Robust Deep Learning Methods for Anomaly Detection

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Overview

Auto-encoders

- Auto-encoder
- Variational Auto-Encoders (VAE)
- Adversarial Auto-Encoders (AAE)
- Wasserstein Auto-Encoders (WAE)

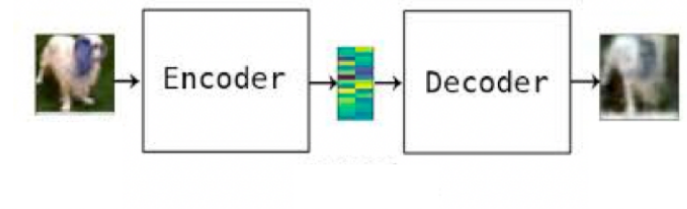
Extending Auto-encoders

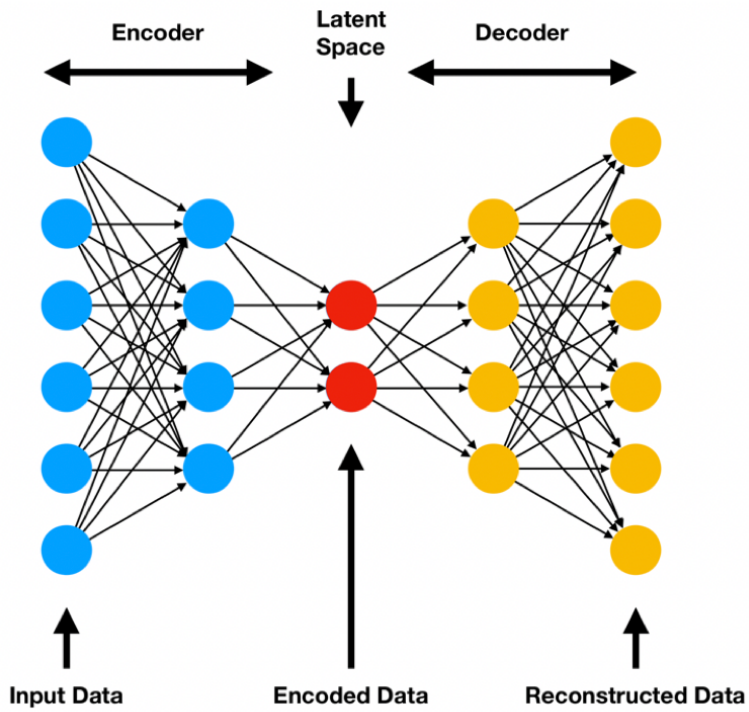
- One-Class Deep SVDD (Deep SVDD)
- One-Class Neural Networks (OCNN)

Modified Autoencoder Training and Scoring

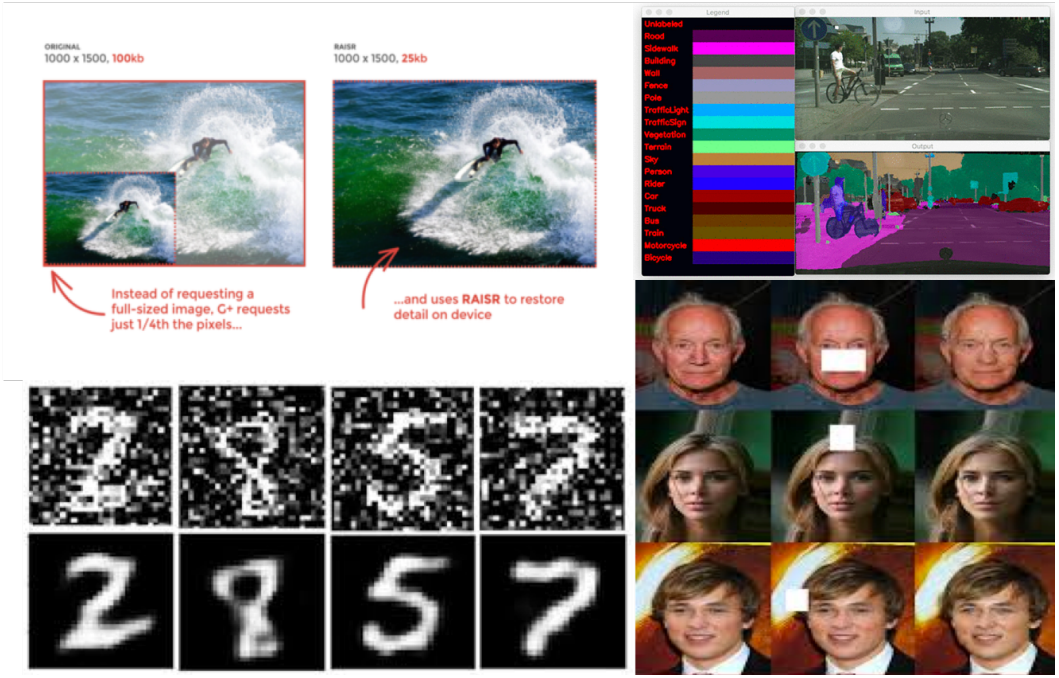
Basic Auto-encoder

- Data specific learned nonlinear compression.
- Compute the reconstruction loss with respect to input.





