Adversarially Robust One-class Novelty Detection

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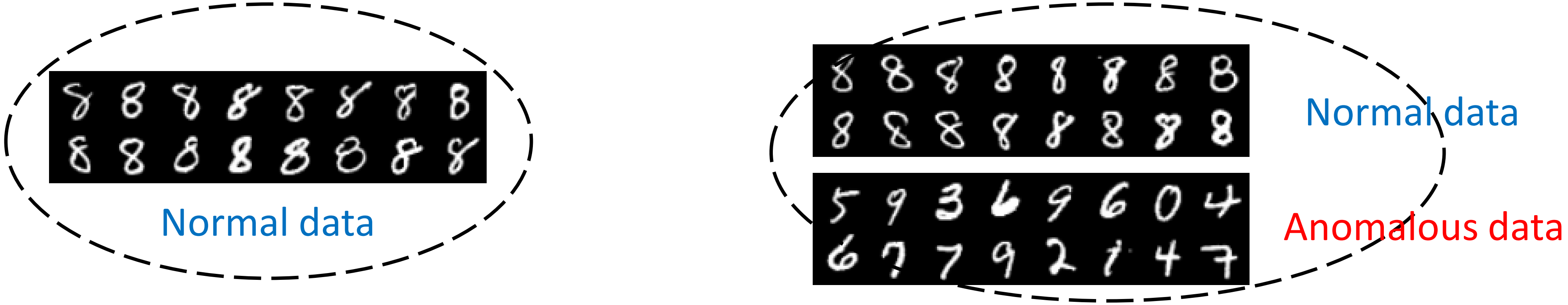
Recall: One-class Novelty Detection

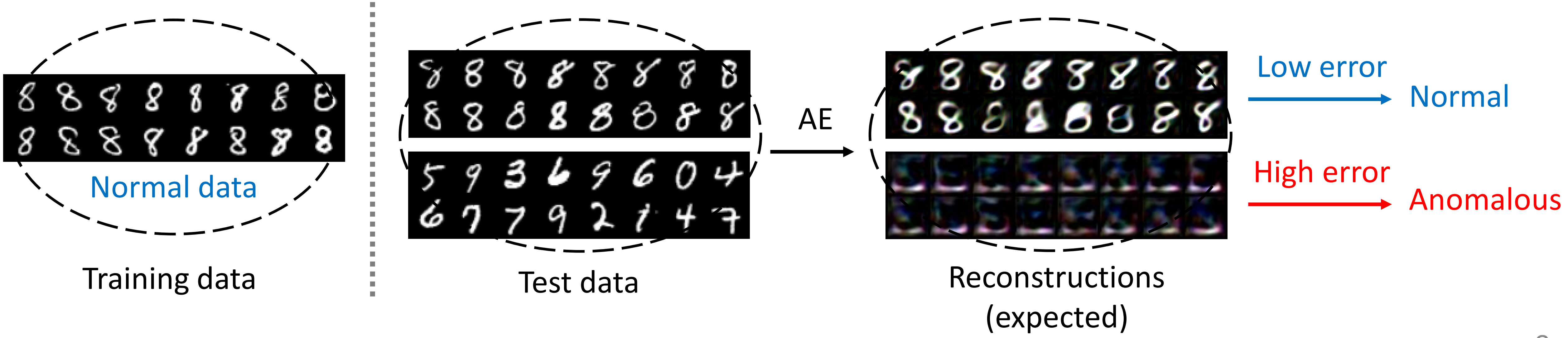
- One-class novelty detection model is trained with examples of **a particular class** and is asked to identify whether a query example belongs to the same known class.
- Example:
  - **Known class** (normal data): 8
  - **Novel classes** (anomalous data): 0-7 & 9 (the rest of classes)



Training data
Test data

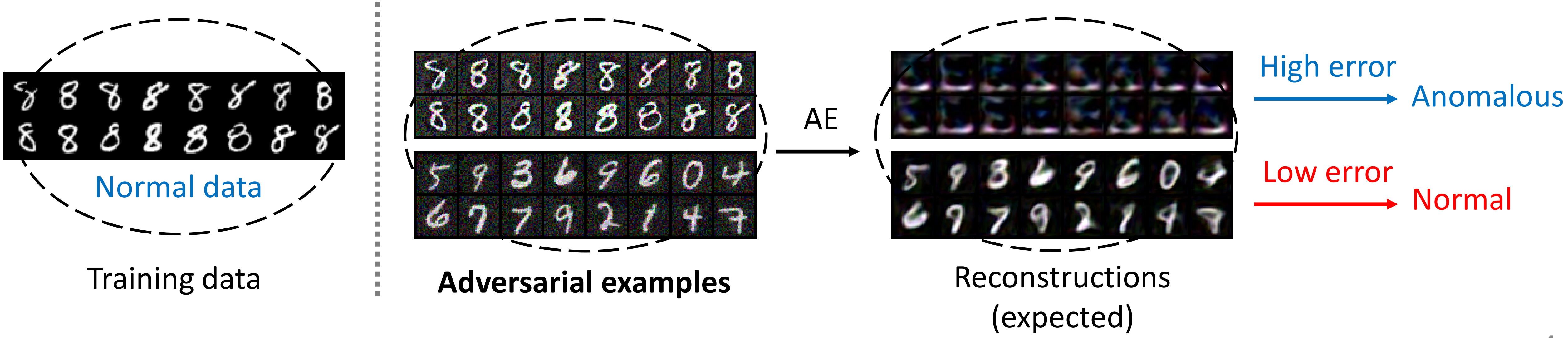
Recall: One-class Novelty Detection

- Most recent advances are based on the **autoencoder** architecture.
- Given an autoencoder that learns the distribution of the known class, we expect that the **normal data** are reconstructed accurately while the **anomalous data** are not.



