

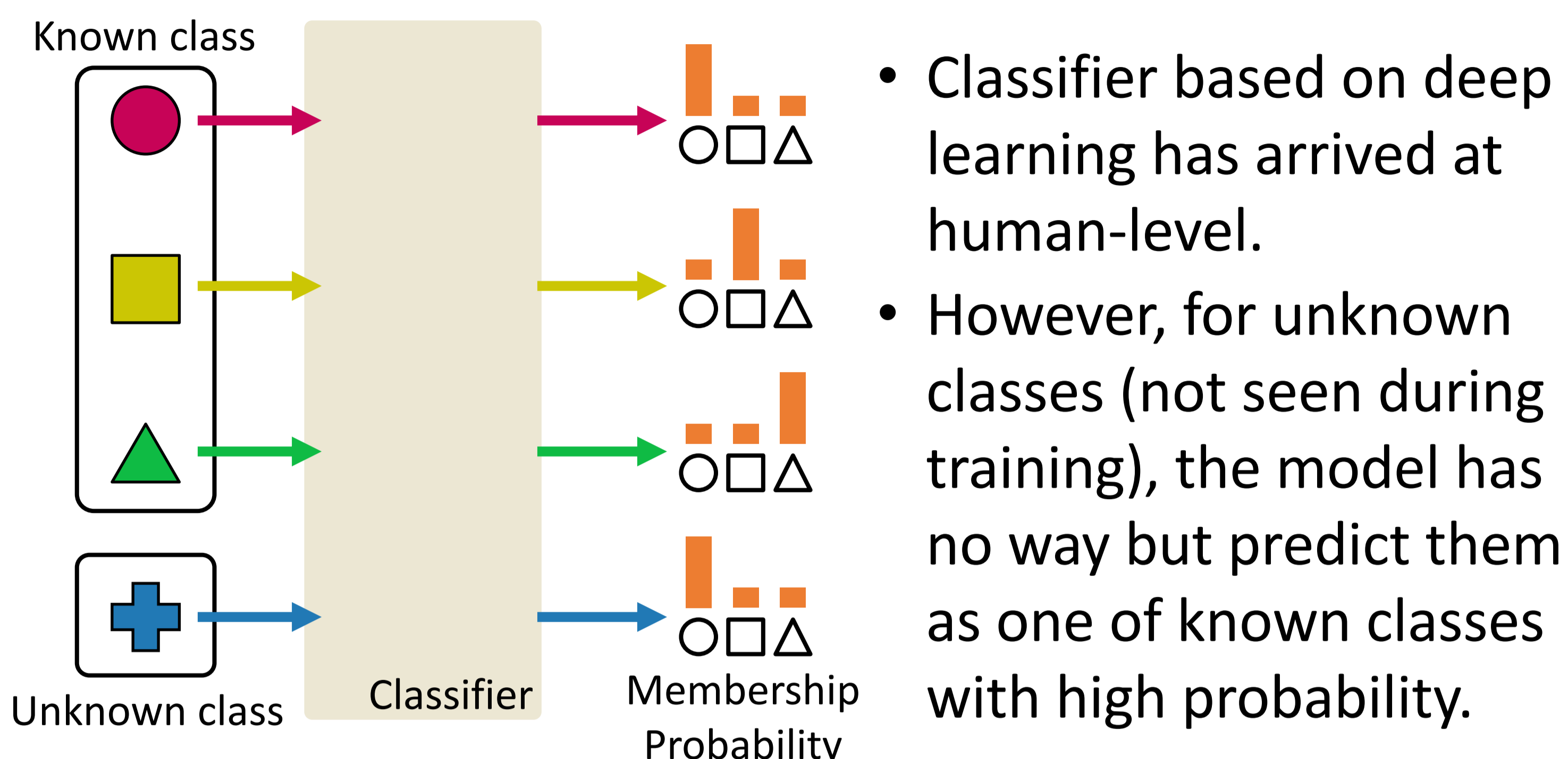


# OPEN SET RECOGNITION BY REGULARISING CLASSIFIER WITH FAKE DATA GENERATED BY GENERATIVE ADVERSARIAL NETWORKS

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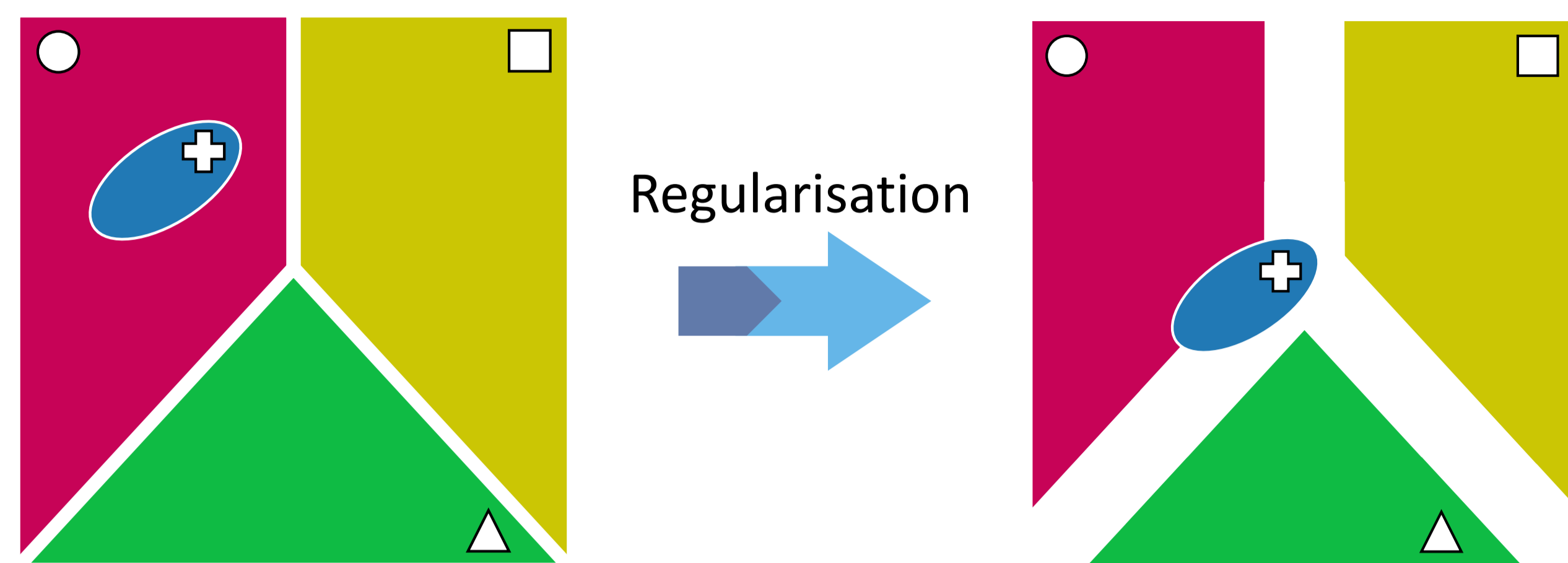
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## Introduction and Motivation



## GAN-Marginal DFM (GAN-MDFM)

❖ Problematic behavior of classifier



Decision boundary on feature space of classifier  
Known class (circle, square, triangle), Unknown class (cross)

- If we could generate fake data located on feature space nearby space of known classes, classifier would be easily trained by minimising cross entropy and maximising entropy of fake data.
- To train classifier end-to-end, fake data is necessary.
  - ➔ Tightening decision boundary.
  - ➔ Separating unknown classes from known classes on feature space.

