}$ respectively. A gradient descent method $\Gamma$, e.g. Adam is used for training parameters $\theta_{\text{enc}}, \theta_{2}$ and $\theta_{\text{ora}}$ corresponding to $f_{\text{enc}}, f_{\text{2}}$ and $f_{\text{ora}}$.

In the second stage, we train the discriminator $f_{\text{dis}}$ to maximize [4] based on the well-located encoder after the first training stage. The input $x$ is first encoded into the Gaussian mean $\mu(x)$ and variance $\sigma(x)$ in the latent space. Then the positives are sampled from $z_{\text{true}} \sim \mathcal{N}(\mu(x; \theta_{\text{enc}}), \sigma(x; \theta_{\text{enc}}))$, while the negatives are sampled from standard Gaussian $z_{\text{fake}} \sim \mathcal{N}(0, I)$. A gradient descent method $\Gamma$ is applied to only update the parameters $\theta_{\text{dis}}$ in the discriminator $f_{\text{dis}}$. This two stage optimization algorithm is described in Table[1].

2.4 Generating targeted examples as image transition

In order to conduct Type I attack, which means to generate $x'$ satisfying $f_{1}(x) = f_{1}(x')$ and $f_{2}(x) \neq f_{2}(x')$ as the right definition in [1], we first consider the image transition task, e.g. transforming the input image $x$ with label $y$ into another image $x'$ with different label $y'$ by utilizing supervised
information from the oracle \( f_2 \) in SVAE. In our framework, the class information is not directly given e.g. in the conditional generation methods but comes from the supervised term in the oracle classifier. The latent variables are revised iteratively according to the gradients from the \( f_2 \) and recovered into images through the decoder. The objective function for generating targeted examples is:

\[
J_{IT} = J_2(z, y') + \alpha(1 - f_{\text{dis}}(z)) + \gamma \|z\|_2
= -y' \log f_2(z) + \alpha(1 - f_{\text{dis}}(z)) + \gamma \|z\|_2,
\]

where the cross-entropy loss is applied to \( f_2 \), and it is a common choice in classification tasks \([1][2]\). Besides, a loss term with weight \( \alpha \) from discriminator \( f_{\text{dis}} \) is also added in order to prevent \( z \) from moving outside of the manifold in the latent space. An \( l_2 \) regularization term on \( z \) with weight \( \gamma \) is used to restrict \( z \) to locate in the standard Gaussian space as the ambient space of the manifold.

### 2.5 Generating adversarial examples for Type I

Based on the image transition, the attacked classifier \( f_1 \) can be incorporated as illustrated in Figure 1(b) to generate the Type I adversarial example for \( f_1 \). The trained SVAE model can be used as an oracle with a generative model for the Type I attack. Given a classifier \( f_1 \) with its loss function \( J_1 \), we can find targeted adversarial example \( x' \) with target label \( y' \) of an input \( x \) with original label \( y \) through minimizing the following function:

\[
J_{SA} = J_{IT} + k_t J_1(x', y', \cdot)
= -y' \log f_2(z) + \alpha(1 - f_{\text{dis}}(z)) + k_t J_1(f_{\text{dec}}(z), y, \cdot) + \gamma \|z\|_2.
\]  

(5)

The positive parameter \( k_t \) in (5) controls the weights of effectiveness of the attacked classifier. \( J_1(x', \cdot) \) is the loss function of the attacked classifier varying from the specific tasks. In multi-class classification tasks\([1][2]\), \( f_1(x) \) is usually a vector of probabilities for each class. While in face recognition tasks\([1][2]\), \( f_1(x) \) is often a feature vector in Euclidean space, where the smaller \( l_2 \) distance \( \|f_1(x') - f_1(x)\|_2 \) it is, the more likely \( x \) and \( x' \) are the same person. Here are two examples:

\[
J_1(x', \cdot) = \begin{cases} 
-y' \log f_1(x') & \text{classification tasks} \\
\|f_1(x') - f_1(x)\|_2 & \text{face recognition tasks}
\end{cases}
\]  

(6)

Inspired by \([18]\), in order to better control the equilibrium between the losses of oracle \( J_2 \) and the attacked classifier \( J_1 \), a hyper parameter \( \beta \) is introduced:

\[
\beta = \frac{J_2(z, y')}{J_1(f_{\text{dec}}(z), y, \cdot)} = \frac{J_2(z, y')}{J_1(f_{\text{dec}}(z), y, \cdot)}.
\]  

(7)

