4 Deep Generative Models

BVM 2018 Tutorial: Advanced Deep Learning Methods

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Div. of Medical Image Computing, DKFZ Heidelberg

Faculty of Physics & Astronomy, Heidelberg University

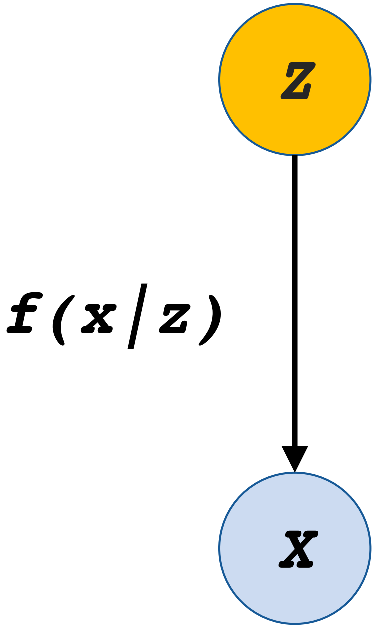
Challenges in MIC

Data Shortage

Transfer learning

Noisy labels and data

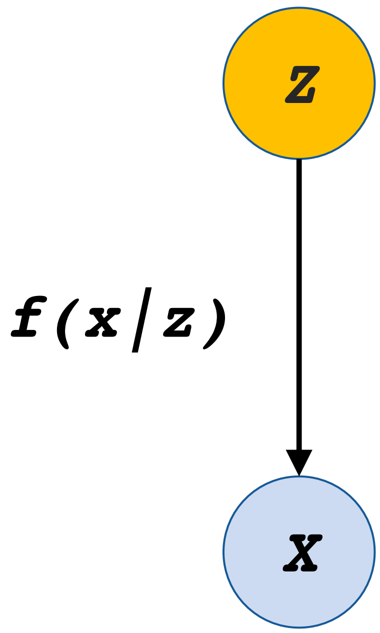
Basic Principle of Generative Models



Assumption

Observations x generated from latent variables z via mapping f

Basic Principle of Generative Models



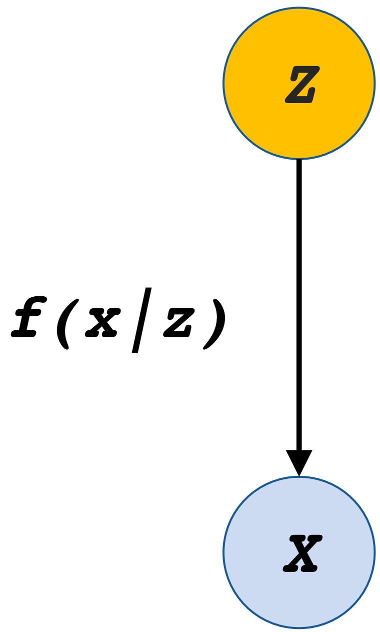
Assumption

Observations x generated from latent variables z via mapping f

Goal

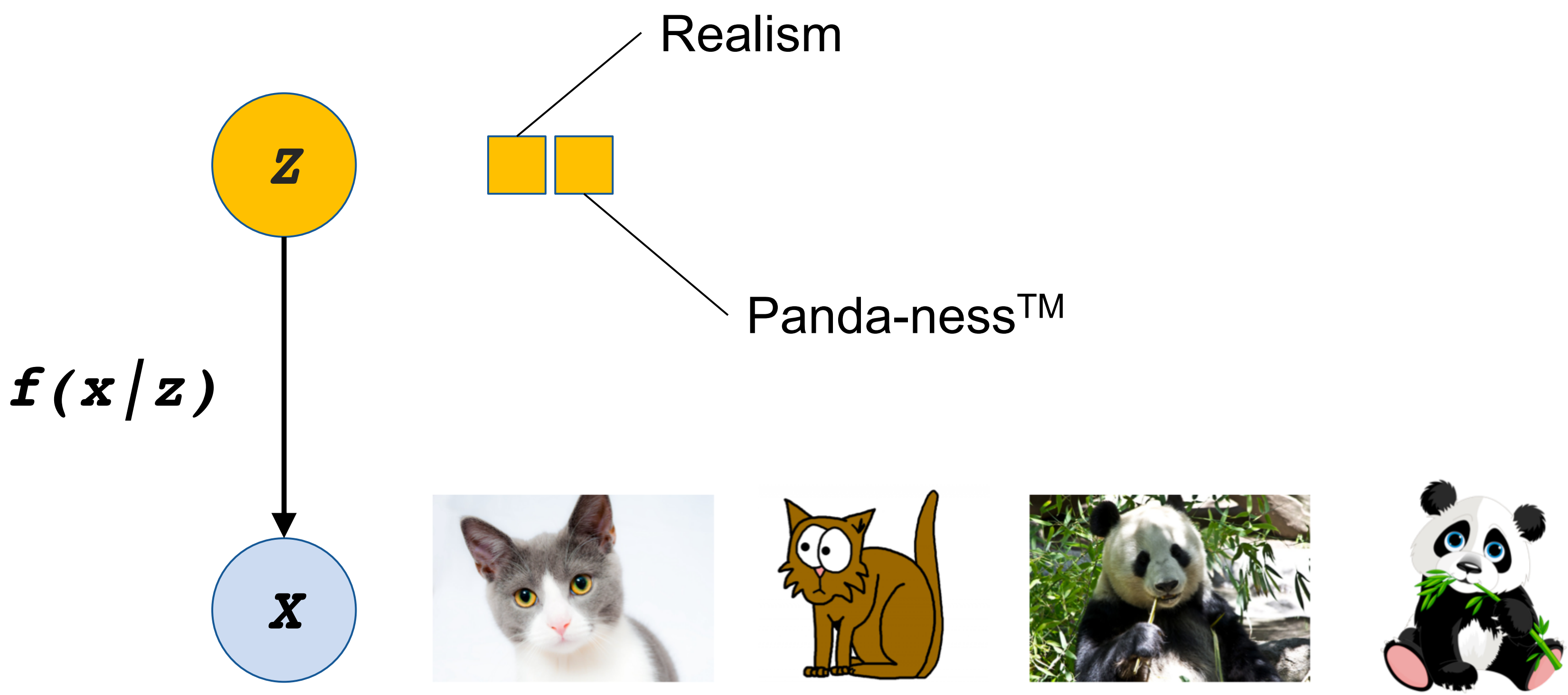
- Be able to generate more samples that follow distribution of x
- z interpretable in some way

Basic Principle of Deep Generative Models



[pexels.com, pixabay.com, pngimg.com]

Basic Principle of Deep Generative Models

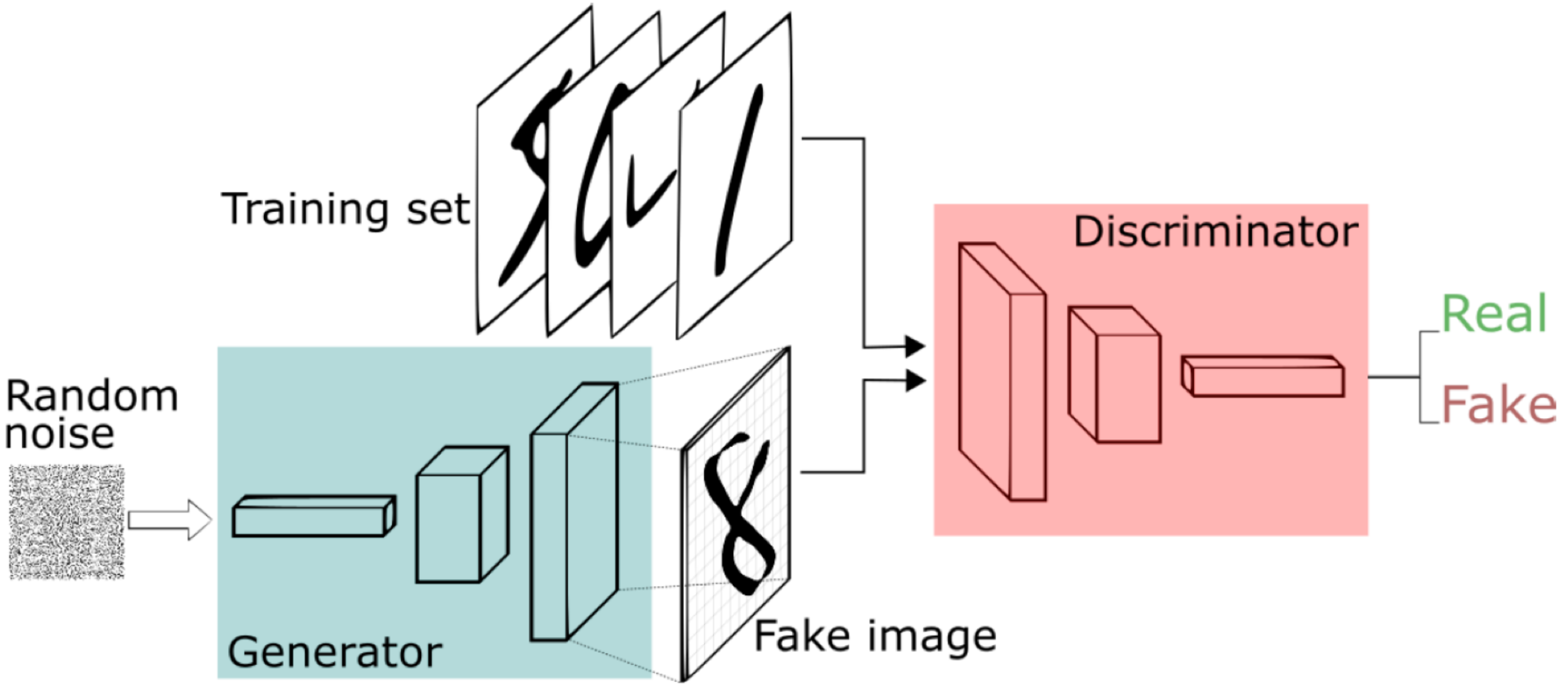


[pexels.com, pixabay.com, pngimg.com]

