FakeSafe: Human Level Data Protection by Disinformation Mapping using Cycle-consistent Adversarial Network

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Introduction

One of the best ways for data protection is to hide real information in fake information. The English term “disinformation” is defined as “false information with the intention to deceive opinion” with slightly negative meaning. However, the idea of disinformation can be borrowed into data science world for private data protection. As more and more data are becoming digitized, efficiency of data transfer, replication and usage has increased significantly in recent years. In addition, due to the development of system like federated data networks, data sharing among large number of institutions and devices becomes possible (Jordon, Yoon, and van der Schaar 2018; Liu, Diligach, and Miller 2019; Mukherjee et al. 2019; Shao, Liu, and Liu 2019). These advances bring convenience to our society. Nevertheless, they also raise big concerns on data security and privacy, especially in sensitive fields like healthcare and personal finance. Despite efforts in data encryption, secure computation and other methods trying to protect data, there is always a chance that data can be leaked due to either technological or human reasons. In addition to technological level protection of data, human level protection is often overlooked (Jensen 2013; Lee and Gostin 2009; Joly et al. 2016). In this study, we aim at developing a technology that provides an additional layer of protection of private data by mapping the original information onto a fake domain that looks realistic but unidentifiable to human. By doing this, even if the data is leaked, the malicious attackers will not be able to know whether the data they obtained are fake, and, therefore, unable to retrieve the original real information, which is similar to the concept of disinformation.

One of the biggest promises of deep learning is its ability to discover rich representation and approximate complex mapping functions (Goodfellow et al. 2014; Bengio and others 2009). Recent advances in generative models such as generative adversarial networks (GANs) utilized these properties of deep learning and significantly simplified some previously difficult tasks such as image-to-image translation and images based text generation (Zhu et al. 2017; Mirza and Osindero 2014). Derivatives and modifications of GAN based models have been used and achieved outstanding performance in many fields (Odena, Olah, and Shlens 2017; Makhzani et al. 2015; Radford, Metz, and Chintala 2015). These tools can also be used to protect data privacy.

GANs and its derivatives have achieved impressive result in data generation, style transferring and many other fields (Goodfellow et al. 2014; Zhu et al. 2017). The ability of GAN related models to generate data that are indistinguishable from the real data comes from the idea of adversarial loss. Cycle consistency is a concept originated from machine translation, where a phrase translated from one language to another, after translated back, should be identical to the original phrase. Cycle consistency has been widely applied in machine learning especially in computer vision related tasks (Konečný et al. 2017; Zhou et al. 2016). One recent success in combing GANs and cycle consistency was in image style transferring by CycleGAN (Zhu et al. 2017). In this study, we combined GANs and consistency loss to develop a method named FakeSafe to map the private information onto a fake message that looks indistinguishable from the real messages. The fake message can be either from the same domain of the original private information, or from a completely different domain. FakeSafe can be used during data transfer, data storage, data usage or other scenarios in combination of traditional encryption and security technologies. Using toy data sets as well as real world clinical data set, we conducted a proof-of-concept experiments to explore how well FakeSafe can help protect private information at human level and the quality of reconstructed data from fake domain.

FakeSafe

Motivation and formulation

The purpose of FakeSafe method is to map the original private information onto a fake but realistically looking message. The method consists of two parts: 1) a function $F$ that maps a private message $X$ to a fake message $X_{fake}$, i.e. $X_{fake} = F(X)$. $X_{fake}$ can be from the same domain as $X$, such as a human face image, or a completely different domain. 2) a reconstruction function $R$ that maps the fake message back to original message. $F$ and $R$ are specific to each data set.
System

In our system of interest, we are assuming there is a sender of private information, a targeted receiver of information. The data transfer/storage infrastructure is not 100% safe and the malicious attackers might try to steal the private information. Only the data sender has access to function $F$ to map the private data to fake domain. Only targeted receiver has access to function $R$ to retrieve the original data. Even if the attacker obtains $X^{fake}$, without additional information, it is impossible for him or her to know that the data is fake, because $X^{fake}$ looks realistic. If $X$ and $X^{fake}$ are from the same data domain, e.g. mapping a set of human faces into another set of human faces, even if the attacker knows before hand what the data is supposed to look like, it is difficult to notice if the data has been mapped by FakeSafe method into fake messages.