Attacking One-class Novelty Detection

- How to generate adversarial examples against a novelty detector?
- If a test example is **normal**, **maximize** the reconstruction error.
- If a test example is **anomalous**, **minimize** the reconstruction error.

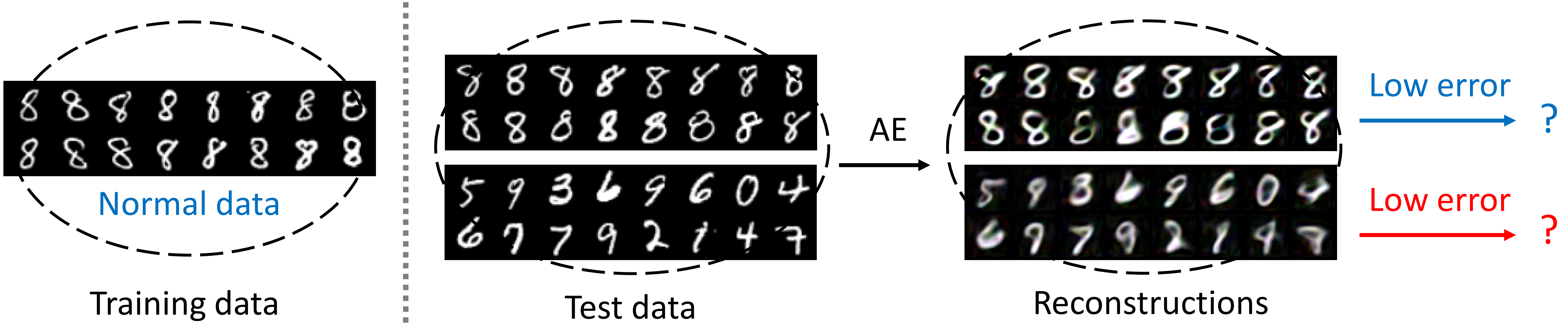


Goal: Adversarially Robust Novelty Detection

- Novelty detectors are **vulnerable** to adversarial attacks.
- Adversarially robust method specifically designed for novelty detectors is needed.
- A **new** research problem.

