Mining GOLD Samples for Conditional GANs

Sangwoo Mo*
KAIST
swmo@kaist.ac.kr

Chiheon Kim
Kakao Brain
chiheon.kim@kakaobrain.com

Sungwoong Kim
Kakao Brain
swkim@kakaobrain.com

Minsu Cho
POSTECH
mscho@postech.ac.kr

Jinwoo Shin
KAIST, AItrics
jinwoos@kaist.ac.kr

2020.01.21

Presented by Yonggyu Kim

Introduction

Training GANs (including cGANs) are known to be often hard and highly unstable.

Numerous techniques have thus been proposed to tackle the issue from different angles.
- Improving architectures : SAGAN, SNGAN
- Losses and regularizers : WGAN-GP
- Other training heuristics : Self-supervised GAN

One promising direction for improving GANs would be to make GANs diagnose their own training and prescribe proper remedies.

Most previous methods on this line focus on classic unconditional GANs (data-only densities), whereas discrepancy measures specialized for cGANs (data-attribute joint densities) have rarely been explored.

Contribution
- The paper propose a novel discrepancy measure for cGANs that estimates the gap of log-densities(GOLD) of data and model distributions on given samples.

- The authors present three applications of the GOLD estimator : example re-weighting, rejection sampling, and active learning

Preliminary : Conditional GANs

There are two ways to use the attribute information:

(a) Providing it as an additional input to the discriminator (CGAN)
- The model learns the joint distribution p(x, c)

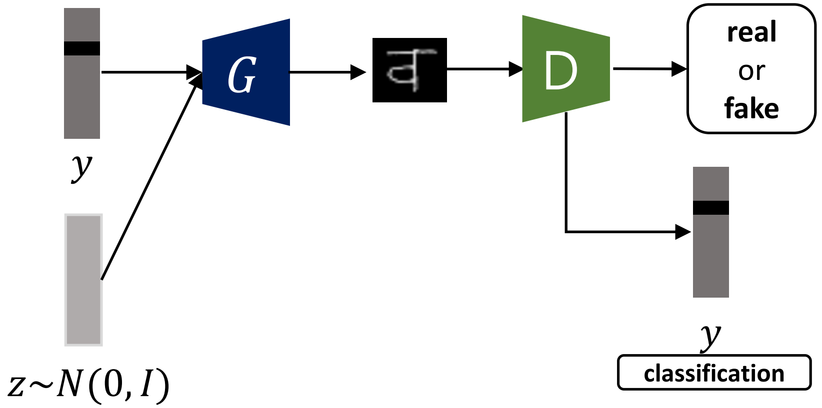
(b) Using it to train an auxiliary classifier for the attribute (ACGAN)
- The model separately learns the marginal p(x) and the conditional p(c|x)

They address training cGANs in a semi-supervised setting.

They consider the gap of log-densities (GOLD)

$$\log p_{\text{data}}(x,c) - \log p_g(x,c) = \underbrace{\log \frac{p_{\text{data}}(x)}{p_g(x)}}_{\text{marginal}} + \underbrace{\log \frac{p_{\text{data}}(c|x)}{p_g(c|x)}}_{\text{conditional}}$$

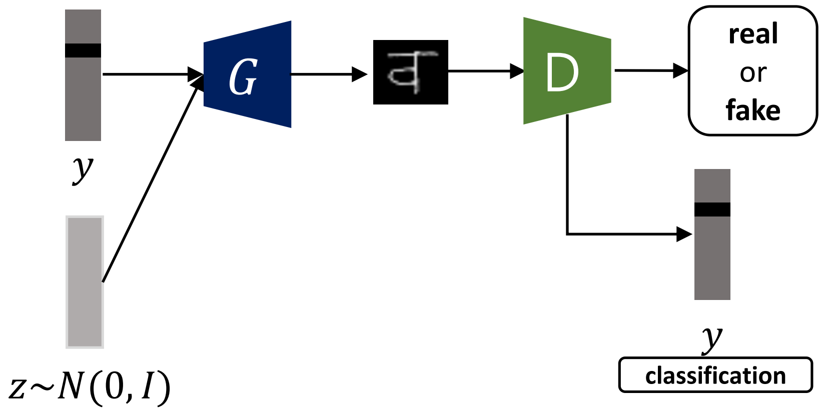
Image quality Class accuracy



$$\mathcal{L}_{\text{GAN}} = \mathbb{E}_{(x,c)\sim p_{\text{data}}(x,c)}[-\log D_G(x)] + \mathbb{E}_{(z,c)\sim p_g(z,c)}[\log D_G(G(z,c))],$$

$$\mathcal{L}_{\text{AC}} = \mathbb{E}_{(x,c)\sim p_{\text{data}}(x,c)}[-\log D_C(c|x)] + \lambda_c \mathbb{E}_{(z,c)\sim p_g(z,c)}[-\log D_C(c|G(z,c))],$$