Generative Adversarial Networks

[https://twitter.com/goodfellow_ian]

Basic GAN Layout



[https://deeplearning4j.org/generative-adversarial-network]
[1] *Generative Adversarial Networks*, Goodfellow et al., 2014, NIPS

GAN Learning Objective

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

GAN Learning Objective

D(real) → 1

D(fake) → 0

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D(fake) → 1

- Trying to find saddle point
  → Very hard to optimize
- Lot of work on different objectives and „tricks“ for training

[2] *Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks*
Radford et al., 2015, arXiv:1511.06434
[3] *Are GANs Created Equal? A Large Scale Study*, Lucic et al., 2017, arXiv:1711.10337

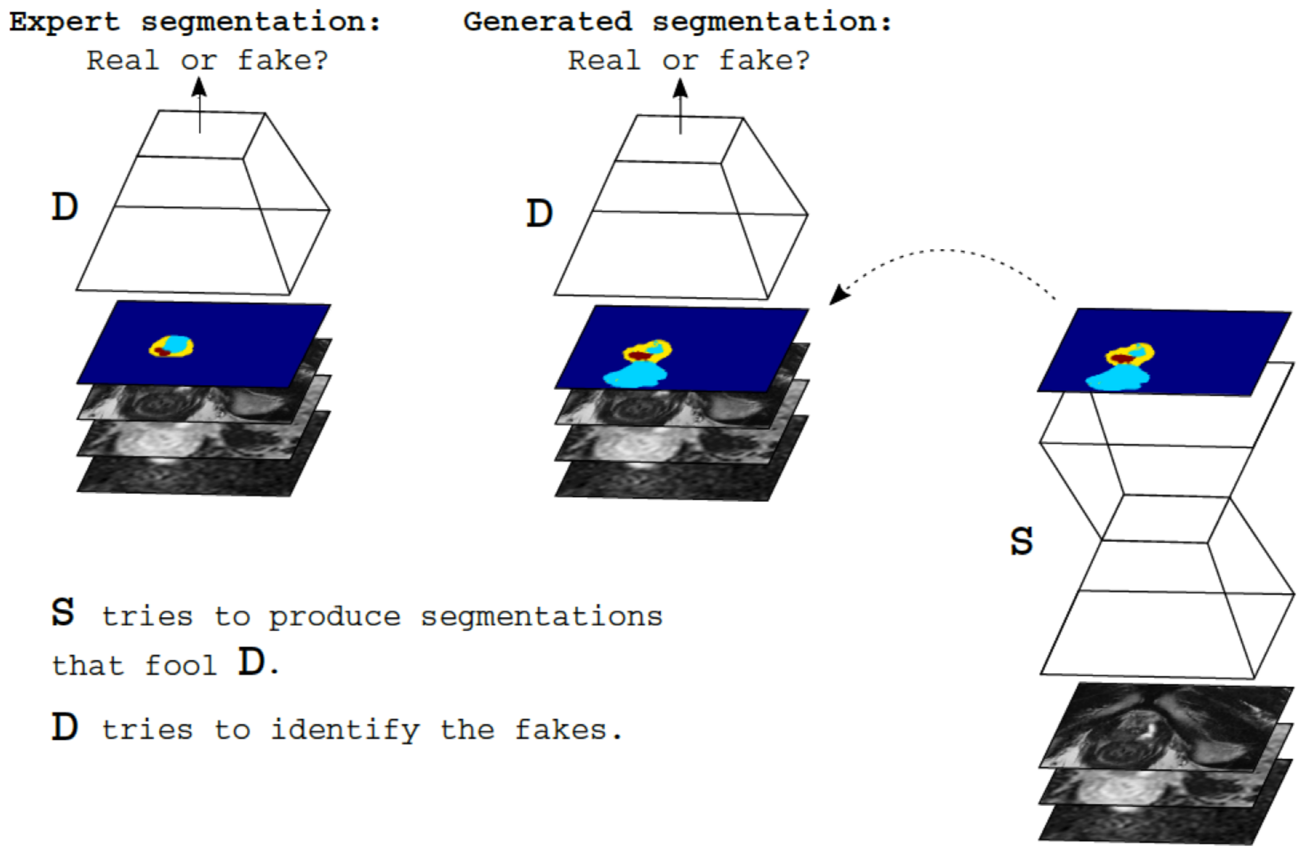
Original Examples

General case

Generative models make no default assumptions for p(z)

→ Could be random noise and/or real data

Important Concepts Conditional GAN



[4] *Adversarial Networks for the Detection of Aggressive Prostate Cancer*, Kohl et al., 2017, NIPS Workshop

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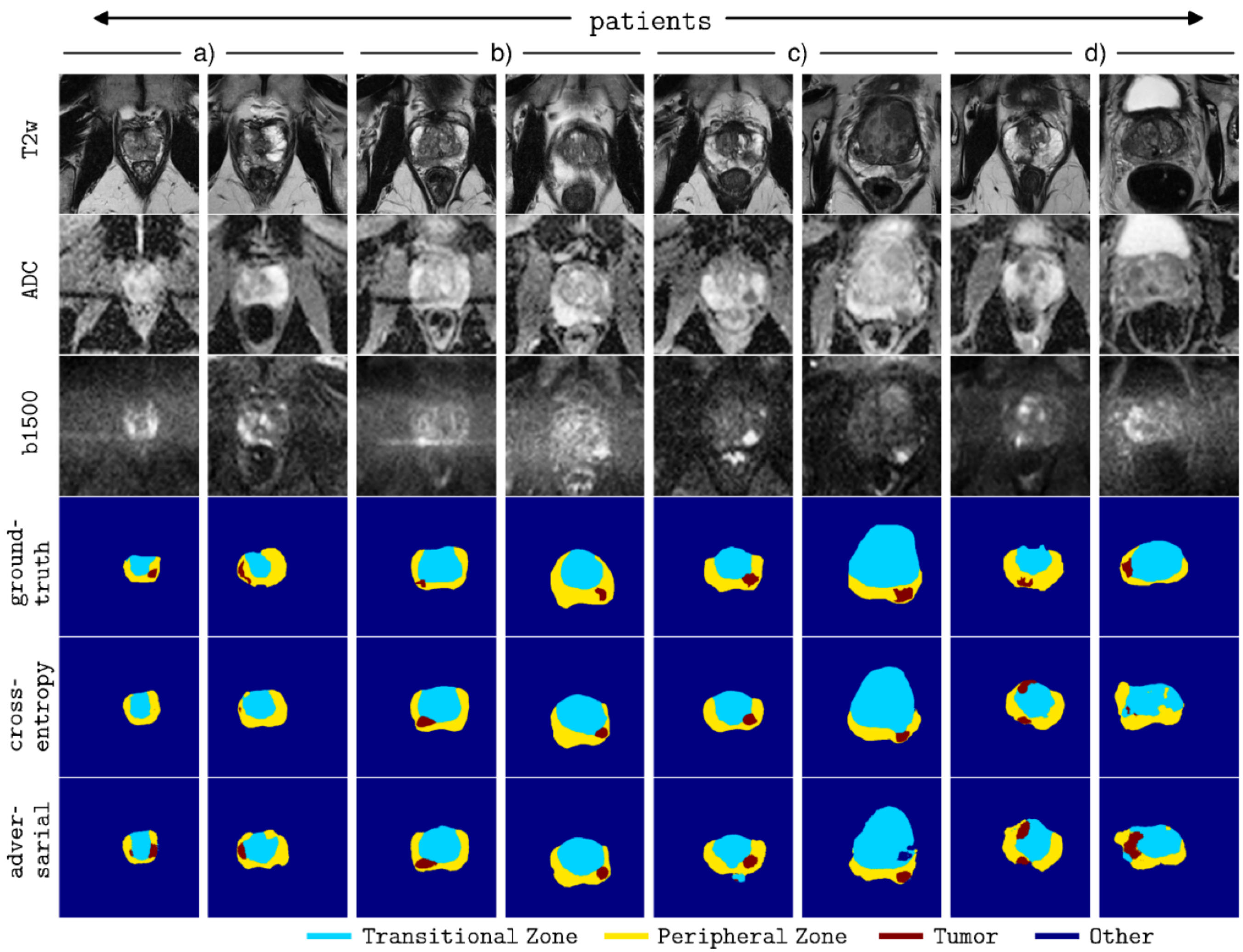

[4] *Adversarial Networks for the Detection of Aggressive Prostate Cancer*, Kohl et al., 2017, NIPS Workshop

Assumption

Have two unpaired sets A,B of images with some set-specific characteristic (e.g. photos & paintings)

Goal

Be able to transform image so it looks like images in different set

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Naive Approach

GANs that take images from A(B) and create images that similar to others from B(A)

