TRAINING CONFIDENCE-CALIBRATED CLASSIFIERS FOR DETECTING OUT-OF-DISTRIBUTION SAMPLES

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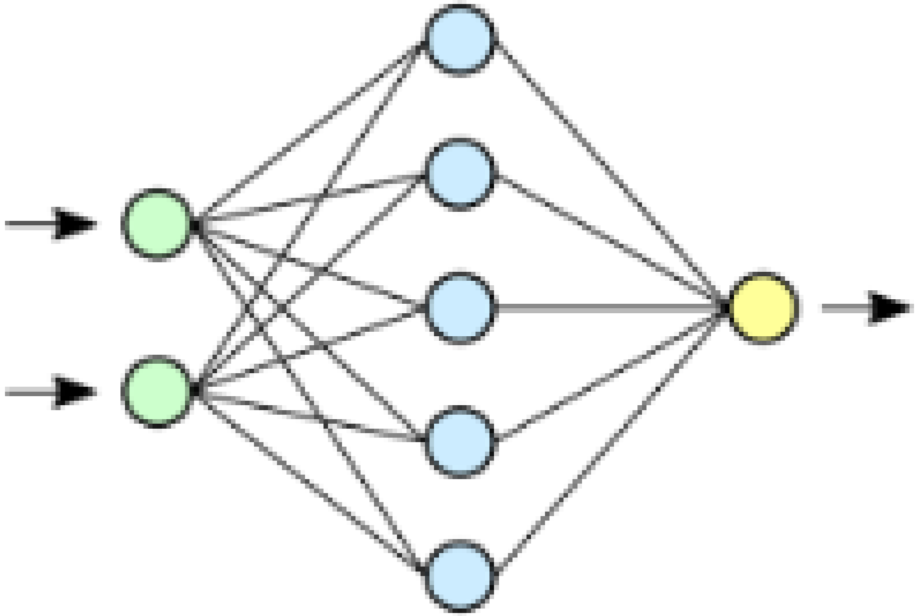
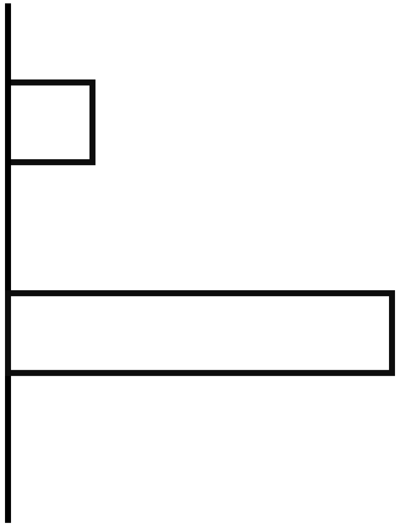
0. Contents

