Adversarially Learned One-Class Classifier for Novelty Detection

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Poster

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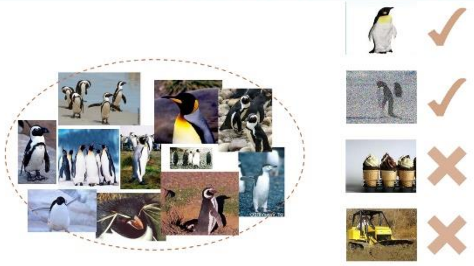
Motivation and Problem Statement



One-Class Classifier Applications:
- Novelty Detection
  - Outlier
  - Anomaly

- In reality, the novelty class is
  - absent during training, — No samples to train based on
  - poorly sampled, or — Too few samples (highly imbalanced classification)
  - not well defined — What is novelty?

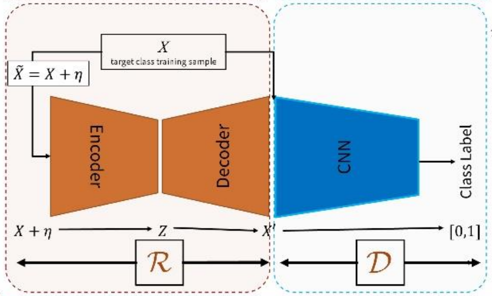
- Due to the unavailability of data from the novelty class, training an end-to-end deep network is challenging.

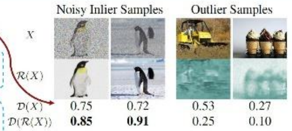
Method

Better discrimination power

Learns to **Reconstruct** the positive samples (samples from target class)

Learns the concept characterized by all positive samples (novelty **Detector**)





If exposed to negative samples (novelty), $\mathcal{R}$ decimates/distorts them.

The networks compete during training, but collaborate in testing.

Using the two networks at the testing time improves the results.

Joint Training of $\mathcal{R}+\mathcal{D}$

$\mathcal{R} \Rightarrow \tilde{X} = (X \sim p_t) + (\eta \sim \mathcal{N}(0, \sigma^2 \mathbf{I})) \longrightarrow X' \sim p_t$

$\mathcal{D} \Rightarrow \mathcal{R}(\tilde{X}) \sim p_t$?

$\mathcal{L}_{\mathcal{R}} = \|X - X'\|^2$

$\mathcal{L} = \mathcal{L}_{\mathcal{R}+\mathcal{D}} + \lambda \mathcal{L}_{\mathcal{R}}$

$$\min_{\mathcal{R}} \max_{\mathcal{D}} \Big(\mathbb{E}_{X \sim p_t}[\log(\mathcal{D}(X))] + \mathbb{E}_{\tilde{X} \sim p_t + \mathcal{N}_\sigma}[\log(1 - \mathcal{D}(\mathcal{R}(\tilde{X})))] \Big)$$

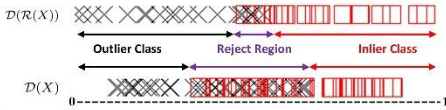
Similar to Generative Adversarial Networks (GANs)

Similar to denoising autoencoders (but for a target concept): $\mathcal{R}(X \sim p_t + \eta) \longrightarrow X' \sim p_t$

New concept? Does not know what to do, maps it to unknown distribution: $\mathcal{R}(\hat{X} \nsim p_t + \eta) \longrightarrow \hat{X}' \nsim p_?$ — Outlier or novelty sample

$\mathcal{D}$ is trained only to detect target samples, not novelty samples: $\mathcal{D}(X' \sim p_t) > \mathcal{D}(\hat{X}' \nsim p_t)$

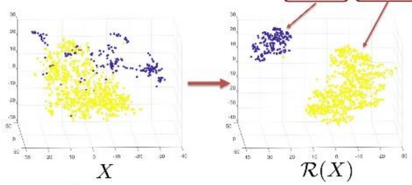
Output of $\mathcal{R}$ is more separable than the original input images: $\mathcal{D}(\mathcal{R}(X \sim p_t)) - \mathcal{D}(\mathcal{R}(\hat{X} \nsim p_t)) > \mathcal{D}(X \sim p_t) - \mathcal{D}(\hat{X} \nsim p_t)$

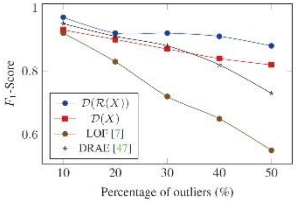


$$OCC_2(X) = \begin{cases} \text{Target Class} & \text{if } \mathcal{D}(\mathcal{R}(X)) > \tau, \\ \text{Novelty (Outlier)} & \text{otherwise.} \end{cases}$$

Experiments

- Outlier Detection (MNIST)
  - Trained to detect each digit separately
  - Other digits pose as outliers (10 to 50 percent)
  - Averaged results over all 10 digits are reported.



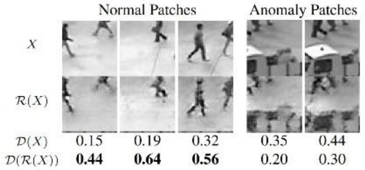


Experiments (cont'd)

- Outlier Detection (Caltech-256)
  - Similar to previous works [52], we repeat the procedure three times and use images from n={1; 3; 5} randomly chosen categories as inliers (i.e., target).
  - Outliers are randomly selected from the "clutter" category, such that each experiment has exactly 50% outliers.

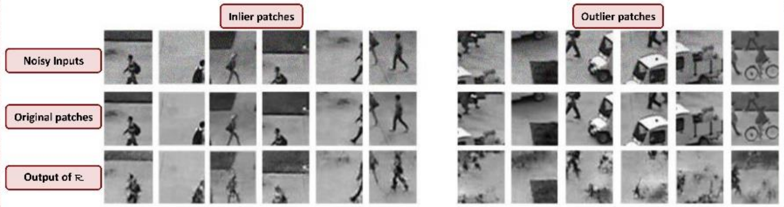
		CoP [32]	REAPER [22]	OutlierPursuit [50]	LRR [24]	DPCP [45]	R-graph [52]	Ours $\mathcal{D}(X)$	Ours $\mathcal{D}(\mathcal{R}(X))$
1 outlier category	AUC	0.905	0.816	0.837	0.907	0.783	**0.948**	0.932	*0.942*
	F_1	0.880	0.808	0.823	0.893	0.785	0.914	*0.916*	**0.928**
3 outlier categories	AUC	0.676	0.796	0.788	0.479	0.798	0.929	*0.930*	**0.938**
	F_1	0.718	0.784	0.779	0.671	0.777	0.880	*0.902*	**0.913**
5 outlier categories	AUC	0.487	0.657	0.629	0.337	0.676	*0.913*	*0.913*	**0.923**
	F_1	0.672	0.716	0.711	0.667	0.715	0.858	*0.890*	**0.905**

- Video Anomaly Detection (UCSD Ped2)