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Goal

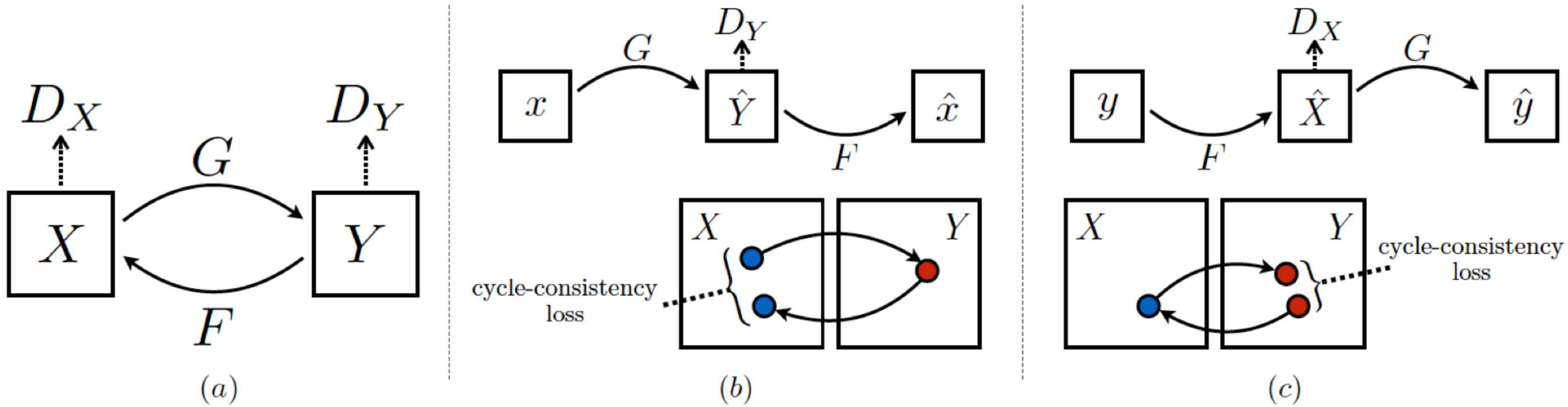
Be able to transform image so it looks like images in different set

Naive Approach

GANs that take images from A(B) and create images that similar to others from B(A)

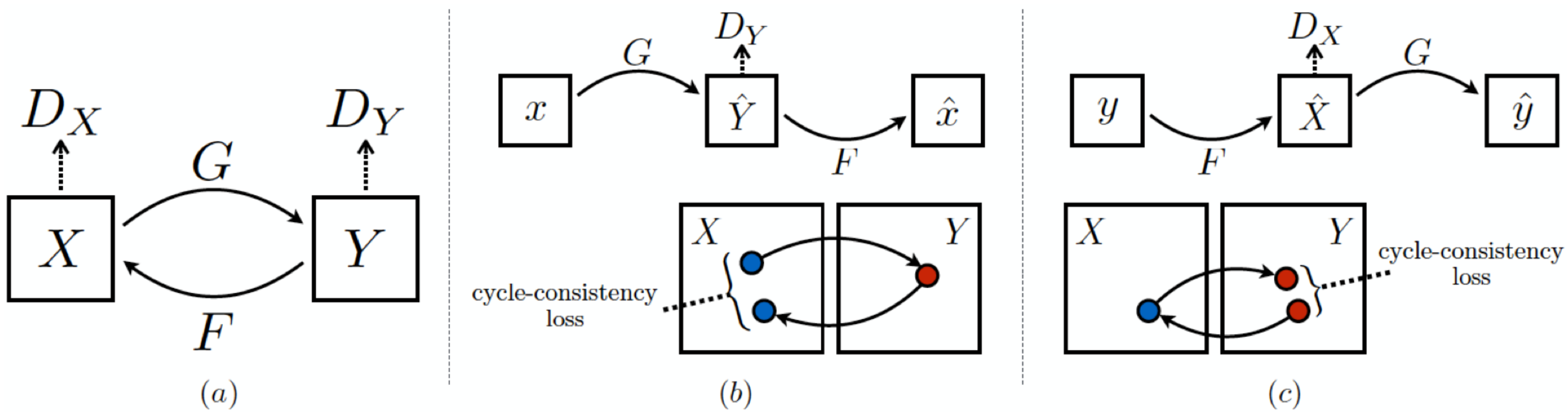
→ **no guarantee that output looks similar to input**

Important Concepts CycleGAN



[5] *Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks*, Zhu et al., 2017, arXiv:1703.10593

Important Concepts **CycleGAN**



L1-Norm
Cycle consistency loss

[5] *Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks*, Zhu et al., 2017, arXiv:1703.10593

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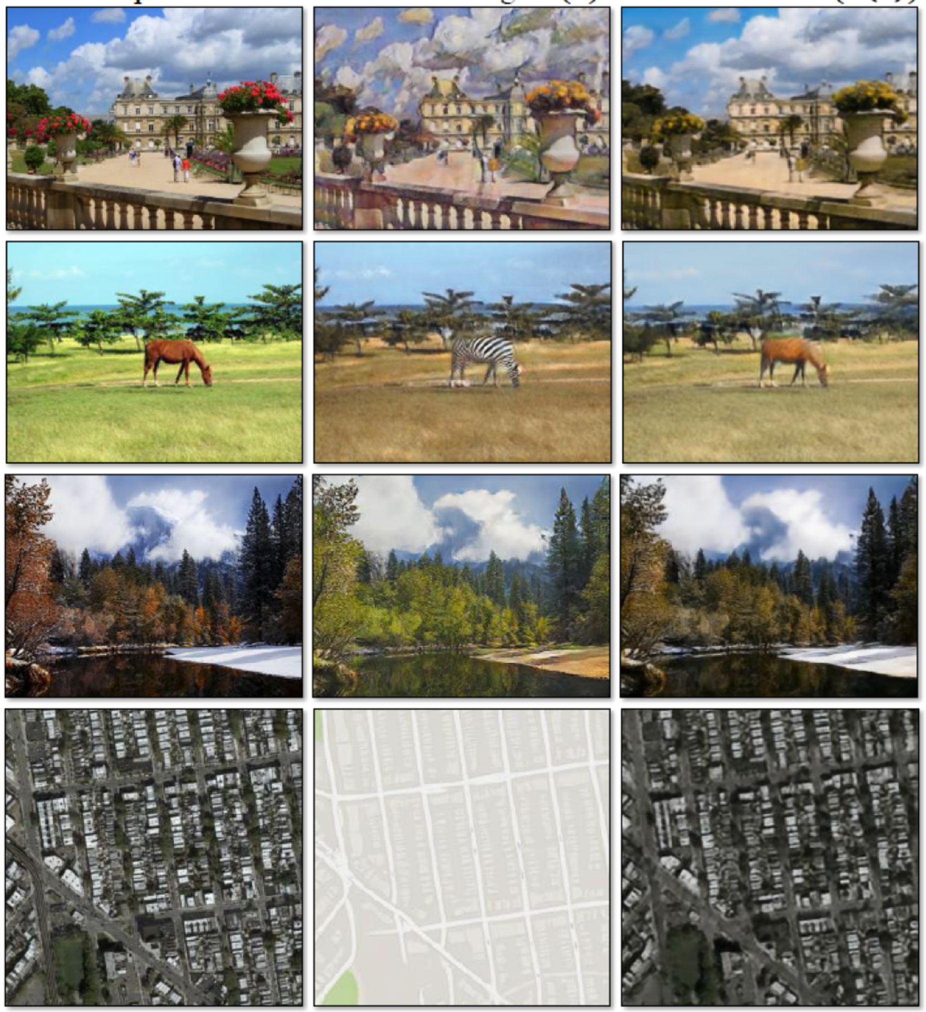


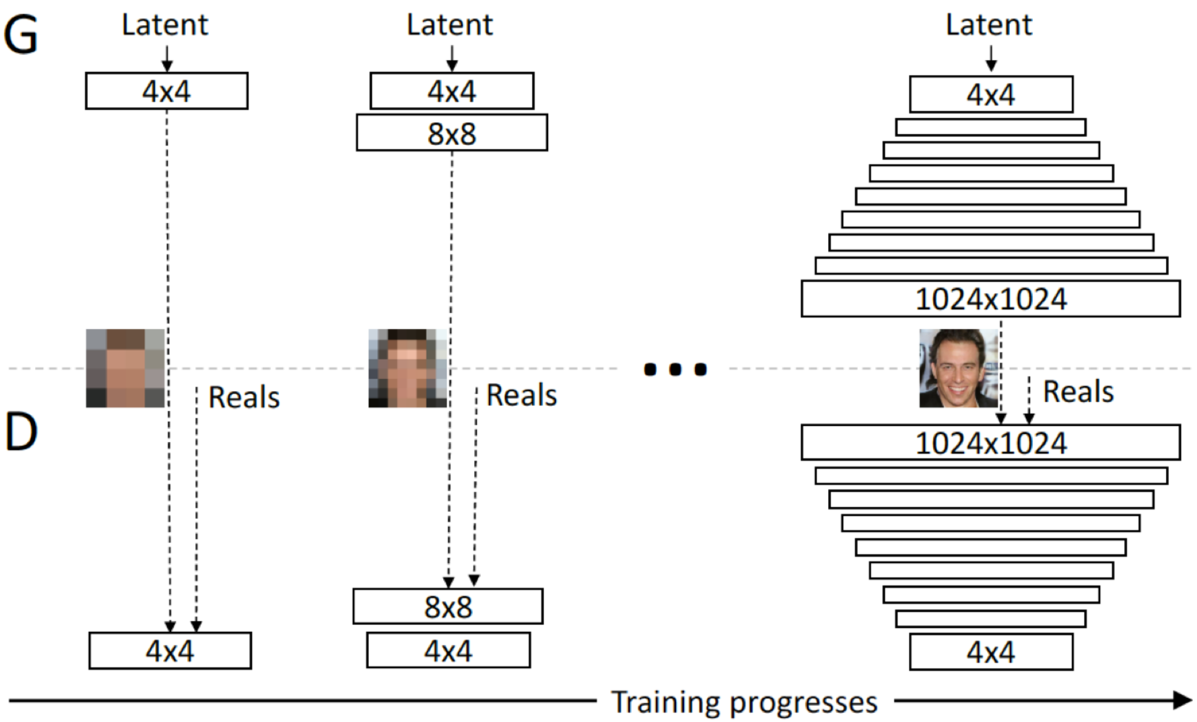
[5] *Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks*, Zhu et al., 2017, arXiv:1703.10593