Method



They consider the gap of log-densities (GOLD)

$$\log p_{\text{data}}(x,c) - \log p_g(x,c) = \underbrace{\log \frac{p_{\text{data}}(x)}{p_g(x)}}_{\text{marginal}} + \underbrace{\log \frac{p_{\text{data}}(c|x)}{p_g(c|x)}}_{\text{conditional}}$$

They assume the ideal (or optimal) discriminator $D^* = (D_G^*, D_C^*)$

$$d(x, c_x) := \begin{cases} \log \frac{D_G(x)}{1-D_G(x)} + \log D_C(c_x|x) & \text{if } x \text{ is a generated sample of class } c_x \\ \log \frac{D_G(x)}{1-D_G(x)} - \log D_C(c_x|x) & \text{if } x \text{ is a real sample of class } c_x \end{cases}$$

$$D_G^*(x) = \frac{p_{\text{data}}(x)}{p_{\text{data}}(x)+p_g(x)}$$

They often observe that the scale of marginal term is significantly larger than the conditional term

$$d_{\texttt{bal}}(x, c_x) := \begin{cases} \log \frac{D_G(x)}{1-D_G(x)} + \frac{\sigma_G}{\sigma_C} \log D_C(c_x|x) & \text{if } x \text{ is a generated sample of class } c_x \\ \log \frac{D_G(x)}{1-D_G(x)} - \frac{\sigma_G}{\sigma_C} \log D_C(c_x|x) & \text{if } x \text{ is a real sample of class } c_x \end{cases}$$

where σ_G and σ_C are the standard deviations of marginal and conditional terms (among samples), respectively.

수렴을 증명x

Method & Experiments

$$d(x, c_x) := \begin{cases} \log \frac{D_G(x)}{1-D_G(x)} + \log D_C(c_x|x) & \text{if } x \text{ is a generated sample of class } c_x \\ \log \frac{D_G(x)}{1-D_G(x)} - \log D_C(c_x|x) & \text{if } x \text{ is a real sample of class } c_x \end{cases}$$

Example re-weighting

A high value of the GOLD sample (x, c) is under-estimated with respect to the joint distribution.

$$\mathcal{L}'_{\text{GAN}} = \mathbb{E}_{(x,c)\sim p_{\text{data}}(x,c)}[-\log D_G(x)] + \mathbb{E}_{(z,c)\sim p_g(z,c)}[d(G(z,c),c)^\beta \cdot \log D_G(G(z,c))],$$

$$\mathcal{L}'_{\text{AC}} = \mathbb{E}_{(x,c)\sim p_{\text{data}}(x,c)}[-\log D_C(c|x)] + \lambda_c \mathbb{E}_{(z,c)\sim p_g(z,c)}[-d(G(z,c),c)^\beta \cdot \log D_C(c|G(z,c))],$$

where $\beta \geq 0$ is a hyper-parameter to control the level of re-weighting and we use $x^\beta = -|x|^\beta$ for $x < 0$.