Frame-level comparisons

Method	EER	Method	EER
IBC [6]	13%	RE [36]	15%
MPCCA [19]	30%	Ravanbakhsh et al. [34]	13%
MDT [26]	24%	Ravanbakhsh et al. [33]	14%
Bertini et al. [4]	30%	Dan Xu et al. [48]	17%
Dan Xu et al. [49]	20%	Sabokrou et al. [37]	19%
Li et al. [23]	18.5%	Deep-cascade [39]	**9%**
Ours - $\mathcal{D}(X)$	**16%**	Ours - $\mathcal{D}(\mathcal{R}(X))$	**13%**



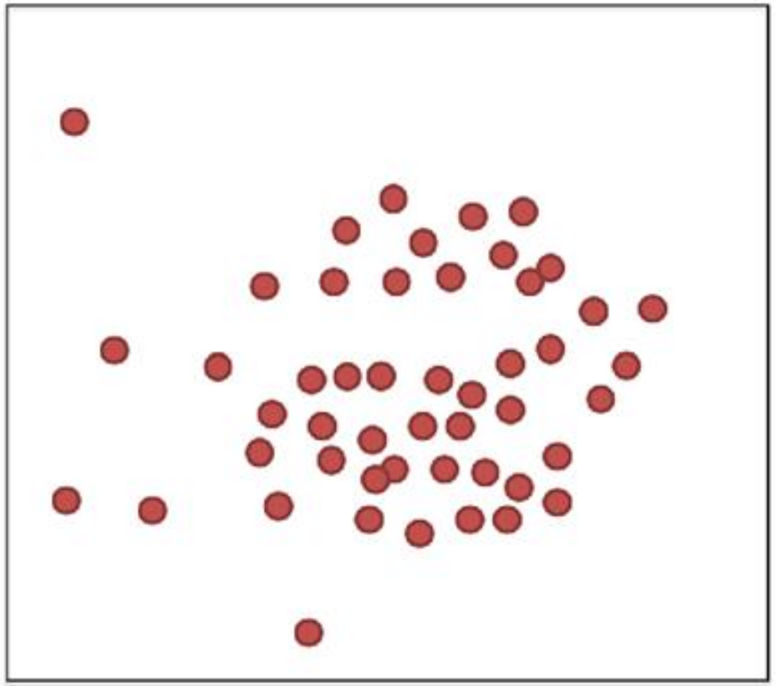
Conclusion

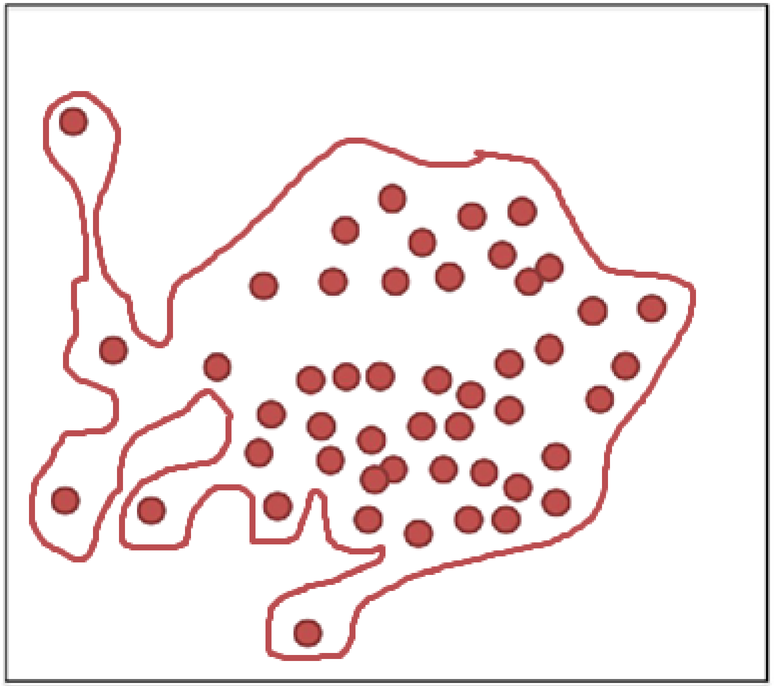
- Unlike majority of GAN applications, here, both trained networks are used in testing.
- After training the model, $\mathcal{R}$ can reconstruct target class samples correctly, while it distorts samples that do not have the concept shared among the target class samples, which indeed helps $\mathcal{D}$.
- No significant problems with Mode Collapse, as $\mathcal{R}$ directly sees all possible samples of the target class data and implicitly learns the manifold spanned by the target data distribution.
- **Questions:** sabokro@ipm.ir, eadeli@cs.stanford.edu, khalooei@aut.ac.ir

Outlines

- Definitions
- Motivation and problem statement
- Our method
- Joint training of R + D
- Experiments
- Our extended versions
- Summary!

Definitions

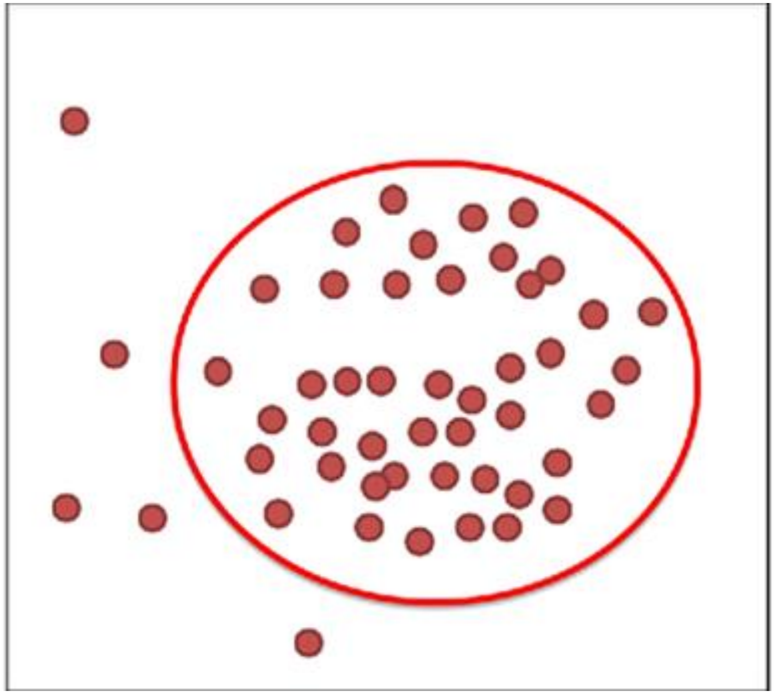




Very complex!

Overfit!