A lower \( \beta \) leads to the generated adversarial sample \( x' \) more likely belonging to the targeted label \( y' \) yet higher probability for \( f_2 \) to judge that \( f_2(x) \neq f_2(x') \). In our method, a self-adaptive weight variables \( k_t \) is designed to maintain such equilibrium in \([1]\):

\[
k_{t+1} = k_t + \eta \left( \beta J_1(f_{\text{dec}}(z), y, \cdot) - J_2(z, y') + \max \left\{ J_1(f_{\text{dec}}(z), y, \cdot) - \hat{J}_1, 0 \right\} \right). \]  

(8)

In order to improve the image quality and success rate for Type I attack, we can sacrifice a little confidence properly in \( f_1 \) to concentrate more on \( f_2 \) which leads to the input image really changing into a new image with different class. Therefore, a target loss \( \hat{J}_1 \) for the attacked classifier is added with a hinge loss term in \([8]\). After updating the equilibrium weight \( k_t \) in each step though \([8]\), it is clipped into \([0, 0.001]\) in our experiments.

Rather than optimizing the parameters in those networks above, we update the latent variables \( z \) iteratively to minimize the objective function in \([5]\) after all those networks are well trained. At the start, we initialize \( z \) to be the mean of the Gaussian \( z_{\text{init}} = \mu(f_{\text{enc}}(x)) \) according to the given input \( x \). Similar to training networks, we here use Adam \([19]\) to optimize \([5]\) only on the latent variables \( z \) iteratively. The overall algorithm for generating Type I adversarial examples is illustrated in Table 2. Obviously, 0 is a lower bound of \( J_{SA} \) in both case of classification and recognition tasks. Therefore, the convergence is guaranteed when optimizing \( J_{SA} \) through the gradient descend methods. Codes are provided in SM and will be published in the future.
Figure 2: Illustration of supervised image class transition by SV AE on (a) MNIST and (b) CelebA datasets. The target class for digital image $i$ is $i + 1$ (the target of "9" is "0") and for male/female face images is the opposite.

3 Experiment

3.1 Setup

Our framework is trained by Adam [19] with learning rate 0.0002. The hyper parameters $\alpha$ and $\gamma$ in (5) are 0.01 and 0.0001 respectively. $\beta$ for equilibrium in (8) is 0.001. During the attacking iterations, we also use Adam to update latent variable $z$ with learning rate 0.005. The target loss $\hat{J}_1$ in (8) is set to 0.01 as the cross entropy loss for digital image classification task and 1.00 as the $l_2$ Euclidean distance for face recognition task in our experiments. The detail of SV AE’s architectures is provided in the SM. All the experiments in this paper are implemented in Tensorflow [20] on an NVIDIA TITAN X GPU with 12GB memory.

We test our SV AE model for supervised image transition and Type I attack algorithms on MNIST [21] and CelebA [22] datasets. MNIST dataset contains 60K handwritten digital images of size 28x28. Following the common split, we use 50K images for training and rest for testing. CelebA dataset includes over than 200K face images with 40 attribute annotations. We simply split CelebA dataset into Male/Female subsets according to their gender labels, which are then normalized and centrally cropped into size 64x64.

3.2 Ability of SV AE for image class transition

Here, we validate the ability of SV AE for image class transition on MNIST and CelebA datasets. In this experiment, the attacked classifier $f_1$ is ignored by setting $k_t = 0$ in (5) at each iterative step. In Figure 2(a), we show the generated examples on MNIST from SV AE at different iterative steps, where the $i$th row is generated by setting $y' = i$ ($i = 1, 2, \cdots, 9$) and $y' = 0$ when $i = 10$ in (5). Fig 2(b) is the result for gender transition on CelebA dataset, where the face images of male/female are transformed into the females/males.

In this experiment, we can find that how an image is transformed into another image with different label on the view of the oracle in our framework. Since the latent variables $z$ are updated according to the gradients from $f_2$ at each iterative step, the generated images always attempt to be transformed into the target class through minimum changes. Therefore, most features both in the original and transformed images are remaining unchanged, such as the hair color, face direction and facial expression. SV AE may benefit from such property to attack other classifiers that cannot capture all the important features for the desired classification task in the image.
Do not hallucinate.

Figure 3: Illustration of the log loss terms of the oracle classifier $f_2$, the discriminator $f_{dis}$ and the MLP $f_1$ by setting $y' = 5$ for the oracle and $y = 4$ for the MLP in $\hat{J}_1$. The lower loss of the MLP, the more it is believe the generated image belongs to class "4". Until convergence, the MLP still classifies it as "4" with 99.41% confidence.

3.3 Ability of SVAE for Type I attack on weak classifier

To validate the effectiveness of SVAE model and the algorithm for generating Type I adversarial examples in Table 2, we train SVAE model and an MLP with 128 hidden units as the attacked classifier separately on MNIST dataset. The classification error rate of the oracle classifier in SVAE and the MLP on the test set are 1.36% and 2.73% respectively. We here regard such MLP as a weak classifier due to its simpler architecture and higher error rate.