1. Detecting Out of distribution Detector





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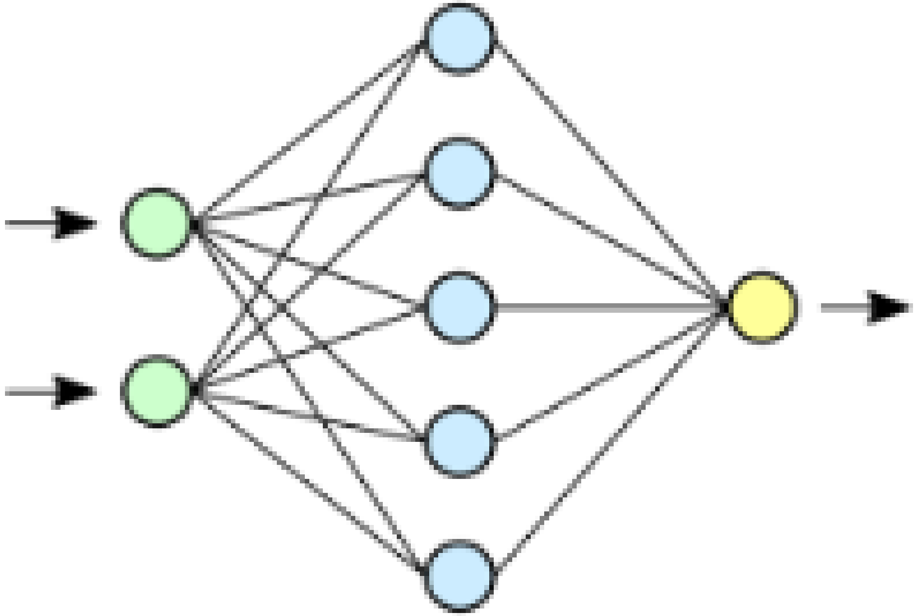
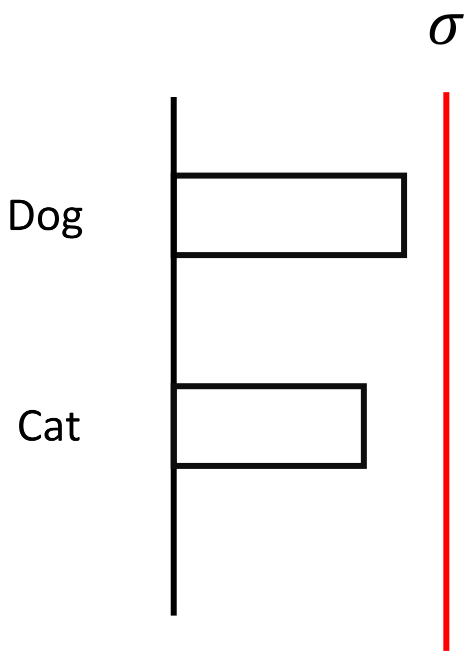
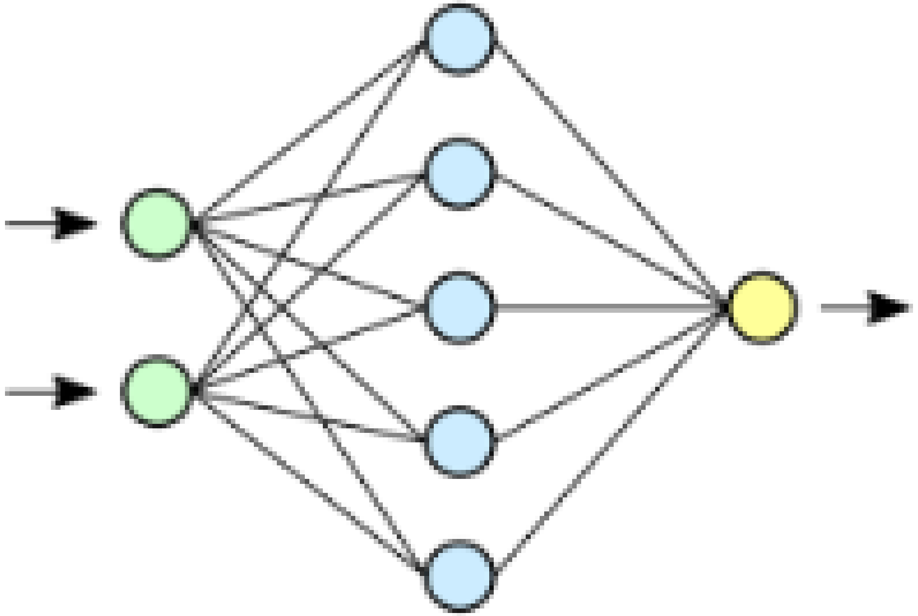
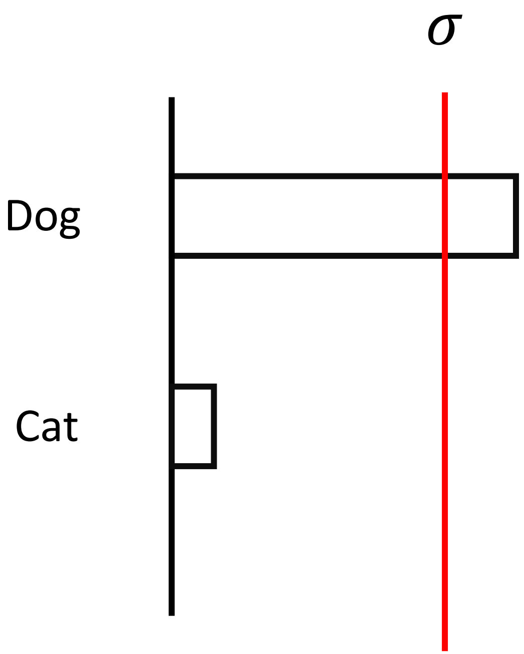