Definitions



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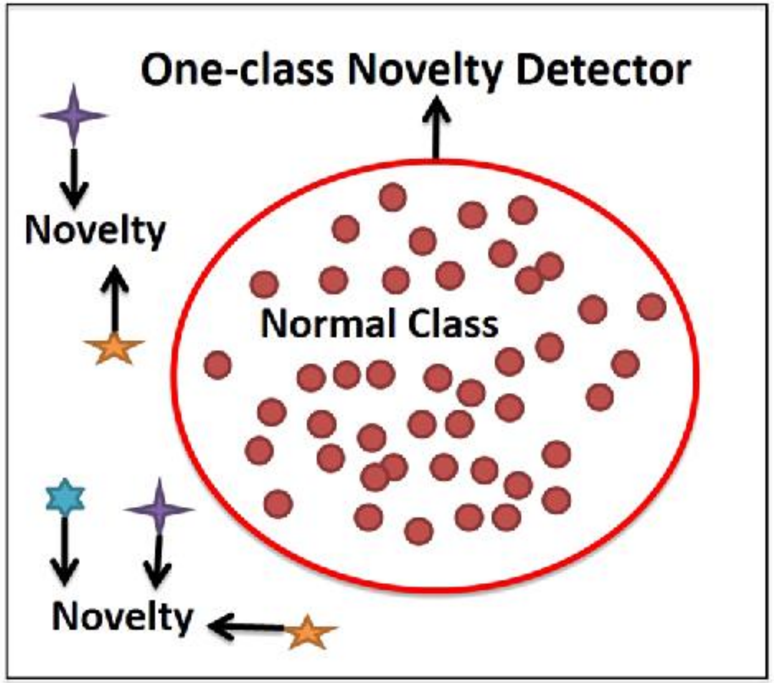

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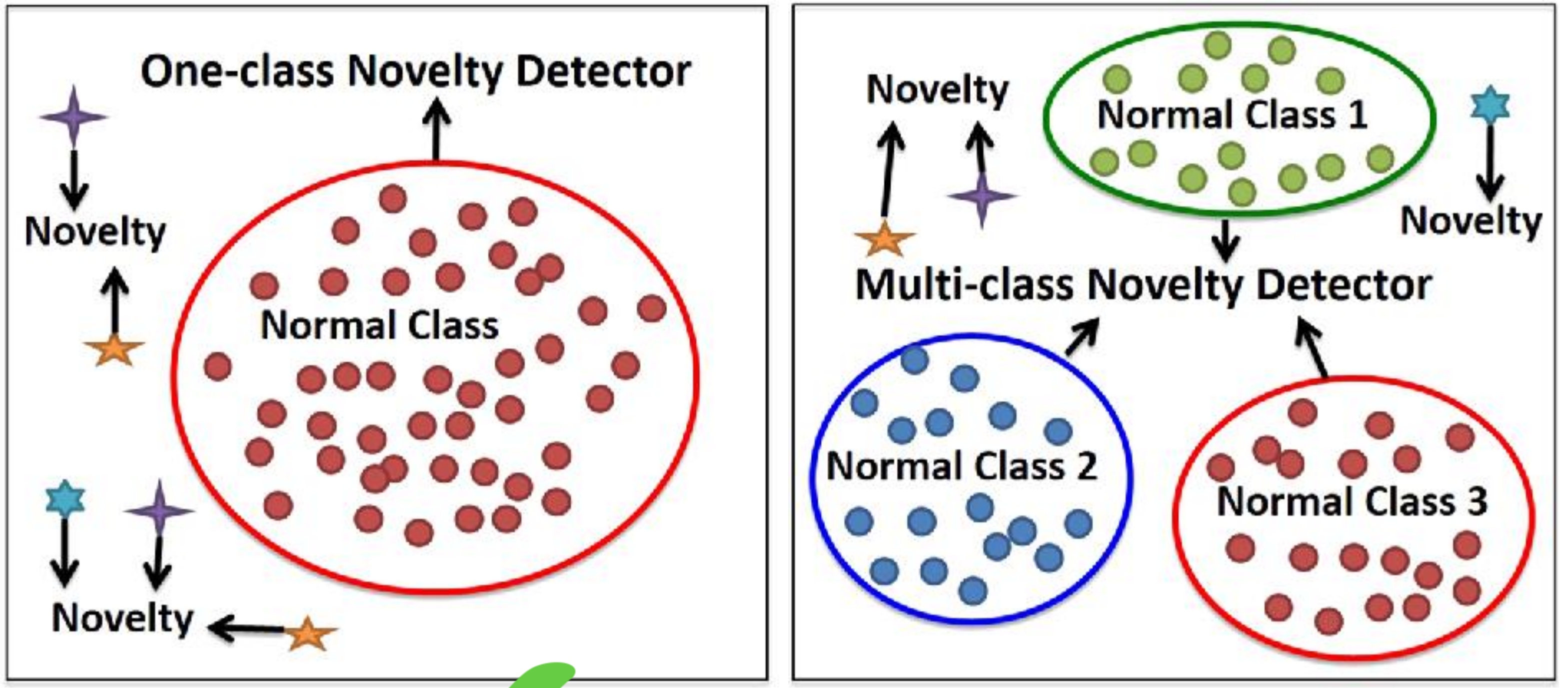
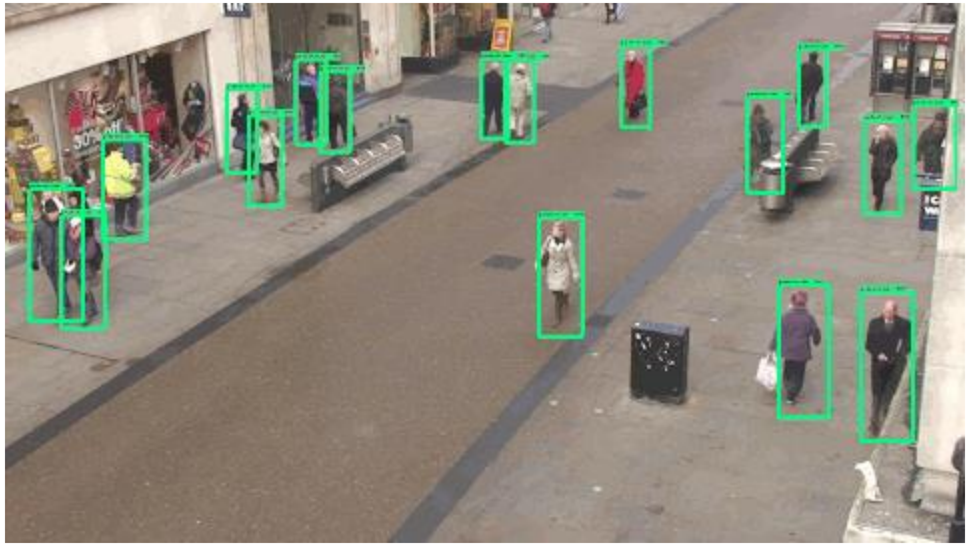


Our focus

10.1007/s00521-017-3270-7 LGND: a new method for multi-class novelty detection

Pedestrian detection



https://medium.com/nanonets/how-to-automate-surveillance-easily-with-deep-learning-4eb4fa0cd68d

