Tutorial on Generative Adversarial Networks - From basics to current state-of-the-art, and towards key applications in medicine

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- GAN basics
- State-of-the-art
- Key applications in computer vision and medicine
- Preliminary results on three different medical datasets

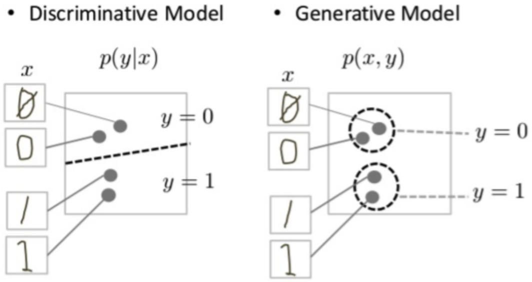
- Generative: can generate new data instances

$$p(X, Y)$$

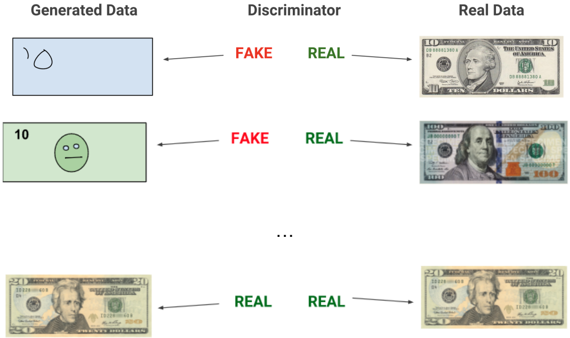
- Discriminative: discriminates between different kinds of data instances

$$p(Y|X)$$

X = image
Y = label/score

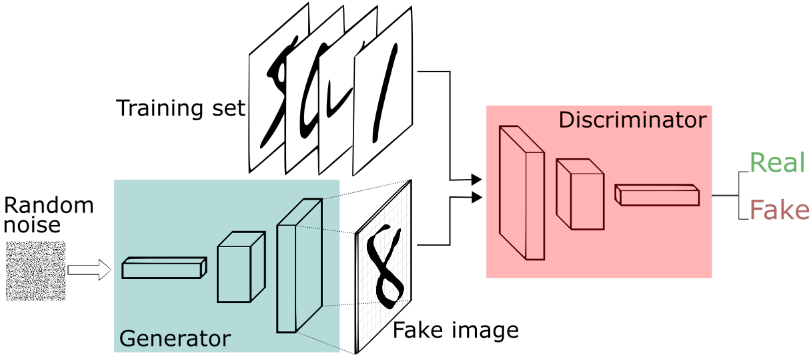


- Introduced by Goodfellow et al, 2014
- Two adversaries (generator + discriminator) compete with each other
- Over time, the generator gets better at generating images



- Generator attempts to generate good images to fool the discriminator
- Discriminator attempts to tell apart the fake images from the real ones
- Loss function:

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



Towards the state-of-the-art in Generative Adversarial Networks

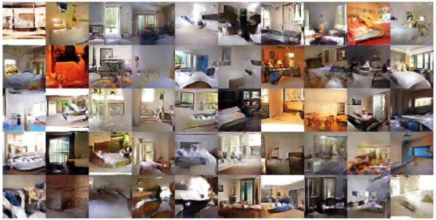
Initial GAN results (DCGAN, Radford et al, 2015)

- Initial results looked promising, but still a long way from photorealism

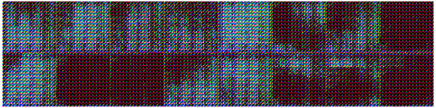
- Other problems persisted:
  - Training collapse
  - Mode collapse
  - Low coverage

- Dynamics between G & D not well understood

Standard samples



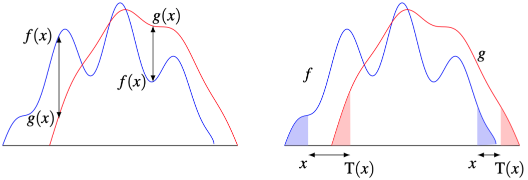
Training collapse



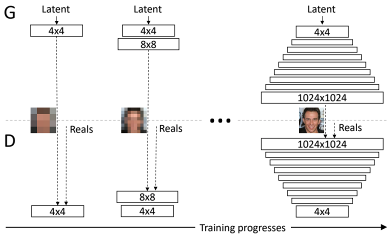
Mode collapse

Wasserstein GANs (Arjovski et al, 2017)

- Original GANs were very hard to train
- Problem: They optimise the Jensen-Shannon divergence, a "vertical" distance $\rightarrow$ no good gradients when distributions far away
- A "horizontal" distance (e.g. Wasserstein) ensures gradients are non-zero when distributions don't have support (i.e. far away)
- GAN trained with the new Wasserstein metric collapses less often, and generates better images