Application : Auto-encoder



- Helps save bandwidth : Data Transmission.
- Image Segmentation : Autonomous Driving.
- Image Denoising : Remove Noise
- Neural Inpainting : Fill in missing image portion, remove watermarks

Auto-encoders for anomaly detection.

- Auto encoder with single **hidden layer**

$$\min_{\mathbf{U},\mathbf{V}} \|\mathbf{X} - \mathbf{f}(\mathbf{XU})\mathbf{V}\|_{\mathbf{F}}^{2} \tag{1}$$

- $\hat{\mathbf{X}} = f(\mathbf{XU})\mathbf{V}$ is **reconstruction error measure.**

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  - **U**: Weights (input $\rightarrow$ hidden),
  - **V**: Weights (hidden $\rightarrow$ output),

- **XU** projects **X** into K dimensional space
  $\mathbf{U} \in \mathbf{R}^{\mathbf{D}\times\mathbf{K}}$, $\mathbf{V} \in \mathbf{R}^{\mathbf{K}\times\mathbf{D}}$.

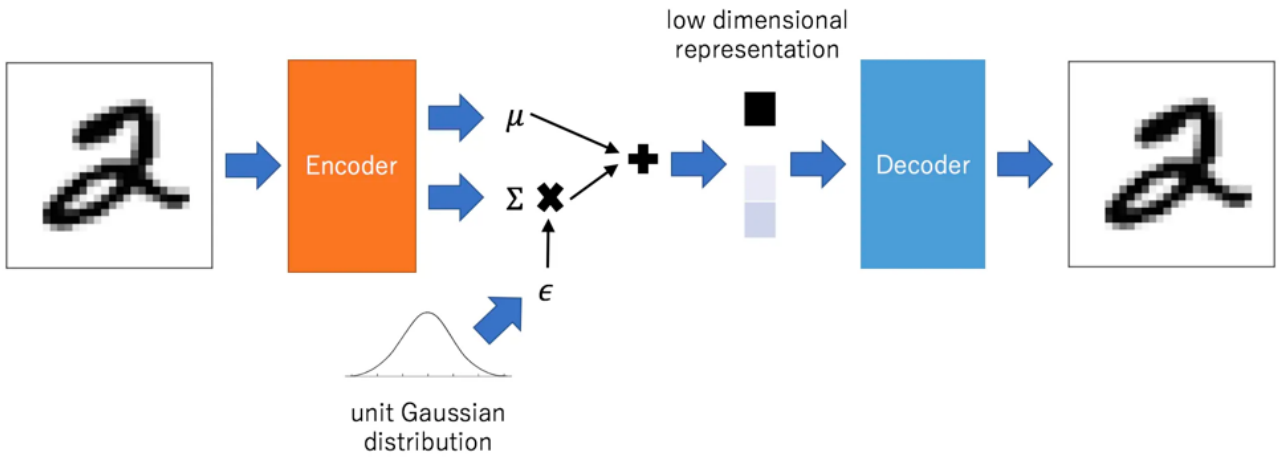
Auto-encoders for anomaly detection.

- Auto encoder with single **hidden layer**

$$\min_{\mathbf{U},\mathbf{V}} \|\mathbf{X} - \mathbf{f}(\mathbf{XU})\mathbf{V}\|_{\mathbf{F}}^{\mathbf{2}} \tag{1}$$

- $\hat{\mathbf{X}} = f(\mathbf{XU})\mathbf{V}$ is **reconstruction error measure.**
  - **U**: Weights (input $\rightarrow$ hidden),
  - **V**: Weights (hidden $\rightarrow$ output),
  - activation function: $f : \mathbb{R} \rightarrow \mathbb{R}$
- **XU** projects **X** into K dimensional space
  $\mathbf{U} \in \mathbf{R}^{\mathbf{D}\times\mathbf{K}}$, $\mathbf{V} \in \mathbf{R}^{\mathbf{K}\times\mathbf{D}}$.
- Non linear projection: **sigmoid** $f(\cdot) := (1 + \exp(-a))^{-1}$

Variational Auto-encoder (VAE)



- Map Input to distribution instead of a vector.
- Bottleneck embeddings consists of two separate vectors (mean, standard deviation) of distribution.
- Sampled vector is vector to fed into decoder for reconstruction.

Training Variational Auto-encoder (VAE)