Novelty detection

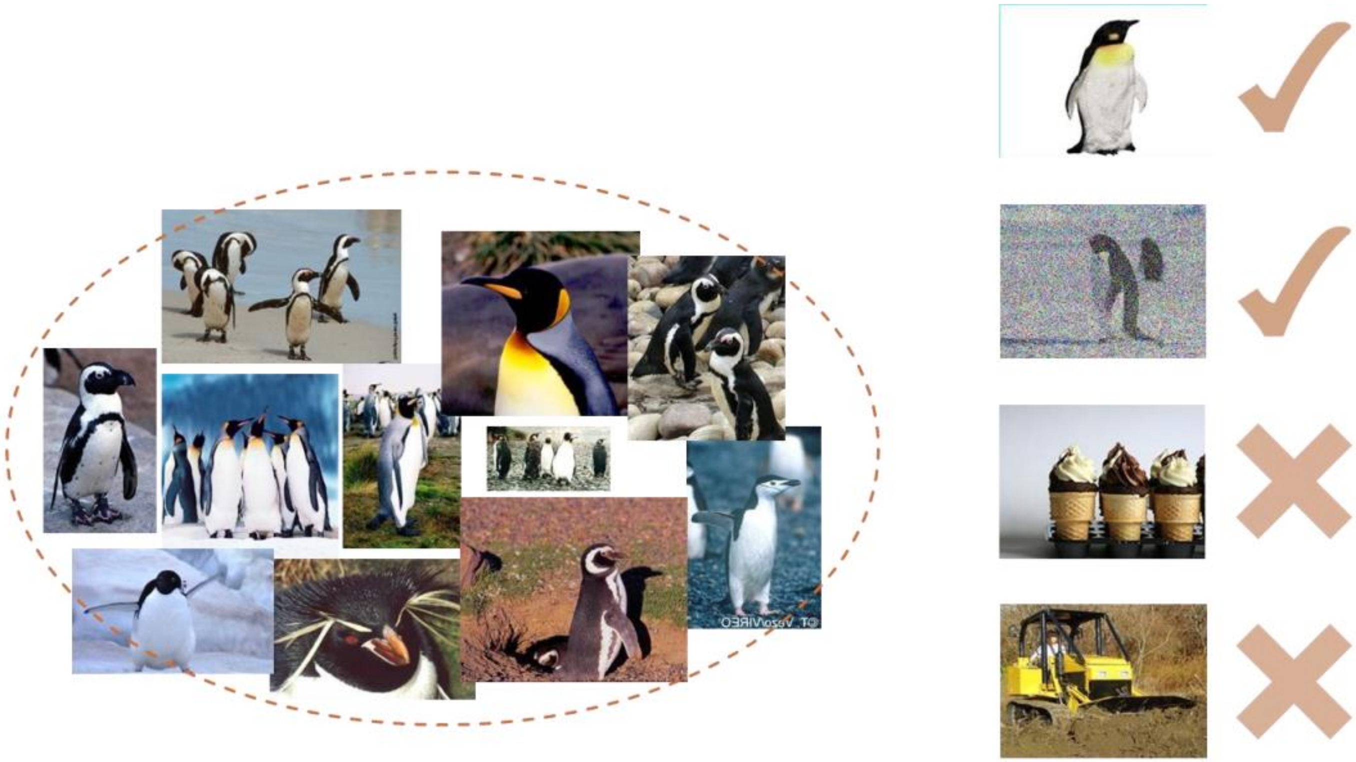
https://www.sciencedirect.com/science/article/abs/pii/S0167865513004613

https://www.groundai.com/project/the-wildtrack-multi-camera-person-dataset/1

Novelty detection

https://artificial-intelligence.leeds.ac.uk/anomaly-detection-using-a-convolutional-winner-take-all-autoencoder/

https://www.groundai.com/project/the-wildtrack-multi-camera-person-dataset/1



Training

Testing

Motivations

One-Class Classifier Applications:

- Novelty Detection
    - Outlier
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- In reality, the novelty class is
    - absent during training,
    - poorly sampled, or
    - not well defined