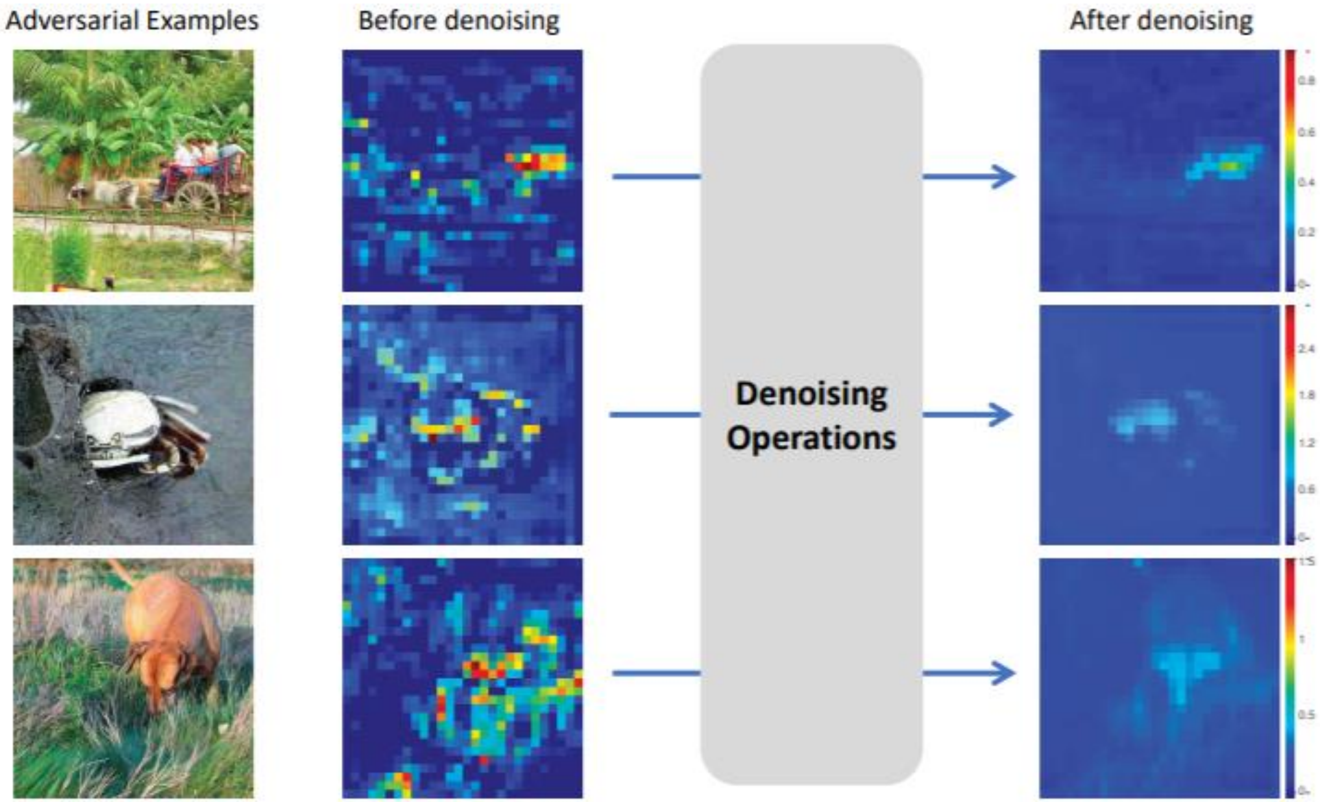
Observation: Generalizability

- Unique property: Preference for **poor** generalization of reconstruction ability.
- However, autoencoders have **good** generalizability.



Observation: Feature Denoising

- Adversarial perturbations can be removed in the **feature** domain.



[Xie et al. CVPR'19]

Our Solution

- **Observations**: Generalizability and Feature Denoising.

- **Assumption**: One can **largely** manipulate the latent space of a novelty detector to remove adversaries to a great extent, and this would not hurt the model capacity but **helps** if in a proper way.

- **Solution**: Learning **principal latent space**.

PCA Rephrased

- *h()* computes the **mean vector** and the first *k* **principal components** of the given data collection *X*:

$$h(\mathbf{X}, k) : \mathbf{X} \rightarrow \{\boldsymbol{\mu}, \tilde{\mathbf{U}}\}$$

- *f()* performs the forward PCA:

$$f(\mathbf{X}; \boldsymbol{\mu}, \tilde{\mathbf{U}}) = (\mathbf{X} - \boldsymbol{\mu}\mathbf{1}^\top)\tilde{\mathbf{U}}$$

$$\mathbf{X}_{pca} = f(\mathbf{X}; \boldsymbol{\mu}, \tilde{\mathbf{U}})$$

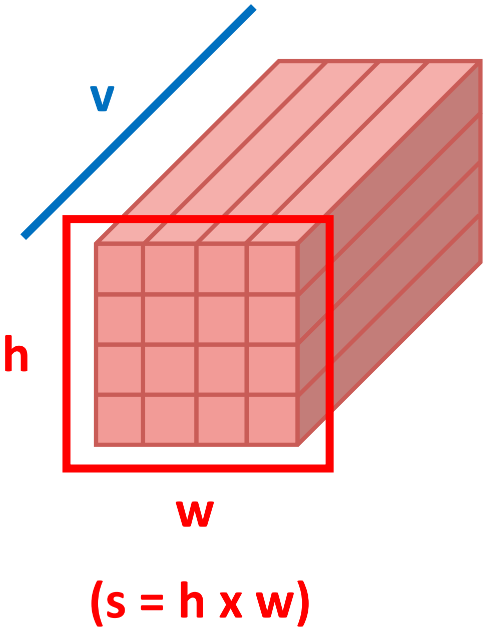
- *g()* performs the inverse PCA:

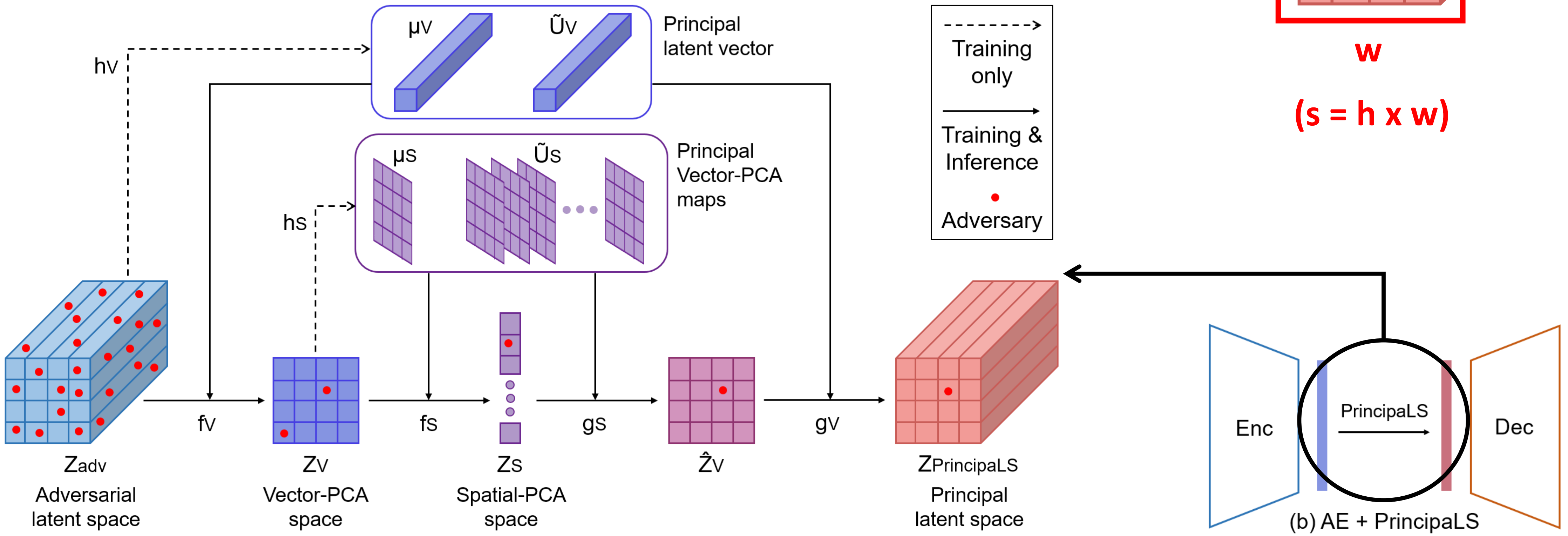
$$g(\mathbf{X}_{pca}; \boldsymbol{\mu}, \tilde{\mathbf{U}}) = \mathbf{X}_{pca}\tilde{\mathbf{U}}^\top + \boldsymbol{\mu}\mathbf{1}^\top$$