1. Detecting Out of distribution Detector

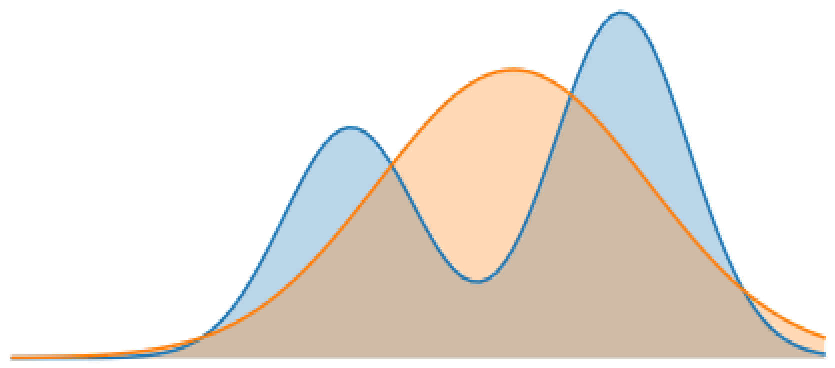




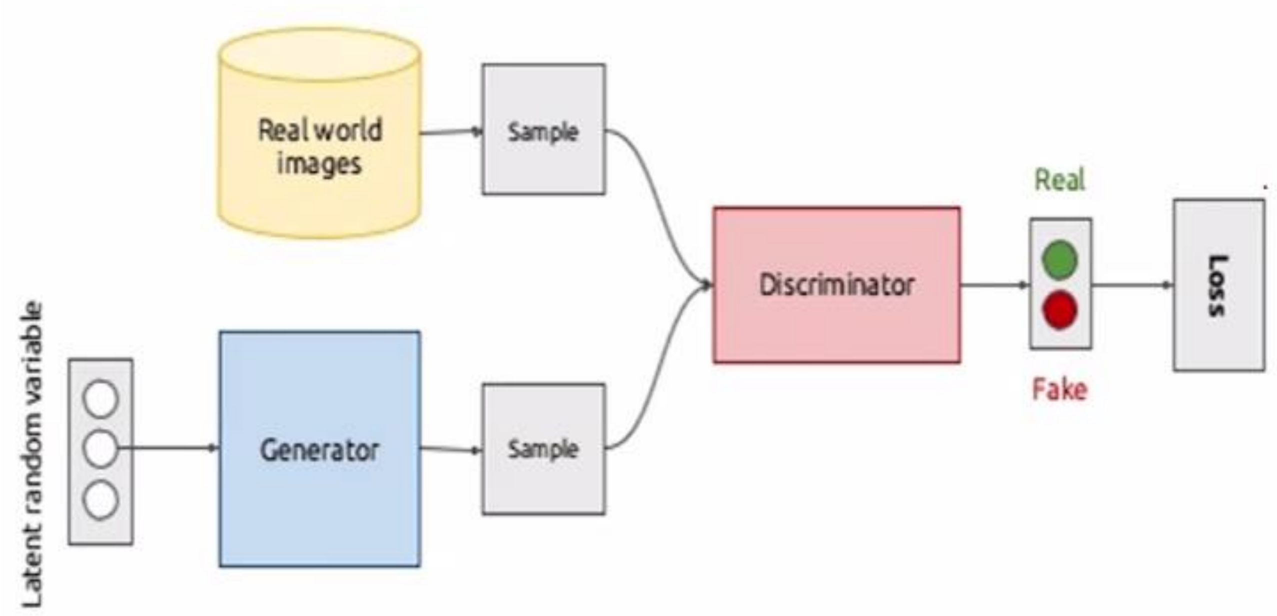
- 이전 Out of Distribution Network 는 pretrain된 모델을 기반으로 동작
- inference 단계만 사용하기 때문에 training 결과에 많이 의존

2. CONTRIBUTION

(KL) divergence



generative adversarial network (GAN)