Generative adversarial networks (GAN) with cycle consistency loss

GAN was used as the function $F$ to map private information to fake message in this study due its good performance in generating fake data sets that look realistic to human. Generative model $F(X)$ is trained against discriminator $D$ to make the outputs of $X^{fake} = F(X)$ look indistinguishable from the samples used to train $D$. We name this type of $X^{fake}$ messages as FakeSafe messages. $D$ and $F$ were trained in an alternating manner. The objective loss function for training generator and discriminator is:

$$L(x, x^{fake}, F, D) = E[log(D(X^{fake}))] + E[log(1 − D(F(X)))]$$  \hspace{1cm} (1)

$F$ generates data points that look indistinguishable from real data in fake message domain. Least loss was used to train the GAN due to reported stability (Zhu et al. 2017). Therefore, when training GAN, we train $F$ to minimize $E[1 − D(F(X))]^2$ and train $D$ to minimize $E[D(F(X))]^2$.

After the other party receives the FakeSafe message, it will be recovered using a trained model $R$ such that $R(F(X)) \approx X$. To enable the ability of $R$ to retrieve the original message from $X^{fake}$, cycle-consistency was used to make reconstructed data $R(X^{fake})$ matching the original data $X$. The loss function is

$$L(F, R, X) = E[||R(F(X)) − X||]$$

For reconstruction errors, we used absolute loss. For simplicity, fully connected neural network with leaky ReLU was used in both generator and discriminator models.

Model implementation

As this is a proof-of-concept study, 1) for the image-image generator model, we used a simple 3 layer fully connected neural network with 256, 512 and 1024 units. 2) For the text-image generator model, we used a 4 layer fully connected neural network with 64, 256, 512 and 1024 units. Leaky ReLU was used as the activation functions for hidden layers and batch normalization was applied in both image-image and text-image generator model. 3) For the image-text generator model, we used a 4 layer fully connected neural network with 128, 256, 512 and 1024 units. Leaky ReLU was also used as the activation function, and a dropout with rate 0.2 was introduced to avoid over-fitting. The adam optimization with learning rate of 0.0002 was used in the above 3 cases.

Experiments and results

In order to understand whether our FakeSafe method works in protecting information transfer, we conducted three types of proof-of-concept experiments. First, we encoded information into fake messages from the same data domain, using MNIST and MNIST fashion as example. Second, we encoded information into fake messages from a different domain, such as MNIST digitals to MNIST fashion. Last, we explored the possibility of multi-step FakeSafe encoding of
Figure 2: FakeSafe method uses a Generative Adversarial Network (GAN) with cycle consistency to map original private data to fake data (A) and reconstruct original information from the fake message (B).

FakeSafe mapping onto the same data domain

One potential application of FakeSafe is to map private information on other same data domain but different data points. We conducted four experiments: \( \text{MNIST} \rightarrow F \rightarrow \text{MNIST} \rightarrow R \rightarrow \text{MNIST} \), \( \text{Fashion} \rightarrow F \rightarrow \text{Fashion} \rightarrow R \rightarrow \text{Fashion} \), \( \text{Face} \rightarrow F \rightarrow \text{Face} \rightarrow R \rightarrow \text{Face} \) and \( \text{Word} \rightarrow F \rightarrow \text{Word} \rightarrow R \rightarrow \text{Word} \).

When conducting experiments on MNIST, Models \( F, D, R \) were all trained using the training sets with images of 10 handwritten digits. Therefore, \( X^{\text{fake}} = F(X) \) can be any possible number from the training set and might not have to be the same digits as \( X \). As shown in figure , the recovered images \( R(F(X)) \) have the same labels as the original images \( X \), while the FakeSafe images \( F(X) \) are different.

In a similar manner, when conducting experiments on MNIST fashion data set which contain objects from 10 different categories, such as "shoe" or "dress", \( R(F(X)) \) have the same labels as the original message \( X \) and could differ from labels of \( X^{\text{fake}} = F(X) \).