Examples Progressive Growing

Progressive Growing of GANs for Improved Quality, Stability, and Variation

Tero Karras NVIDIA
Timo Aila NVIDIA
Samuli Laine NVIDIA
Jaakko Lehtinen NVIDIA and Aalto University
{tkarras,taila,slaine,jlehtinen}@nvidia.com

Examples Progressive Growing



Examples Progressive Growing

Samples

Nearest Neighbours

Image Similarity

- Pixel similarity
  - mean squared error (= L2 norm)
  - other norms

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- Pixel similarity
  - mean squared error (= L2 norm)
  - other norms

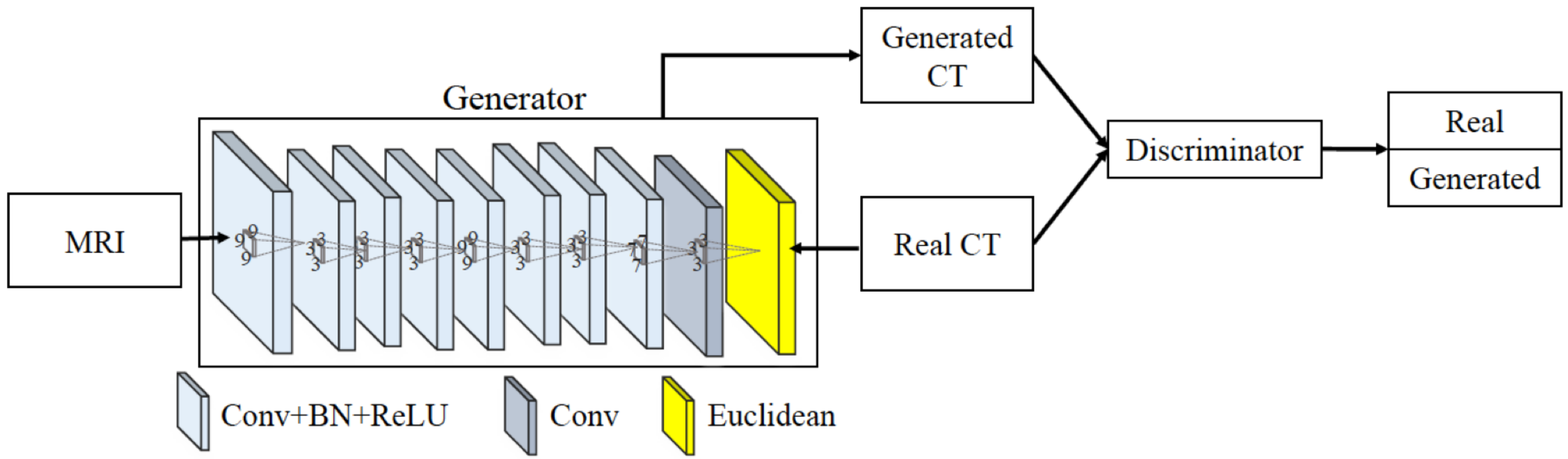
- Semantic similarity
  - Inception score (score for entire model)
  - Combined distance of multiple feature layers in discriminator
  - Human evaluation (e.g. Mechanical Turk)

Medical Image Synthesis with Context-Aware Generative Adversarial Networks

Dong Nie[1⋆], Roger Trullo[2⋆], Caroline Petitjean[2], Su Ruan[2], and Dinggang Shen[1⋆⋆]

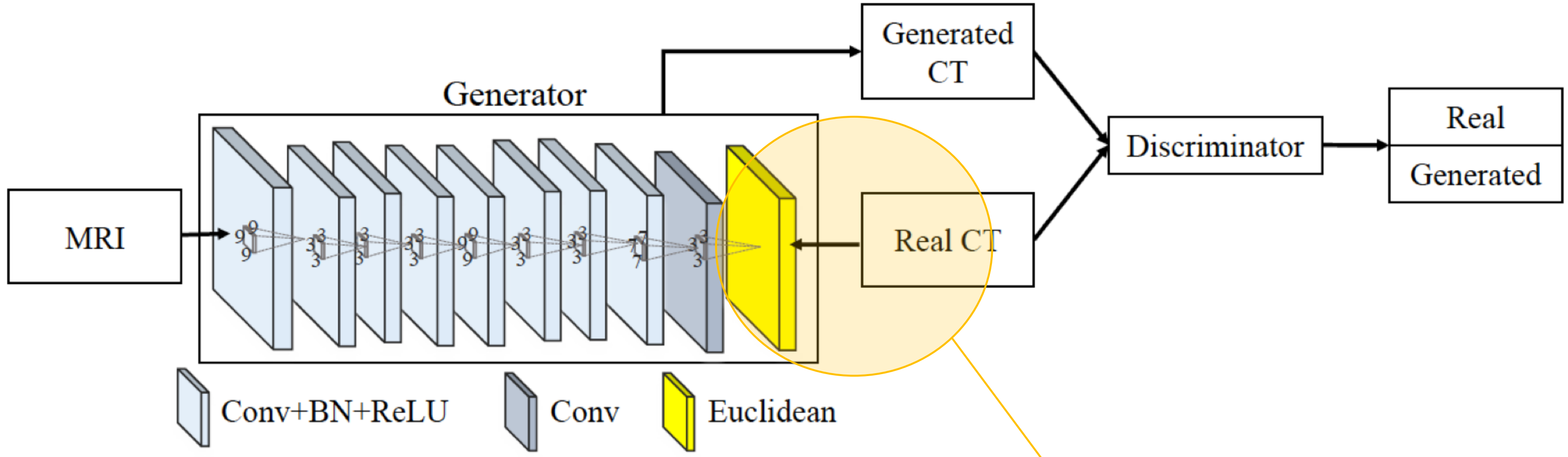
[1] University of North Carolina at Chapel Hill, USA
[2] Normandie Univ, UNIROUEN, UNIHAVRE, INSA Rouen, LITIS, 76000 Rouen, France

Examples MRI to CT Image Synthesis



FCN architecture

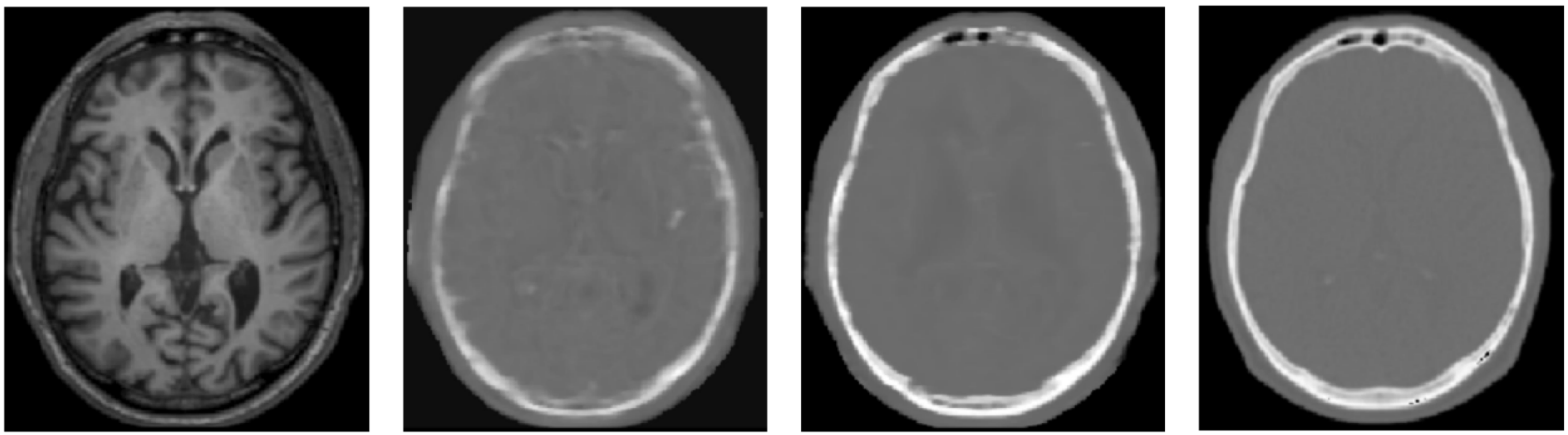
Examples MRI to CT Image Synthesis



FCN architecture

Combined adversarial & MSE loss

Examples MRI to CT Image Synthesis



MRI FCN GAN Ground Truth

Unsupervised domain adaptation in brain lesion segmentation with adversarial networks