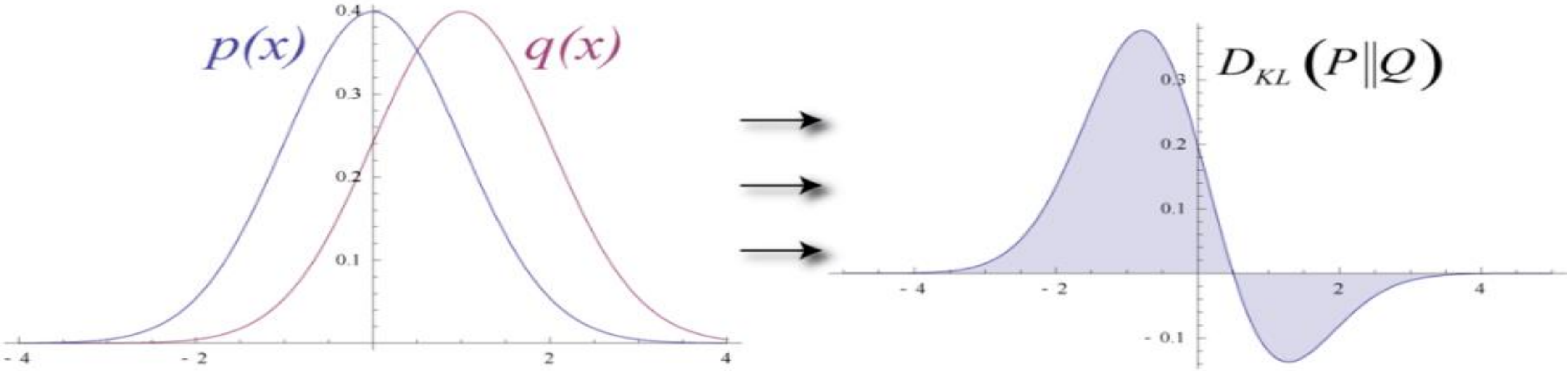


- KL-Div를 이용한 새로운 loss function을 제시
- GAN을 이용해 학습에 가장 효과적인 out-of-distribution Data를 생성

2. CONTRIBUTION

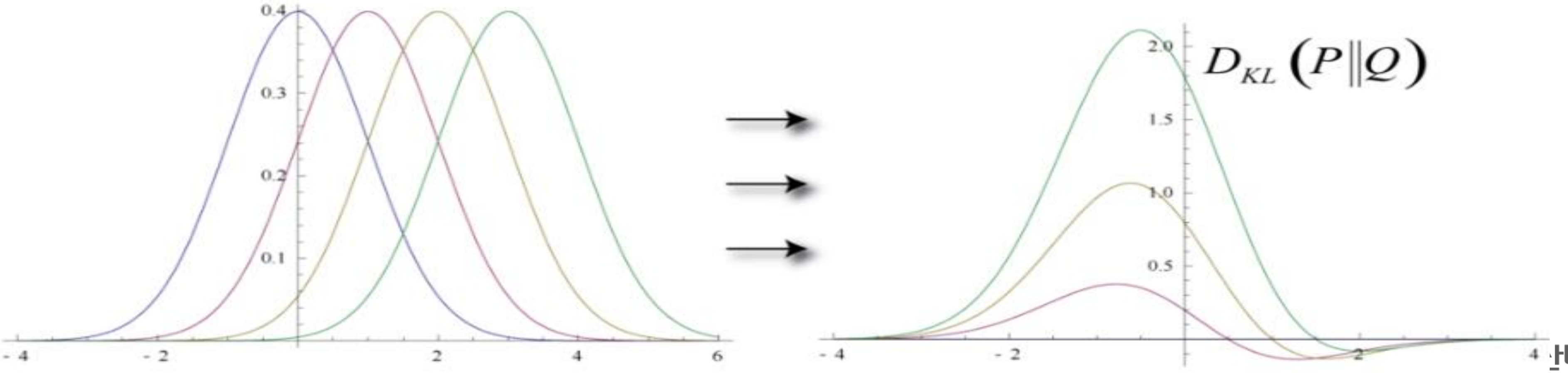
(KL) divergence

$$D_{\mathrm{KL}}(P \parallel Q) = \sum_{x \in \mathcal{X}} P(x) \log\left(\frac{P(x)}{Q(x)}\right).$$



Original Gaussian PDF's

KL Area to be Integrated



2. CONFIDENCE LOSS

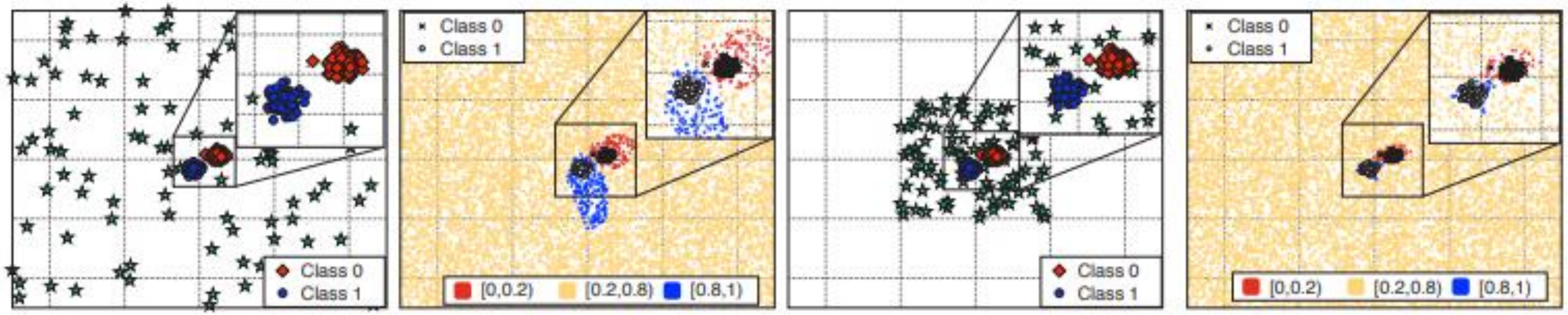
$$\min_{\theta} \boxed{\mathbb{E}_{P_{\text{in}}(\hat{\mathbf{x}},\hat{y})}\left[-\log P_{\theta}\left(y=\hat{y}|\hat{\mathbf{x}}\right)\right]} + \boxed{\beta\mathbb{E}_{P_{\text{out}}(\mathbf{x})}\left[KL\left(\mathcal{U}\left(y\right) \parallel P_{\theta}\left(y|\mathbf{x}\right)\right)\right]}$$

