Adversarial Variational Transfer for Semi-supervised Domain Adaptation

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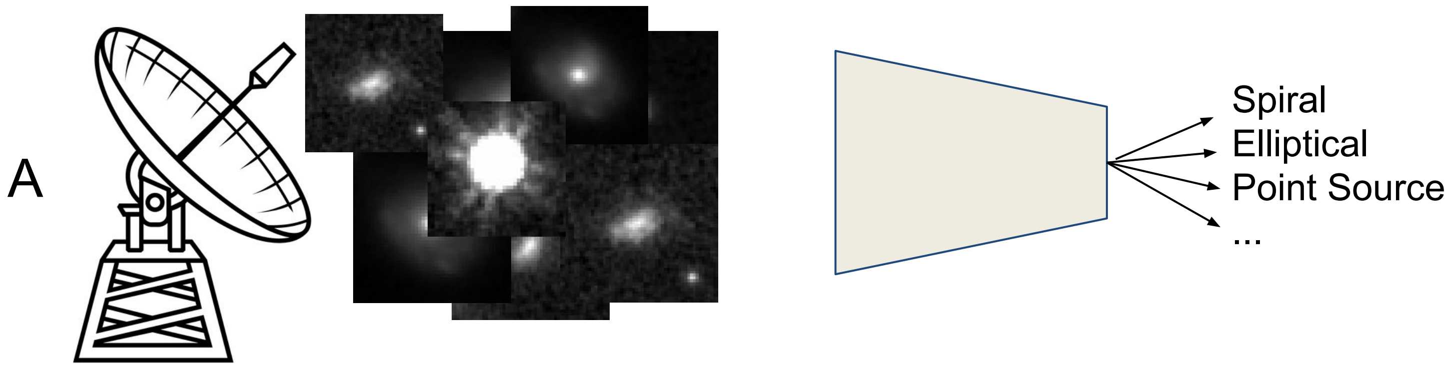
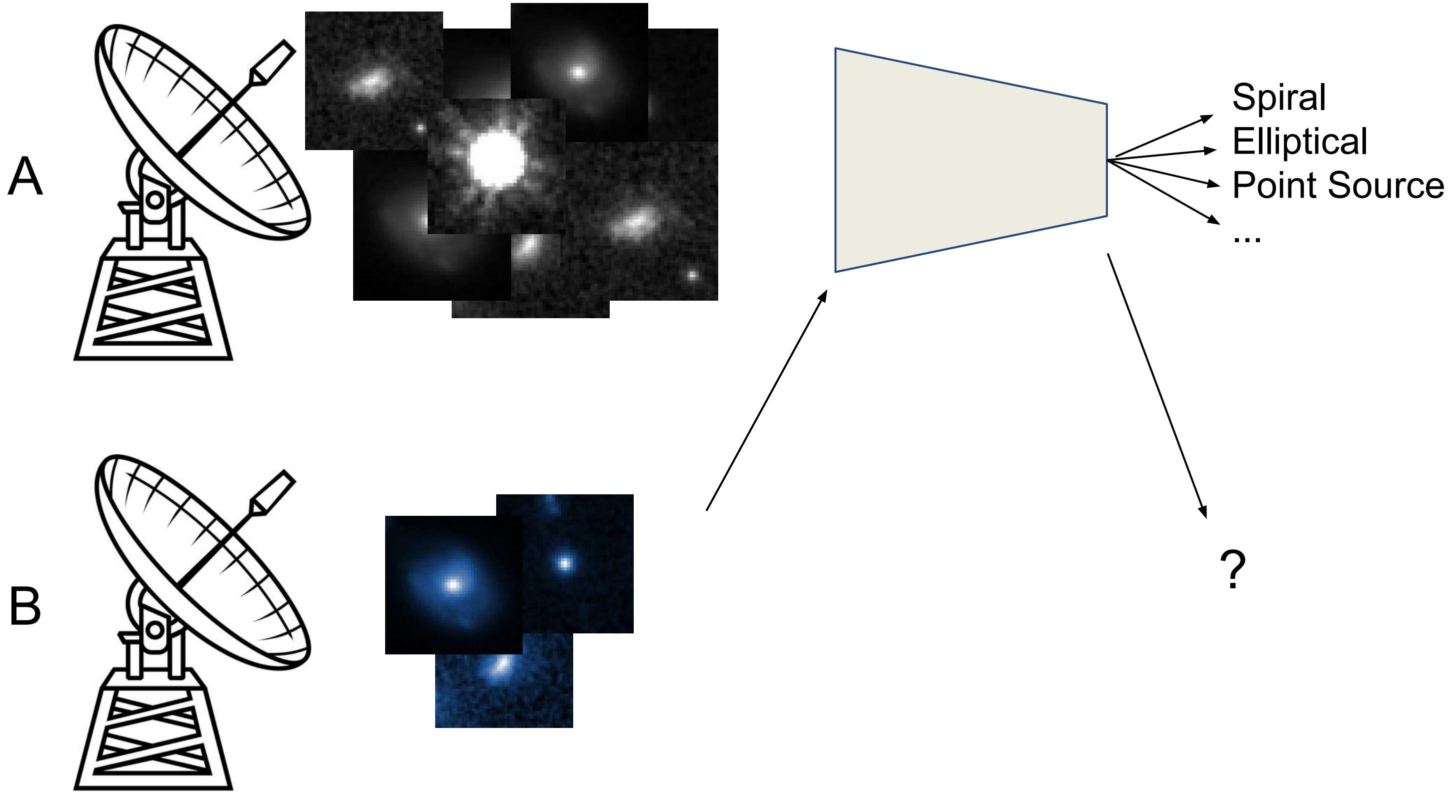
Outline

- Introduction
- Background: Neural Networks, Autoencoders, Adversarial Learning
- Related Domain Adaptation works.
- Adversarial Variational Transfer
- Results