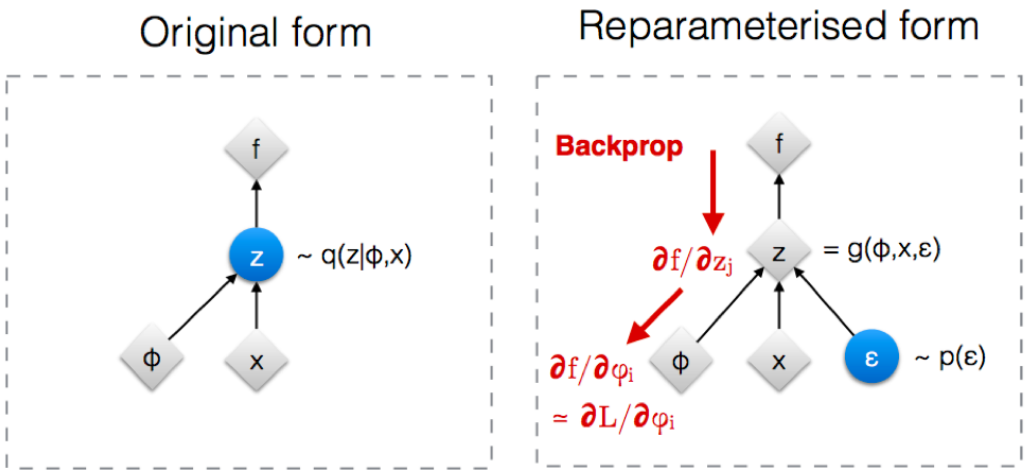
- Loss function consists of two terms (reconstruction loss, KL divergence term)

$$-\underbrace{\mathbb{E}_{\mathbf{z}\sim q(\mathbf{z}|\mathbf{x})}\left[\log p(\mathbf{x}|\mathbf{z})\right]}_{\text{reconstruction error}}+\underbrace{\mathbf{KL}\left(q_\phi(\mathbf{z}|\mathbf{x})||p(\mathbf{z})\right)}_{\text{regularization}}$$

- Reconstruction loss consists of expectation term since we are learning a distribution instead of latent vector.
- KL divergence enforces learned latent distribution to be relatively close to Normal distribution (mean, standard deviation: $\mu = 0, \sigma = 1$).
- Challenge: Backpropogation through sampling vector solved : Re-parameterization trick.

Training VAE: Re-parameterization trick

- ϵ introduced to separate the stochastic behaviour.



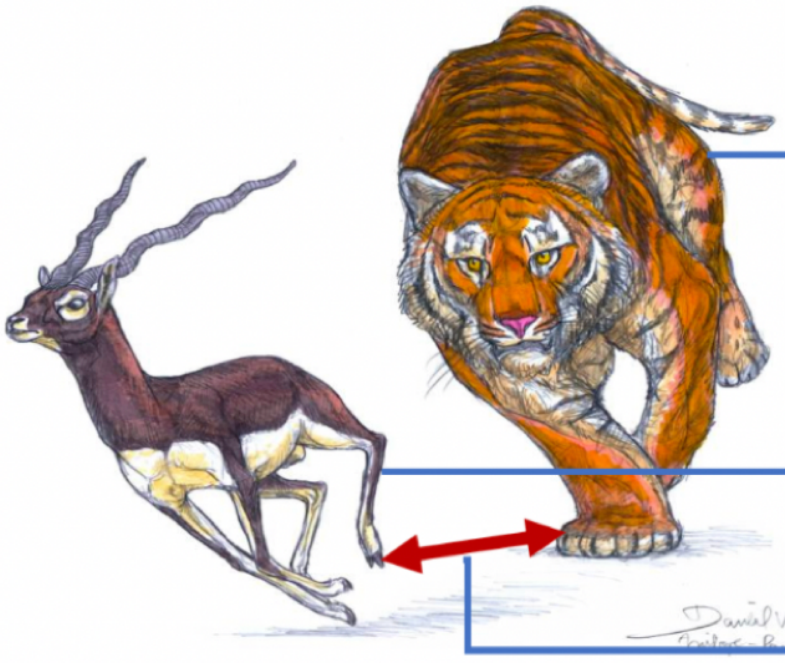
[Kingma, 2013]
[Bengio, 2013]
[Kingma and Welling 2014]
[Rezende et al 2014]

$$\mathbf{z} = \boldsymbol{\mu} + \boldsymbol{\sigma} \odot \boldsymbol{\epsilon}$$
$$\boldsymbol{\epsilon} \sim \mathcal{N}(0, \boldsymbol{I})$$

Limitations of VAE

- Challenges VAE:
  - KL divergence limits learning to Normal distributions (required for closed form solution).
  - Encoded latent distribution and Decoder may be separated far away.
  - Proposed Solution:
    - Use Jensen-Shannon Divergence (JSD) : **Adversarial Auto-encoders**
    - Wasserstein distance based loss function: **Wasserstein Auto-encoders**

Working Principle of Adversarial Networks



Generator
[Tries to generate distribution (minimize) closer to p(z)]