Konstantinos Kamnitsas[1,4*], Christian Baumgartner[1], Christian Ledig[1], Virginia Newcombe[2,3], Joanna Simpson[2], Andrew Kane[2], David Menon[2,3], Aditya Nori[4], Antonio Criminisi[4], Daniel Rueckert[1], and Ben Glocker[1]

[1] Biomedical Image Analysis Group, Imperial College London, UK
[2] Division of Anaesthesia, Department of Medicine, Cambridge University, UK
[3] Wolfson Brain Imaging Centre, Cambridge University, UK
[4] Microsoft Research Cambridge, UK

Assumption

(X, Y) in source domain, (X*) in target domain

Examples Domain Transfer for Lesion Segmentation

Assumption

(X, Y) in source domain, (X*) in target domain

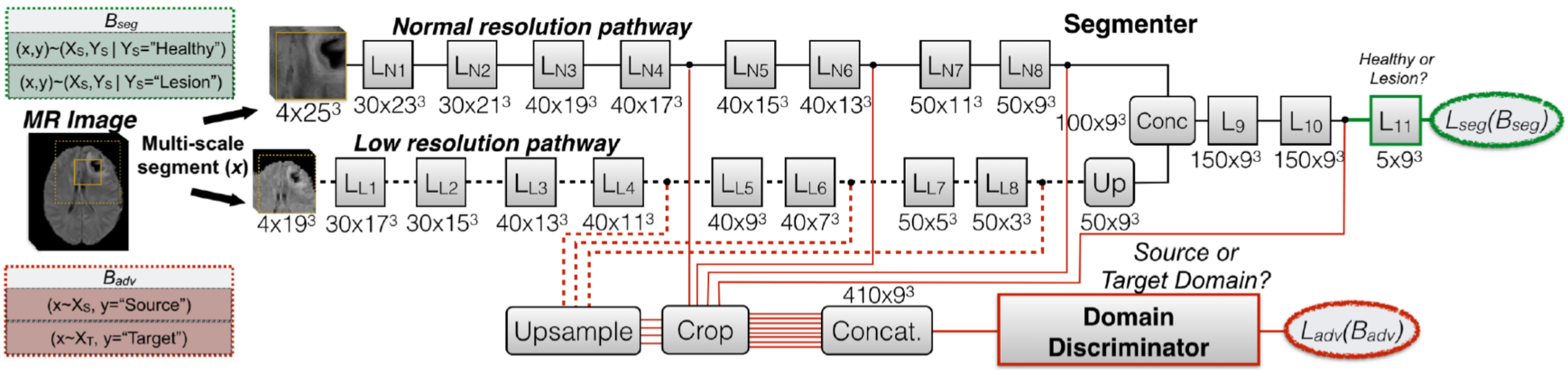
... + GE + Lesion Segmentation in source

... + SWI in target

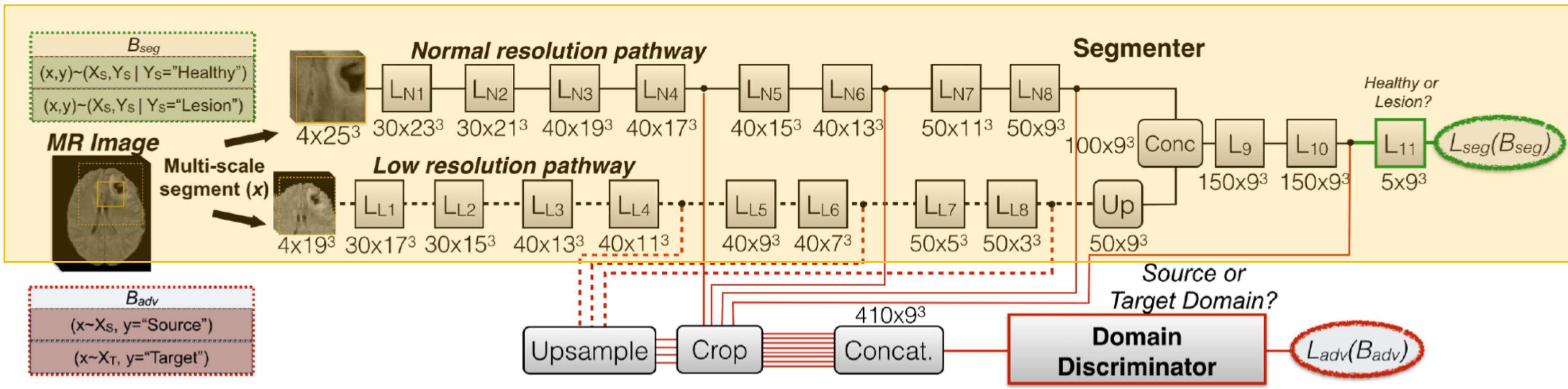
Goal

Segmentation in target domain

Examples Domain Transfer for Lesion Segmentation

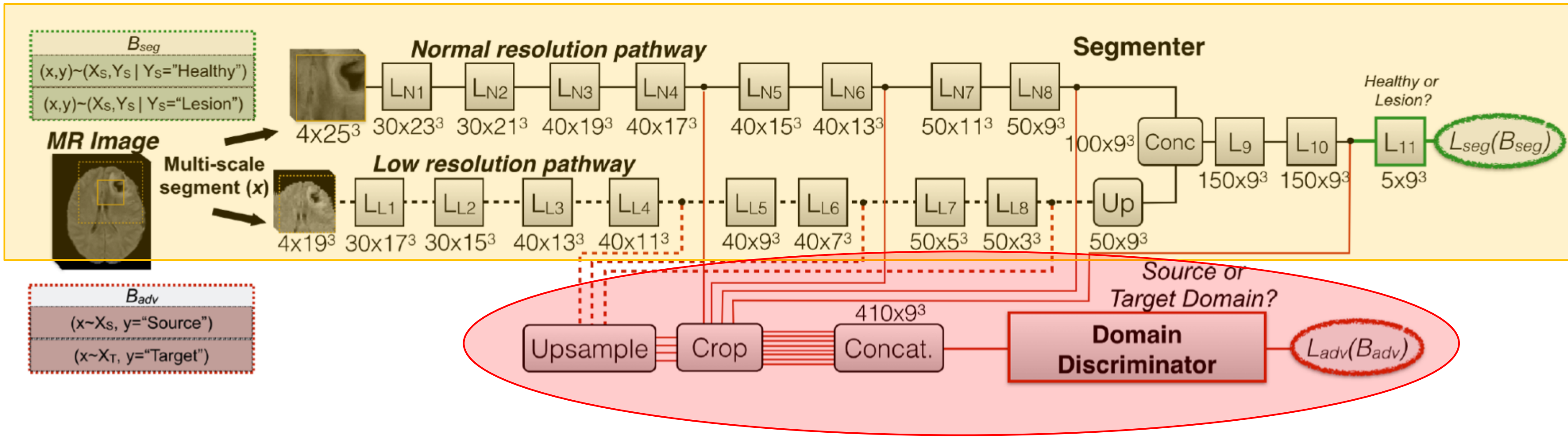


DeepMedic architecture



Examples Domain Transfer for Lesion Segmentation

DeepMedic architecture



Auxiliary adversarial loss ensures domain invariant feature maps

	DSC
Train on S	15.7(13.5)
Train on S (No GE/SWI)	59.7(22.1)
Train on S → UDA to T (ours)	62.7(19.8)
Train on T	63.5(20.2)
Train on S+T	66.5(17.7)
Train on S+T (GE/SWI diff chan.)	64.7(19.2)

Higher is better

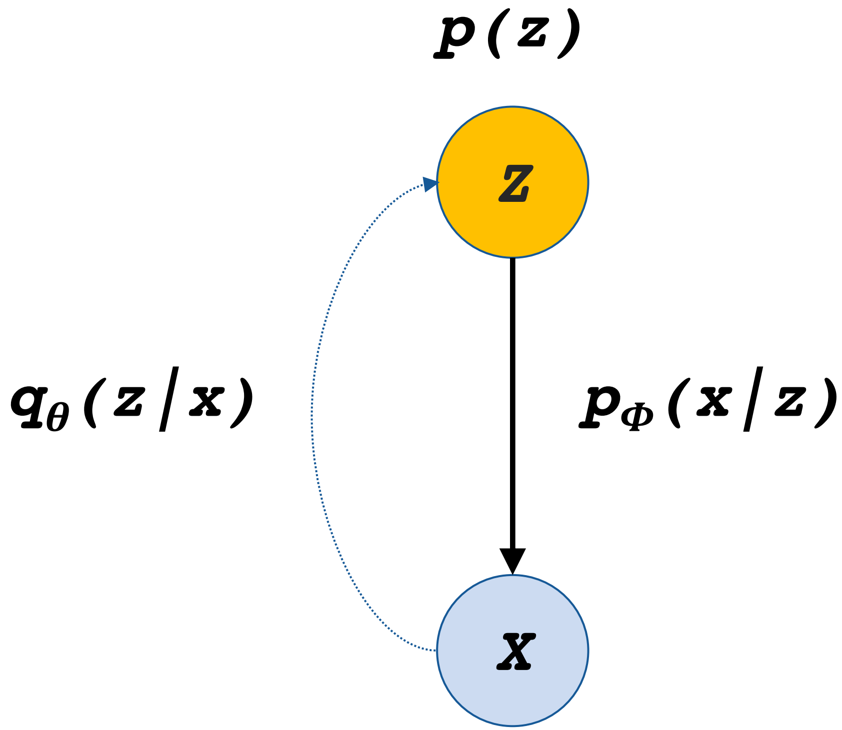
Summary GANs

- ✔ High-quality, high-resolution outputs possible
- ✔ Adversarial training extremely versatile