$$\hat{\mathbf{X}} = g(f(\mathbf{X}; \boldsymbol{\mu}, \tilde{\mathbf{U}}); \boldsymbol{\mu}, \tilde{\mathbf{U}})$$

Cascade PCA Process

- **Vector-PCA** performs PCA on the **vector** dimension.
- **Spatial-PCA** performs PCA on the **spatial** dimension.





Cascade PCA Process

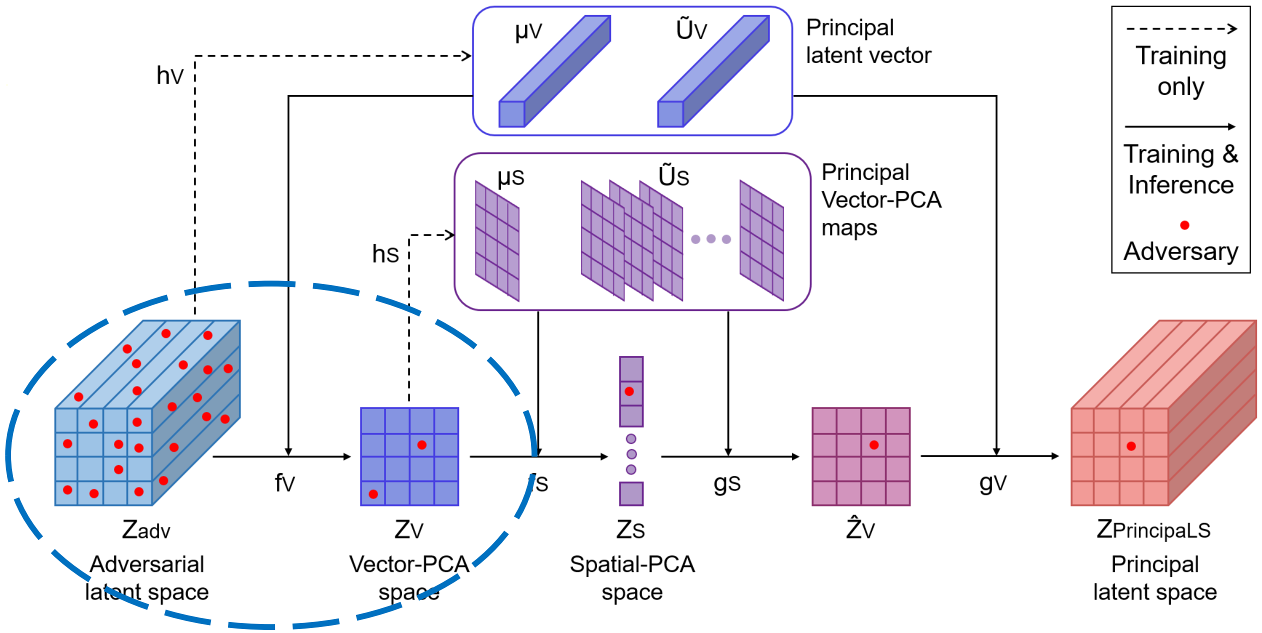
- Step 1: **Forward Vector-PCA**, i.e., *fv()*

$$\boldsymbol{Z}_{adv} \in \mathbb{R}^{s\times v} \longrightarrow \boldsymbol{Z}_V \in \mathbb{R}^{s\times 1}$$