❖ Objective

- Classifier: minimise cross entropy with positive data (known classes)  
maximise entropy with fake negative data (unknown classes)

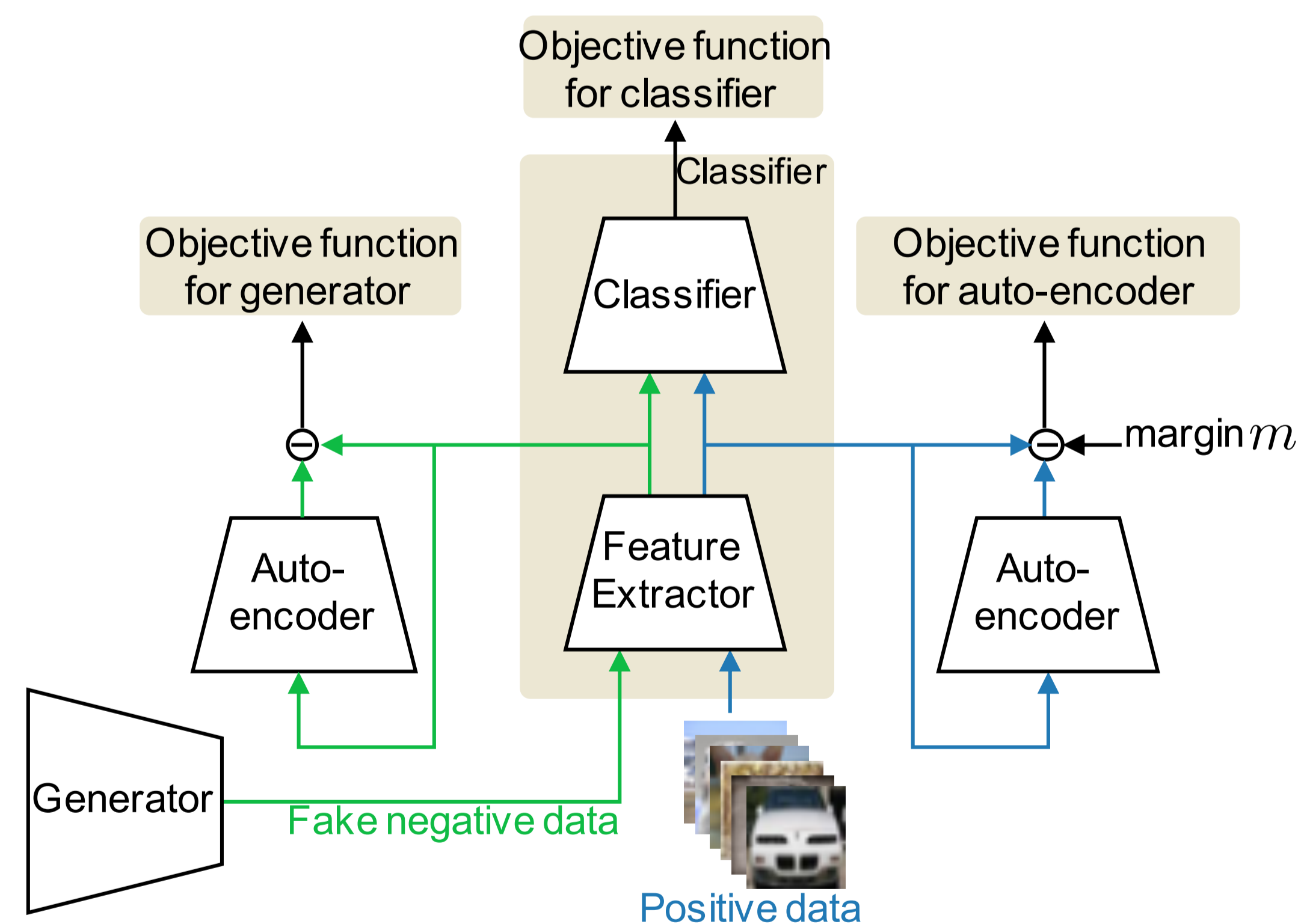
$$\min_C -\mathbb{E}_{\mathbf{x}, y \sim p_{\text{data}}(\mathbf{x}, y)} [\log p_C(y|\mathbf{x})] - \mathbb{E}_{\mathbf{x} \sim p_G(\mathbf{x})} [H(p_C(y|\mathbf{x}))]$$