Introduction



Introduction



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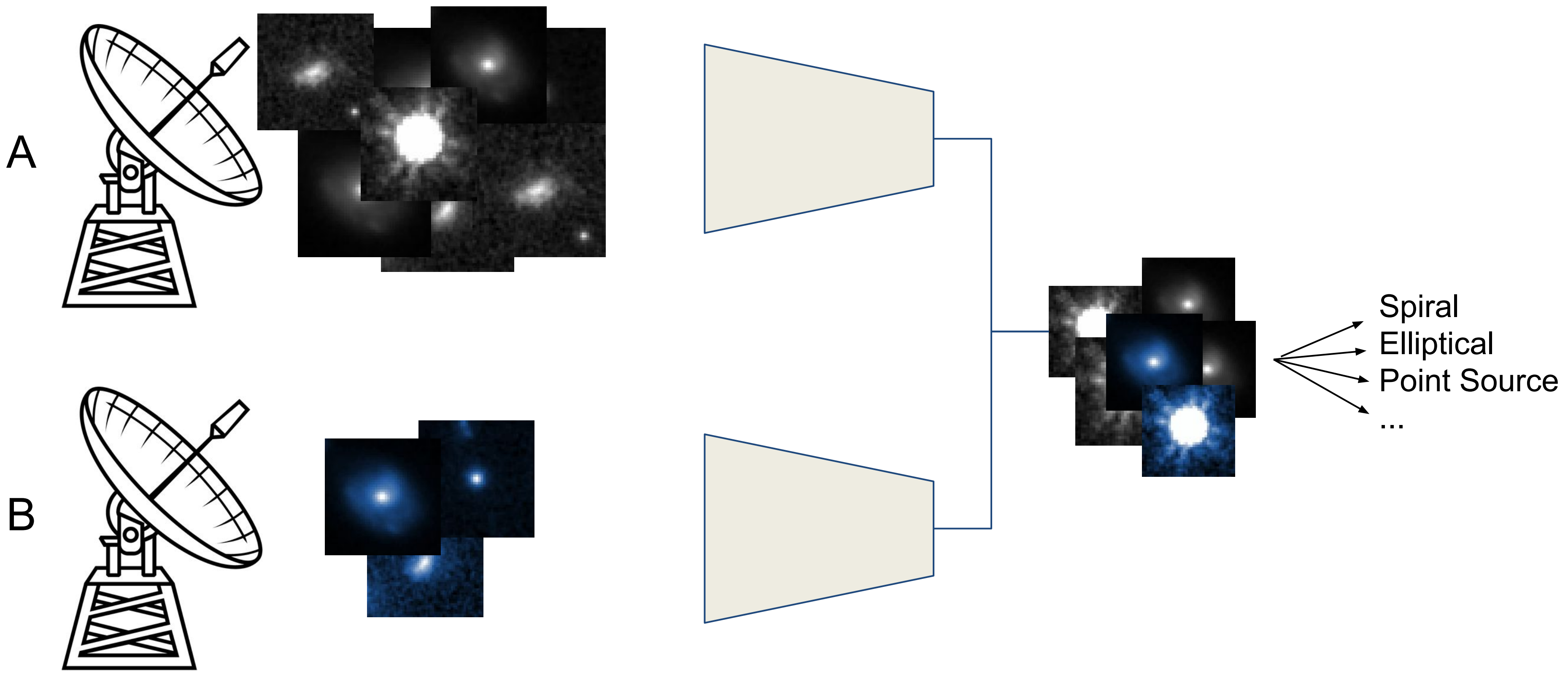

Neural Networks (review)

For an input x and some output y, it is possible to find a mapping from the input space to the output space using a function

$$y = f(x) + \epsilon$$

We can find an approximated function $\hat{f}(x)$ to estimate y using neural networks.

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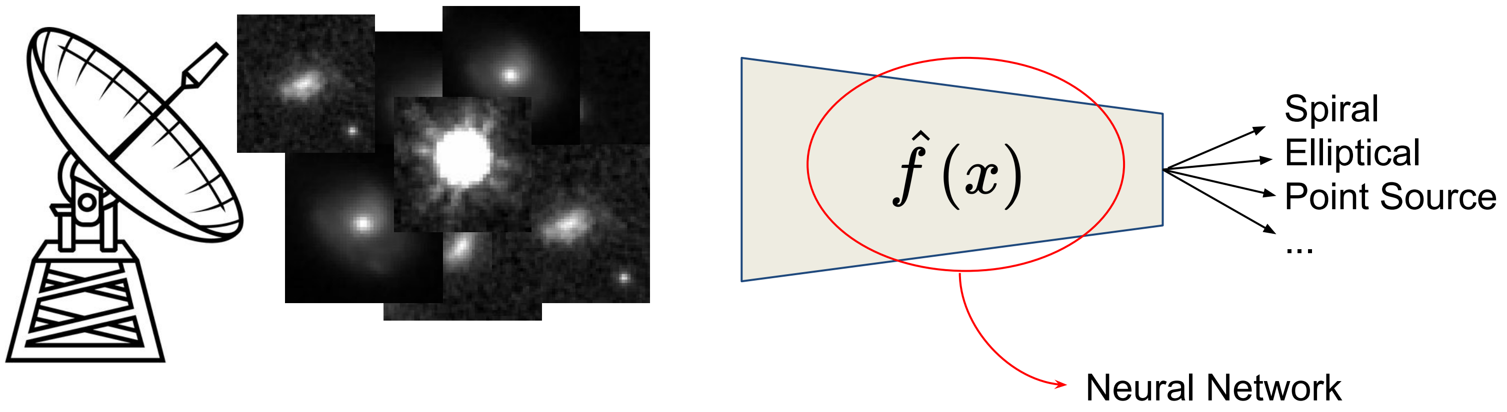
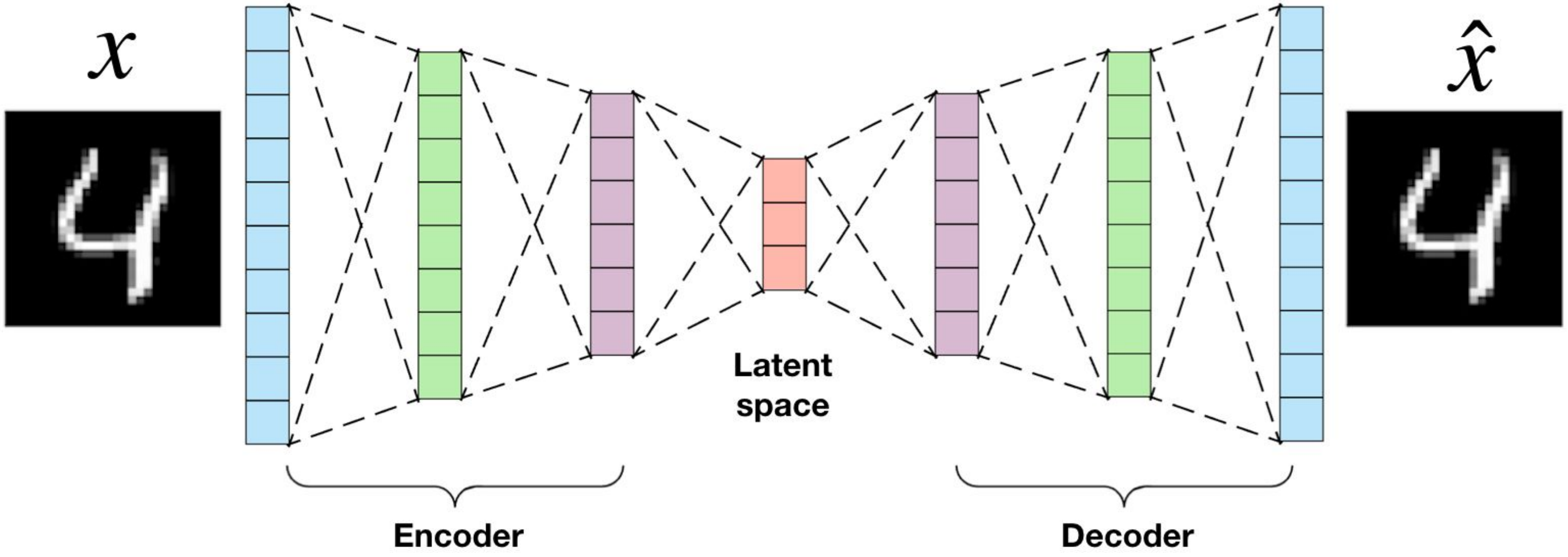


