Adversarially Learned Anomaly Detection

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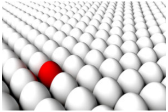
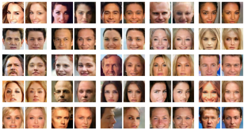
Context

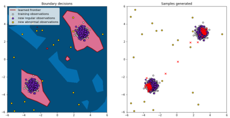
Problem: Perform anomaly detection



We wish to effectively model the data generating distribution ...



... and derive a statistically sound decision criteria for anomaly detection



Outline

Anomaly Detection methods

Brief overview of anomaly detection methods:

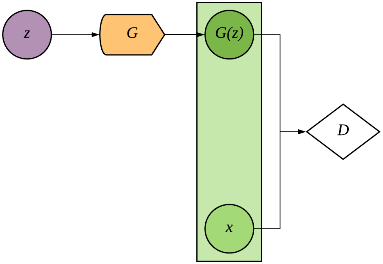
- Distance-based: NN [5]
- One-class classification: OCSVM [18]
- Reconstruction-based: PCA [10, 4]. Auto-encoders [21, 1]
- Energy or GMM based: DEBSM [19] and DAGMM [3]
- GANs method proposed in AnoGAN [17]

Shortcomings:

- For classic machine learning methods: curse of dimensionality in high dimensional data
- Neural network based: better modeling power with GANs
- GAN-based method: computationally highly expensive at inference time

What are GANs?

GANs [8]: two competing networks, generator G / discriminator D.



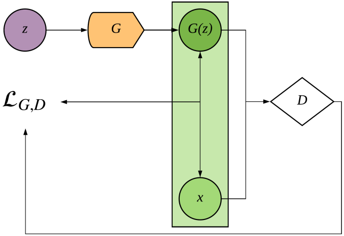
$$\min_G \max_D \mathbb{E}_{x \sim p_{\mathcal{X}}} \left[\log D(x) \right] + \mathbb{E}_{z \sim p_{\mathcal{Z}}} \left[\log \left(1 - D\left(G(z) \right) \right) \right]$$

Can model complex/high dimensional distributions of data [16]

Can we use GANs for Anomaly Detection?

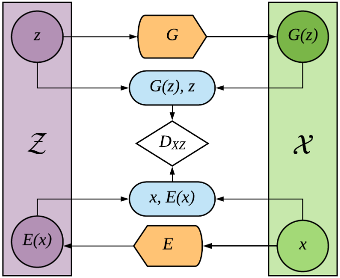
Reconstruction based: need to find latent representations.

AnoGAN [17]: standard GAN



$$z = \arg\min_z \mathcal{L}_{G,D}(z,x)$$

Bi-directionals GANs [7, 6]

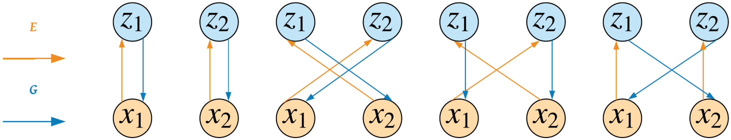


$$z = E(x)$$

500 forward/backward pass for AnoGAN, 1 forward pass for BiGANs

Cycle consistency

Non convergence to the saddle point optimization problem breaks cycle consistency $G(E(x)) \not\approx x$ (ALICE [12]).



Like ALICE [12], we impose a regularizer on the encoder E and the generator G with an additional discriminator network $D_{xx}(x, G(E(x)))$ to enhance $G(E(x)) \approx x$

Stabilizing the training

- Add another constraint on the latent space $D_{zz}(z, E(G(z)))$ to ensure $E(G(z)) \approx z$
- apply spectral normalization [14] on the discriminators of GANs [2, 9, 14, 20] and on the encoder

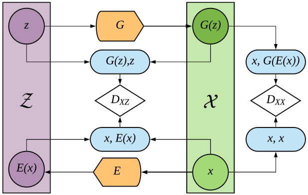


Figure: ALICE [17]

