中国科学技术大学

CNU Beamer Theme

Author

University of Science and Technology of China

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Outline

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1. problem background
   - Data for machine learning
   - Generative model for privacy protection
2. Solution:generate fake data
   - Introduction of GAN
   - problem of generative model
3. How to Solve privacy leakage in Generative Model
   - Review DP
4. How to Solve privacy leakage in Generative Model
   - Review the concept DP
   - How to define privacy and utility in Generative Model
     - Whether an item is sampled from the dataset
     - utility
5. Tasks and Division of work

Data for machine learning

- **Age of big data**

  machine learning becoming a hit
  require a large amount of data from real world

- **Privacy data**

  like human face and fingerprint...
  sensitive and individual but of high practical value
  a tradeoff between data diversity and data utilization

Generative model for privacy protection

- **Generative model**

  adding noise to real data without exposing the original figure
  little significance if only copy input to output

- **Related work**

  DP-SGD[1]
  effective in generating high-dimensional sanitized data
  difficult implement
  PATE
  only train generators with DP guarantees
  high privacy costs
  Fed-Avg GAN
  provide user-level DP guarantees merely works on decentralized data

Introduction of GAN

- **Generator**

  create fake data from random sample
  sample $Z = (z_1, z_2, ...z_n)$
  $\tilde{Z} = G(Z)$

- **Discriminator**

  discriminate between fake and real data

$$D(X, G(Z)) = \begin{cases} 0, & \text{if input} \in G(Z) \\ 1, & \text{if input} \in X \end{cases}$$

- **Task of two part**

  Generator G(Z) closer to X, the better
  Discriminator distinguish G(Z) and X more, the better

$$\min_G \max_D V(G, D)$$

- Most privacy-preserving training algorithms for neural network models is **manipulating** the gradient information generated during backpropagation.
- **Methods**
  Clipping the gradients (to bound sensitivity)
  Adding calibrated random noise (to introduce stochasticity)
- **Problem**:limited in shallow networks and fail to sufficiently capture the sample quality of the original data.

- **Neighboring dataset**

  D, D':differed with only a piece of data

- **(Differential Privacy**

  $Pr[M(D) \in O] \leq e^{\epsilon} Pr[M(D') \in O] + \delta$

  M:a random algorithm
  O: output set
  ϵ: privacy budget
  smallerϵ, $M(D)$ and $M(D')$ closer
  δ:disturbance

Suppose $\mathcal{M} : \mathbb{R}^n \to X$, X is called mapping Space and $\mathcal{M}$ is called map from origin space into mapping space. For two dataset x and x', they only has one-item difference.We call $\mathcal{M}$ satisfies (ϵ, δ)-privacy if following statement is true

$$Pr[\mathcal{M}(x) \in S] \leq e^{\epsilon} Pr(\mathcal{M}(x') \in S) + \delta \tag{1}$$

What is $\mathcal{M}$,input space and mapping space in this scenario?

Acccording the define of [2],$\mathcal{M}$ is the generative model.Its input space is consisted with training data and its mapping space is consisted with its output. Take Conditional-VAE for an example.Suppose training data takes with following formular

$$(X, y) = (x_i, y_i)_{i=1}^{n} \tag{2}$$

it is consisted with n data samples and $x_i \in \mathbb{R}^n, y_i \in \mathbb{R}$,$x_i$ is the data(such as an image) and y_i is the label of the image.$\mathcal{M}$ is a model which generate new data from existing data and label.

privacy define

Possibility is hard to quantify for NN model.So we take several ways to varify our model satisify (ϵ, δ) privacy

From Attackers

One of the goal of the attacker is to varify whether a data is from or not from the dataset.If the privacy dataset $\mathcal{D}$ is revealed.We can build the attacker from $\mathcal{D}$

- sample k data $x \in \mathcal{D}$ and sample k noise from $\mathbb{R}^n$ but $\notin \mathcal{D}$.Denoted as $X = x_1, x_2, \cdots, x_k$ and $Y = y_1, y_2, \cdots, y_k$
- X is true data,we attack label *True* to all its data and Y is fake data which randomly sample from $\mathbb{R}^n$,so we attach *False* label into Y,mixture X, Y and its labels T together
- build a classifier $\mathcal{C}$, which takes true/fake image as input and output the Possibility of whether the input pattern is belonged to True/Generated Data.Train the model with supervised learning method

In this term,privacy true image $\mathcal{X}$ is not provided for training of $\mathcal{C}$.We provided generative training data $\hat{mathcalX}$ which is generated from privacy dataset $\mathcal{D}$.

For Attackers

suppose P is the Possibility attacker could correctly varify the real data through generative data.We define privacy loss

$$privacy\ \ loss = \frac{P - 0.5}{0.5} \tag{3}$$

use generative data for image classifier task.We train the downstream image classifier model with Training data T_{train} and validate the training accuracy with testing data T_{test}.There are four condition for utility measurement.

accuracy / test data / train data	privacy data	generative data
privacy data	p_1	p_2
generative data	p_3	p_4

We call $p_1 - p_2$ accuracy loss from the generative process

Work Schedule

- Gaohaihan: Algorithm design and implementation of main model and add privacy into whole model
- ChenXiaolu: Research of previous work and implementation of Attackers
- Zhangli: Report writing,research of privacy attack and implementation of utility network

Thank you!

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Differentially private data generative models.
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