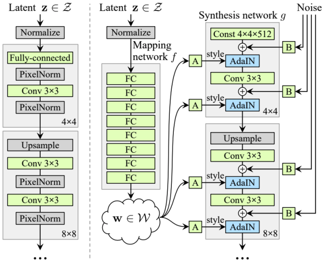


- GAN training unstable if one starts directly in high-resolution
- Key idea: start from low-resolution (4x4) and build up to highest-resolution (1024x1024)
- Each new layer is faded-in slowly



Mao et al. (2016b) (128 × 128) Gulrajani et al. (2017) (128 × 128) Our (256 × 256)

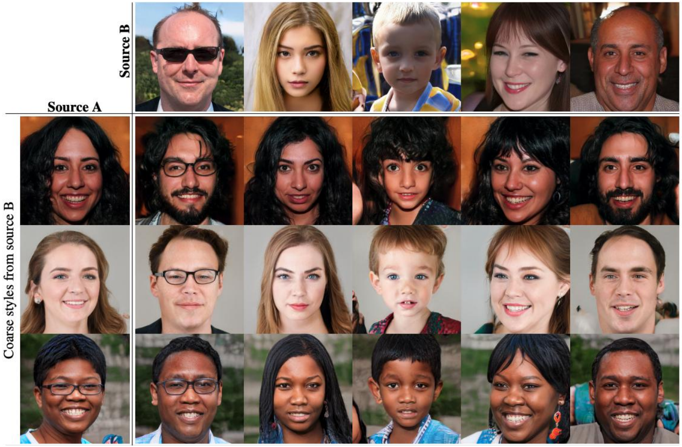
- Borrows ideas from style-transfer literature
- Uses a mapping network to generate "style vectors" at every level in the generator
- Each style vector is intensity-normalized (AdaIN operation)
- Generated images have unprecedented realism and diversity



(a) Traditional (b) Style-based generator

The style-based architecture allows both style-transfer and fine-level stochastic variation

Style-transfer



Fine-level stochastic variation

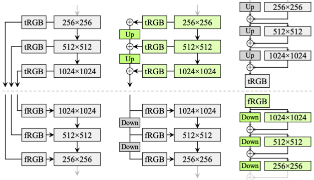
Blob-artefacts caused by AdaIN normalisation

“phase“ artefacts due to progressive growing

Solution: bake normalisation straight into convolution weights:

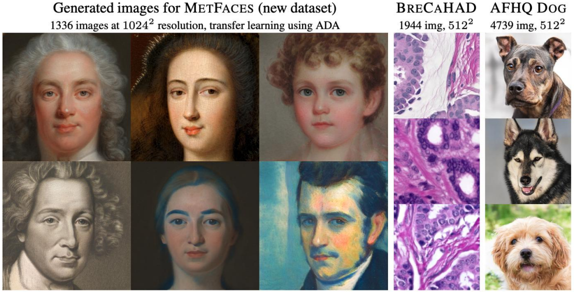
$$w''_{ijk} = w'_{ijk} \Bigg/ \sqrt{\sum_{i,k} {w'_{ijk}}^2 + \epsilon}$$

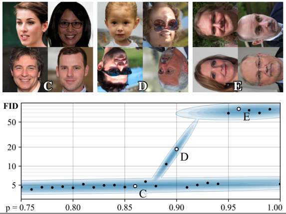
Solution: communicate across resolution levels through skip connections

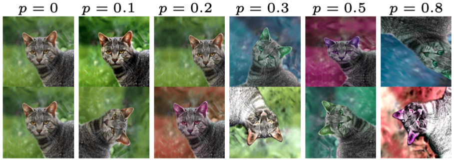


(a) MSG-GAN (b) Input/output skips (c) Residual nets

- Previous StyleGAN2 model needed large number of images for training (≈70,000)
- Aim: Enable training on limited datasets (1000 images) through data-augmentation
- Problem: augmentations leak into the generated images
- This is mitigated by ensuring augmentation probability p is lower than a threshold (≈ 0.9).







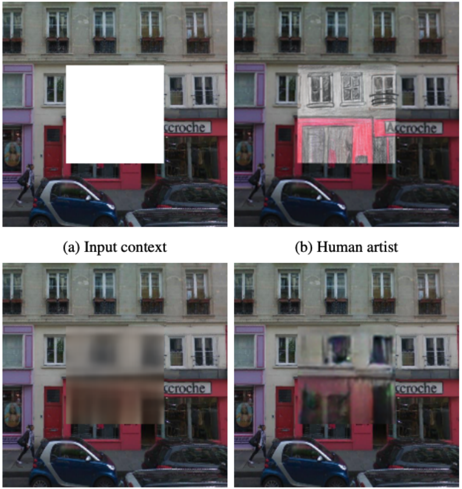
(c) Effect of augmentation probability p

Applications of GANs and other generative models

bicubic	SRResNet	SRGAN	original
(21.59dB/0.6423)	(23.53dB/0.7832)	(21.15dB/0.6868)	

(Ledig et. al., 2017)

- G generates high-res image from low-res input
- D discriminates whether high-res image is fake or real.