- Marginal Denoising Autoencoder (MDAE): model  $m$  noisy feature distribution of known classes

$$\min_M \mathbb{E}_{\mathbf{x} \sim p_{\text{data}}(\mathbf{x})} [\|\Phi(\mathbf{x}) - M(n(\Phi(\mathbf{x})))\|^2 - m]$$

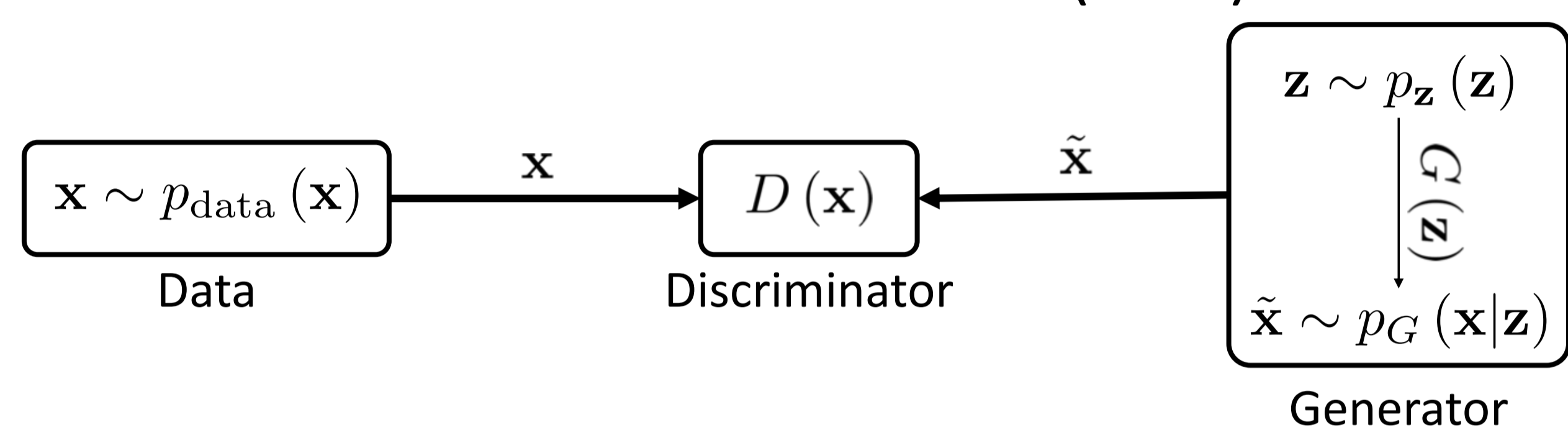
- Generator: generate fake negative data that is located on  $m$  away feature space from the one known classes

$$\min_G \mathbb{E}_{\mathbf{z} \sim p_{\mathbf{z}}(\mathbf{z})} [\|\Phi(G(\mathbf{z})) - \underbrace{M(\Phi(G(\mathbf{z})))}_{\text{fixed}}\|^2]$$