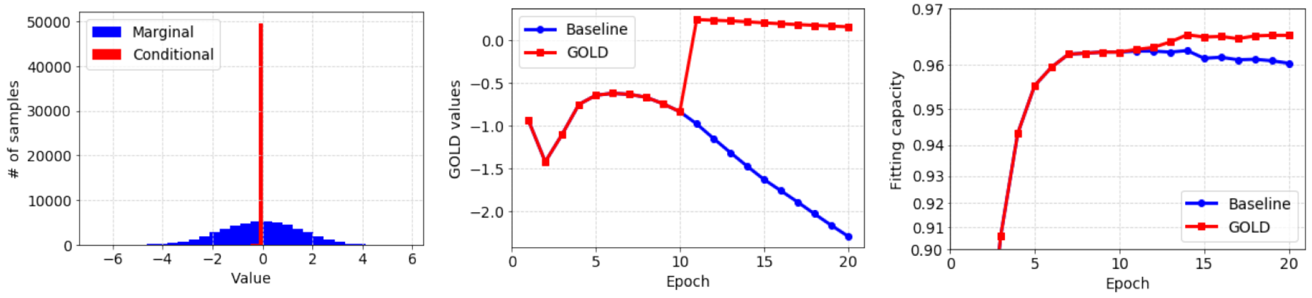
Distance 가 멀 때, stronger feedback을 통해서 위치를 강조

Table 1: Fitting capacity (%) [41] for example re-weighting under various datasets.

	MNIST	FMNIST	SVHN	CIFAR-10	STL-10	LSUN
Baseline	96.43$\pm$0.17	77.97$\pm$1.24	74.43$\pm$0.71	36.76$\pm$0.99	36.73$\pm$0.64	26.35$\pm$0.82
GOLD	**96.62**$\pm$**0.15**	**78.34**$\pm$**1.11**	**76.71**$\pm$**0.94**	**37.06**$\pm$**1.38**	**37.65**$\pm$**0.71**	**28.21**$\pm$**0.86**

Table 2: Fitting capacity (%) for example re-weighting under various levels of supervision.

	Dataset	1%	5%	10%	20%	50%	100%
Baseline	SVHN	72.41$\pm$1.30	72.99$\pm$1.65	73.15$\pm$0.96	73.18$\pm$1.28	74.04$\pm$1.26	74.33$\pm$0.71
GOLD	SVHN	**75.01**$\pm$**1.93**	**75.58**$\pm$**0.86**	**75.78**$\pm$**0.74**	**76.04**$\pm$**1.93**	**76.25**$\pm$**1.40**	**76.71**$\pm$**0.94**
Baseline	CIFAR-10	17.99$\pm$0.78	18.42$\pm$0.71	21.84$\pm$1.14	23.13$\pm$1.95	35.41$\pm$1.03	36.76$\pm$0.99
GOLD	CIFAR-10	**18.28**$\pm$**0.65**	**19.15**$\pm$**0.97**	**21.91**$\pm$**2.56**	**23.89**$\pm$**2.02**	34.95$\pm$1.11	**37.06**$\pm$**1.38**