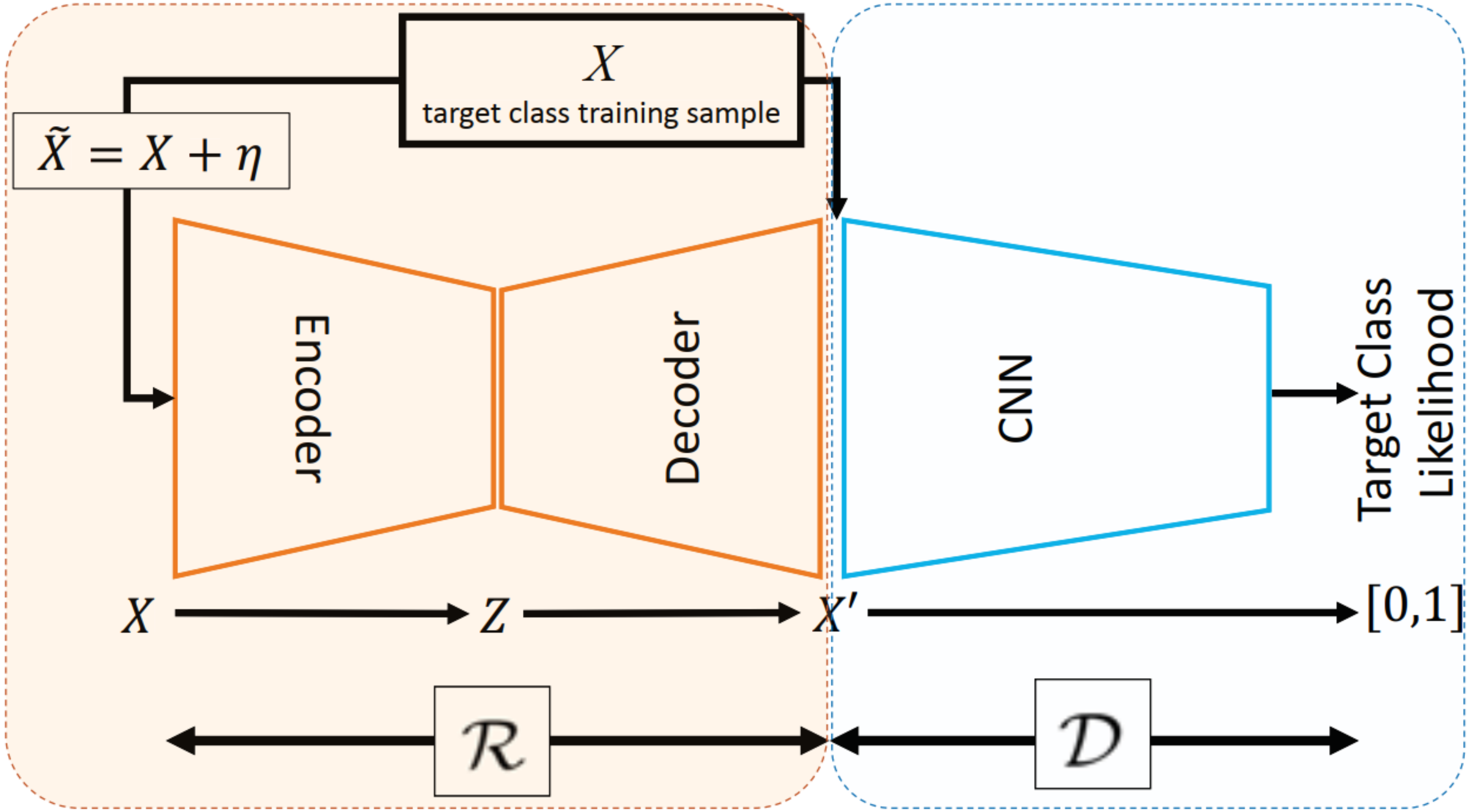
No samples to train based on

Too few samples (highly imbalanced classification)

What is novelty?

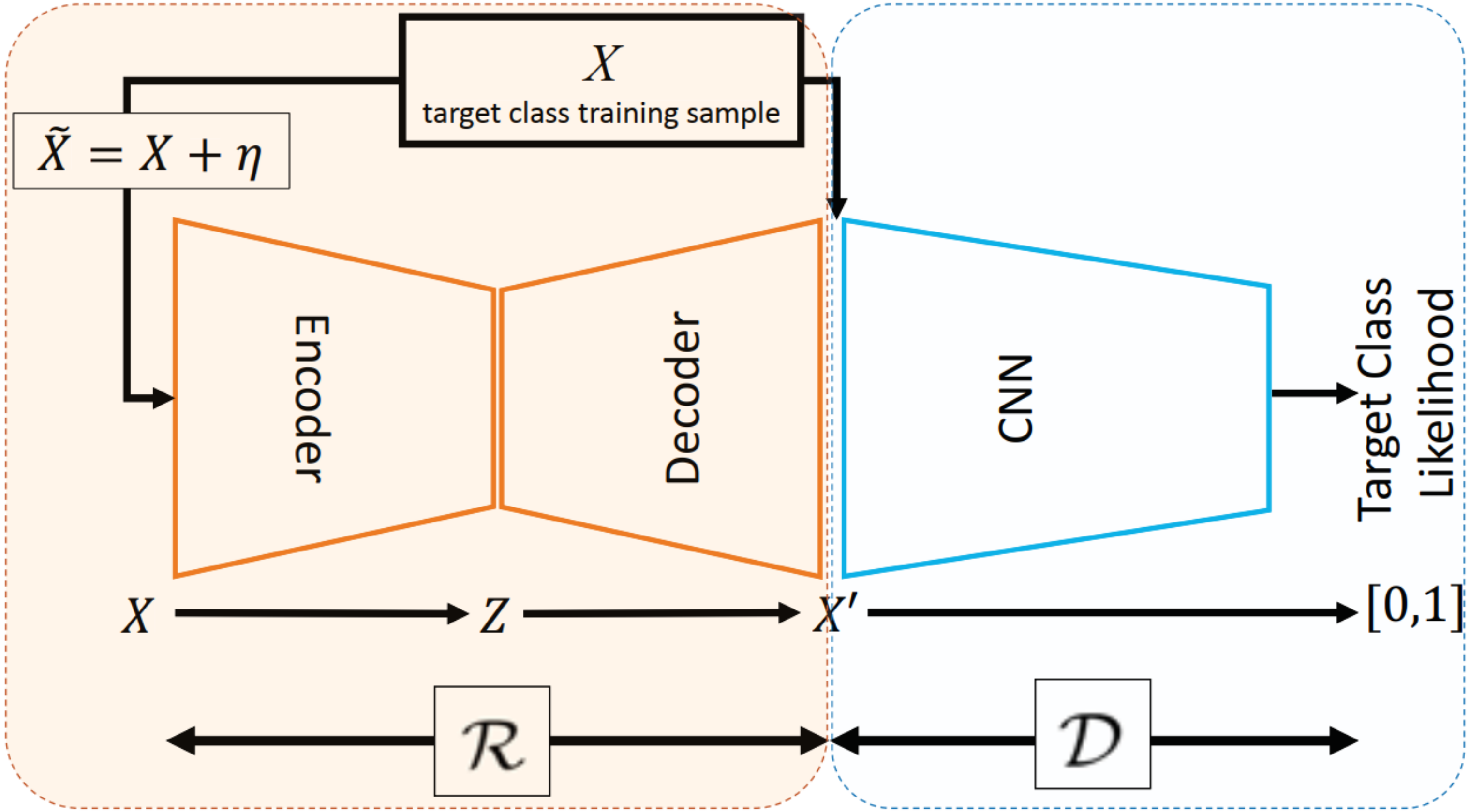
- Due to the unavailability of data from the novelty class, training an end-to-end deep network is challenging.

Our method



X
target class training sample
$\tilde{X} = X + \eta$
Encoder
Decoder
CNN
Target Class Likelihood
X
Z
X'
[0,1]
$\mathcal{R}$
$\mathcal{D}$

Our method



Learns to **Reconstruct** the positive samples (samples from target class)

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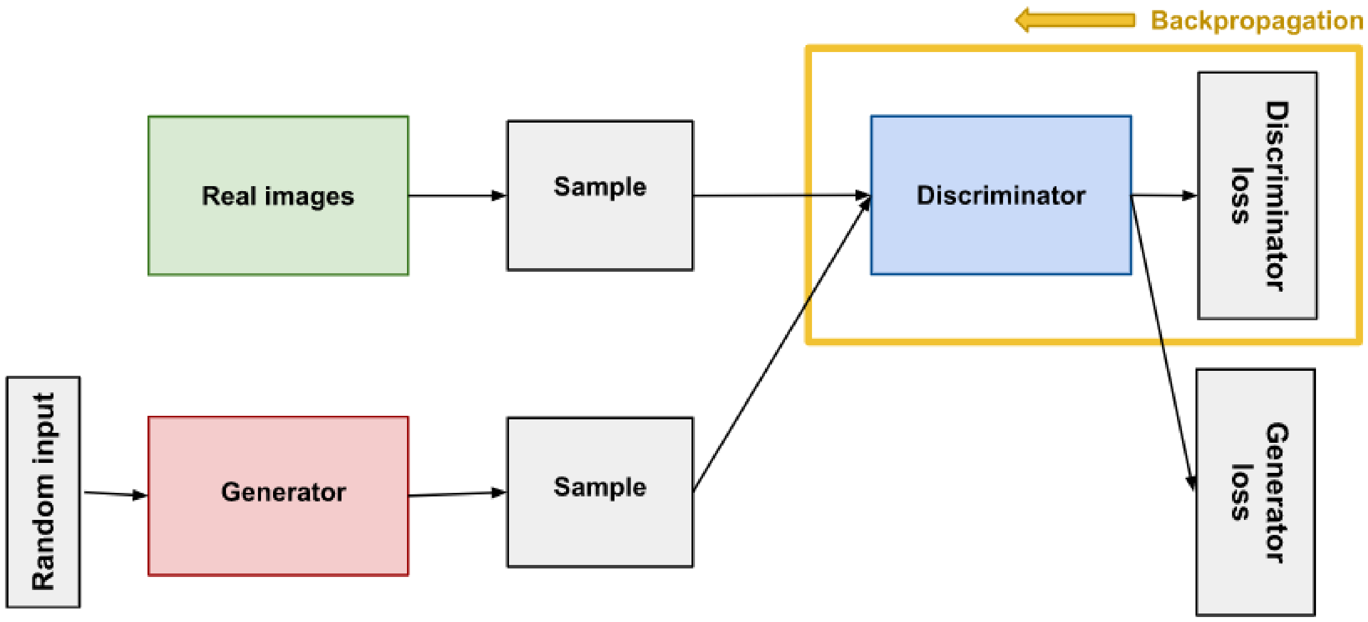
Adversarial Training of $\mathcal{R}$+$\mathcal{D}$