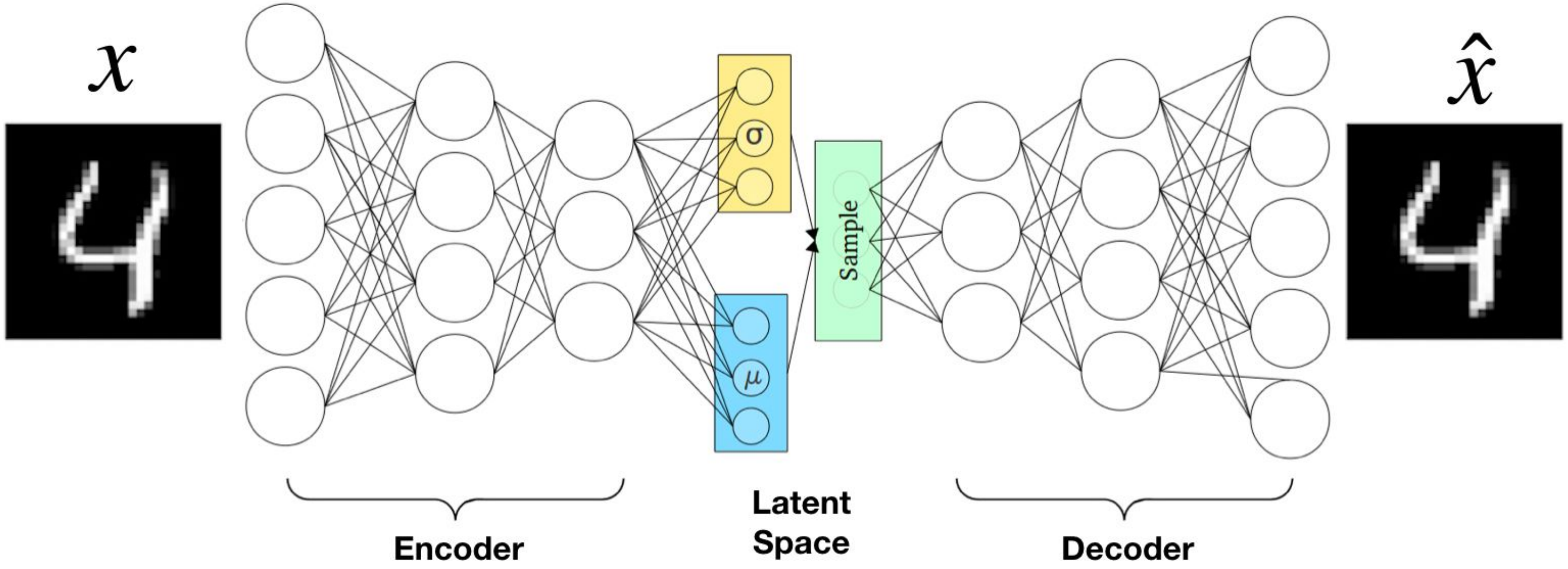
Autoencoders (review)

Autoencoders are models used to learn a function $f(x) = x$ using a compressed representation of the data called latent space.



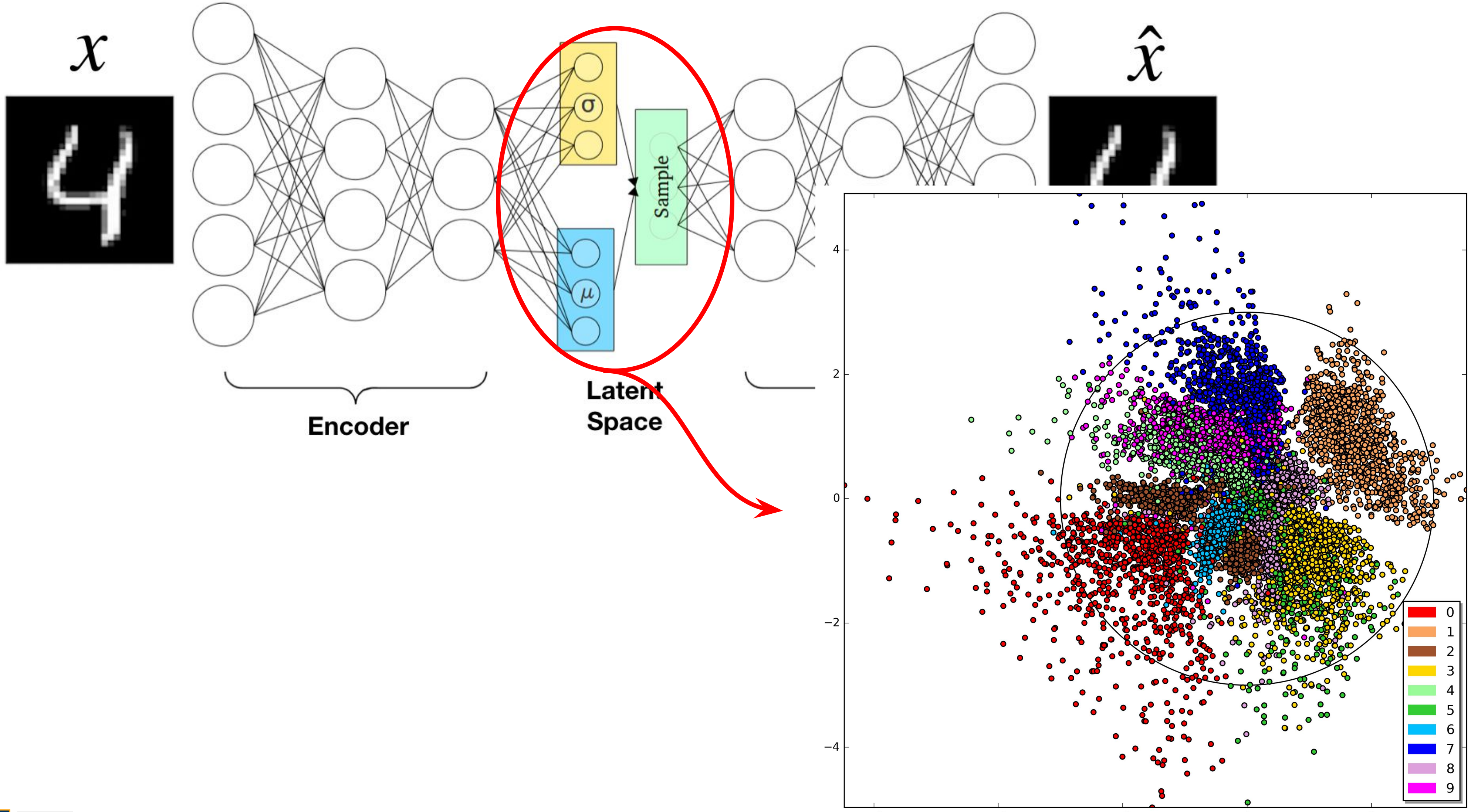
Variational Autoencoders (review)

In Variational Autoencoders we try to learn the function $f(x) = x$ using a latent space z that follows a **known** distribution. Hence, we can sample from it.