(a) Marginal/conditional terms (b) GOLD estimator (c) Fitting capacity

수렴을 증명x

Method & Experiments

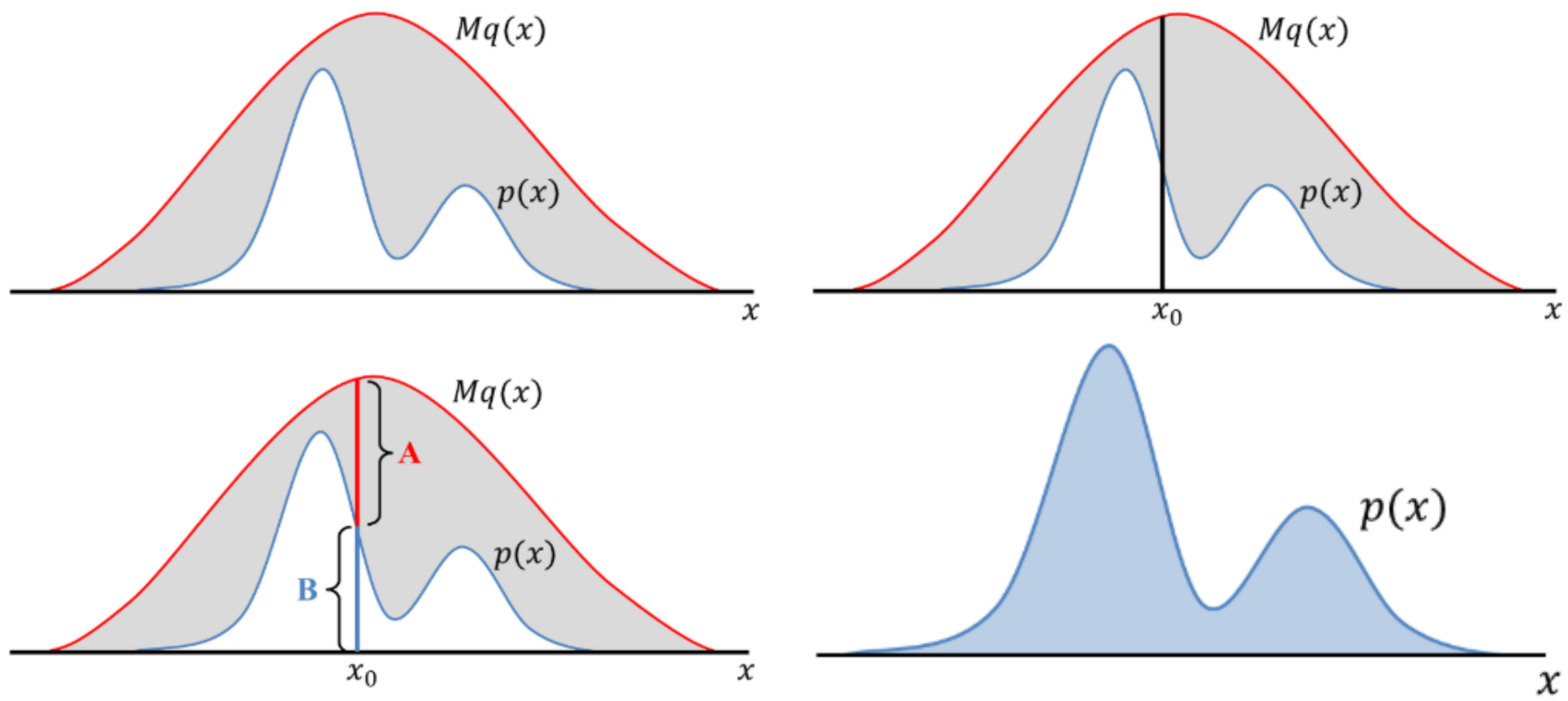
$$d(x, c_x) := \begin{cases} \log \frac{D_G(x)}{1-D_G(x)} + \log D_C(c_x|x) & \text{if } x \text{ is a generated sample of class } c_x \\ \log \frac{D_G(x)}{1-D_G(x)} - \log D_C(c_x|x) & \text{if } x \text{ is a real sample of class } c_x \end{cases}$$

Rejection sampling

$p(x, c)$: purpose distribution (목표 분포) $q(x, c)$: proposal distribution (제안 분포)

$$\frac{p(x,c)}{Mq(x,c)} \leq 1$$

q(x, c) 에서 샘플링 되었지만, p(x, c)에서 sampling 된 것처럼 sample들을 거름.



Algorithm 1: Rejection sampling

Input : the number of samples N, target distribution p, proposal distribution q, a given constant M

Output : samples $X = \{x_1, x_2, ..., x_N\}$

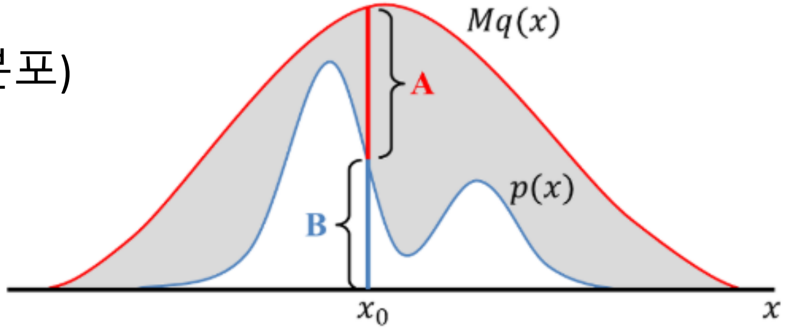
```
X = {}
while n < N do
    x_0 ~ q(x)
    u ~ U(0, 1)
    if u < p(x_0)/(Mq(x_0)) then
        X ← X ∪ {x_0}
        n ← n + 1
    end
end
```

Method & Experiments

$$d(x, c_x) := \begin{cases} \log \frac{D_G(x)}{1-D_G(x)} + \log D_C(c_x|x) & \text{if } x \text{ is a generated sample of class } c_x \\ \log \frac{D_G(x)}{1-D_G(x)} - \log D_C(c_x|x) & \text{if } x \text{ is a real sample of class } c_x \end{cases}$$