Generative Adversarial Networks

Goodfellow et al. 2014

$$\min_{G}\max_{D}\Big(\mathbb{E}_{X\sim p_t}[\log(D(X))] + \mathbb{E}_{Z\sim p_z}[\log(1-D(G(Z)))]\Big). \quad (1)$$



https://developers.google.com/machine-learning/gan/discriminator

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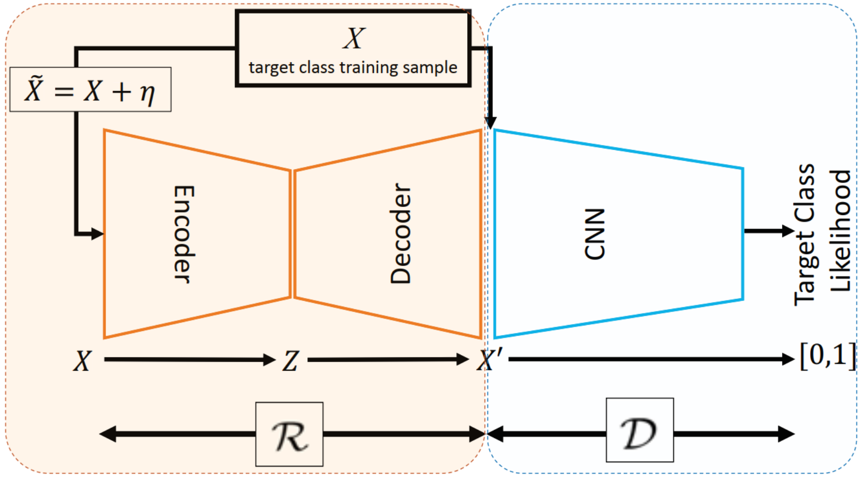
Our ALOCC work

Adversarially Learned One-Class Classifier for Novelty Detection

$$\tilde{X} = (X \sim p_t) + (\eta \sim \mathcal{N}(0, \sigma^2 \mathbf{I})) \longrightarrow X' \sim p_t, \quad (2)$$



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https://developers.google.com/machine-learning/gan/discriminator

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Generative Adversarial Networks

Goodfellow et al. 2014

$$\min_{G}\max_{D}\Big(\mathbb{E}_{X\sim p_t}[\log(D(X))] + \mathbb{E}_{Z\sim p_z}[\log(1-D(G(Z)))]\Big). \tag{1}$$

Our ALOCC work

Adversarially Learned One-Class Classifier for Novelty Detection

$$\tilde{X} = (X \sim p_t) + (\eta \sim \mathcal{N}(0,\sigma^2\mathbf{I})) \longrightarrow X' \sim p_t, \tag{2}$$

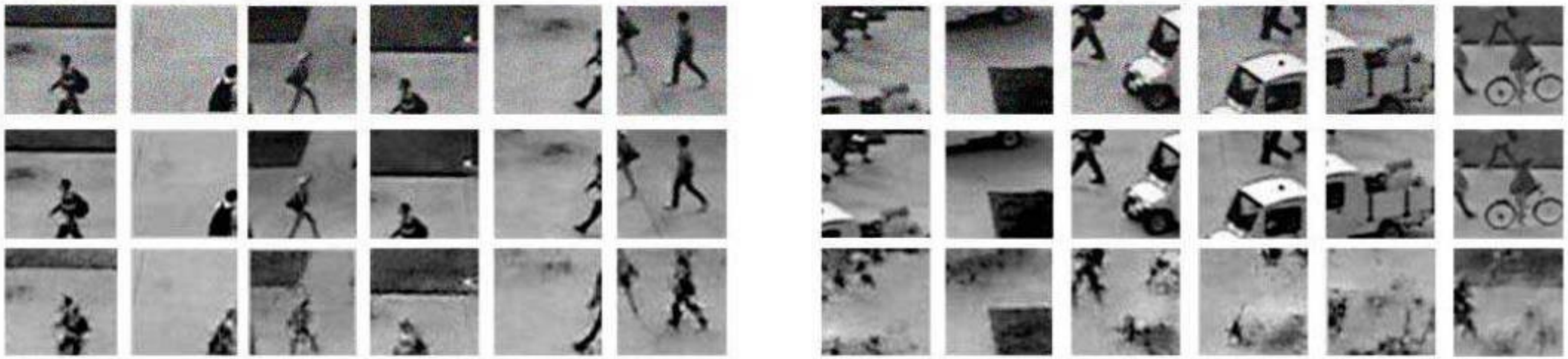
$$\min_{\mathcal{R}}\max_{\mathcal{D}}\Big(\mathbb{E}_{X\sim p_t}[\log(\mathcal{D}(X))] + \mathbb{E}_{\tilde{X}\sim p_t+\mathcal{N}_\sigma}[\log(1-\mathcal{D}(\mathcal{R}(\tilde{X})))]\Big), \tag{3}$$