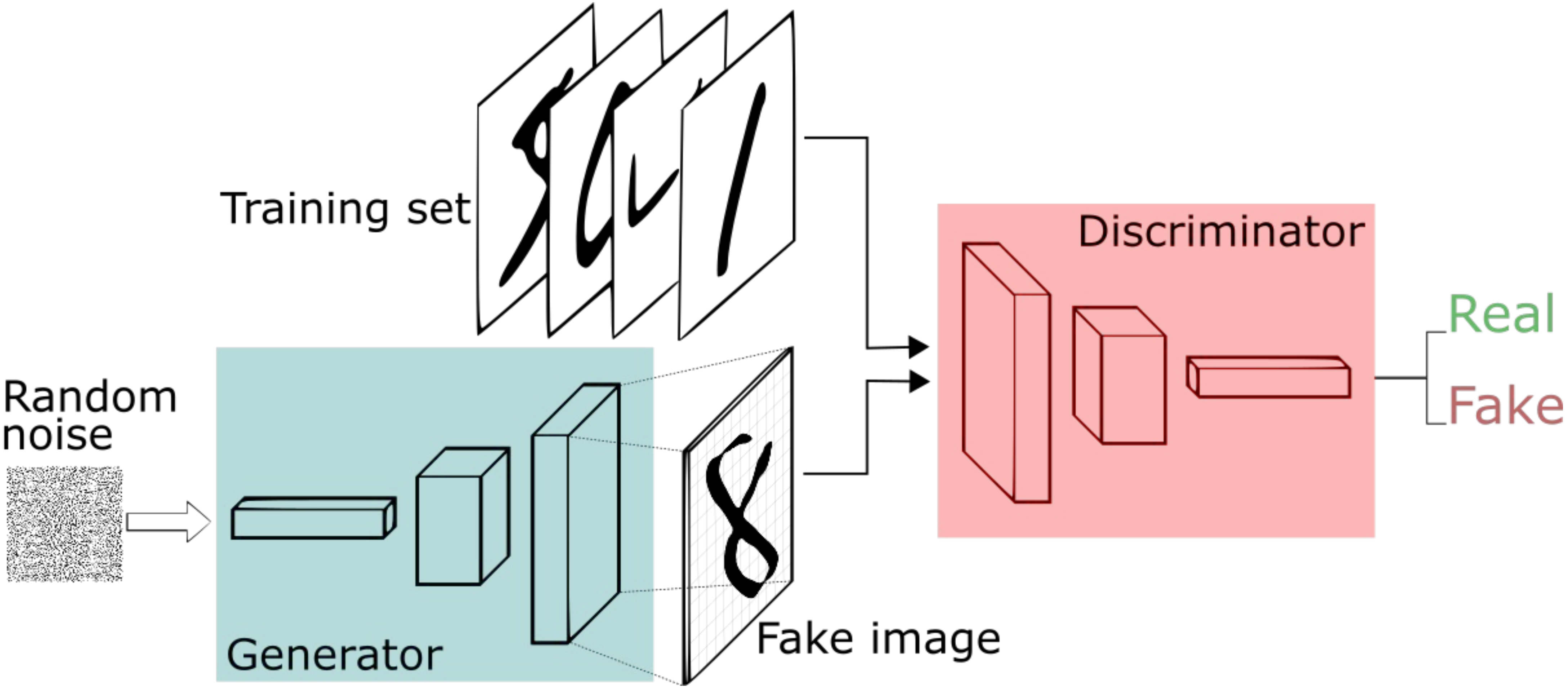


Kingma et al. 2013

Variational Autoencoders (review)