(a) Input context

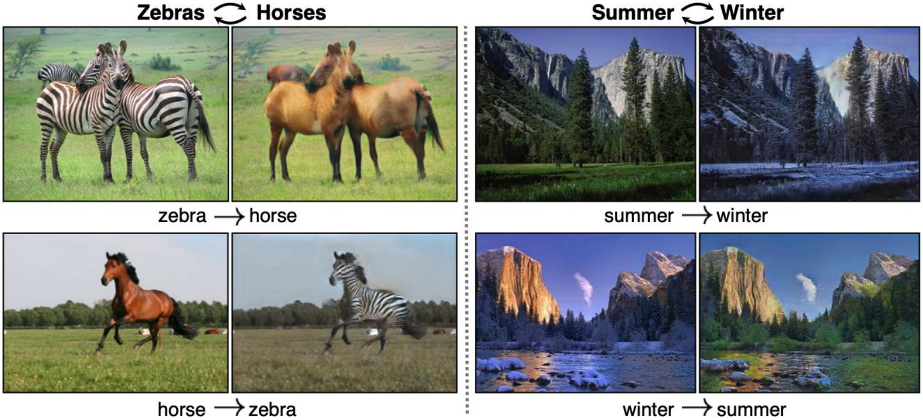
(b) Human artist

(c) Context Encoder ($L2$ loss)

(d) Context Encoder ($L2$ + Adversarial loss)

(Pathak et al, 2016)

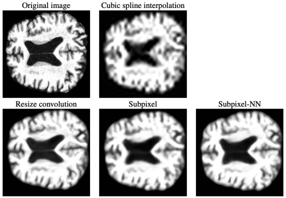
Application 3: Image-to-image translation



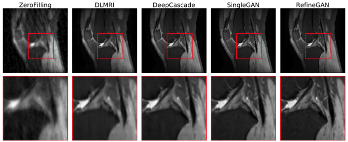
CycleGAN (Jun-Yan Zhu, CVPR, 2016)

Applications in medical imaging

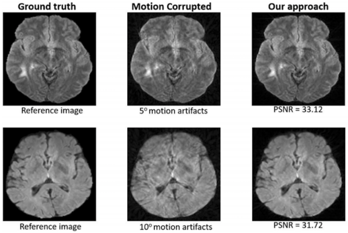
MRI super-resolution (Sanchez et al., 2018)



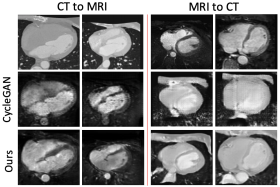
MR Reconstruction from undersampled K-space (Quan et al, 2017, Yang et al, 2017)



MRI motion correction (Usman et al, 2020)

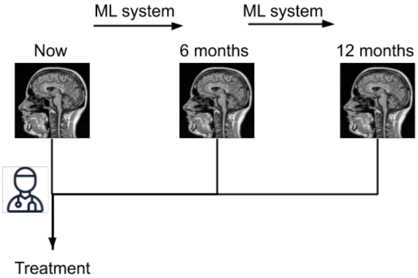


Modality translation (Zhang et al, 2019)



Any image reconstruction task!

- Prediction and visualisation of future of disease progression
- Can assist doctors in assigning treatments



Alzheimer's disease prediction (Ravi et. al., 2019)

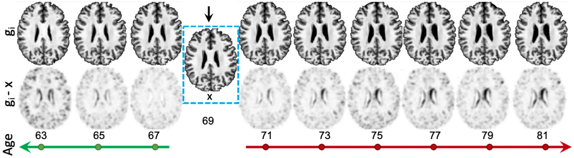
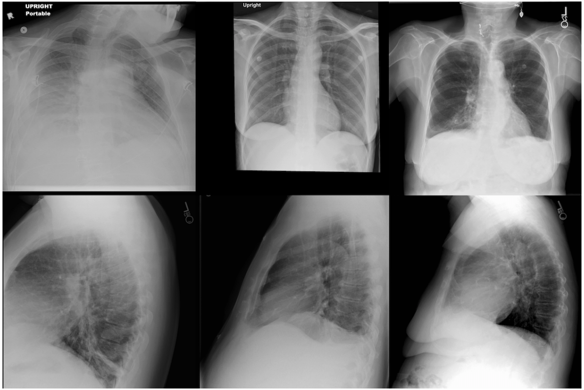


Fig. 4. Neurodegeneration simulation of a 69-year old ADNI participant.