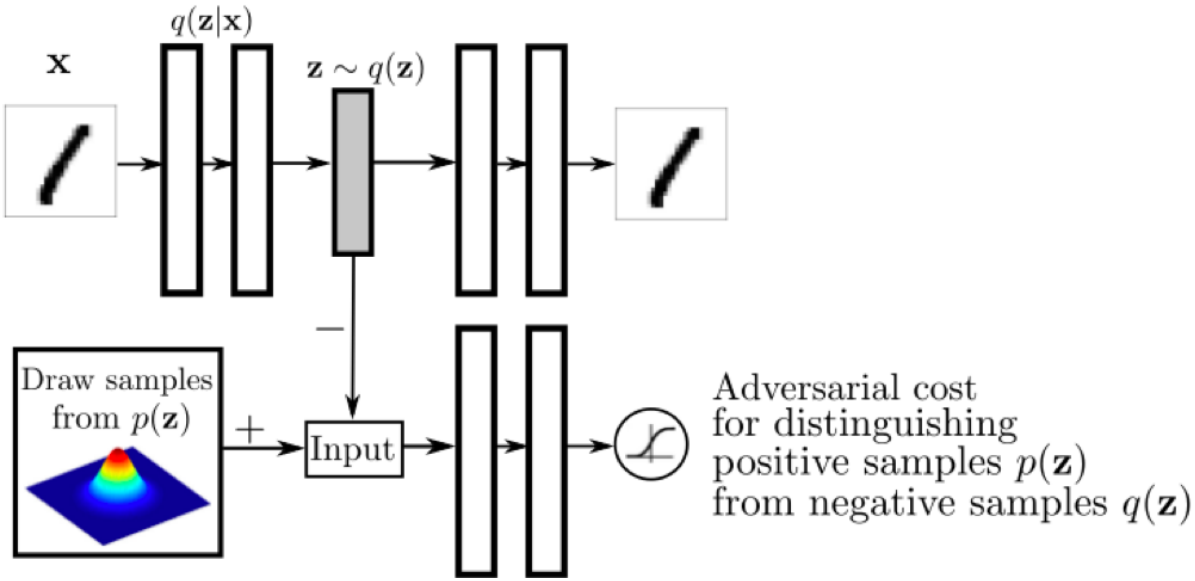
Discriminator
[Tries to maximize separation between generated and input distribution p(z)]

Distance of Separation

$$\min_{\text{Tiger}} \max_{\text{Deer}} \{ \text{Distance of separation} \}$$

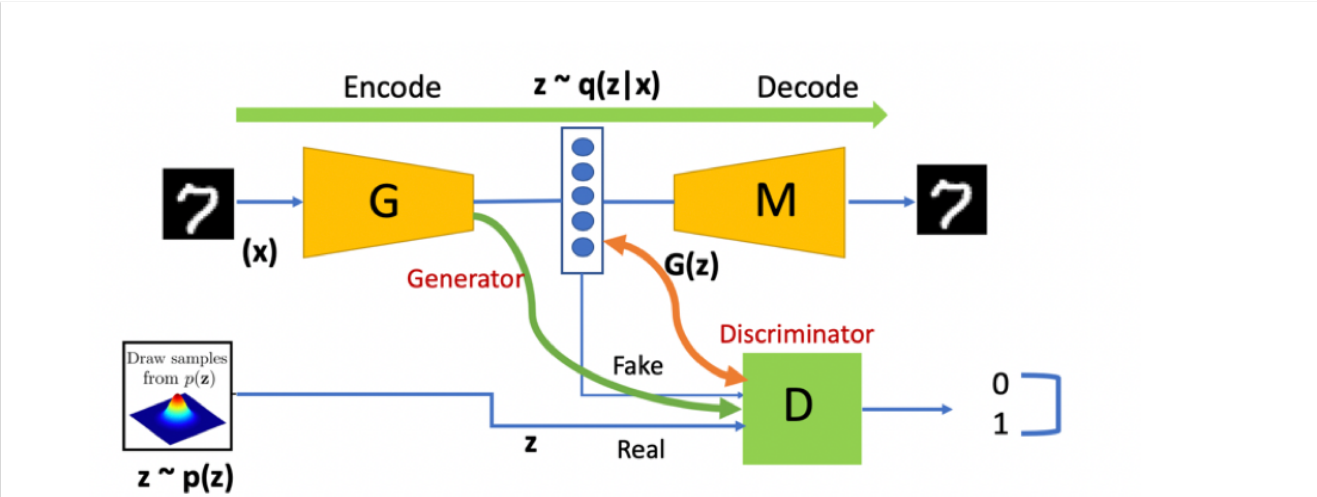
Source: Gredinia from deviantart.com

Adversarial Auto-Encoders (AAE)



- Leverage generator and discriminator networks
- Train VAE and minimize reconstruction loss
- Tune Encoder(Generator) to produce latent embeddings following input p(z) .
- Discriminator aids to tune encoder weights to learn p(z) through back-propagation feedback.

Training AAE



$$\min_G \max_D \mathrm{E}_{\mathrm{x}\sim p_{\mathrm{data}}}[\log D(\mathbf{x})] + \mathrm{E}_{\mathbf{z}\sim p(\mathbf{z})}[\log(1 - D(G(\mathbf{z}))]$$

Reconstruction error

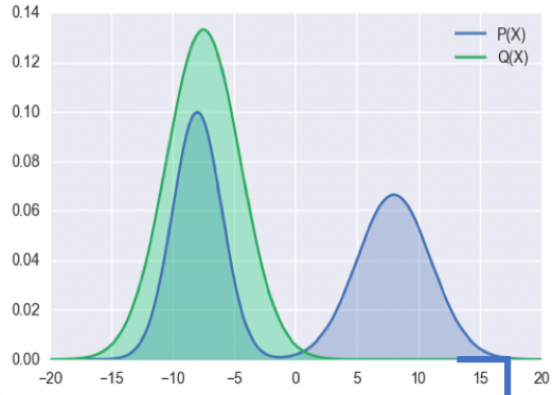
Regularization

- Training is composed of
  - Reconstruction : Autoencoder
  - Regularization : JSD Divergence

