Neural Networks and Learning Systems
TBMI26 / 732A55

Lecture 5
Generative Adversarial Networks

Anders Eklund

anders.eklund@liu.se

Department of Biomedical Engineering (IMT)
Department of Computer and Information Science (IDA)
Center for Medical Image Science and Visualization (CMIV)
Linköping University, Sweden

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Outline

- Data augmentation, increase amount of training data
- Image synthesis, create completely new images
  - Noise-to-image GANs
  - Image-to-image GANs (image translation)
- GAN problems (mode collapse)
- How to evaluate GANs
- Combining different GANs
- GANs raise new ethical questions

Image synthesis / data augmentation

- Add more realistic images to improve CNN training
- Rotations / Mirroring
- Changing colours
- Scaling (change size)
- Elastic (non-linear) deformations
- For "classical" image processing,
  features were designed to be invariant
  to scale and rotation (e.g. log polar transform)
- In deep learning, this is solved with data augmentation

Rotation

What happens if you train a network on 1 million cat images, and then show an upside down cat?

Add randomly rotated versions of all images as training data, add horizontal and vertical flips of training images

SCALE

What happens if you train a network on 1 million cat images,
and then show a much smaller cat?

Add randomly scaled versions of all images as training data

Quality

What happens if you train a network on 1 million cat images,
and then show a blurry cat?

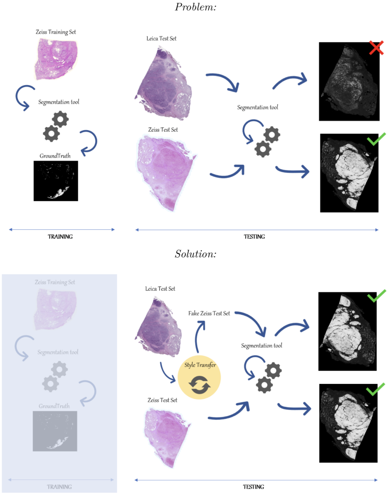
Add blurred versions of all images as training data

Add noise to all training images

Different cameras / scanners

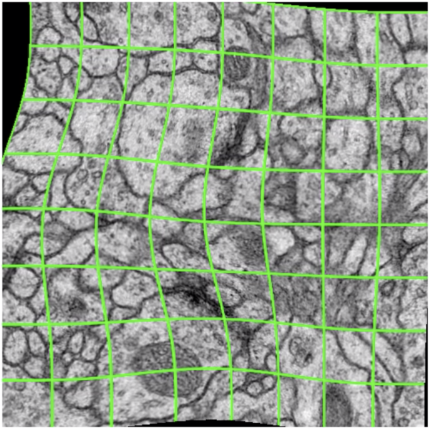
- Deep learning networks are often sensitive to the input data
- A CNN trained on images from camera / scanner A
  will normally not perform well on images from camera / scanner B
- Different cameras / scanners have different noise properties
- Different cameras / scanners have different color histograms
- For improved robustness, train on data from different cameras / scanners or use 'style transfer' techniques to 'translate' images

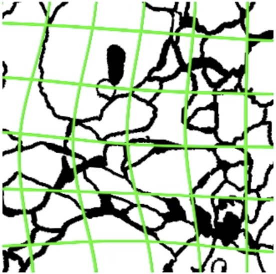
Different cameras / scanners



Alessia de Biase, Generative Adversarial Networks to enhance decision support in digital pathology, LIU-IDA/STAT-A–19/007–SE