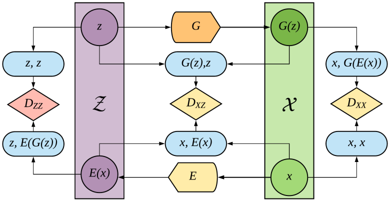
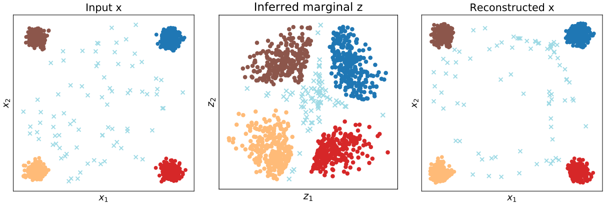


Figure: ALAD

Detecting anomalies

Train a model on the normal data to provide E, G.



Compute $A(x)$: L_1 reconstruction error between samples in the feature space of the cycle-consistency discriminator D_{xx}.

$$A(x) = \left|\left| f_{xx}(x, x) - f_{xx}(x, G(E(x))) \right|\right|_1$$

$f(\cdot, \cdot)$: activations of the layer before the logits (CNN codes) in the D_{xx} network for an input pair x, x'

Reconstructions

Normal
Reconstr.
Abnormal
Reconstr.

Figure: SVHN

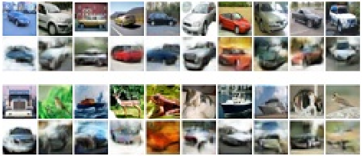


Figure: CIFAR10

Experiments

Experiments on publicly available tabular (KD99, Arrythmia [13]) and image datasets (CIFAR-10, SVHN [11, 15]).

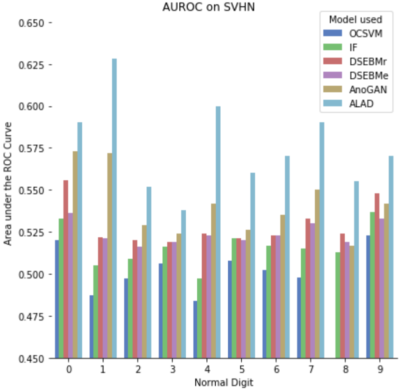


Figure: SVHN

Model	Prec.	Recall	F1
OC-SVM	0.746	0.852	0.795
IF	0.922	0.937	0.929
DSEBM-r	0.852	0.647	0.733
DSEBM-e	0.862	0.645	0.740
DAGMM	0.930	0.944	0.937
AnoGAN	0.879	0.830	0.887
ALAD	**0.943**	**0.958**	**0.950**

Table: KDD99

Ablation Study

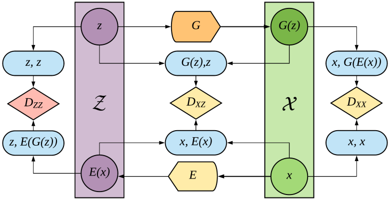


Figure: Spectral Norm (SN, yellow), Discriminator Latent (DL red)

Model	AUROC
Baseline	0.5701 ± 0.1282
Baseline + DL	0.5361 ± 0.1348
Baseline + SN	0.5991 ± 0.1308
Baseline + SN + DL	0.6072 ± 0.1201

Table: Ablation Study on CIFAR-10

Inference time

Dataset	Batch Size	AnoGAN	ALAD	Speed Up
KDD99	50	1235	1.4	~ 900
Arrhythmia	32	1102	41	~ 30
SVHN	32	10496	10.5	~ 1000
CIFAR-10	32	10774	10.5	~ 1000

Table: Average inference time (ms) on a GeForce GTX TITAN X

Conclusion

ALAD, a GAN-based anomaly detection method: not only effective, but also efficient at test time.

- Utilizes the bi-directional class of GANs [7, 6] to enable $\sim$ 1000X faster inference time.
- Better reconstructs samples with cycle-consistency technique [12].
- Uses training stabilization technique for GANs [14]
- Achieves state-of-the-art on a range of highdimensional tabular and image data.

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