$$\mathcal{L}_{\mathcal{R}} = \|X - X'\|^2. \tag{4}$$

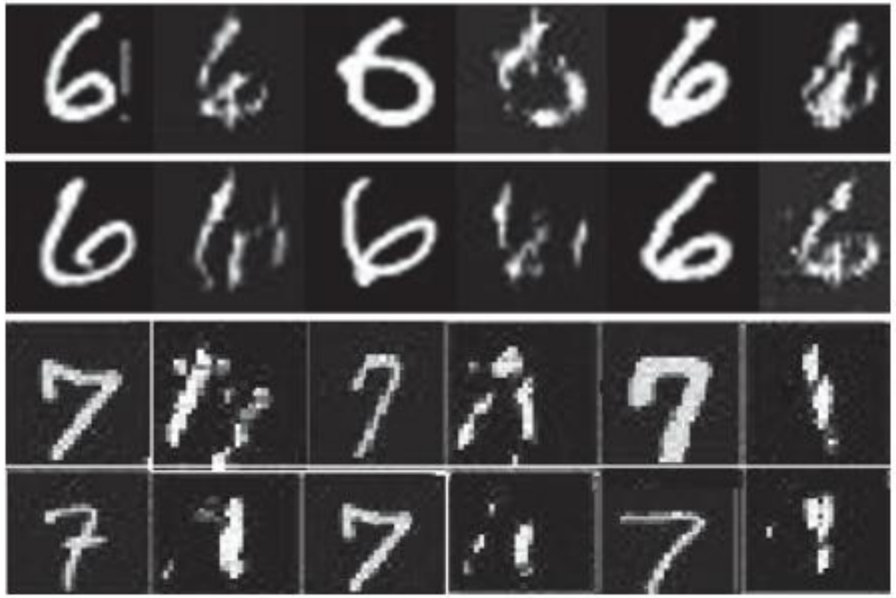
$$\mathcal{L} = \mathcal{L}_{\mathcal{R}+\mathcal{D}} + \lambda\mathcal{L}_{\mathcal{R}}, \tag{5}$$

https://developers.google.com/machine-learning/gan/discriminator

Experiments

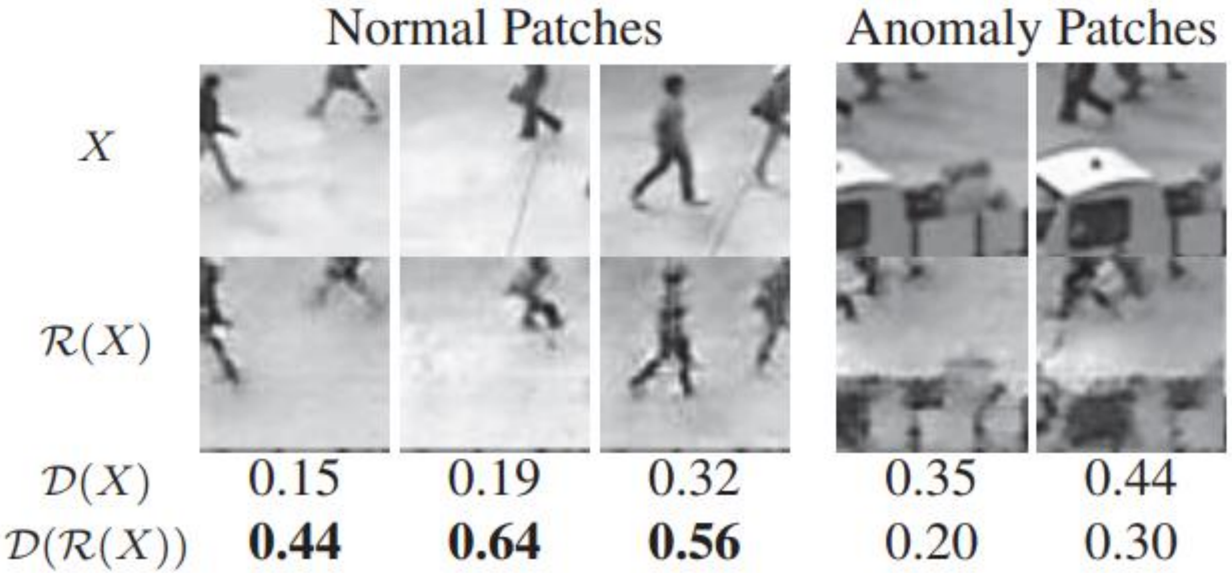


Examples of the output of R for several inlier and outlier samples from the UCSD Ped2 dataset



Outputs of R trained to detect digit "1" on MNIST dataset

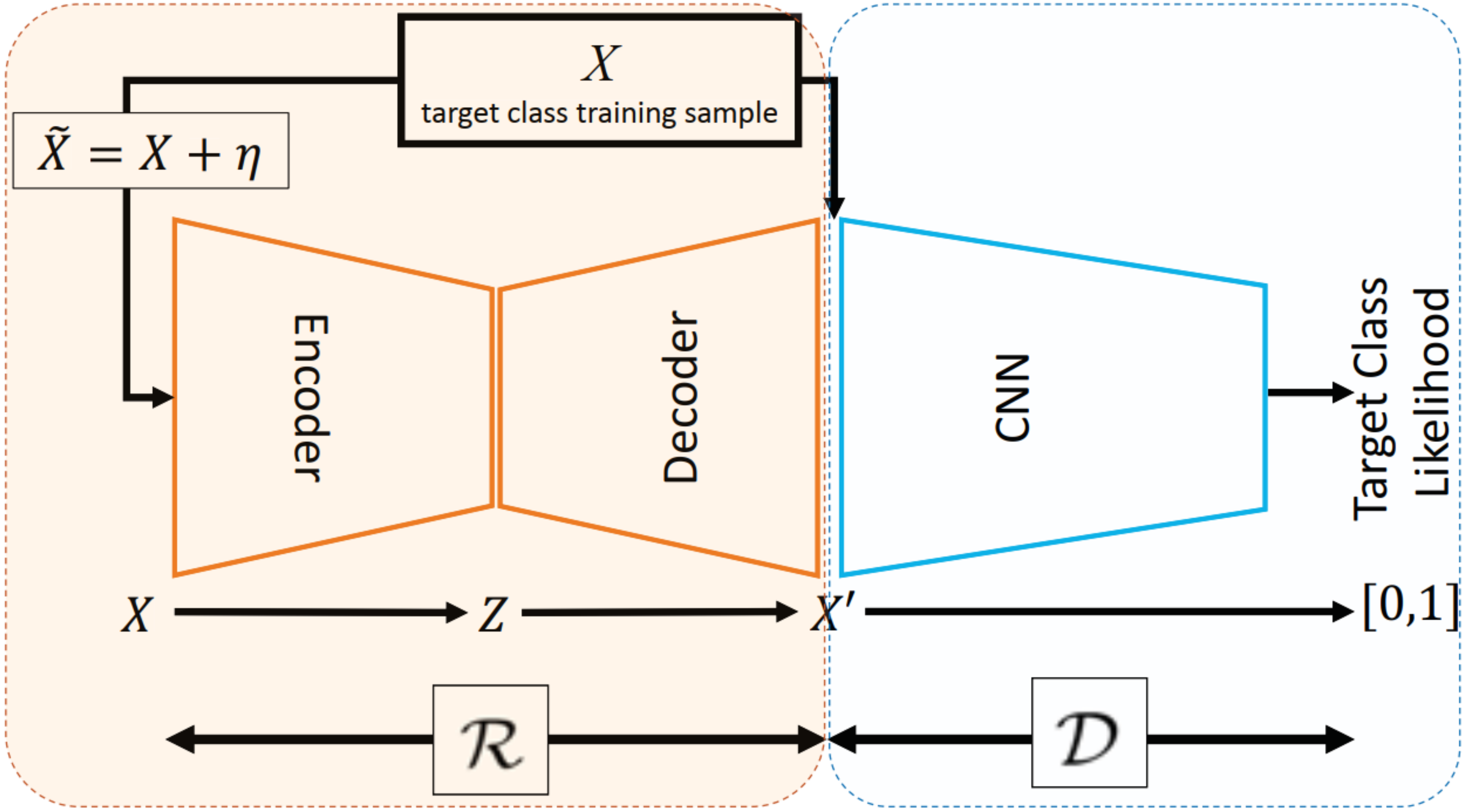
Experiments



Examples of patches (denoted by X) and their reconstructed versions using R (i.e., R(X))