Elastic (non-linear) deformations

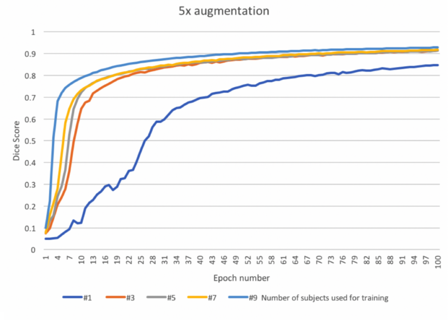


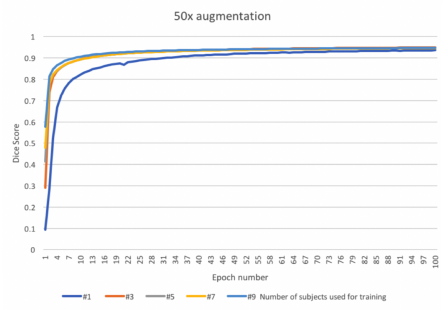


correspondingly deformed manual labels

https://lmb.informatik.uni-freiburg.de/people/ronneber/u-net/

Degree of augmentation





Gaonkar, Bilwaj, et al. Extreme Augmentation: Can deep learning based medical image segmentation be trained using a single manually delineated scan?, arXiv:1810.01621, 2018

Generative adversarial networks

- Standard data augmentation cannot create new images, can only modify existing images through rotations, scaling, ...
- Generative adversarial networks (GANs) can be trained to synthesize new images, given a large set of training images
- A GAN consists of a generator G (e.g. generates new images), and a discriminator D (e.g. classifies an image as real or fake)
- For images, both the generator and discriminator are CNNs
- Goodfellow et al. (2014). Generative adversarial nets. In Advances in neural information processing systems (pp. 2672-2680)

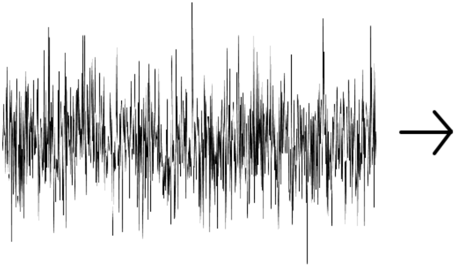
GANS - ANY DATA

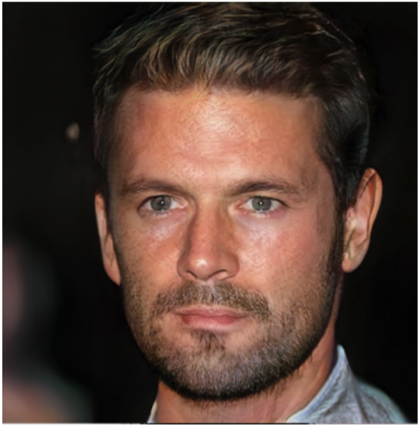
- This presentation will focus on synthesis of images, but GANs can be used to synthesize any kind of data
- https://thisarticledoesnotexist.com
- A human can easily detect a strange / low quality synthetic image (at least for common objects)
- Maybe not as easy for a human to detect a fake genetic / text dataset...

GANS - BASICS

- Adversarial training, generator and discriminator compete
- The generator tries to generate better and better images
- The discriminator tries to be better and better at discriminating real & fake images
- $G(z, \theta_g)$, generator takes noise vector z as input, uses parameters θ_g to generate an image from the data distribution
- $D(x, \theta_d)$, discriminator takes sample x, uses parameters θ_d to output a scalar; the probability that the sample x is real and not from the generator
- Latent (noise) space z, e.g. a noise vector of 128 dimensions, generator maps this noise vector to a manifold of realistic images

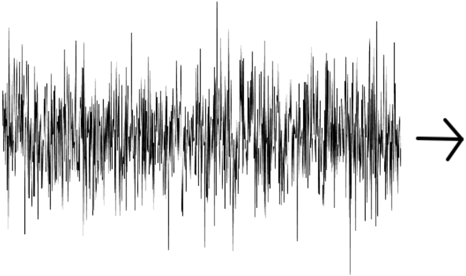
NOISE-TO-IMAGE GAN





Karras, T., Aila, T., Laine, S., & Lehtinen, J. Progressive growing of GANs for improved quality, stability, and variation, ICLR, 2018

NOISE-TO-IMAGE GAN



Karras, T., Aila, T., Laine, S., & Lehtinen, J. Progressive growing of GANs for improved quality, stability, and variation, ICLR, 2018

NOISE-TO-IMAGE GAN

- https://thispersondoesnotexist.com (faces)
- https://thisxdoesnotexist.com (everything)