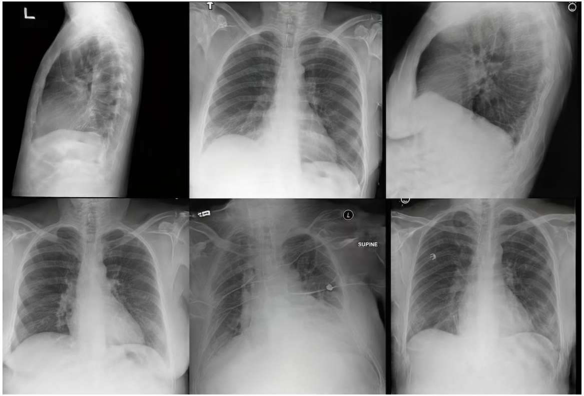
Preliminary results of StyleGAN2 on three medical datasets

Preliminary results of StyleGAN2 on Chest X-rays

Real data



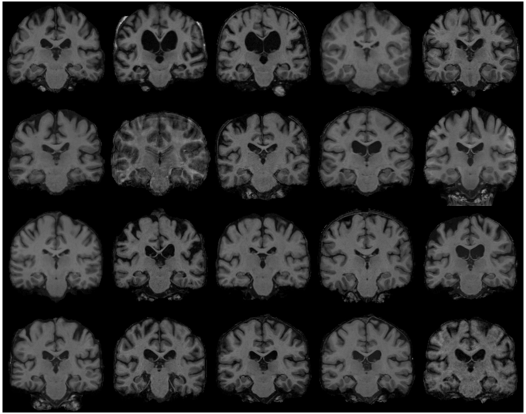
Synthetic data (FID = 23.43, IS=2.4176)



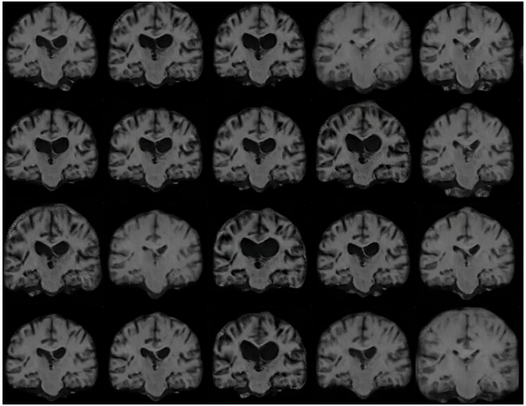
- StyleGAN2 out-of-the box
- Trained on MIMIC III, 360k images of 1024x1024 resolution
- Still some problems to fix:
  - some ribs look "broken"
  - bone contours are not always smooth/straight

Preliminary results of StyleGAN2 on brain MRI

Real data



Synthetic data

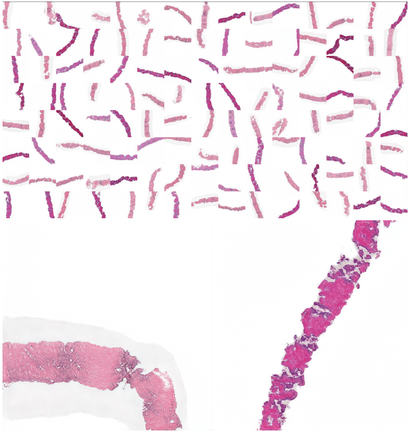


- Still out-of-the-box model (StyleGAN2)
- Trained on 8,000 brain scans (ADNI/OASIS/AIBL/PPMI)
- Next:
  - check if neuroanatomical properties are preserved (e.g. brain/ventricle vols are same)
  - extend StyleGAN2 to 3D

Preliminary results of StyleGAN2 on microscopy images

Real data

Synthetic data



- Out-of-the-box
- Trained on 11,000 microscopy slices with pancreatic cancer (MICCAI PANDAS 2020 challenge dataset)
- 512x512 image crops

- GANs have obtained state-of-the-art results on image generation
- Can generate sharp, realistic images
- Training now stable compared to 2-3 years ago, but can take up to 6-7 days (StyleGAN2) on 8 GPUs.
- Can help solve image reconstruction tasks
- Many potential applications in medical imaging
- Recommendations:
  - Don't build your own, start with a state-of-the-art model (StyleGAN2, BigGAN or Karras, 2020)
  - Download models already pre-trained to explore their capabilities
  - When training, initialise weights from another pre-trained model instead of random
  - PIs: Include costs for buying GPUs/AWS-credits in your grant applications
- Keep an eye on other types of generative models (VAEs, auto-regressive, flow) that have other interesting properties (e.g. density estimation), which enable other tasks e.g. anomaly detection