## Background

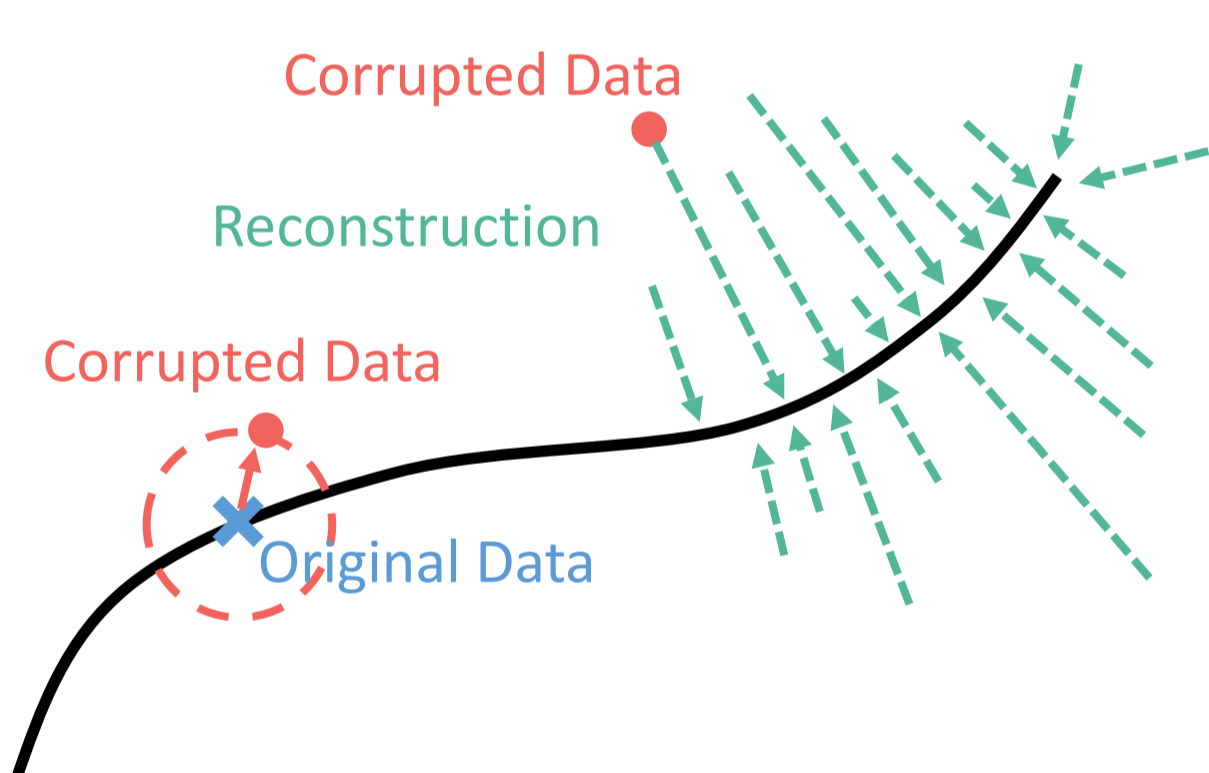
❖ Generative Adversarial Networks (GAN)<sup>1</sup>



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

❖ GAN-DFM<sup>2</sup>

- Denoising autoencoder (DAE) models distribution of training data on feature space of discriminator
- Generator is trained to match distribution of training data on feature space of discriminator (DFM)



$$\min_G \mathbb{E}_{\mathbf{z} \sim p_{\mathbf{z}}(\mathbf{z})} [\|\Phi_D(G(\mathbf{z})) - \underbrace{r(\Phi_D(G(\mathbf{z})))}_{\text{fixed}}\|^2 - \log D(G(\mathbf{z}))]$$

## Selected References

- [1] I. J. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio, "Generative adversarial nets," in Advances in Neural Information Processing Systems (NIPS), 2014.
- [2] D. Warde-Farley and Y. Bengio, "Improving generative adversarial networks with denoising feature matching," in Proceedings of the International Conference on Learning Representations (ICLR), 2017.

## Experimental Results

- Regularisation of GAN-MDFM did not degenerate accuracy at all but even improved on CIFAR10.
- Our model outperformed other methods in terms of Area Under the Curve (AUC).
- Generated data seemed similar to training data but not exactly as our purpose.

## Conclusions

- We have proposed a unknown class generator with assistance of MDAE.
- Our generated data is well-designed augmented data for regularising classifier.

Table 1. Classification accuracy

	Baseline	Convex	PCA	VAE	GAN	GAN-MDFM
MNIST	0.987	0.986	0.987	0.988	<b>0.991</b>	0.987
CIFAR10	0.707	0.654	0.700	0.702	0.616	<b>0.728</b>

Table 2. Area under the curve

	Baseline	Convex	PCA	VAE	GAN	T-scaling	GAN-MDFM
MNIST vs. notMNIST	entropy	0.930	0.976	0.907	0.926	<b>0.987</b>	0.938
	max logit	0.885	0.969	0.840	0.865	0.982	<b>0.991</b>
CIFAR10 vs. CIFAR100	entropy	0.666	0.671	0.656	0.666	0.641	<b>0.729</b>
	max logit	0.696	0.664	0.687	0.691	0.641	<b>0.721</b>