GANS - BASICS

- Train D to maximize the probability of assigning the correct label to both real (x) and fake (z) samples
- Train G to minimize $log(1 - D(G(z))$, i.e. to fool the discriminator as often as possible, as $D(G(z))$ will be 1 if the discriminator thinks that the fake sample is real
- Adversarial loss function
- $$\min_G \max_D V(D, G) = \mathbb{E}_{\boldsymbol{x} \sim p_{\text{data}}(\boldsymbol{x})}[\log D(\boldsymbol{x})] + \mathbb{E}_{\boldsymbol{z} \sim p_{\boldsymbol{z}}(\boldsymbol{z})}[\log(1 - D(G(\boldsymbol{z})))].$$

GANS - BASICS

- In almost all cases it is easier to train the discriminator
- When starting the training, the fake images have very low quality, very easy for the discriminator to classify images as real or fake, will not provide much information for the generator to learn from
- Instead of minimizing $log(1 - D(G(z))$, maximize $log(D(G(z))$, will provide stronger gradients in the beginning of the training

GANS - BASICS

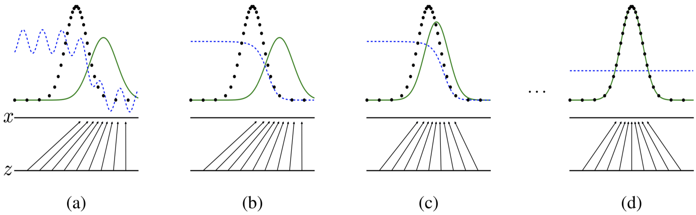


Figure 1: Generative adversarial nets are trained by simultaneously updating the **d**iscriminative distribution (D, blue, dashed line) so that it discriminates between samples from the data generating distribution (black, dotted line) $p_{\boldsymbol{x}}$ from those of the **g**enerative distribution p_g (G) (green, solid line). The lower horizontal line is the domain from which $\boldsymbol{z}$ is sampled, in this case uniformly. The horizontal line above is part of the domain of $\boldsymbol{x}$. The upward arrows show how the mapping $\boldsymbol{x} = G(\boldsymbol{z})$ imposes the non-uniform distribution p_g on transformed samples. G contracts in regions of high density and expands in regions of low density of p_g. (a) Consider an adversarial pair near convergence: p_g is similar to p_{data} and D is a partially accurate classifier. (b) In the inner loop of the algorithm D is trained to discriminate samples from data, converging to $D^*(\boldsymbol{x}) = \frac{p_{\text{data}}(\boldsymbol{x})}{p_{\text{data}}(\boldsymbol{x})+p_g(\boldsymbol{x})}$. (c) After an update to G, gradient of D has guided $G(\boldsymbol{z})$ to flow to regions that are more likely to be classified as data. (d) After several steps of training, if G and D have enough capacity, they will reach a point at which both cannot improve because $p_g = p_{\text{data}}$. The discriminator is unable to differentiate between the two distributions, i.e. $D(\boldsymbol{x}) = \frac{1}{2}$.

Goodfellow et al. (2014). Generative adversarial nets. In Advances in neural information processing systems (pp. 2672-2680)

GANs - Adversarial Training

Algorithm 1 Minibatch stochastic gradient descent training of generative adversarial nets. The number of steps to apply to the discriminator, k, is a hyperparameter. We used $k = 1$, the least expensive option, in our experiments.

for number of training iterations **do**

  for k steps **do**

  - Sample minibatch of m noise samples $\{\boldsymbol{z}^{(1)}, \ldots, \boldsymbol{z}^{(m)}\}$ from noise prior $p_g(\boldsymbol{z})$.
  - Sample minibatch of m examples $\{\boldsymbol{x}^{(1)}, \ldots, \boldsymbol{x}^{(m)}\}$ from data generating distribution $p_{\text{data}}(\boldsymbol{x})$.
  - Update the discriminator by ascending its stochastic gradient:

$$\nabla_{\theta_d} \frac{1}{m} \sum_{i=1}^{m} \left[\log D\left(\boldsymbol{x}^{(i)}\right) + \log\left(1 - D\left(G\left(\boldsymbol{z}^{(i)}\right)\right)\right)\right].$$

  end for

- Sample minibatch of m noise samples $\{\boldsymbol{z}^{(1)}, \ldots, \boldsymbol{z}^{(m)}\}$ from noise prior $p_g(\boldsymbol{z})$.
- Update the generator by descending its stochastic gradient:

$$\nabla_{\theta_g} \frac{1}{m} \sum_{i=1}^{m} \log\left(1 - D\left(G\left(\boldsymbol{z}^{(i)}\right)\right)\right).$$

end for

The gradient-based updates can use any standard gradient-based learning rule. We used momentum in our experiments.