Cross Entropy loss

KL-Div. Term for Out of-dist. data

- Cross Entropy loss 같은 경우는 In-distribution data가 올바른 클래스를 예측하는 데 얼마나 잘 수행되는지
- KL-Div. Term 은 out-of-distribution data가 uniform한 분포를 가지도록 유도하는 과정
- 결론적으로는 In-dist 와 out-of-dist data가 모두 필요

2. CONFIDENCE LOSS



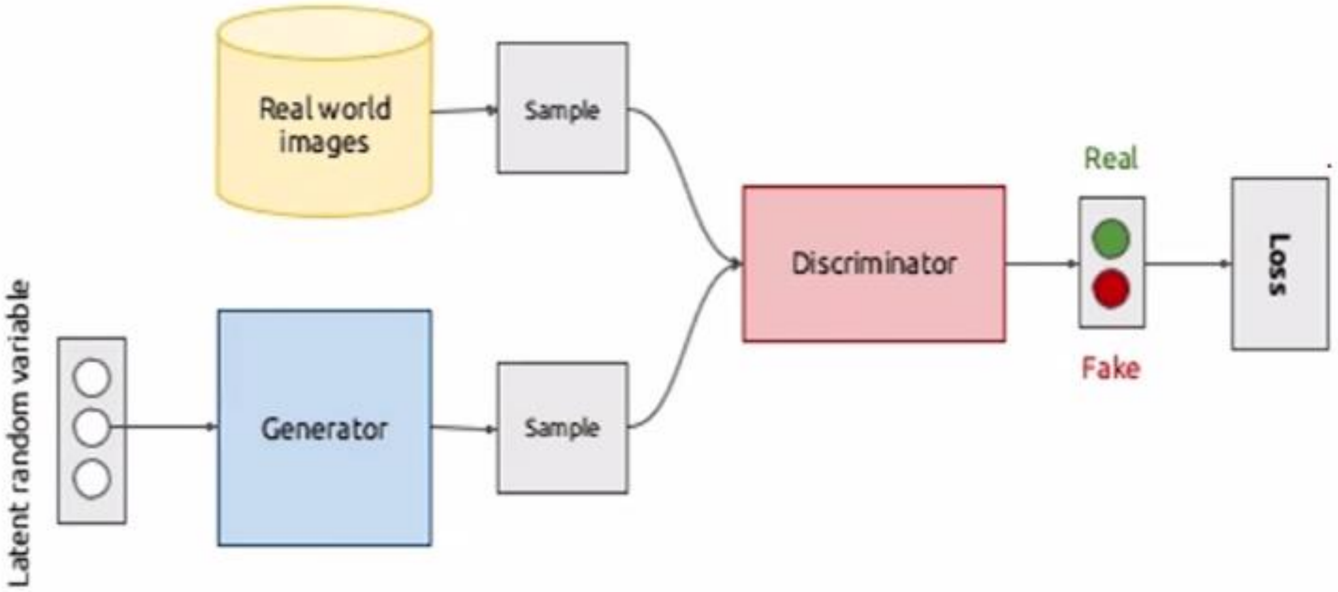
(a) (b) (c) (d)

Figure 1: Illustrating the behavior of classifier under different out-of-distribution training datasets. We generate the out-of-distribution samples from (a) 2D box $[-50, 50]^2$, and show (b) the corresponding decision boundary of classifier. We also generate the out-of-distribution samples from (c) 2D box $[-20, 20]^2$, and show (d) the corresponding decision boundary of classifier.