Rejection sampling

$p(x, c)$: purpose distribution (목표 분포) $q(x, c)$: proposal distribution (제안 분포)



$$r(x) := \frac{1}{M} \exp\left(d_{\texttt{bal}}(x, c_x)\right) = \frac{1}{M} \exp\left(\log \frac{D_G(x)}{1 - D_G(x)} + \frac{\sigma_G}{\sigma_C} \log D_C(c_x|x)\right)$$

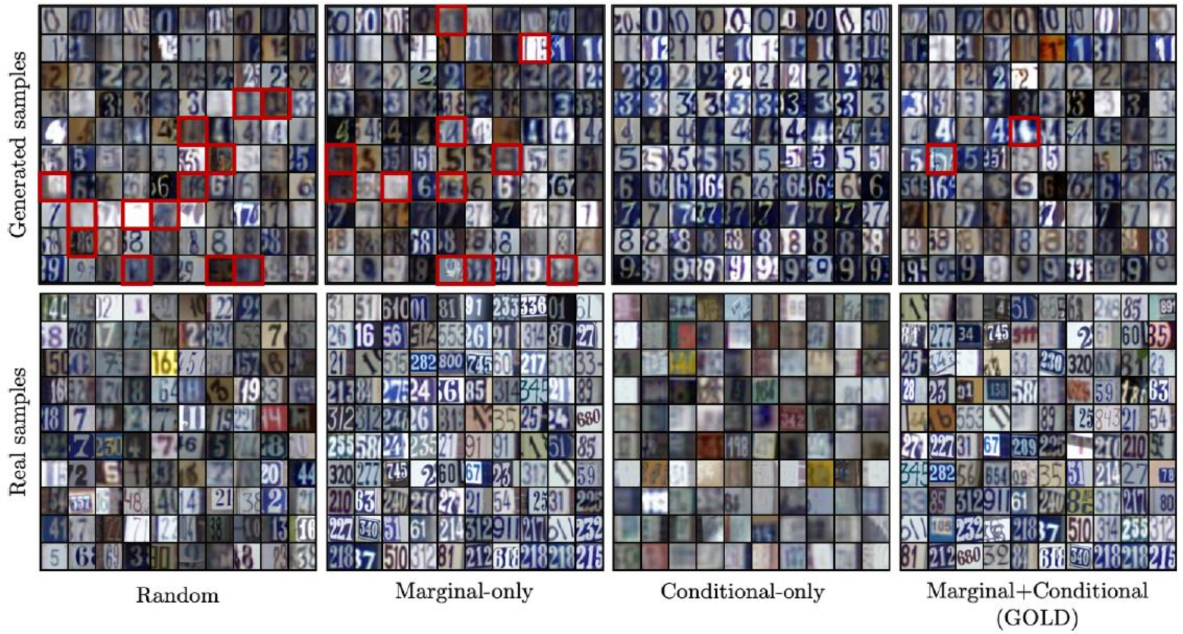


Table 3: Fitting capacity (%) for rejection sampling under various datasets.

	MNIST	FMNIST	SVHN	CIFAR-10	STL-10	LSUN
Baseline	$96.05_{\pm 0.41}$	$77.94_{\pm 0.83}$	$73.58_{\pm 0.72}$	$35.15_{\pm 0.51}$	$34.33_{\pm 0.30}$	$26.43_{\pm 0.14}$
GOLD	**96.17**$_{\pm 0.63}$	**78.25**$_{\pm 0.30}$	**75.06**$_{\pm 0.71}$	**35.98**$_{\pm 1.15}$	**35.21**$_{\pm 1.02}$	**26.79**$_{\pm 0.42}$

Table 4: Fitting capacity (%) for rejection sampling under CIFAR-10 and various p values.