Research Path VAE to WAE

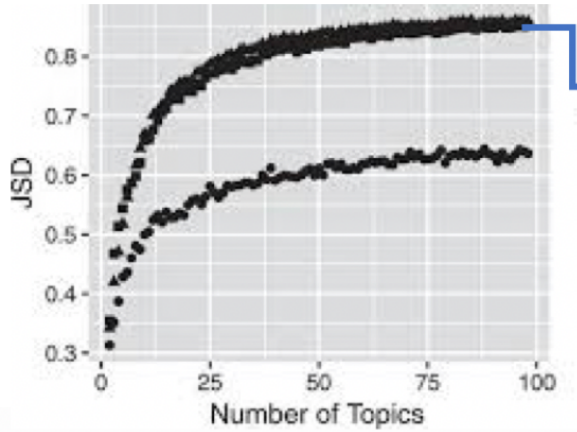
- Kullback–Leibler (KL) Divergence: VAE
- Jensen-Shannon Divergence (JSD): AAE | GAN
- Wasserstein Distance : WAE
- **VAE $<$ AAE $<$ WAE**

Motivation 1: Wasserstein Auto-Encoders (WAE)



$$D_{KL}(p\|q) = \int_x p(x) \log \frac{p(x)}{q(x)} dx \quad \rightarrow \infty$$

(a) KL Divergence



$$D_{JS}(p\|q) = \frac{1}{2} D_{KL}(p\|\frac{p+q}{2}) + \frac{1}{2} D_{KL}(q\|\frac{p+q}{2})$$

(b) Jensen Shannon Divergence (JSD)

- Need stable metric for probability distribution comparision.

Motivation 2: Wasserstein Auto-Encoders (WAE)

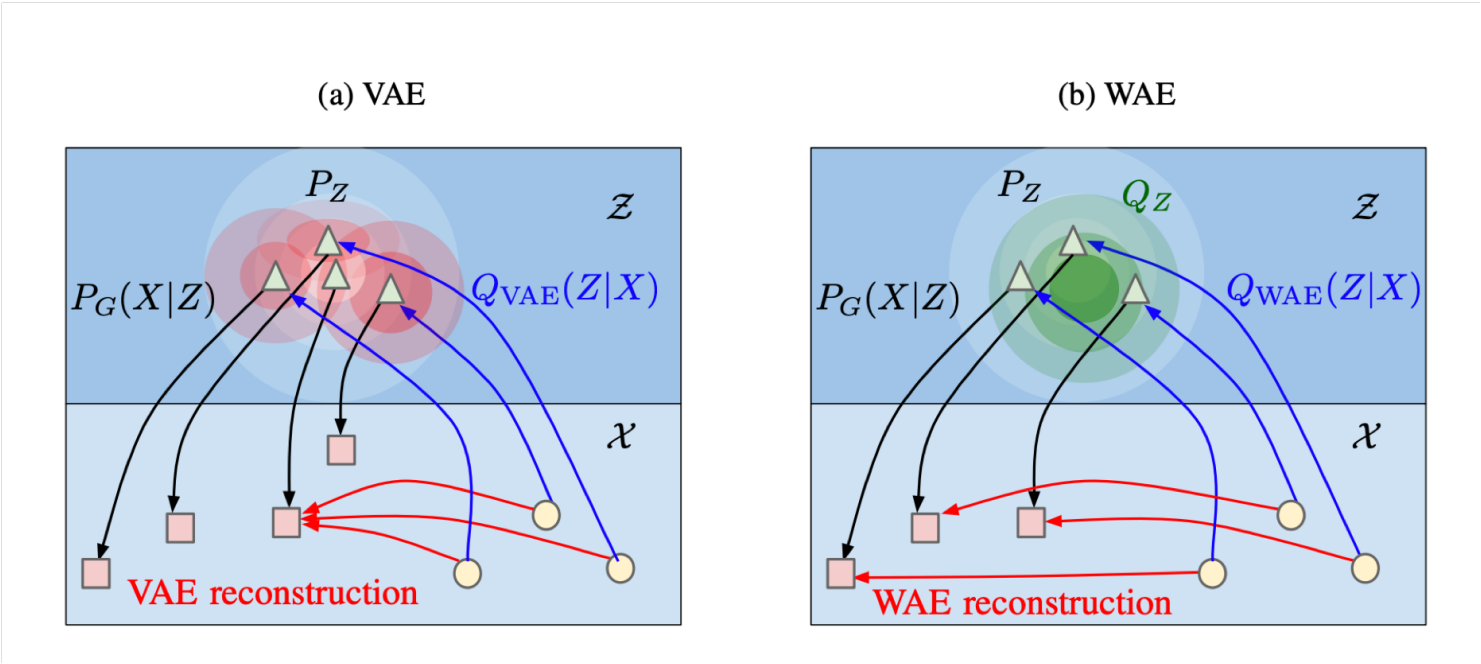
$$\min_G \max_D \mathrm{E}_{\mathrm{x}\sim p_{\mathrm{data}}}[\log D(\mathbf{x})] + \mathrm{E}_{\mathbf{z}\sim p(\mathbf{z})}[\log(1 - D(G(\mathbf{z}))]$$