- (a) Out-of-distribution에 대한 전체 데이터 분포를 구성
- (b) CONFIDENCE CLASSIFIERS 을 이용해 학습한 데이터 분포
- (c) In-distribution 경계에 있는 Out-of-distribution 데이터 분포를 구성

3. ADVERSARIAL GENERATOR

GAN



Sample x from real data distribution

Sample latent code z from Gaussian distribution

$$\min_G \max_D V(D,G) = E_{x\sim p_{data}(x)}[\log D(x)] + E_{z\sim p_z(z)}[\log(1 - D(G(z)))]$$

D should maximize $V(D,G)$

Maximum when $D(x) = 1$

Maximum when $D(G(z)) = 0$

Modified GAN

$$\min_{G}\max_{D}\quad \beta\,\underbrace{\mathbb{E}_{P_G(\mathbf{x})}\left[KL\left(\mathcal{U}\left(y\right)\parallel P_\theta\left(y|\mathbf{x}\right)\right)\right]}_{\text{(a)}}$$
$$+\underbrace{\mathbb{E}_{P_{\text{in}}(\mathbf{x})}\left[\log D\left(\mathbf{x}\right)\right]+\mathbb{E}_{P_G(\mathbf{x})}\left[\log\left(1-D\left(\mathbf{x}\right)\right)\right]}_{\text{(b)}},$$

- (a) data가 out of distribution 과 비슷하게 만드는 Generator loss
- (b) in-distribution data 대해 올바르게 분류하고 생성자가 생성한 가짜 데이터가 실제와 구분 안되게 학습

3. JOINT OBJECT FUNCTION

JOINT TRAINING METHOD OF CONFIDENT CLASSIFIER AND ADVERSARIAL GENERATOR

Cross Entropy loss

KL-Div. Term for Out of-dist. data

$$\min_G \max_D \min_\theta \underbrace{\mathbb{E}_{P_{\text{in}}(\hat{\mathbf{x}},\hat{y})}\left[-\log P_\theta\left(y=\hat{y}|\hat{\mathbf{x}}\right)\right]}_{(c)} + \beta \underbrace{\mathbb{E}_{P_G(\mathbf{x})}\left[KL\left(\mathcal{U}\left(y\right) \parallel P_\theta\left(y|\mathbf{x}\right)\right)\right]}_{(d)}$$

$$\underbrace{+\mathbb{E}_{P_{\text{in}}(\hat{\mathbf{x}})}\left[\log D\left(\hat{\mathbf{x}}\right)\right] + \mathbb{E}_{P_G(\mathbf{x})}\left[\log\left(1-D\left(\mathbf{x}\right)\right)\right]}_{(e)}.$$

Modified GAN objective function

3. EXPERIMENTS

MI2L

In-dist	Out-of-dist	Classification accuracy	TNR at TPR 95%	AUROC	Detection accuracy	AUPR in	AUPR out
		Cross entropy loss / Confidence loss					
SVHN	CIFAR-10 (seen)	93.82 / **94.23**	47.4 / **99.9**	62.6 / **99.9**	78.6 / **99.9**	71.6 / **99.9**	91.2 / **99.4**
	TinyImageNet (unseen)		49.0 / **100.0**	64.6 / **100.0**	79.6 / **100.0**	72.7 / **100.0**	91.6 / **99.4**
	LSUN (unseen)		46.3 / **100.0**	61.8 / **100.0**	78.2 / **100.0**	71.1 / **100.0**	90.8 / **99.4**
	Gaussian (unseen)		56.1 / **100.0**	72.0 / **100.0**	83.4 / **100.0**	77.2 / **100.0**	92.8 / **99.4**
CIFAR-10	SVHN (seen)	80.14 / **80.56**	13.7 / **99.8**	46.6 / **99.9**	66.6 / **99.8**	61.4 / **99.9**	73.5 / **99.8**
	TinyImageNet (unseen)		**13.6** / 9.9	**39.6** / 31.8	**62.6** / 58.6	**58.3** / 55.3	**71.0** / 66.1
	LSUN (unseen)		**14.0** / 10.5	**40.7** / 34.8	**63.2** / 60.2	**58.7** / 56.4	**71.5** / 68.0
	Gaussian (unseen)		2.8 / **3.3**	10.2 / **14.1**	50.0 / 50.0	48.1 / **49.4**	39.9 / **47.0**

Table 1: Performance of the baseline detector (Hendrycks & Gimpel, 2016) using VGGNet. All values are percentages and boldface values indicate relative the better results. For each in-distribution, we minimize the KL divergence term in (1) using training samples from an out-of-distribution dataset denoted by "seen", where other "unseen" out-of-distributions were only used for testing.