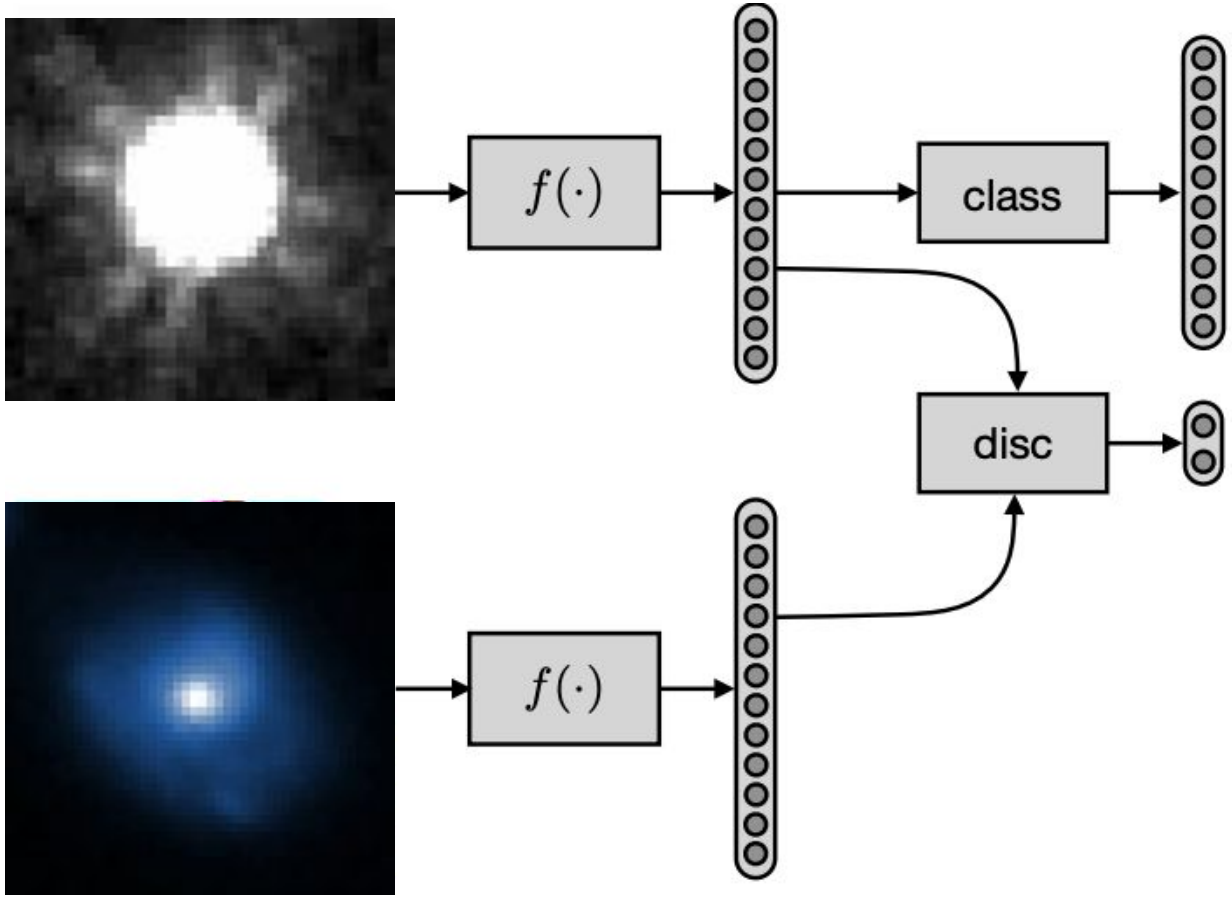


Adversarial Learning: review

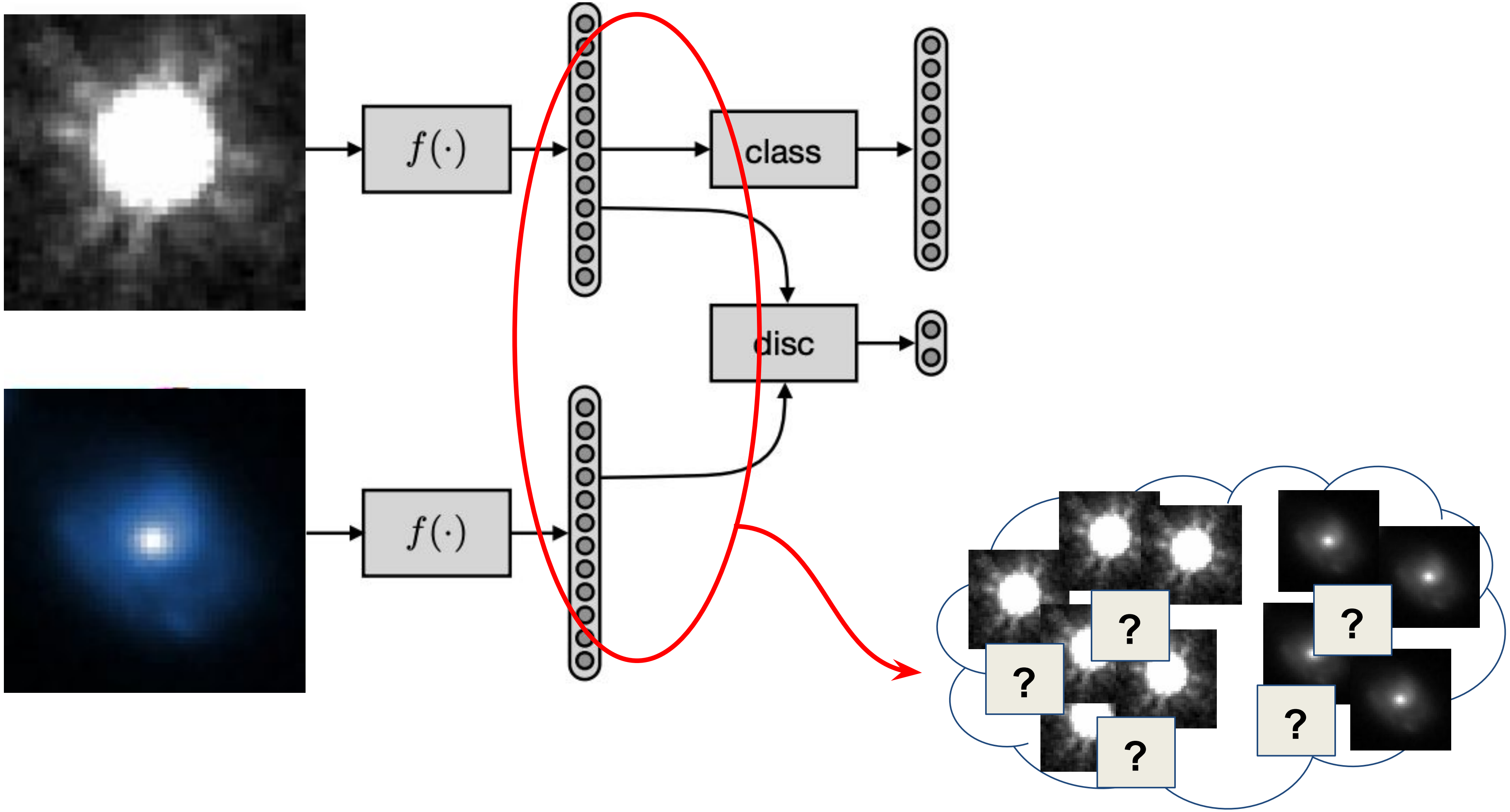


Goodfellow et al. 2014

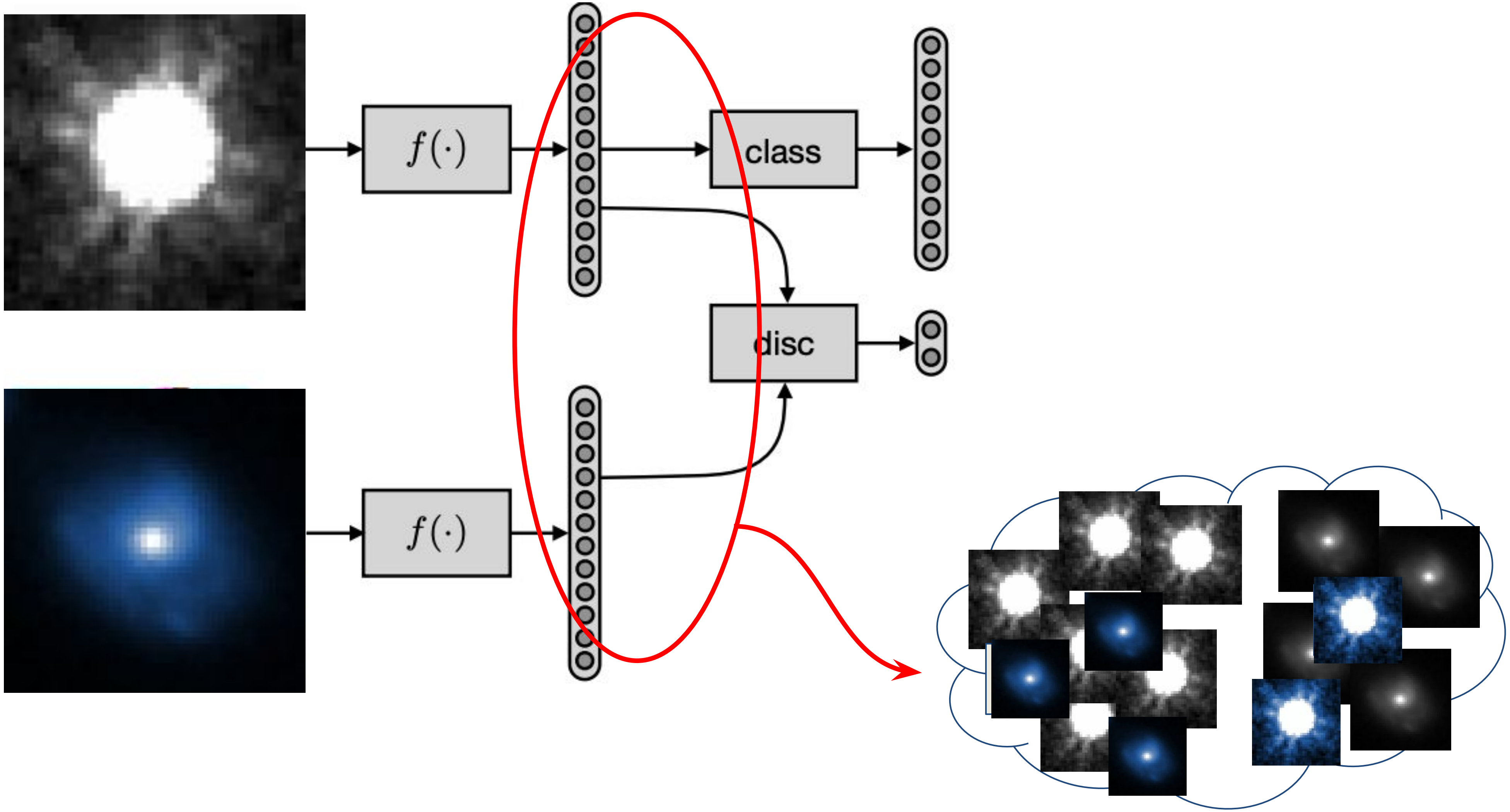
Domain Adaptation: Unsupervised