Links

https://github.com/khalooei/ALOCC-CVPR2018



Learns to **Reconstruct** the positive samples (samples from target class)

Learns the concept characterized by all positive samples (novelty **Detector**)

Extended version of ALOCC (our approach)

- Generative Probabilistic Novelty Detection with Adversarial Autoencoders

  Stanislav Pidhorskyi, Ranya Almohsen, Gianfranco Doretto (NeurIPS)

- f-AnoGAN: Fast unsupervised anomaly detection with generative adversarial networks

  T. Schlegl, Philipp Seeböck, S. Waldstein, G. Langs, U. Schmidt-Erfurth (Medical Image Analysis)

- Latent Space Autoregression for Novelty Detection

  Davide Abati, Angelo Porrello, Simone Calderara, Rita Cucchiara (CVPR)

- OCGAN: One-Class Novelty Detection Using GANs With Constrained Latent Representations

  Pramuditha Perera, Ramesh Nallapati, Bing Xiang (CVPR)

- Memorizing Normality to Detect Anomaly: Memory-Augmented Deep Autoencoder for Unsupervised Anomaly Detection

  Dong Gong, Lingqiao Liu, Vuong Le, Budhaditya Saha, Moussa Reda Mansour, Svetha Venkatesh, Anton van den Hengel (CVPR)

- AVID: Adversarial Visual Irregularity Detection

  Mohammad Sabokrou, Masoud Pourreza, Mohsen Fayyaz, Rahim Entezari, Mahmood Fathy, Jürgen Gall,Ehsan Adeli (ACCV)

… etc

https://scholar.google.com/scholar?oi=bibs&hl=en&cites=13603058643518336613&as_sdt=5

Next idea …

- Self-Supervised Representation Learning via Neighborhood-Relational Encoding (ICCV)

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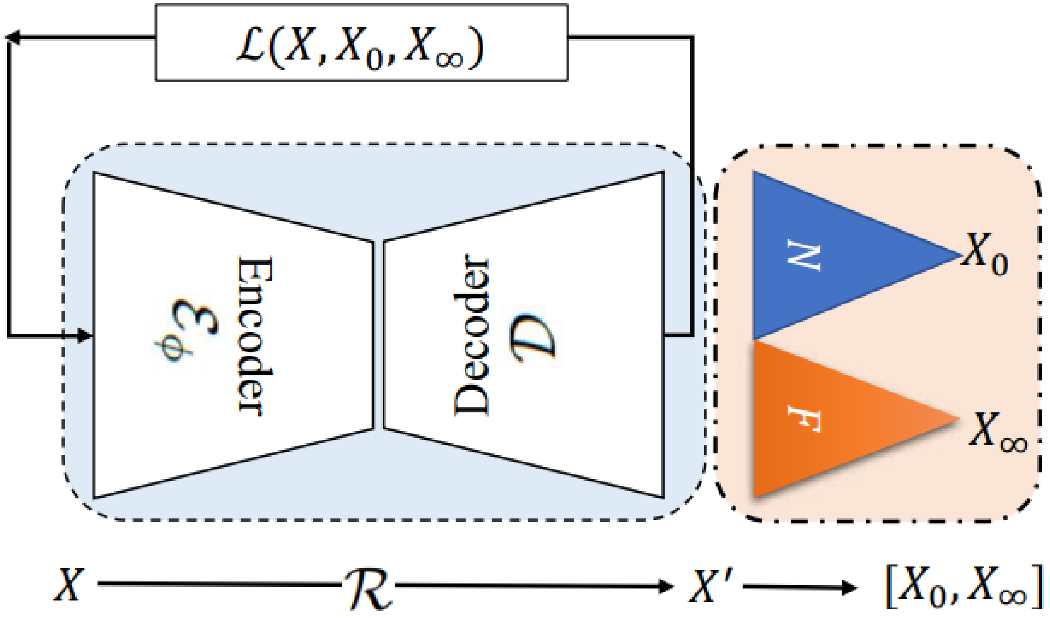

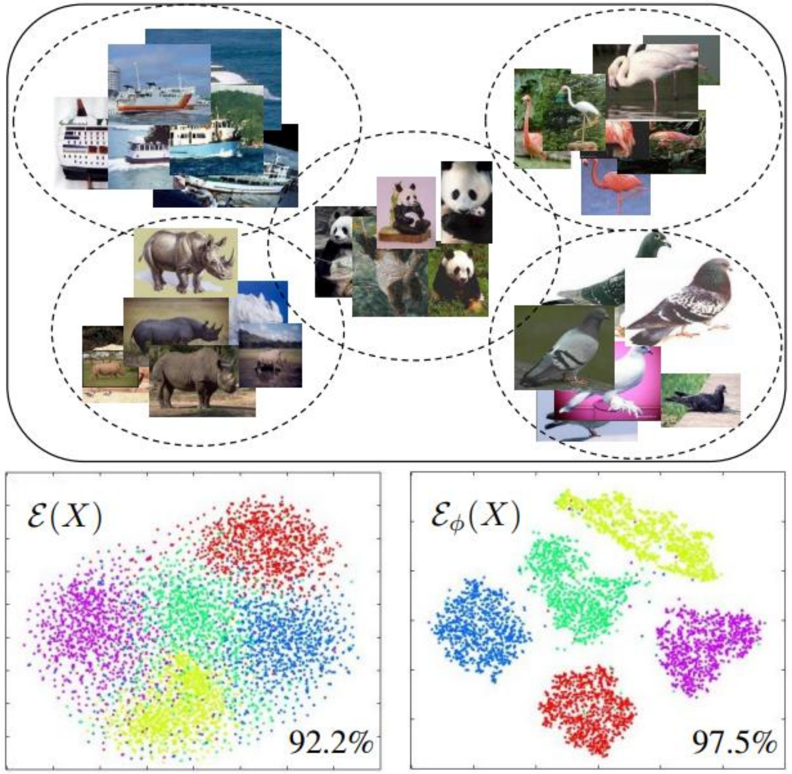

https://ieeexplore.ieee.org/document/9010354

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https://ceit.aut.ac.ir/~khalooei