- ✖ Difficult to train
- ✖ No inference (latent representation from data)

Variational Autoencoders

Probabilistic Perspective



[6] *Auto-encoding variational Bayes*, Kingma & Welling, 2014, ICLR
[7] *Stochastic backpropagation and approximate inference in deep generative models*, Rezende et al., 2014, ICML

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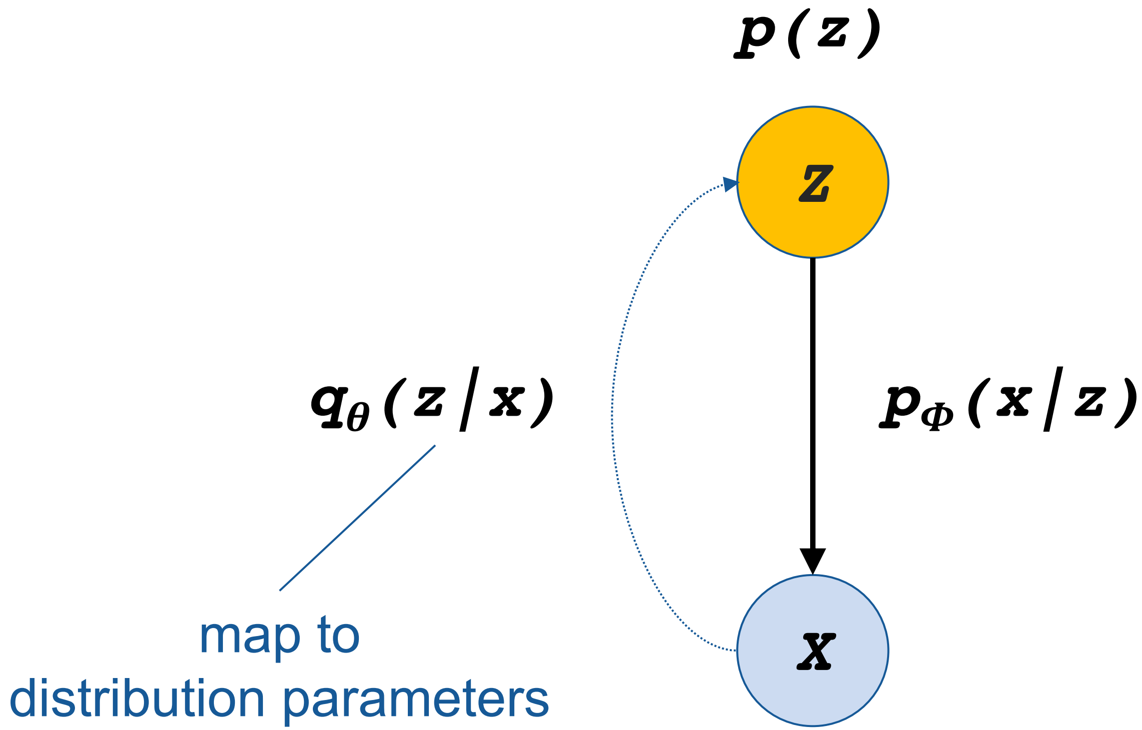

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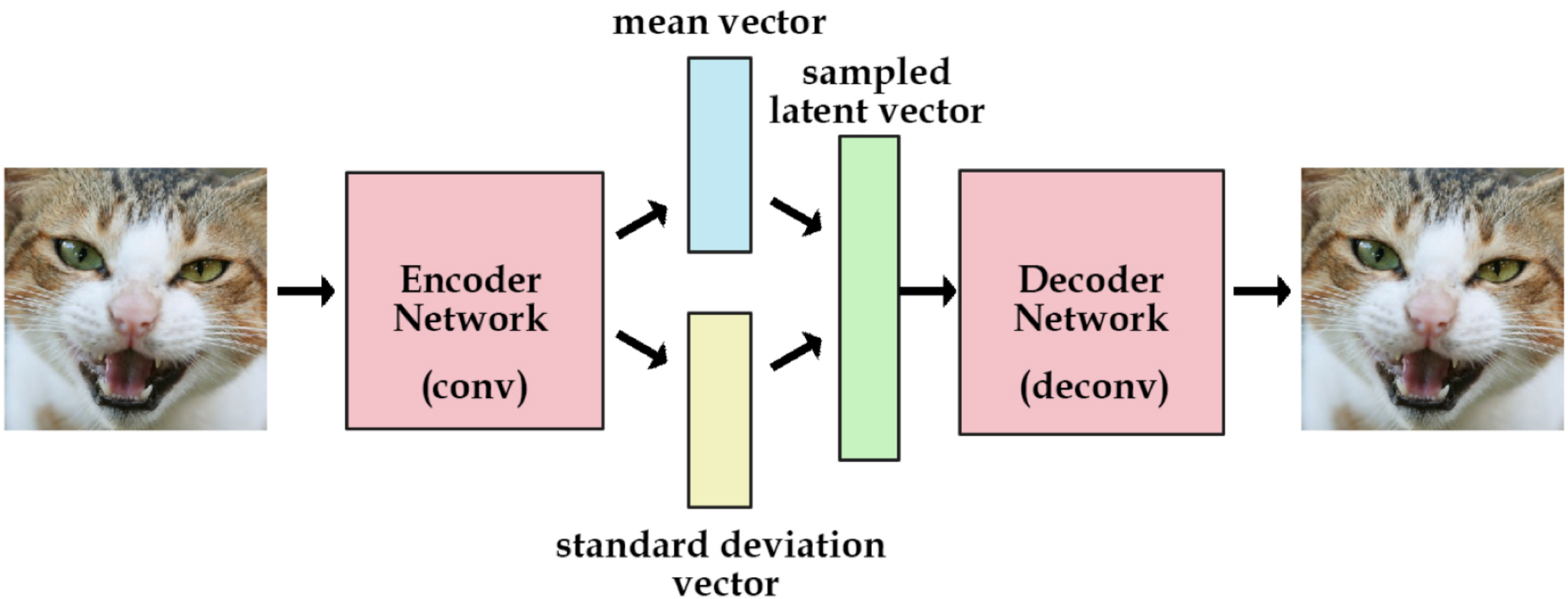
It looks like an autoencoder



[http://kvfrans.com/variational-autoencoders-explained/]

Reparametrization Trick

$$z \sim \mathcal{F}(z;\theta) \qquad y = f(z) \longrightarrow \frac{\partial y}{\partial \theta} = \frac{\partial f}{\partial z}\frac{\partial z}{\partial \theta}$$

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$z = g(\theta;\varepsilon) \qquad \varepsilon \sim \mathcal{F}^*(\varepsilon;\theta^*) \longrightarrow \frac{\partial y}{\partial \theta} = \frac{\partial f}{\partial g}\frac{\partial g}{\partial \theta}$

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$$z = g(\theta;\varepsilon) \qquad \varepsilon \sim \mathcal{F}^*(\varepsilon;\theta^*) \longrightarrow \frac{\partial y}{\partial \theta} = \frac{\partial f}{\partial g}\frac{\partial g}{\partial \theta}$$

$$\boxed{z \sim \mathrm{N}(z;\mu,\sigma) \longleftrightarrow z = \mu + \sigma * \varepsilon \quad \varepsilon \sim \mathrm{N}(\varepsilon;0,1)}$$

VAE Learning Objective

$$l_i(\theta, \phi) = -E_{z \sim q_\theta(z|x_i)}[\log p_\phi(x_i|z)] + KL(q_\theta(z|x_i)||p(z))$$

VAE Learning Objective

Maximize reconstruction fidelity (e.g. MSE)

$$l_i(\theta, \phi) = -E_{z \sim q_\theta(z|x_i)}[\log p_\phi(x_i|z)] + KL(q_\theta(z|x_i)||p(z))$$

Make encodings conform to prior

Original Examples

Learning Structured Output Representation using Deep Conditional Generative Models

Kihyuk Sohn[*†] **Xinchen Yan**[†] **Honglak Lee**[†]

[*] NEC Laboratories America, Inc.