Latent space — Vector-PCA space

$$\{\boldsymbol{\mu}_V, \tilde{\mathbf{U}}_V\} = h_V(\mathbf{Z}, k_V = 1)$$

$$\mathbf{Z}_V = f_V(\mathbf{Z}; \boldsymbol{\mu}_V, \tilde{\mathbf{U}}_V)$$



Cascade PCA Process

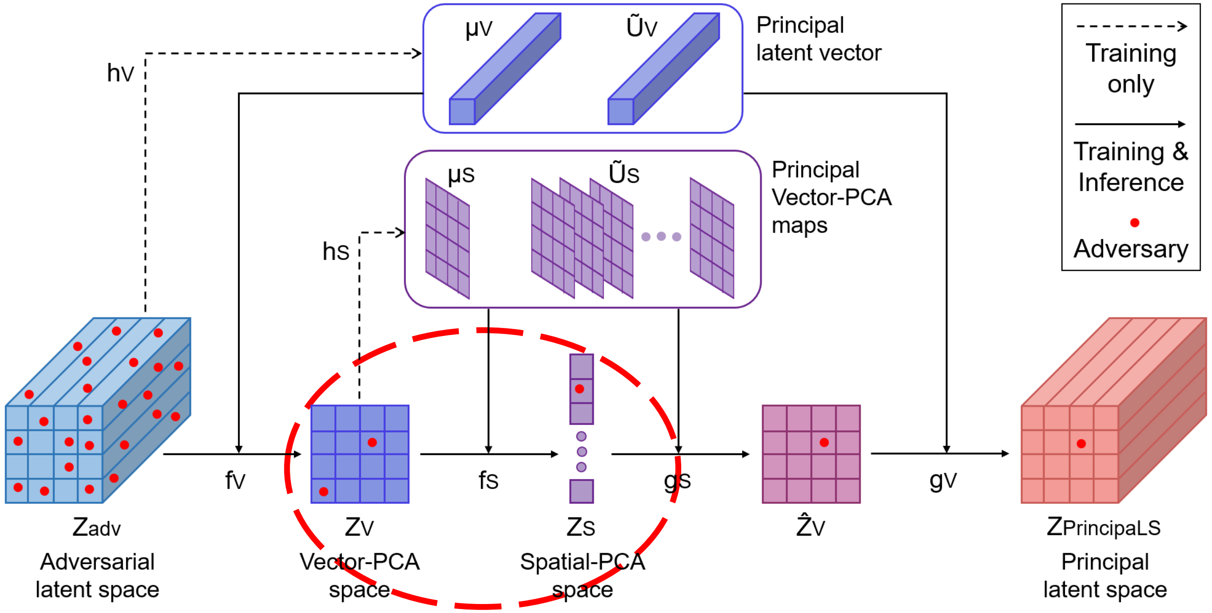
- Step 2: **Forward Spatial-PCA**, i.e., *fs()*

$$\boldsymbol{Z}_V \in \mathbb{R}^{s\times 1} \longrightarrow \boldsymbol{Z}_S \in \mathbb{R}^{k_S\times 1}$$

Vector-PCA space Spatial-PCA space

$$\{\boldsymbol{\mu}_S, \tilde{\mathbf{U}}_S\} = h_S(\mathbf{Z}_V^\top, k_S)$$

$$\mathbf{Z}_S^\top = f_S(\mathbf{Z}_V^\top; \boldsymbol{\mu}_S, \tilde{\mathbf{U}}_S)$$



Cascade PCA Process

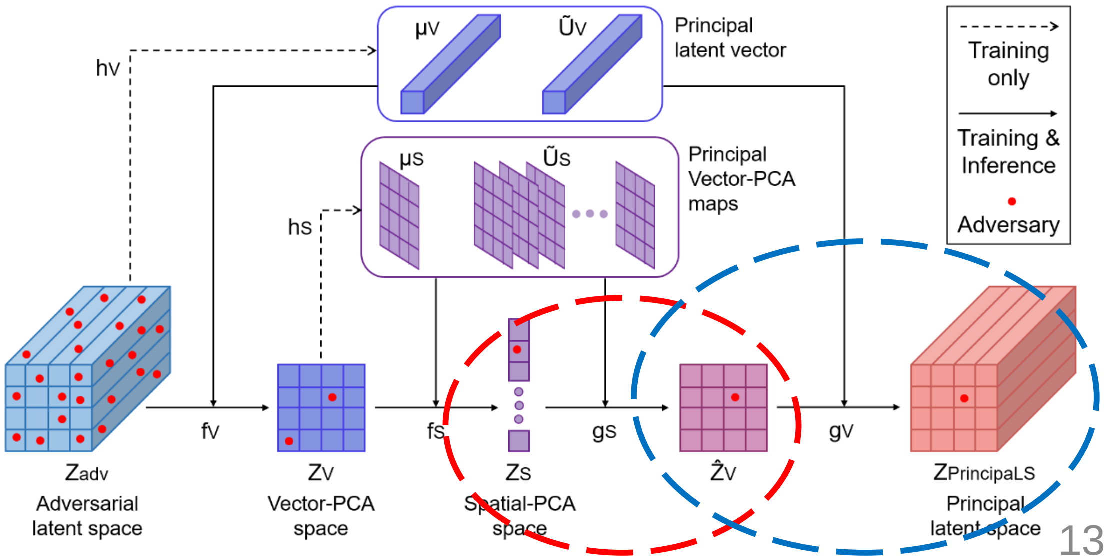
- Step 3: **Inverse Spatial-PCA**, i.e., *gs()*
- Step 4: **Inverse Vector-PCA**, i.e., *gv()*

$$\boldsymbol{Z}_S \in \mathbb{R}^{k_S \times 1} \longrightarrow \boldsymbol{Z}_{pls} \in \mathbb{R}^{s \times v}$$