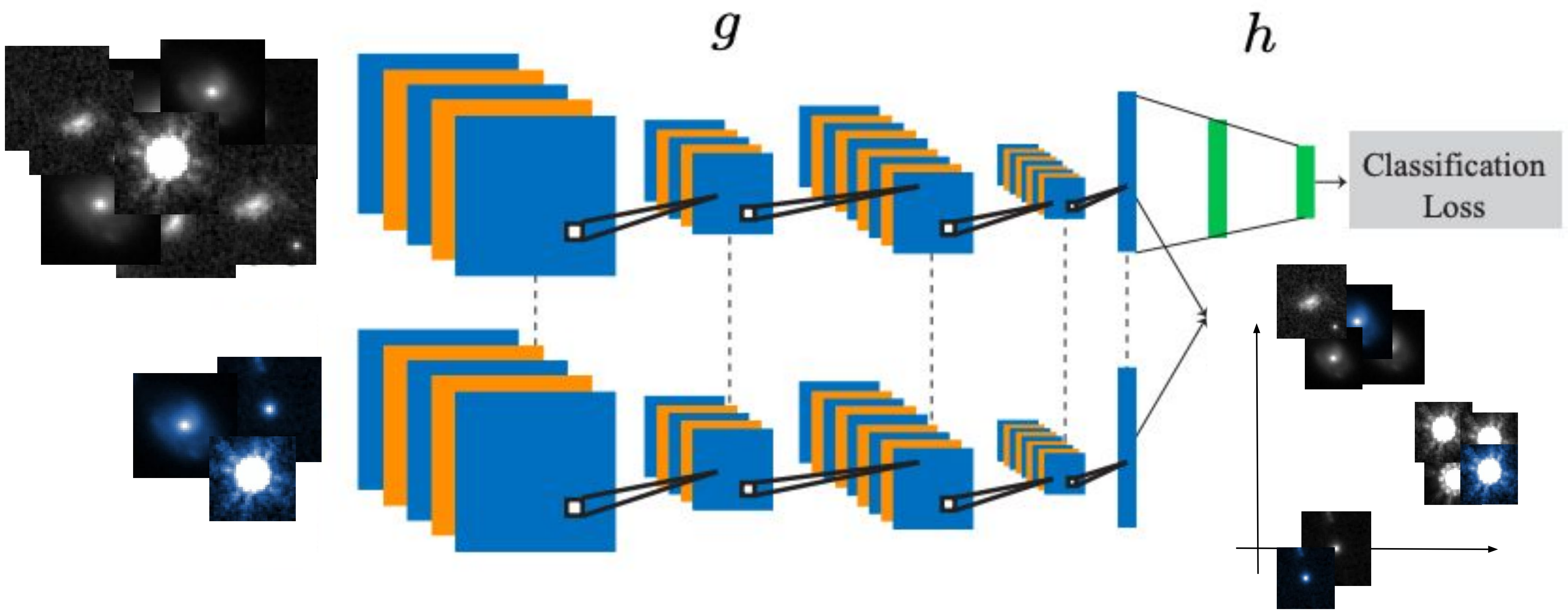
Domain Adaptation: Unsupervised



Domain Adaptation: Unsupervised

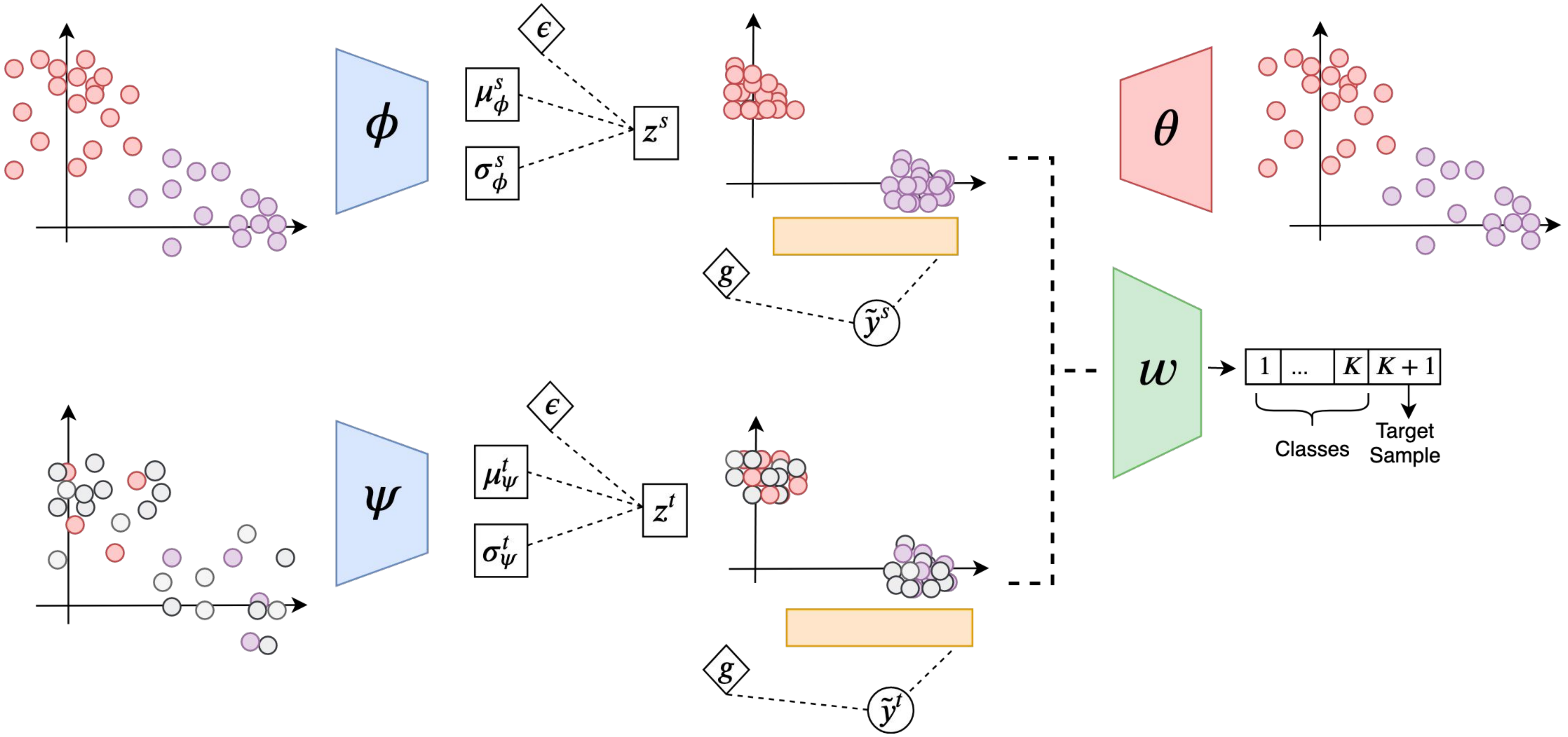


Domain Adaptation: Supervised