Goodfellow et al. (2014). Generative adversarial nets. In Advances in neural information processing systems (pp. 2672-2680)

GANS - FIRST RESULTS

Figure 2: Visualization of samples from the model. Rightmost column shows the nearest training example of the neighboring sample, in order to demonstrate that the model has not memorized the training set. Samples are fair random draws, not cherry-picked. Unlike most other visualizations of deep generative models, these images show actual samples from the model distributions, not conditional means given samples of hidden units. Moreover, these samples are uncorrelated because the sampling process does not depend on Markov chain mixing. a) MNIST b) TFD c) CIFAR-10 (fully connected model) d) CIFAR-10 (convolutional discriminator and "deconvolutional" generator)

Goodfellow et al. (2014). Generative adversarial nets. In Advances in neural information processing systems (pp. 2672-2680)

DEEP CONVOLUTIONAL GAN - DCGAN

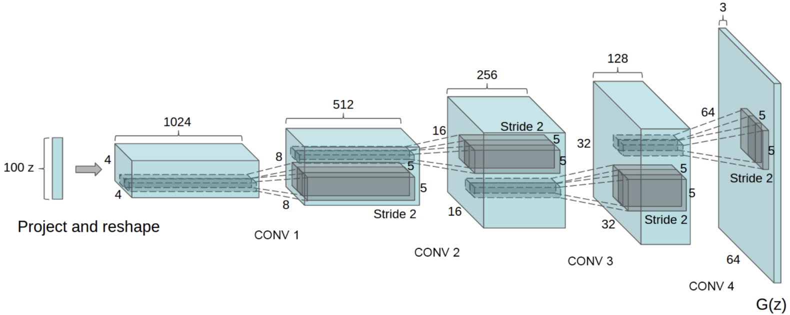


Figure 1: DCGAN generator used for LSUN scene modeling. A 100 dimensional uniform distribution Z is projected to a small spatial extent convolutional representation with many feature maps. A series of four fractionally-strided convolutions (in some recent papers, these are wrongly called deconvolutions) then convert this high level representation into a 64×64 pixel image. Notably, no fully connected or pooling layers are used.

Radford, A., Metz, L., & Chintala, S. (2015). Unsupervised representation learning with deep convolutional generative adversarial networks. arXiv:1511.06434.

DCGAN - FULL ARCHITECTURE

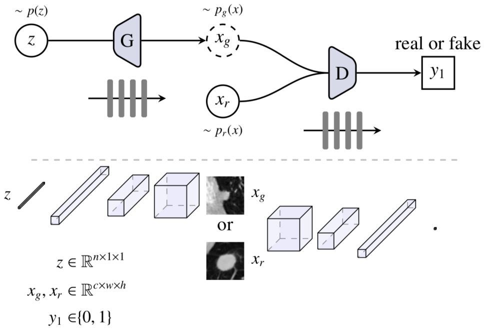


Figure 2: Schematic view of the vanilla GAN for synthesis of lung nodule on CT images. Top of the figure shows the network configuration. The part below shows the input, output and the internal feature representations of the generator G and discriminator D. G transforms a sample z from $p(z)$ into a generated nodule x_g. D is a binary classifier that differentiates the generated and real images of lung nodule formed by x_g and x_r respectively.

Yi, X., Walia, E., & Babyn, P. (2019). Generative adversarial network in medical imaging: A review, Medical Image Analysis

DEEP CONVOLUTIONAL GAN - DCGAN

Figure 3: Generated bedrooms after five epochs of training. There appears to be evidence of visual under-fitting via repeated noise textures across multiple samples such as the base boards of some of the beds.

Radford, A., Metz, L., & Chintala, S. (2015). Unsupervised representation learning with deep convolutional generative adversarial networks. arXiv:1511.06434.