When conducting experiments on human face images, original data \( X \) is a human face image which was mapped to another human image \( X^{\text{fake}} = F(X) \) that could be from the same person or a different person.

When conducting experiments on English words, original data \( X \) is a 50-dimension word embeddings which was mapped to another 300-dimension word embeddings \( X^{\text{fake}} = F(X) \) that could be from the same word or a different word.

In order to evaluate quality of the reconstructed message \( R(F(X)) \), two metrics were used. First, reconstruction errors between \( R(F(X)) \) and \( X \) were calculated as...
mean squared errors. Second, in order to know whether the reconstructed messages $R(F(X))$ still look like from the same class or individual as $X$ to human, we trained a classifier $C$ on $X$ in the training set to classify their labels, i.e. the digits, fashion category or individual ID, and apply $C$ onto reconstructed data $R(F(X))$. The accuracy, F1 score, precision and recall of $C(R(F(X)))$ were compared with the original labels of $X$.

The MNIST→F→MNIST→R→MNIST FakeSafe experiment achieved a reconstruction error of 1.62, classifier precision of 0.90, recall of 0.80 and F1 score of 0.81. In the Fashion→F→Fashion→R→Fashion experiment (Table 1), FakeSafe achieved a reconstruction error of 1.2, classifier precision of 0.71, recall of 0.72 and F1 score of 0.70. The real world human face image data set, FakeSafe method achieved a reconstruction error of 1.06, precision of 0.95, recall of 0.92 and F1 score of 0.92.

FakeSafe mapping onto a different data domain

Hide privacy information onto fake messages of the same type can help protect the information by misleading the malicious attackers. However, sometimes it is better not to expose the original information domain at all. Therefore, we conducted experiments to FakeSafe map information into the message in a different domain. We conducted 4 experiments, MNIST→F→Fashion→R→MNIST, Fashion→F→MNIST→R→Fashion, Face→F→MNIST→R→Face and Word→F→Fashion→R→Word. The performances are comparable to FakeSafe mapping onto the same data domain (Table 1).

Specifically, for the experiment Word→F→Fashion→R→Word, we have tried two different approaches to map the original messages. In the first approach, we will tokenize the original messages, which are the English words, and then map the tokens to MNIST fashion images using FakeSafe. During the decoding process, we will map the MNIST fashion images back to tokens, which will be eventually converted back to English words. In the second approach, we will first convert the words to word embeddings with 50 dimensions, using GloVe Word Embeddings, and then map the word embeddings to MNIST fashion images. During the decoding process, we will use FakeSafe to map the MNIST fashion images back to word embeddings, and then decode back to the original words by finding the word with the smallest cosine similarity with the decoded word embeddings. It is noteworthy that, the second approach, which uses word embeddings as the original messages, is proved to achieve better performance than the first approach, which only uses word tokens as the original messages.

Deeper FakeSafe mapping

To guarantee the safety of sensitive data, one may ask why not map the original private multiple times using a cascade of different $F$ functions, so that even if the attacker knows the message is fake, he or she will not know how many steps the messages were mapped. In order to explore the feasibility of deeper FakeSafe mapping, we conducted a series of experiments of 2-step and 3-step FakeSafe using MNIST, fashion and face images (Figure and Table 2). Our results suggest that even it is possible to conduct multi-step FakeSafe mapping, the reconstruction error increased and classification accuracy decreased dramatically.
Table 1: Performance of FakeSafe mapping onto the same domain or different domain