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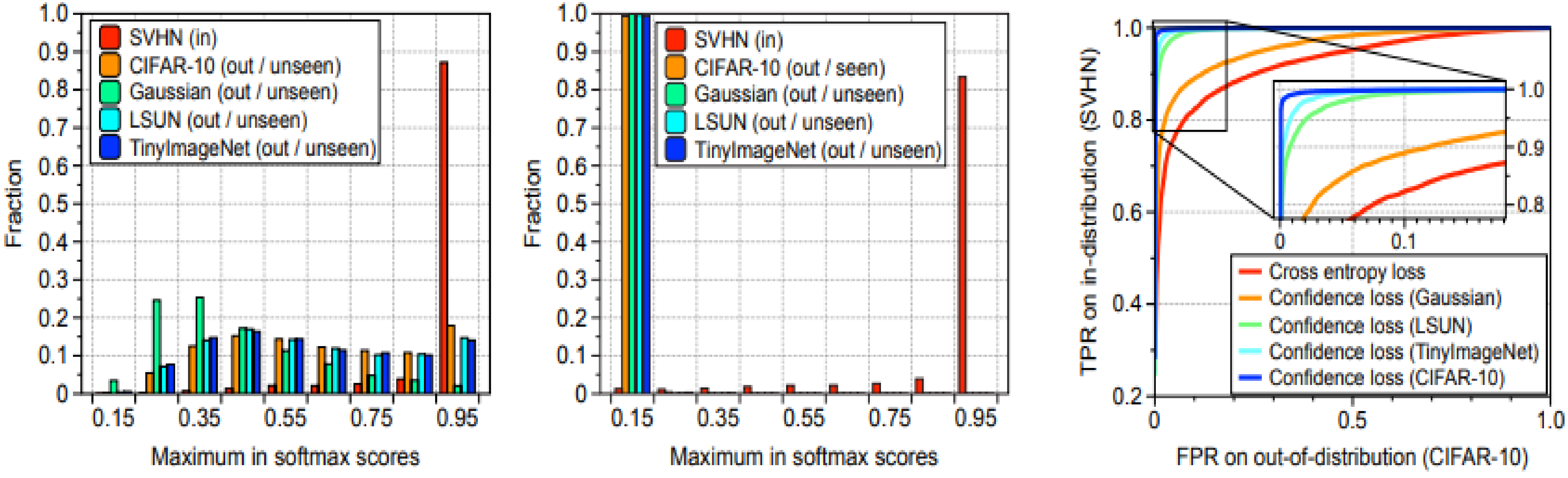
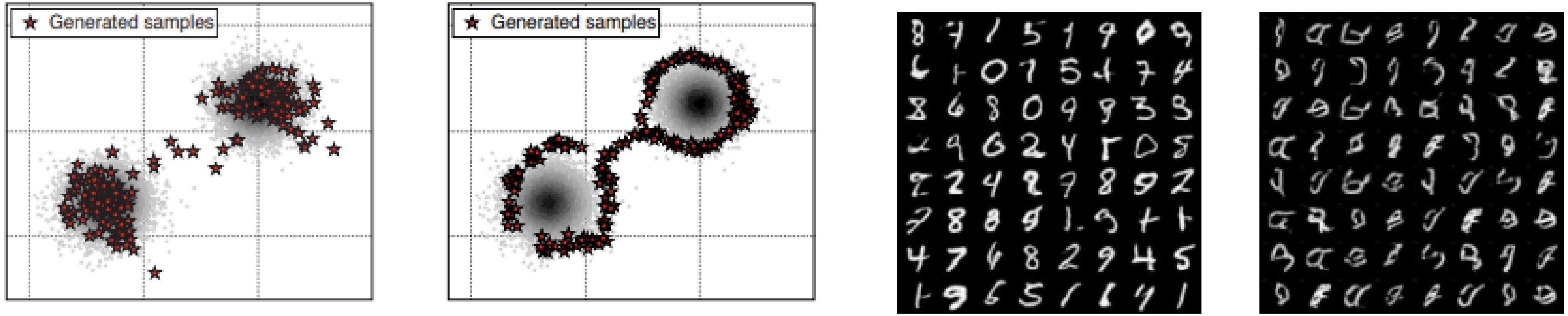
3. EXPERIMENTS