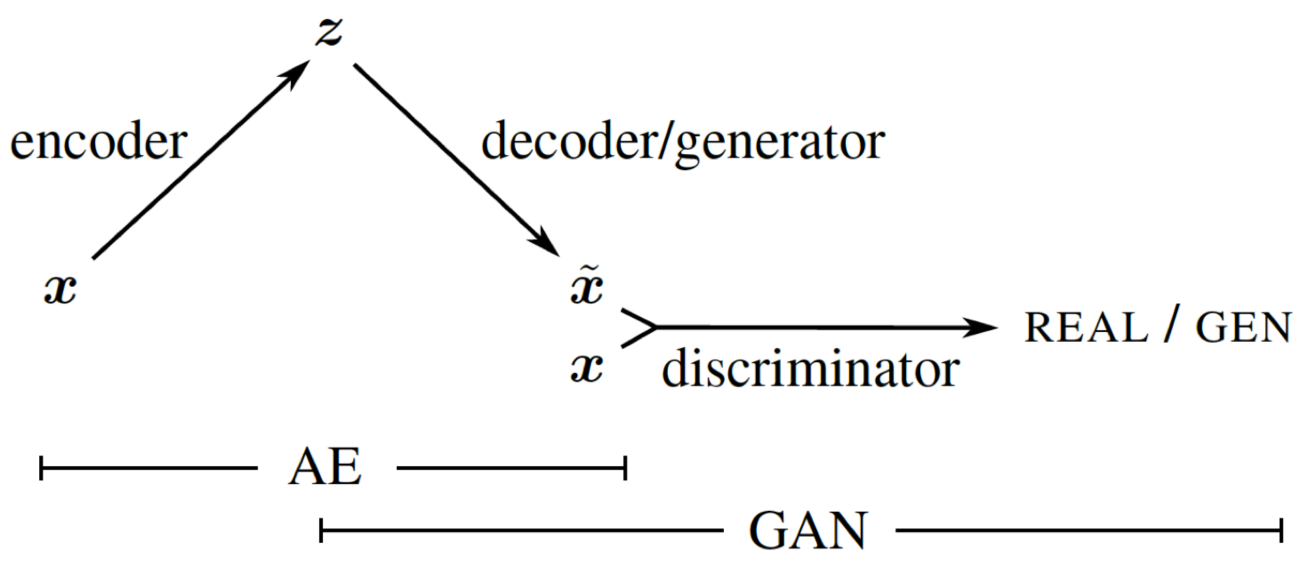
[†] University of Michigan, Ann Arbor

ksohn@nec-labs.com, {xcyan,honglak}@umich.edu

Example **Corrupted Data**

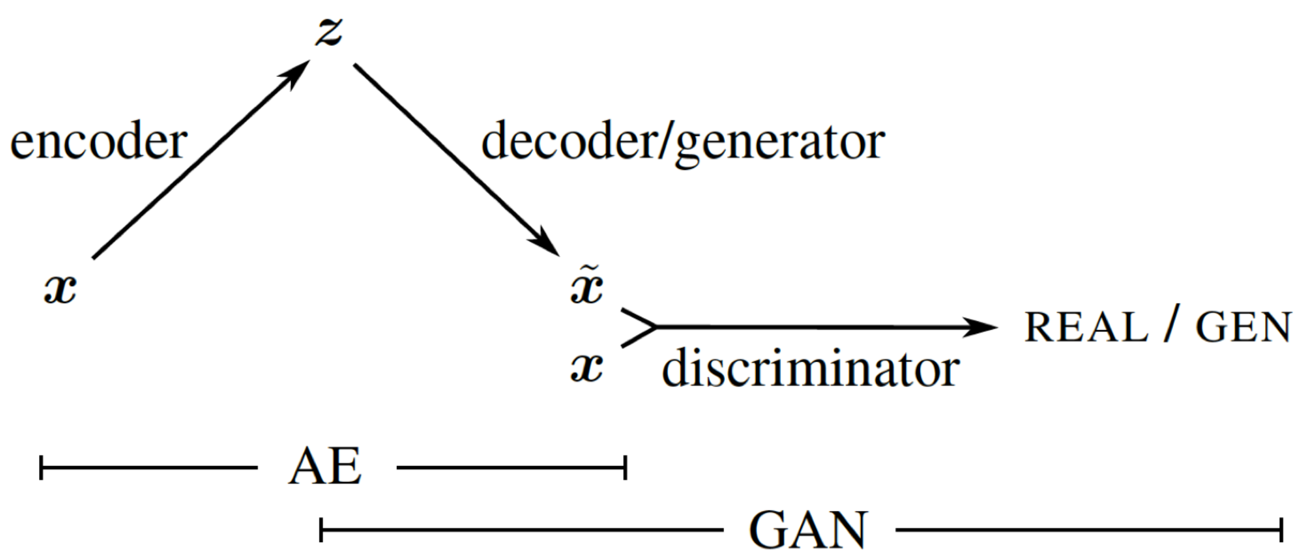
Autoencoding beyond pixels using a learned similarity metric

Anders Boesen Lindbo Larsen[1] ABLL@DTU.DK
Søren Kaae Sønderby[2] SKAAESONDERBY@GMAIL.COM
Hugo Larochelle[3] HLAROCHELLE@TWITTER.COM
Ole Winther[1,2] OLWI@DTU.DK
[1] Department for Applied Mathematics and Computer Science, Technical University of Denmark
[2] Bioinformatics Centre, Department of Biology, University of Copenhagen, Denmark
[3] Twitter, Cambridge, MA, USA



z
encoder
decoder/generator
x
$\tilde{x}$
x
discriminator
REAL / GEN
AE
GAN

Example Combining GANs & VAEs



$$\mathcal{L}_{\text{VAE}} = \mathcal{L}_{\text{llike}}^{\text{pixel}} + \mathcal{L}_{\text{prior}}$$

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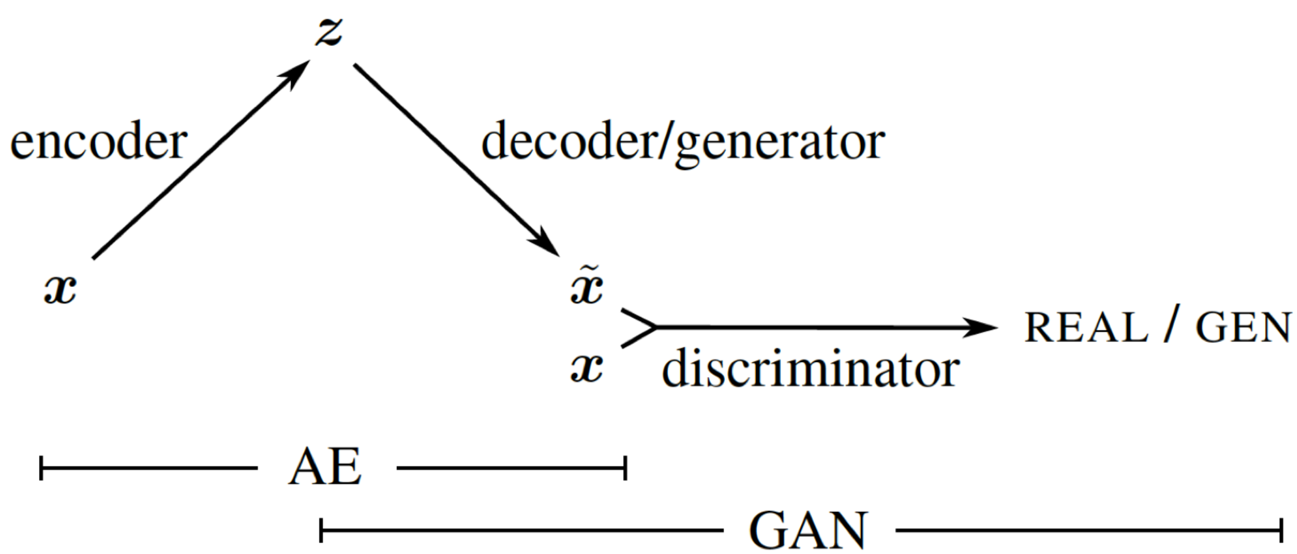

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$$\mathcal{L}_{\mathrm{llike}}^{\mathrm{pixel}} = -\mathbb{E}_{q(\boldsymbol{z}|\boldsymbol{x})}\left[\log p(\boldsymbol{x}|\boldsymbol{z})\right] \longrightarrow \mathcal{L}_{\mathrm{llike}}^{\mathrm{Dis}_l} = -\mathbb{E}_{q(\boldsymbol{z}|\boldsymbol{x})}\left[\log p(\mathrm{Dis}_l(\boldsymbol{x})|\boldsymbol{z})\right]$$

l-th layer discriminator

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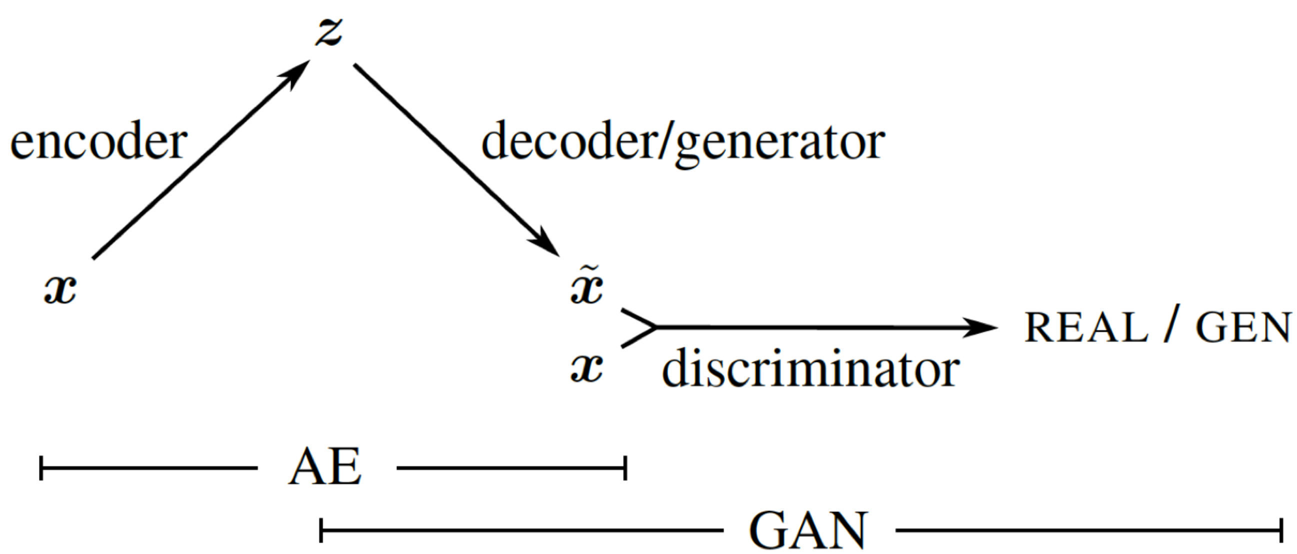