In Figure 3, we illustrate the log loss terms of the oracle classifier $f_2$, the discriminator $f_{dis}$ and the MLP $f_1$ where SVAE tries to conduct a Type I attack to transform image from "4" to "5" while the MLP still classifies it as "4". The images on the top are the generated adversarial examples $x'$ at the corresponding iterations. Notice that the loss for the oracle $f_2$ is relative to $y' = 5$ while the MLP $f_1$ with respect to $y = 4$. Therefore, at the beginning, the loss of $f_2$ is much higher than $f_1$ due to the fact that the original image is the number "4". Then, through minimizing $\hat{J}_{SA}$ in (5), the image is gradually converted to number "5" while the loss of $f_1$ is increasing, since the target loss $\hat{J}_1$ is set to 0.01 and the weight for $J_1$ in (8) is clipped into 0. At the same time, the loss of the discriminator is increasing since the latent variables have to walk beyond the manifold in the latent space. When $J_1$ increases beyond $\hat{J}_1$ and $J_2$ is lower than the equilibrium described in (7), the adaptive weight $k_t$ for $J_1$ increases which pulls down $J_1$ until convergence. Although the loss of the oracle $f_2$ decreases rapidly at the beginning, the supervised information from the oracle is not very reliable since its performance is unpredictable outside the manifold in the latent space. The discriminator, therefore, plays a key role in restraining the latent variables into the manifold, which makes the oracle in SVAE to provide convincible gradients. In Figure 4(a), we show the attacking process with the probabilities of its prediction of the MLP on MNIST dataset.

3.4 Ability of SVAE for Type I attack on strong classifier

The above experiments illustrate the MLP as a weak classifier is cheated through the Type I adversarial examples. The next implies it is also possible to attack a strong classifier using the diversity of the generated images from SVAE. In this experiment, SVAE is trained on CelebA dataset with a gender classification oracle of 94.9% accuracy, which is designed to attack FaceNet [17] in face recognition task. We directly use the trained FaceNet model [24] which achieves 99.05% accuracy on LFW [23] dataset for face recognition. The same face alignment, whitening and other pre-processing procedures are carried out as recommended in [17] in our experiment. FaceNet model is regarded as a strong classifier compared to SVAE trained for gender classification, because the same gender is a necessary condition of the same person and the network of FaceNet is much deeper than SVAE. Here,
we calculate the success rate (SR) of Type I attack on the first 1000 images of the validation set in CelebA. The successful attack criterion for image pair \((x, x')\) is defined to satisfy the three conditions: \(f_1(x) = f_1(x')\); \(x\) and \(x'\) are of different gender; \(x'\) is clean for judgement. As recommended in FaceNet, the distance threshold is set to 1.242 \([17]\) in \(k\). Several human experts are invited to make judgements of the last two conditions. More examples are provided in SM.

The SR of Type I attack through SVAE is more than two thirds among the first thousand images on CelebA validation dataset. Some of the examples are illustrated in Figure 4(b). The results show that a weak classifier in SVAE can also conduct Type I attack against a relatively strong classifier in high success rate.

### 4 Discussion and Conclusion

False positive and false negative rates are both important evaluation criteria for the performance of classifiers. Type I adversarial attack by generating a totally new and meaningful image, which is misclassified into the same class by the attacked classifier, is almost blank in research, since it is more difficult than cheating classifier by adding small disturbance on the sample to judge it into another class as Type II adversarial attack.

In this paper, a supervised variational auto-encoder framework is proposed as a generative method to generate adversarial examples for Type I attack. In this framework, the oracle classifier is modelled explicitly to provide supervised information for generating a new and meaningful adversarial example. Rather than directly manipulating in the image space which leads to noise eventually, we propose a generating algorithm for Type I attack by revising the latent variables in the latent space according to the gradients both from the oracle and the attacked classifier, and then those updated variables are recovered into images through a decoder. In order to obtain stable and convincible gradients from the oracle, a discriminator is designed to restrict latent variables to locate on the manifold through the iterative generating algorithm. Our experiments show that even a relatively weak oracle in our framework can generate Type I adversarial examples to cheat strong classifier due to the diversity of generative ability of SVAE model.

The image size and quality may be further improved through the latest researches on generative methods. We hope our results stimulate a more comprehensive view on adversarial examples and inspire the consideration of the adversarial co-training among classifiers in different classification tasks through a generative model as the bridge to increase their generalization abilities, of which there remains much scope.
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