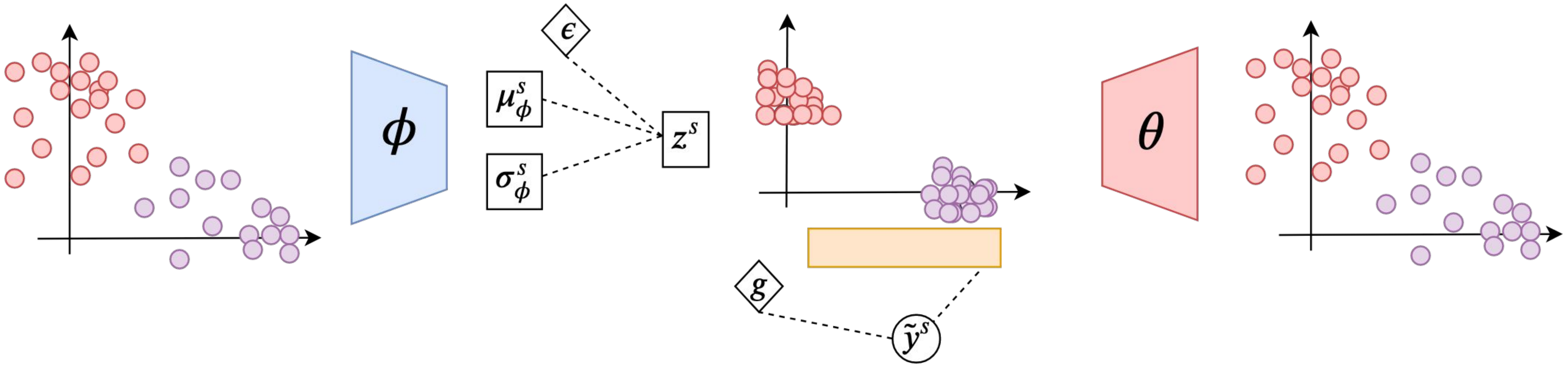


Mottian et al. 2017

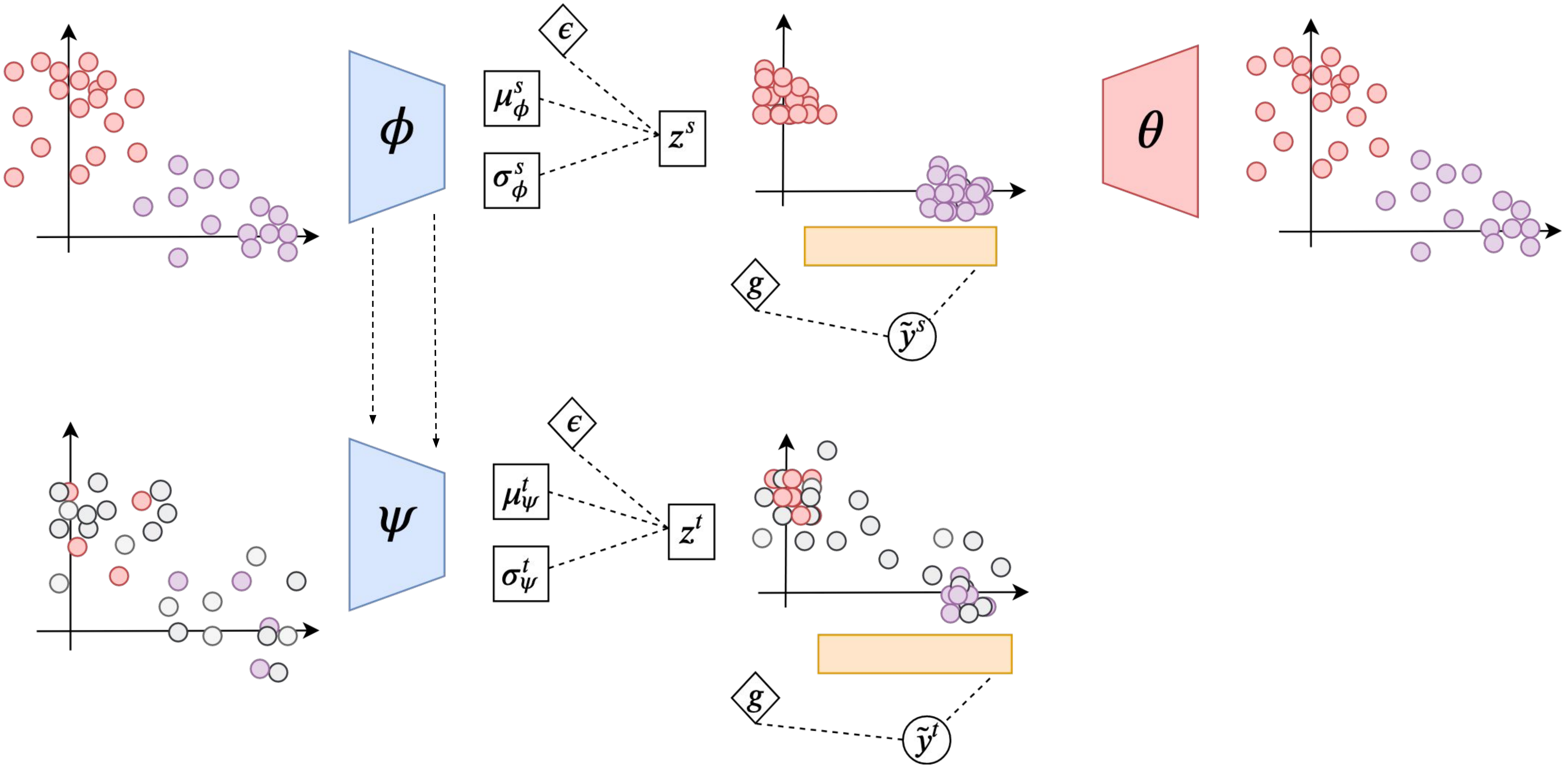
Adversarial Variational Transfer



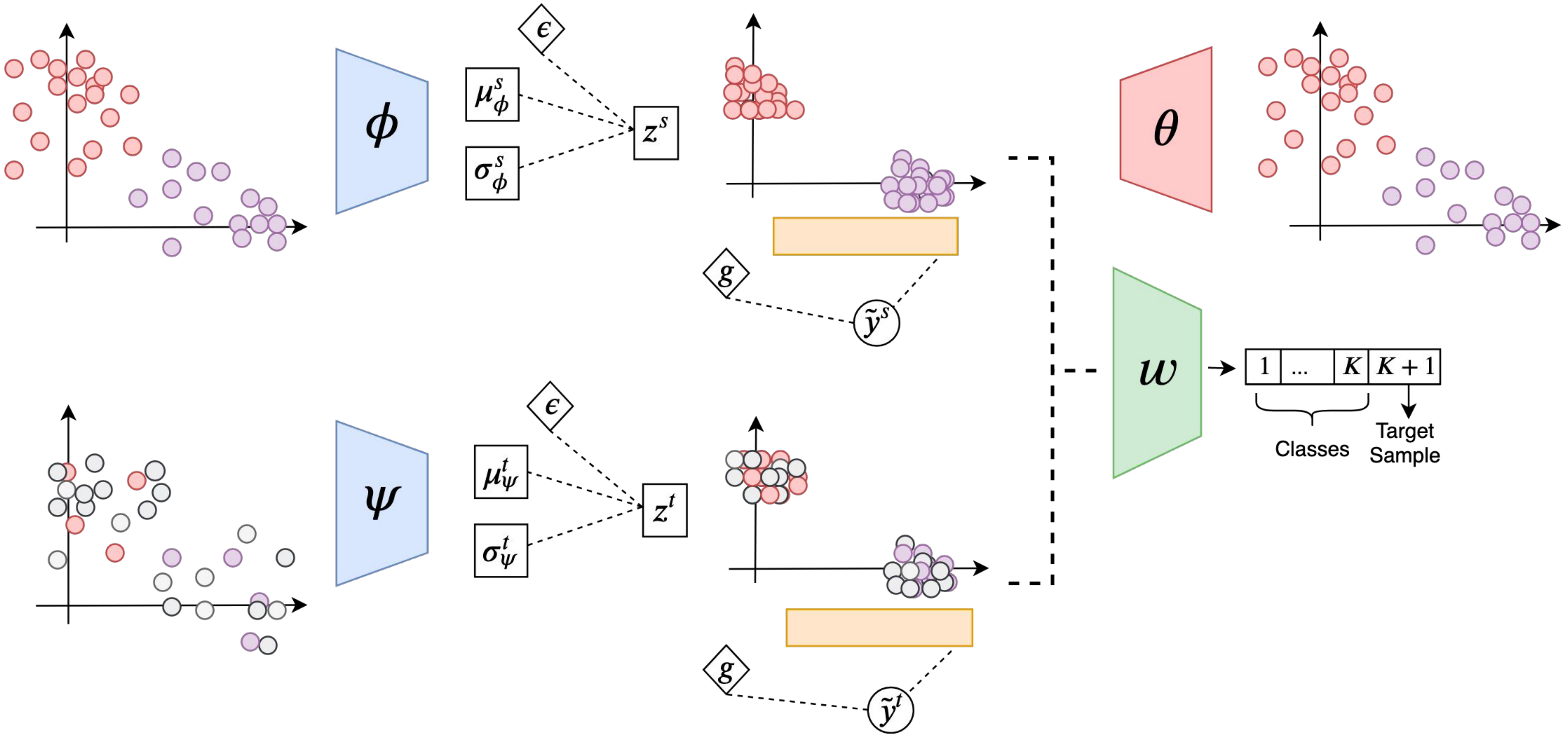
Adversarial Variational Transfer: Step 1