$$D^* = \frac{p_{data}}{p_{gen} + p_{data}}$$

$$L(G, D^*) = JSD(p_{data}||p_{gen}) - 2log(2)$$
$$\nabla(L(G, D^*) = 0$$

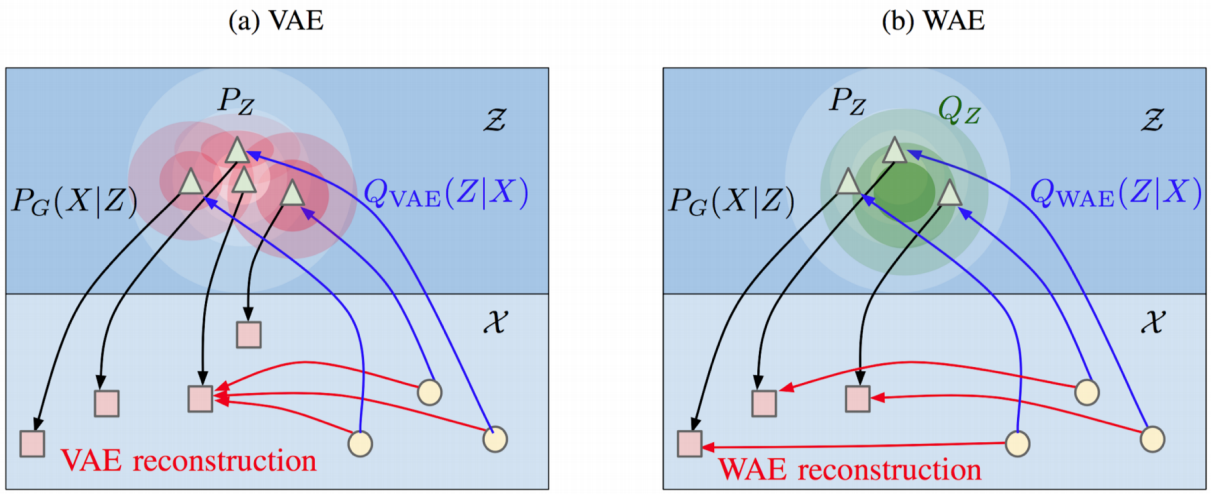
- No learning taking place in initial stages of backpropogation (Min, Max Game).

Wasserstein Auto-Encoders (WAE)



- VAE, $Q(Z|X)$ matches the prior P_z for each point in input.
- WAE, matches the prior in an aggregated global sense to $Q(Z|X)$ with penalized form of the Wasserstein distance.
- WAE latent code for different examples are mapped to be well separately.

Training (WAE)



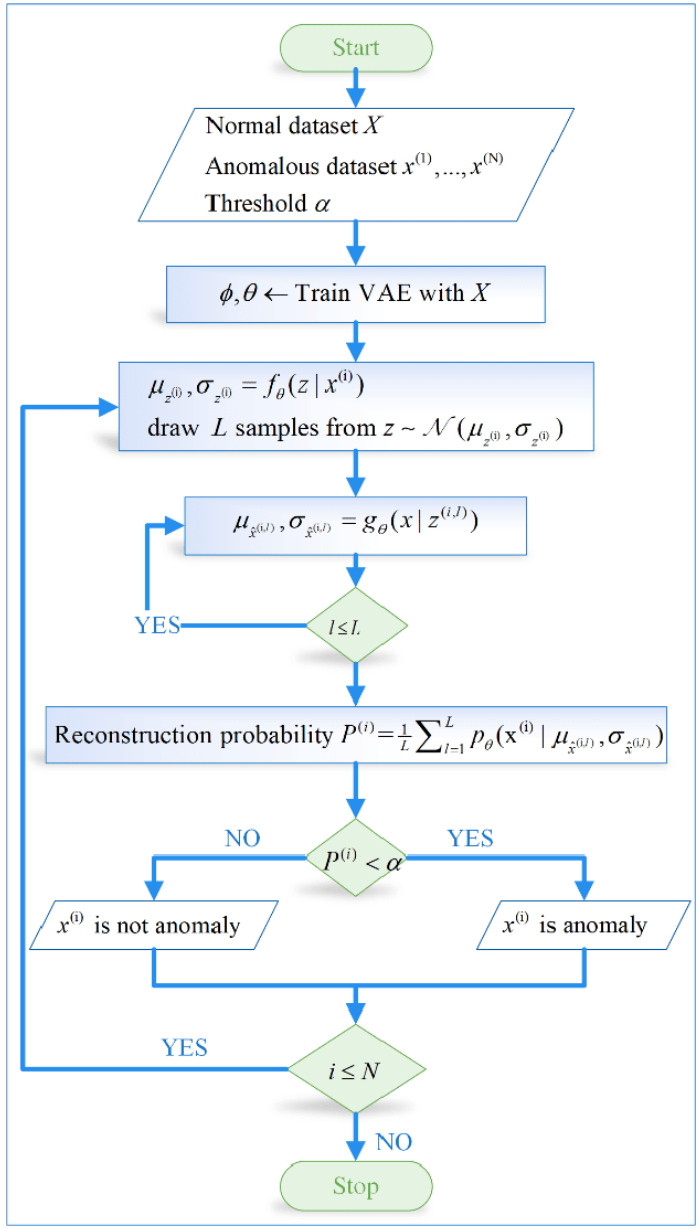
VAE: $\inf_{P_G} \inf_{Q \in \mathcal{Q}} \mathbb{E}_{P_X} \mathbb{E}_{Q(Z|X)}[-\log p_G(X|Z)] + \mathbb{E}_{P_X}[\mathrm{KL}(Q(Z|X), P_Z)]$