Spatial-PCA space — **Principal latent space**

$$\hat{\mathbf{Z}}_V^\top = g_S(\mathbf{Z}_S^\top; \boldsymbol{\mu}_S, \tilde{\mathbf{U}}_S)$$

$$\mathbf{Z}_{plr} = g_V(\hat{\mathbf{Z}}_V; \boldsymbol{\mu}_V, \tilde{\mathbf{U}}_V)$$



Learning Principal Latent Components

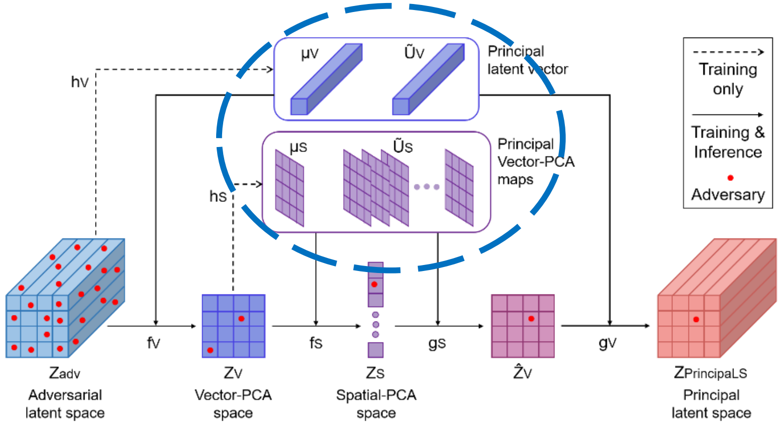
- **Principal latent components**:

$$\{\boldsymbol{\mu}_V, \tilde{\mathbf{U}}_V, \boldsymbol{\mu}_S, \tilde{\mathbf{U}}_S\}$$

- **Training time**: Train along with the network weights by exponential moving average (EMA).

$$\{\boldsymbol{\mu}_V^t, \tilde{\mathbf{U}}_V^t\} = \{\boldsymbol{\mu}_V^{t-1}, \tilde{\mathbf{U}}_V^{t-1}\} + \eta_V(h_V(\mathbf{Z}^t) - \{\boldsymbol{\mu}_V^{t-1}, \tilde{\mathbf{U}}_V^{t-1}\})$$

$$\{\boldsymbol{\mu}_S^t, \tilde{\mathbf{U}}_S^t\} = \{\boldsymbol{\mu}_S^{t-1}, \tilde{\mathbf{U}}_S^{t-1}\} + \eta_S(h_S(\mathbf{Z}^t) - \{\boldsymbol{\mu}_S^{t-1}, \tilde{\mathbf{U}}_S^{t-1}\})$$