| Experiment | Original message | FakeSafe message | Reconstruction error | Precision | Recall | F1 Score | Type | Remark |
|------------|------------------|------------------|----------------------|-----------|--------|----------|------|--------|
| Face->Face | Face image       | Face image       | 1.06                 | 0.95      | 0.92   | 0.92     | Same domain | -     |
| MNIST->Fashion->MNIST | MNIST digits | Fashion digits | 1.82                 | 0.79      | 0.87   | 0.81     | Same domain | -     |
| Fashion->Fashion->Fashion | Fashion image | Fashion image | 1.2                  | 0.74      | 0.73   | 0.73     | Same domain | -     |
| Word->Word->Word->Word | English words (50d embeddings) | English words (50d embeddings) | NA        | 0.65      | 0.68   | 0.66     | Same domain | All 202 words |
| Face->MNIST->Fashion->Face | Face image | MNIST digits | 0.1                  | 1         | 1      | 1        | Cross domain | -     |
| MNIST->Fashion->Fashion->MNIST | MNIST digits | Fashion image | 1.3                  | 0.91      | 0.88   | 0.88     | Cross domain | -     |
| Fashion->Fashion->Word->Word | Fashion image | English words (50d embeddings) | NA        | 0.96      | 0.96   | 0.96     | Cross domain | Top 100 frequent words |
| Word->Fashion->Fashion->Fashion->Word | English words (300d embeddings) | Fashion image | NA        | 0.65      | 0.68   | 0.66     | Cross domain | All 202 words |

Figure 5: Multi-step FakeSafe mapping. The reconstruction errors increase with depth.

Table 2: Performance of multi-step FakeSafe mapping

| Experiment | Reconstruction error | Precision | Recall | F1 Score | Type |
|------------|----------------------|-----------|--------|----------|------|
| mnist->mnist->mnist->mnist->mnist->mnist | 9.4 | 0.75 | 0.64 | 0.63 | two-step |
| fashion->mnist->mnist->mnist->mnist->fashion | 11 | 0.81 | 0.72 | 0.73 | two-step |
| face->fashion->mnist->mnist->fashion->face | 37.1 | 0.66 | 0.56 | 0.59 | two-step |
| mnist->mnist->mnist->fashion->fashion->fashion->mnist->mnist | 17.3 | 0.48 | 0.44 | 0.39 | three-step |
| face->mnist->fashion->fashion->fashion->fashion->mnist->face | 88.8 | 0.29 | 0.36 | 0.29 | three-step |
Conclusion

In this article, we propose a method, named FakeSafe, to provide human-level private data protection by mapping each data point into a fake message that looks realistic to human. We utilized GANs with cycle-consistency to build a function to map the original data to fake message and another function to map the fake message back to the original data. Both functions are data set specific and can be easily adjusted for the other data sets. FakeSafe method gives users flexibility to map private data onto different data domains depending on use cases. In addition, FakeSafe can be easily used in combination with traditional data protection technologies but focus on human-level protection which takes human factors in data security and privacy into consideration.

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Table 3: Performance of Supplementary Experiments

| Experiment | Original message | FakeSafe message | BLEU score | Type | Data set | Remark |
|------------|-----------------|-----------------|------------|------|---------|--------|
| Sentence→F→Fashion→R→Sentence | Sentence states | Fashion image | 0.04 | Cross domain | Tatoeba (7761 words) | Use seq2seq model |
| Sentence→F→Fashion→R→Sentence | Sentence states | Fashion image | 0.33 | Cross domain | small_vocab_en (202 words) | Use seq2seq model |
| Sentence→F→Fashion→R→Sentence | English words (50d embeddings) | Fashion image | 0.48 | Cross domain | small_vocab_en (202 words) | Use word embeddings |

**Appendix**

Furthermore, we have also conducted a supplementary FakeSafe experiment case Sentence→F→Fashion→R→Sentence, the performance of which is demonstrated in Table 3. We have tried two different approaches to conduct the experiment.

In the first approach, we have trained a Seq2Seq model using the GRU layer, which will encode the sentence sequence to the internal hidden states, and then decode back to the original sentence sequence. Then we will map the internal states, which are generated by the Seq2Seq encoder, to MNIST fashion images. During the decoding process, we will use FakeSafe to map the MNIST fashion images back to the internal states used by the Seq2Seq model, and further decode back to the sentence.

In the second approach, considering that Word→F→Fashion→R→Word model achieves good performance on 50-dimension words embeddings, we have attempted to train a Word→F→Fashion→R→Word model first. Then we have split the sentence into a list of words, and each of the words will be encoded into a MNIST fashion image. Eventually, the MNIST fashion images will be decoded back to the list of words, which will be further converted to the sentences.