(a) Cross entropy loss (b) Confidence loss in (1) (c) ROC curve

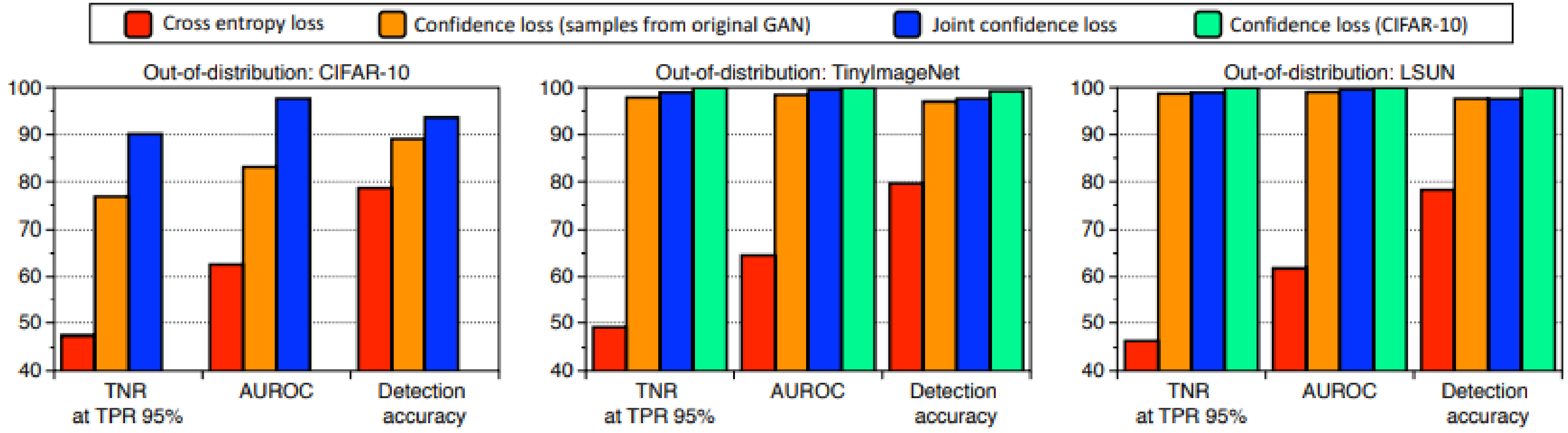
3. EXPERIMENTS



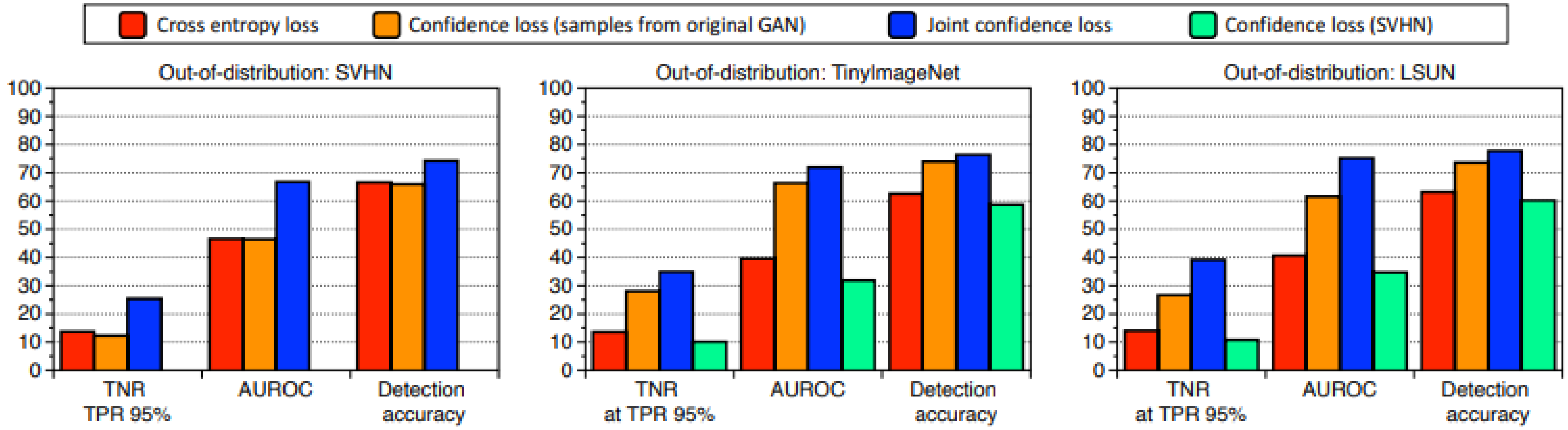
(a) (b) (c) (d)

Figure 3: The generated samples from original GAN (a)/(c) and proposed GAN (b)/(d). In (a)/(b), the grey area is the 2D histogram of training in-distribution samples drawn from a mixture of two Gaussian distributions and red points indicate generated samples by GANs.

3. EXPERIMENTS



(a) In-distribution: SVHN



(b) In-distribution: CIFAR-10