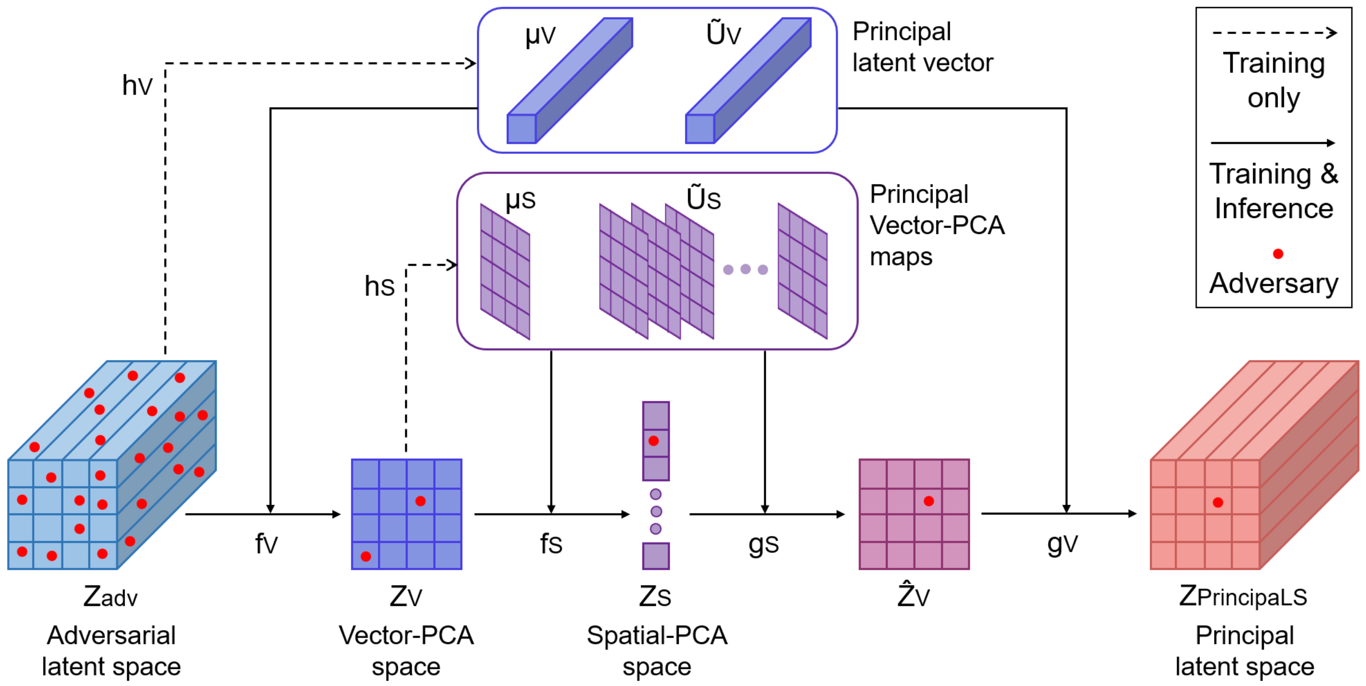


- **Inference time**: Perform the cascade PCA process with the fixed and well-trained parameters:

$$\{\boldsymbol{\mu}_V^*, \tilde{\mathbf{U}}_V^*, \boldsymbol{\mu}_S^*, \tilde{\mathbf{U}}_S^*\}$$

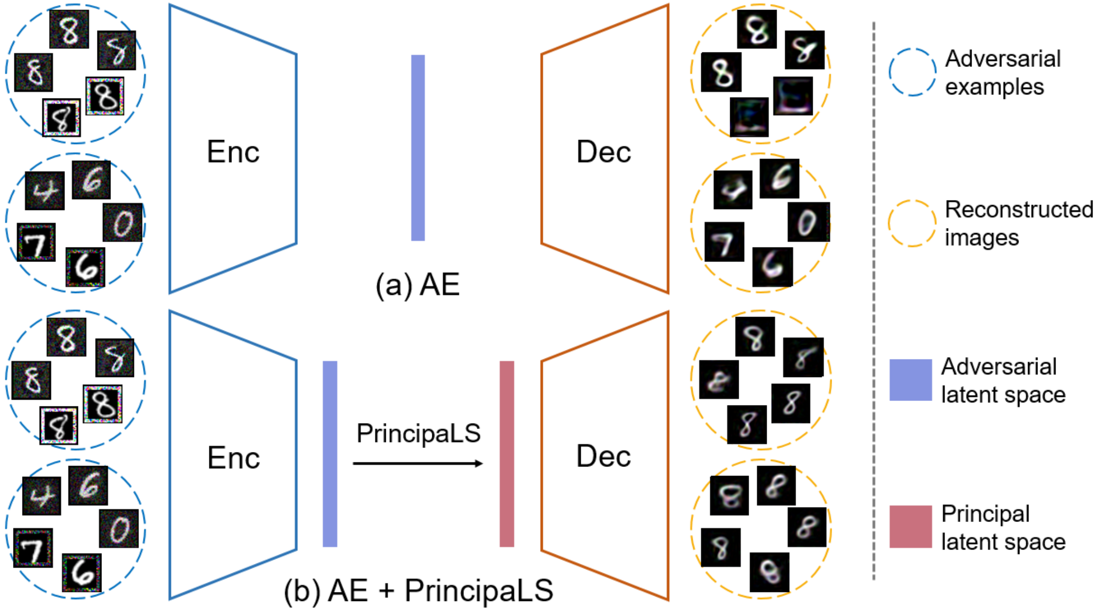
Defense Mechanism

- **Vector-PCA** replaces the perturbed latent vectors with the clean principal latent vector.
- **Spatial-PCA** removes the remaining perturbations on the Vector-PCA map.



Defense Mechanism

- Combine **adversarial training**.
- The proposed PrincipaLS process can robustify **any** AE-based novelty detectors.
  - AE, VAE, AAE, ALOCC (CVPR'18), GPND (NeurIPS'18), etc.