Baseline	p = 0.1	p = 0.3	p = 0.5	p = 0.7	p = 0.9
$35.15_{\pm 0.51}$	$35.80_{\pm 0.42}$	$35.87_{\pm 0.61}$	**35.98**$_{\pm 1.15}$	$35.85_{\pm 0.53}$	$35.33_{\pm 0.53}$

Method & Experiments

Active learning

$$d(x, c_x) := \begin{cases} \log \frac{D_G(x)}{1-D_G(x)} + \log D_C(c_x|x) & \text{if } x \text{ is a generated sample of class } c_x \\ \log \frac{D_G(x)}{1-D_G(x)} - \log D_C(c_x|x) & \text{if } x \text{ is a real sample of class } c_x \end{cases}$$

$$d_{\texttt{unlabel}}(x) := \log \frac{D_G(x)}{1 - D_G(x)} + \mathcal{H}[D_C(c|x)],$$

$$-\log D_C(c_x|x) \approx \mathbb{E}_{c\sim D_C(c|x)}[-\log D_C(c|x))] = \mathcal{H}[D_C(c|x)]$$

$$d_{\texttt{unlabel-bal}}(x) := \log \frac{D_G(x)}{1 - D_G(x)} + \frac{\sigma_G}{\sigma_C} \cdot \mathcal{H}[D_C(c|x)]$$

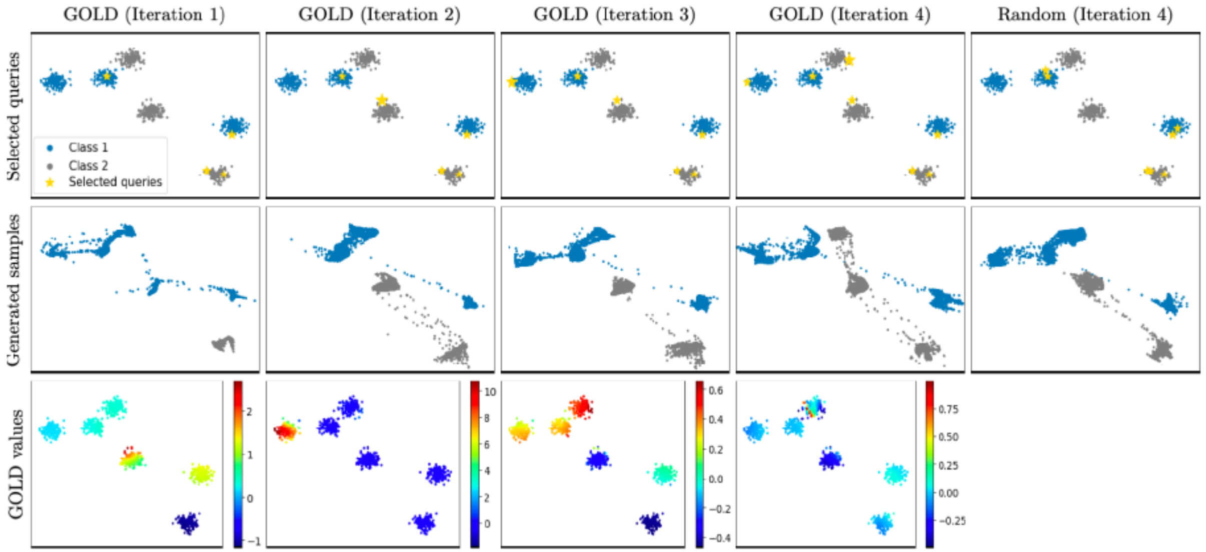
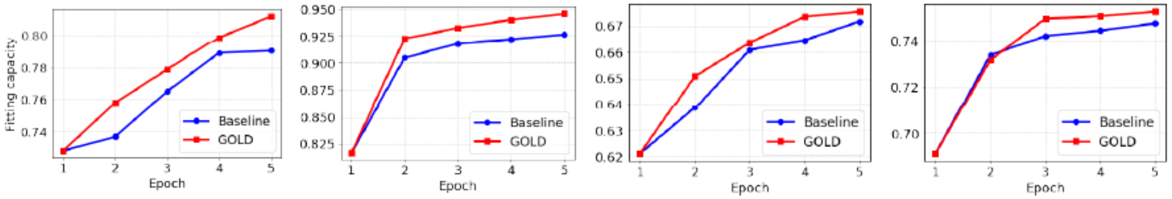


Figure 3: Visualization of the query selection based on the GOLD estimator. The first and second row are selected queries and generated samples, respectively. The third row is the GOLD estimator values, that the sample with the highest value is selected for the next iteration.



(a) Synthetic (b) MNIST (c) FMNIST (d) SVHN

Figure 4: Fitting capacity for active learning under various datasets.