WAE: $\inf_{P_G} \inf_{Q \in \mathcal{Q}} \mathbb{E}_{P_X} \mathbb{E}_{Q(Z|X)}[c(X, G(Z))] + \lambda \cdot \mathcal{D}_Z(\mathbb{E}_{P_X}[Q(Z|X)], P_Z)$

- WAEs can be used with any encoders and decoders. .
- Used with any prior distributions P_Z with D_Z = arbitrary divergence (P_Z, Q_Z)
- WAEs can be readily used with any reconstruction cost function.

Anomaly Detection using VAE || AAE || WAE

- Flow chart for anomaly detection [Sultan Zavrak et.al]
- Thesis: Anomalies have higher reconstruction error.



Anomaly Detection using VAE || AAE || WAE

Input : Set of points $\mathbf{X} = \{x_1, ..., x_N\}$, **input** $\mathcal{G} = \left(\mathbf{G}(m)\right)_{m \in \{1,2,...,M\}}$ normal reference images.

Output: Anomaly scores **S** for input points **X**

$f_\phi, g_\psi \leftarrow$ train a VAE || AAE using the input points **X**

for *(m = 1 to M)* **do**

  for *(n = 1 to N)* **do**

    $\mu_z(i), \sigma_z(i) = f_\phi(z|x^{(i)})$

  end

  $(\mu_z,\ \sigma_z) = \sum_{n=1}^{N}(\mu_z(i), \sigma_z(i))$

  draw a sample from $z \sim \mathcal{N}(\mu_z,\ \sigma_z)$

  reconstruct sample using decoder $X_m^{(ref)} = g_\psi(x|z)$

  `/* compute distance this reference group instance` $X_m^{(ref)}$ `*/`

  for *(j = 1 to N)* **do**

    compute the score $s_j = d(X_m^{(ref)}, x_j)$

  end

  sort the images by descending order of score

  S= $(s_j >, s_{j-1} > ..., s_N)$

  points which are farthest from $X_m^{(ref)}$ **constitute group anomalies.**

end

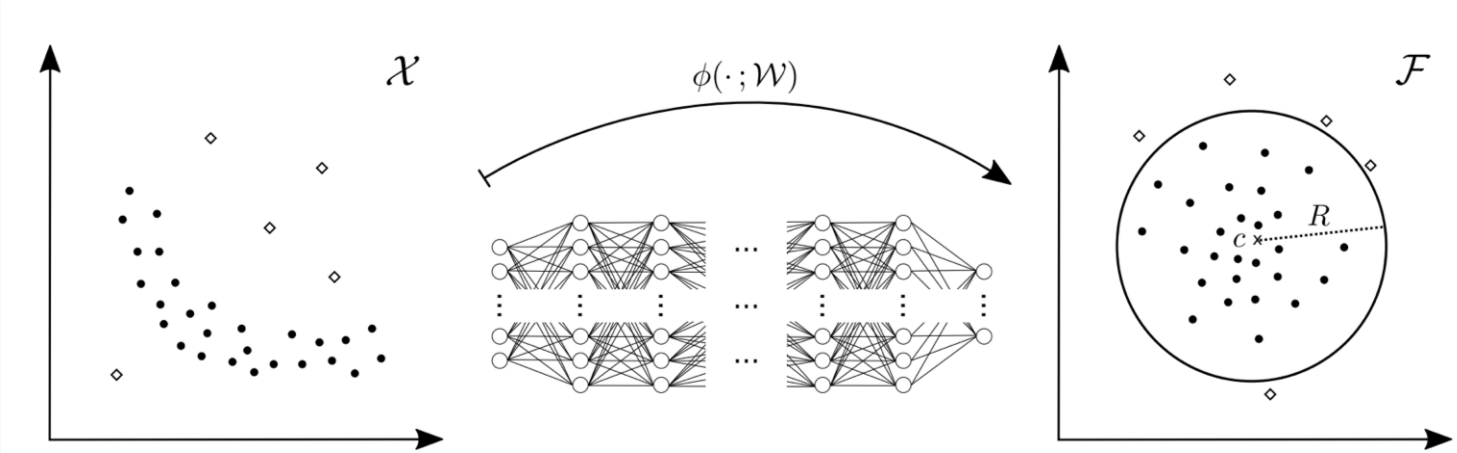
return S

Algorithm: Anomaly detection using generative models VAE || AAE

Notebooks

- Notebook : AE || VAE || AAE || WAE.