Adversarial Variational Transfer: Step 2



Adversarial Variational Transfer: Step 3



Results: Digits

MNIST

USPS

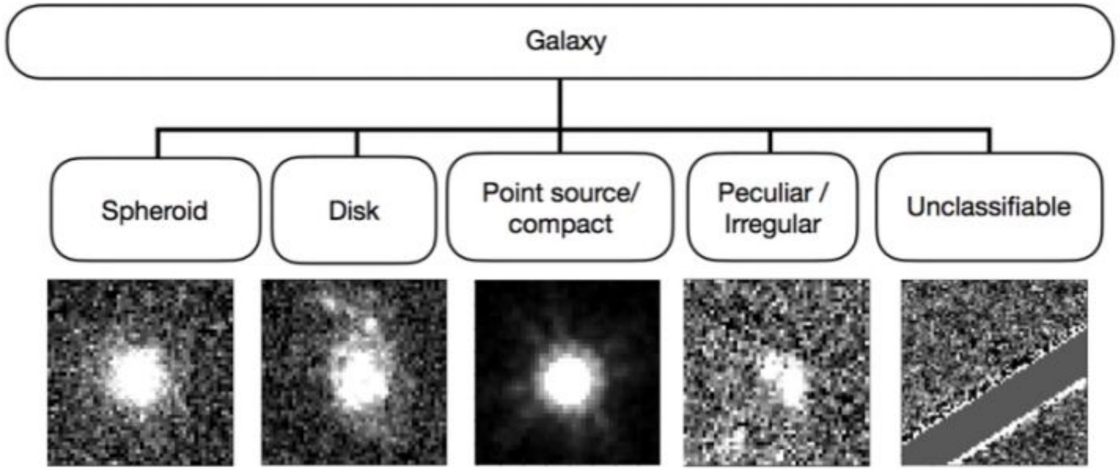
SVHN

Method	1-shot			5-shot		
	M → U	U → M	S → M	M → U	U → M	S → M
CCSA [47]	85.0	78.4	-	92.4	88.8	-
FADA [46]	89.1	81.1	72.8	93.4	91.1	86.1
F-CADA [87]	97.2	97.5	94.8	98.3	98.6	95.6
AVDA (ours) best	**98.76**	**98.60**	**95.11**	**98.88**	**98.65**	**96.65**

Results: Digits

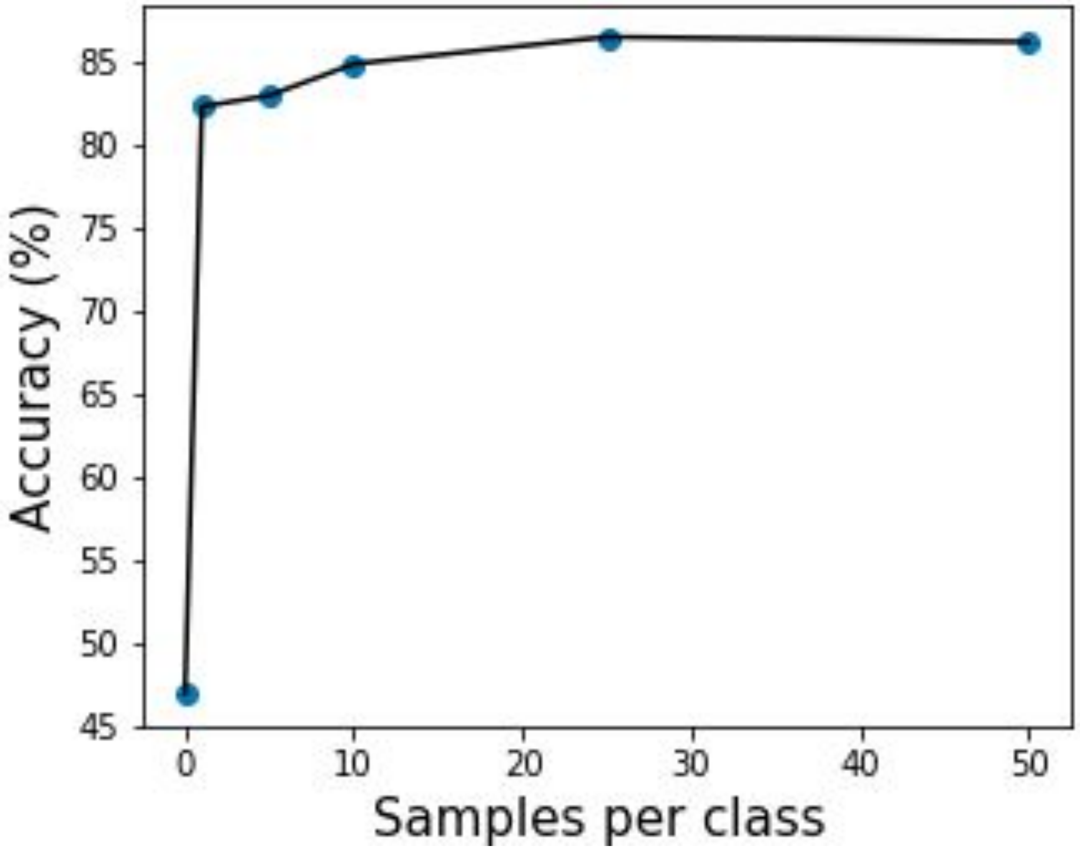
Method	Unsupervised		
	M → U	U → M	S → M
UNIT [41]	95.97	93.58	90.53
SBADA-GAN [62]	97.6	95.0	76.1
CyCADA [24]	95.6 ± 0.2	96.5 ± 0.1	90.4 ± 0.4
CDAN [43]	95.6	98.0	89.2
DupGAN [26]	96.01	**98.75**	92.46
ACAL [25]	98.31	97.16	**96.51**
CADA [87]	96.4 ± 0.1	97.0 ± 0.1	90.9 ± 0.2
AVDA (ours) best	**98.60**	98.29	78.81

Results: Galaxies



Kartaltepe et al. 2014
Perez-Carrasco et al. 2018

CANDELS -> CLASH



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