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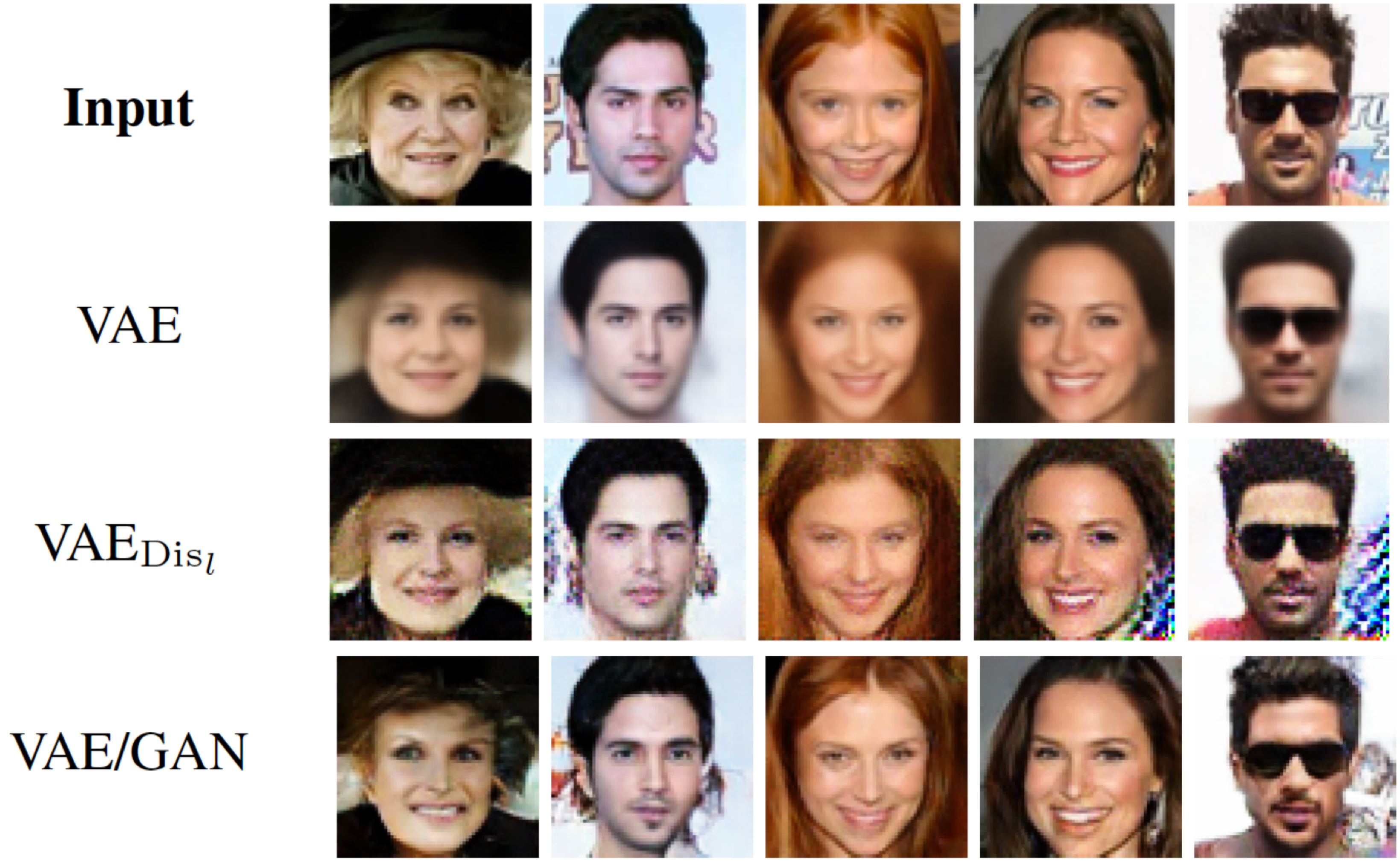
$$\boxed{\mathcal{L} = \mathcal{L}_{\text{prior}} + \mathcal{L}_{\text{llike}}^{\text{Dis}_l} + \mathcal{L}_{\text{GAN}}}$$

l-th layer discriminator

Example Combining GANs & VAEs



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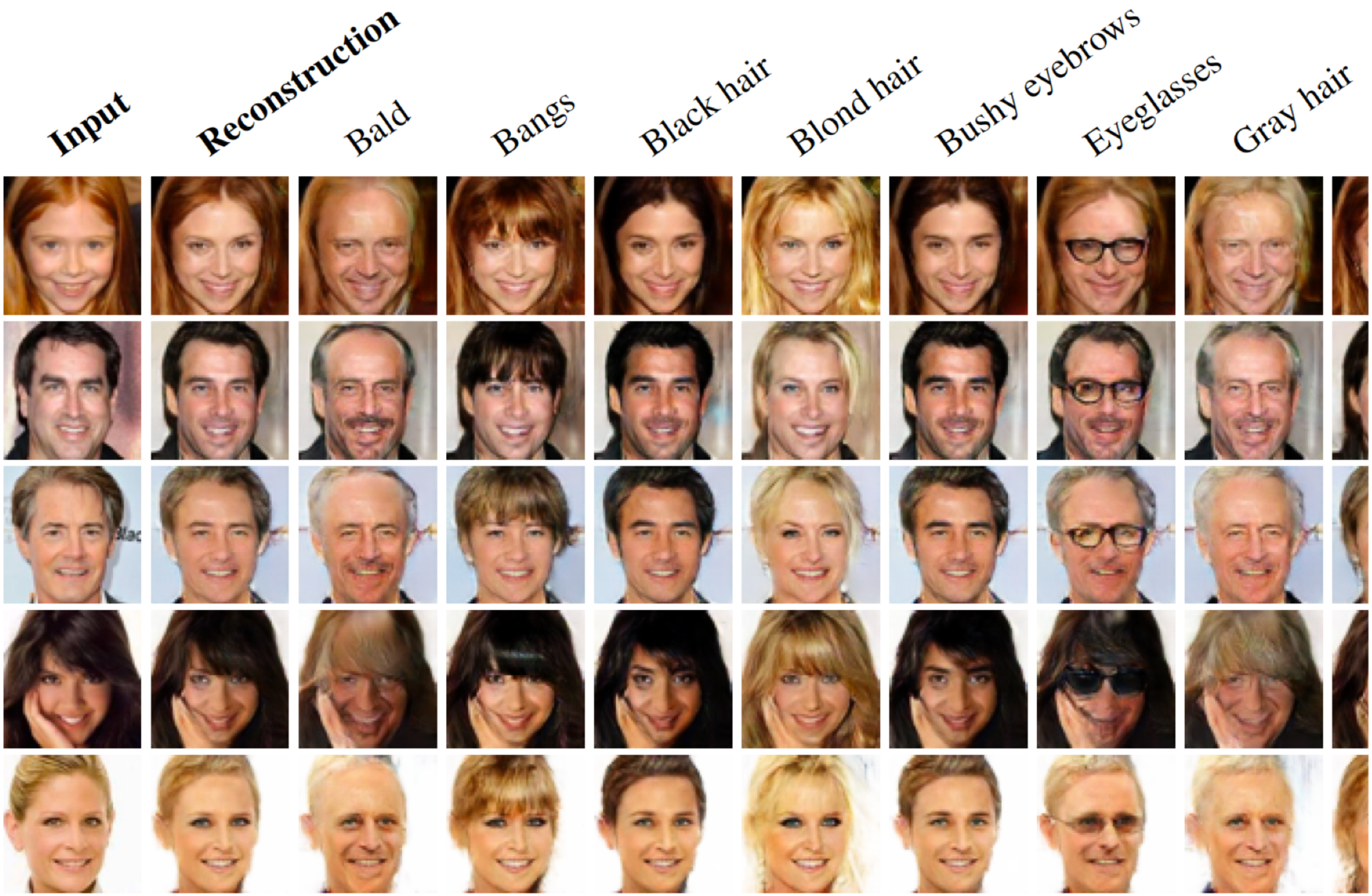

Notes on VAEs

- GANs designed to generate new data
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- GANs designed to generate new data
- VAEs designed to find interpretable latent representation
  - can go from data to latent representation
  - good for uncertainty estimation
  - latent representation tends to focus on most important features
- Hard to produce high quality outputs
  - Need better image similarity measure than MSE
  - Combination with GANs promising

Further Reading

- Literature overview GANs
  https://github.com/nightrome/really-awesome-gan
- Literature overview GANs for MIC
  https://github.com/xinario/awesome-gan-for-medical-imaging
- VAE Tutorial (Doersch)
  https://arxiv.org/abs/1606.05908
- PyTorch DCGAN
  https://github.com/pytorch/examples/tree/master/dcgan
- PyTorch VAE
  https://github.com/pytorch/examples/tree/master/vae
- Improving VAE outputs
  (Autoregressive flow) https://arxiv.org/abs/1606.04934
  (Normalizing flows) https://arxiv.org/abs/1505.05770
- Combining GANs and VAEs
  (Adversarial Autoencoder) https://arxiv.org/abs/1511.05644
  (Variational GAN) https://arxiv.org/abs/1706.04987
- Related generative models
  (NICE) https://arxiv.org/abs/1410.8516
  (Real NVP) https://arxiv.org/abs/1605.08803