Deep Support Vector Data Description (Deep SVDD)



- Deep SVDD learns a neural network transformation into a hypersphere.
- Mappings of normal examples fall within, whereas mappings of anomalies fall outside the hypersphere.

Training Deep SVDD

- Soft Boundary Deep SVDD: minimizing the volume of a data-enclosing hypersphere in output.

$$\min_{\mathcal{W}} \quad \frac{1}{n}\sum_{i=1}^{n}\|\phi(\boldsymbol{x}_i;\mathcal{W})-\boldsymbol{c}\|^2+\frac{\lambda}{2}\sum_{\ell=1}^{L}\|\boldsymbol{W}^\ell\|_F^2.$$

- Deep SVDD.

$$\begin{aligned}\min_{R,\mathcal{W}} \quad & R^2+\frac{1}{\nu n}\sum_{i=1}^{n}\max\{0,\|\phi(\boldsymbol{x}_i;\mathcal{W})-\boldsymbol{c}\|^2-R^2\}\\ & +\frac{\lambda}{2}\sum_{\ell=1}^{L}\|\boldsymbol{W}^\ell\|_F^2.\end{aligned}$$

- Anomaly Score:

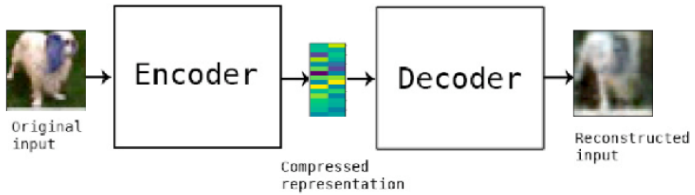
$$s(\boldsymbol{x})=\|\phi(\boldsymbol{x};\mathcal{W}^*)-\boldsymbol{c}\|^2$$

- $\phi(x_i, W^*)$: its associated feature mapping; λ is tuning parameter c, R center and radius of hypersphere,

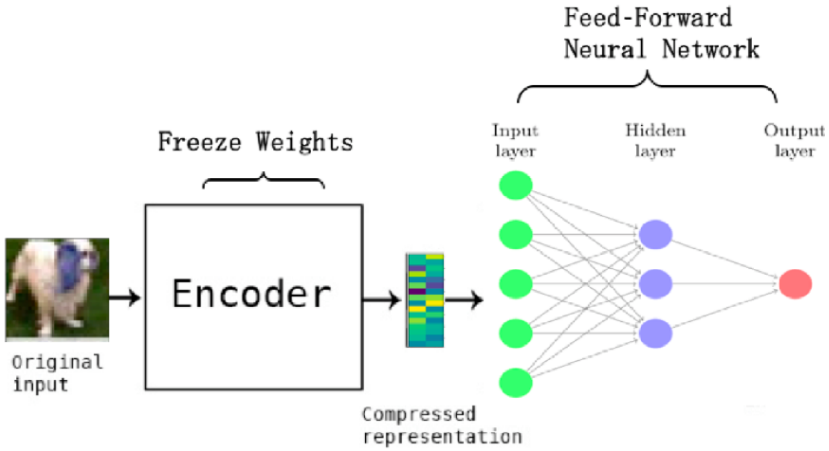
Notebook

- Notebook : Deep SVDD.

One-Class Neural Networks (OCNN)



(a) Autoencoder.



(b) One-class neural networks.

- OC-NN objective is customized for anomaly detection.
- OC-NN uses one-class SVM (OC-SVM) like loss function to train a neural network.

Training OCNN

- One-class Neural Network (OCNN).

$$\min_{w,V,r} \frac{1}{2}\|w\|_2^2 + \frac{1}{2}\|V\|_F^2 + \frac{1}{\nu} \cdot \frac{1}{N} \sum_{n=1}^{N} \max(0, r - \langle w, g(V\mathbf{X}_{n:})\rangle) - r$$

- OCNN Algorithm for anomaly detection:

Algorithm 1 one-class neural network (OC-NN) algorithm

Input: Set of points $\mathbf{X}_{n:}$, $n : 1, ..., N$
Output: A Set of decision scores $S_{n:} = \hat{y}_{n:}$, n: 1,...,N for X
Initialise $r^{(0)}$
$t \leftarrow 0$
while (no convergence achieved) **do**
    Find $(w^{(t+1)}, V^{(t+1)})$ ▷ Optimize Equation 4 using BP.
    $r^{t+1} \leftarrow \nu^{\text{th}}$ quantile of $\{\hat{y}_n^{t+1}\}_{n=1}^N$
    $t \leftarrow t + 1$
end
Compute decision score $S_{n:} = \hat{y}_n - r$ for each $\mathbf{X}_{n:}$
if $(S_{n:} \geq 0)$ **then**
    $\mathbf{X}_{n:}$ is normal point
else
    $\mathbf{X}_{n:}$ is anomalous
return $\{S_n\}$

- Key insight is to replace scalar dot product with feature representations within neural network

Notebook

- Notebook : One-class Neural Network (OCNN).

References

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