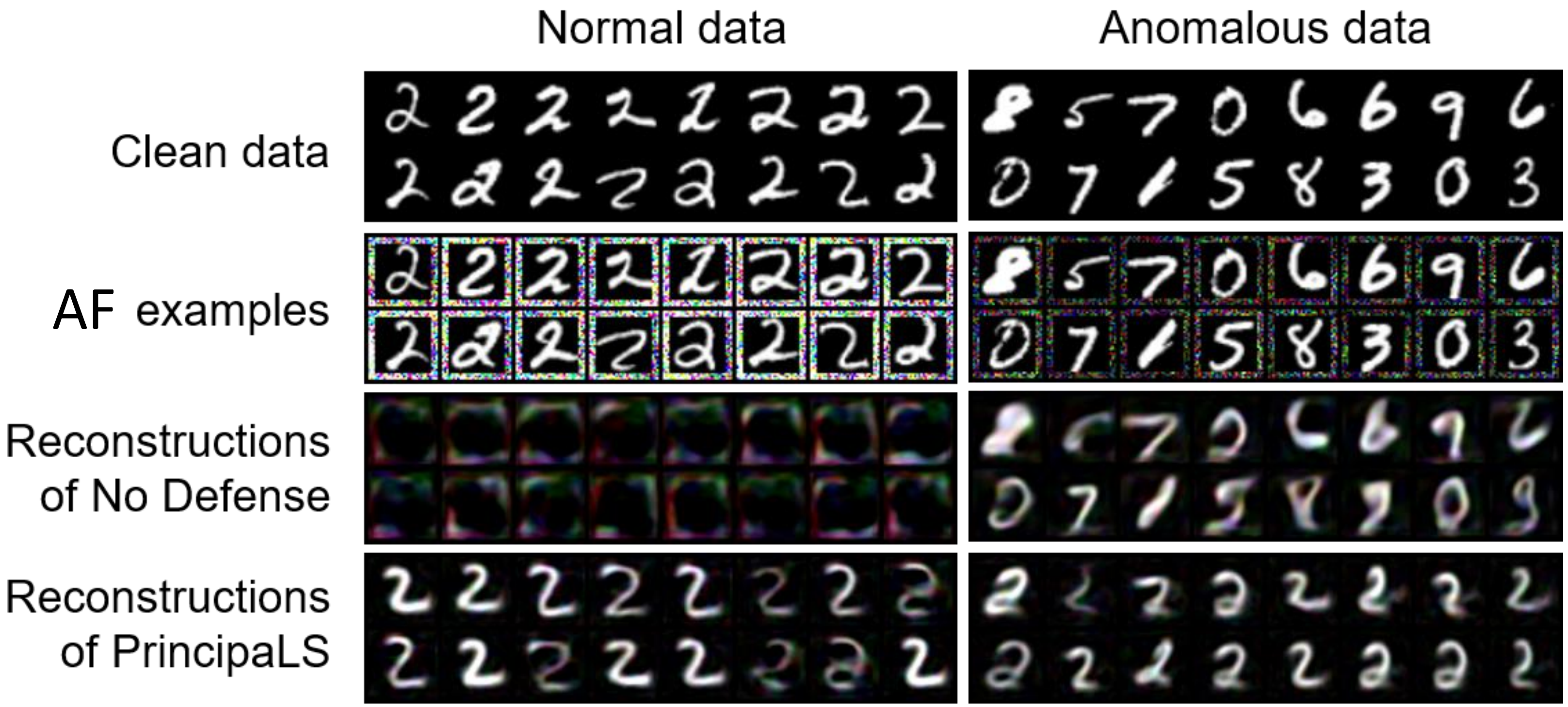
Results

- Evaluation metric: mean of AUROC
- PrincipaLS is effective on **5** datasets against **6** attacks for **7** novelty detection methods.

Dataset	Defense	Clean	FGSM [11]	PGD [27]	MI-FGSM [36]	MultAdv [37]	AF [38]	Black-box [47]	Average
MNIST [48]	No Defense	0.964	0.350	0.051	0.022	0.170	0.014	0.790	0.337
	PGD-AT [27]	0.961	0.604	0.357	0.369	0.444	0.155	0.691	0.512
	FD [15]	0.963	0.612	0.366	0.379	0.453	0.142	0.700	0.516
	SAT [23]	0.947	0.527	0.295	0.306	0.370	0.142	0.652	0.463
	RotNet-AT [21]	0.967	0.598	0.333	0.333	0.424	0.101	0.695	0.493
	SOAP [22]	0.940	0.686	0.504	0.506	0.433	0.088	0.863	0.574
	APAE [46]	0.925	0.428	0.104	0.105	0.251	0.022	0.730	0.366
	PrincipaLS (ours)	**0.973**	**0.812**	**0.706**	**0.707**	**0.725**	**0.636**	**0.866**	**0.775**
SHTech [52]	No Defense	0.523	0.204	0.034	0.038	0.006	0.000	0.220	0.146
	PGD-AT [27]	0.527	0.217	0.168	0.154	0.100	0.000	0.221	0.198
	FD [15]	0.528	0.226	0.189	0.181	0.132	0.002	0.229	0.212
	SAT [23]	**0.529**	0.184	0.110	0.092	0.040	0.000	0.199	0.165
	RotNet-AT [21]	0.516	0.220	0.163	0.158	0.113	0.000	0.229	0.200
	SOAP [22]	0.432	0.024	0.002	0.000	0.002	**0.181**	0.202	0.120
	APAE [46]	0.510	0.215	0.048	0.050	0.011	0.000	0.207	0.149
	PrincipaLS (ours)	0.498	**0.274**	**0.223**	**0.217**	**0.175**	0.051	**0.308**	**0.249**

Analysis

- PrincipaLS reconstructs **every** input example to the known class (digit 2).



(b) AF attack

Analysis

- (a) No Defense under clean data (b) No Defense under PGD attack
  (c) PGD-AT under PGD attack (d) PrincipaLS under PGD attack
- PrincipaLS enlarges the reconstruction errors of anomalous data to a great extent.