DEEP CONVOLUTIONAL GAN - DCGAN

- DCGAN can rather easily be used to create low resolution images (64 x 64 pixels)
- Producing images of higher resolution is (much) harder
- Mode collapse problem: generator will generate a single image
- Difficult to balance generator and discriminator, if one is much better than the other the training will stop
- Wasserstein GAN, another algorithm for more stable training
- Arjovsky, M., Chintala, S., & Bottou, L. (2017). Wasserstein GAN, arXiv:1701.07875.

NOISE-TO-IMAGE GAN - PROGRESSIVE

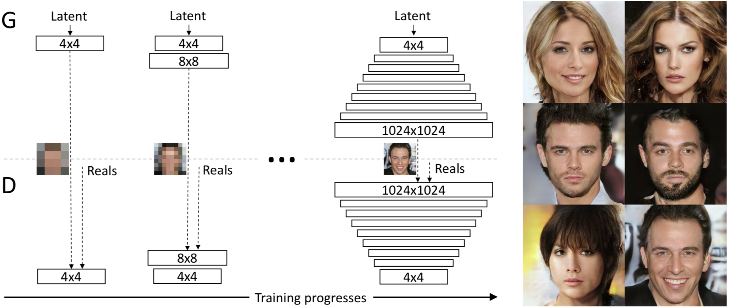
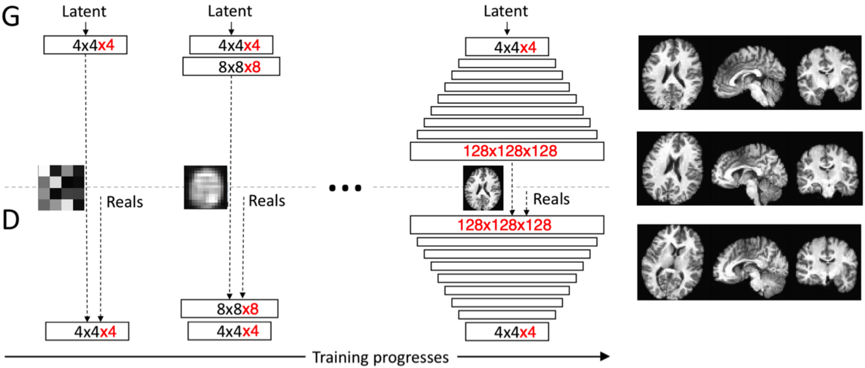


Figure 1: Our training starts with both the generator (G) and discriminator (D) having a low spatial resolution of 4×4 pixels. As the training advances, we incrementally add layers to G and D, thus increasing the spatial resolution of the generated images. All existing layers remain trainable throughout the process. Here $\boxed{N \times N}$ refers to convolutional layers operating on $N \times N$ spatial resolution. This allows stable synthesis in high resolutions and also speeds up training considerably. One the right we show six example images generated using progressive growing at 1024×1024.

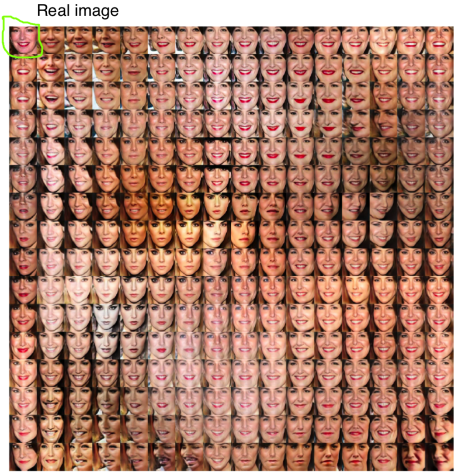
Karras, T., Aila, T., Laine, S., & Lehtinen, J. Progressive growing of GANs for improved quality, stability, and variation, ICLR, 2018

3D progressive noise-to-image GAN



Eklund, A. (2019), Feeding the zombies: Synthesizing brain volumes using a 3D progressive growing GAN. arXiv:1912.05357.

GANS FOR DATA AUGMENTATION



Antoniou, A., Storkey, A., Edwards, H., Data Augmentation Generative Adversarial Networks, arXiv:1711.04340

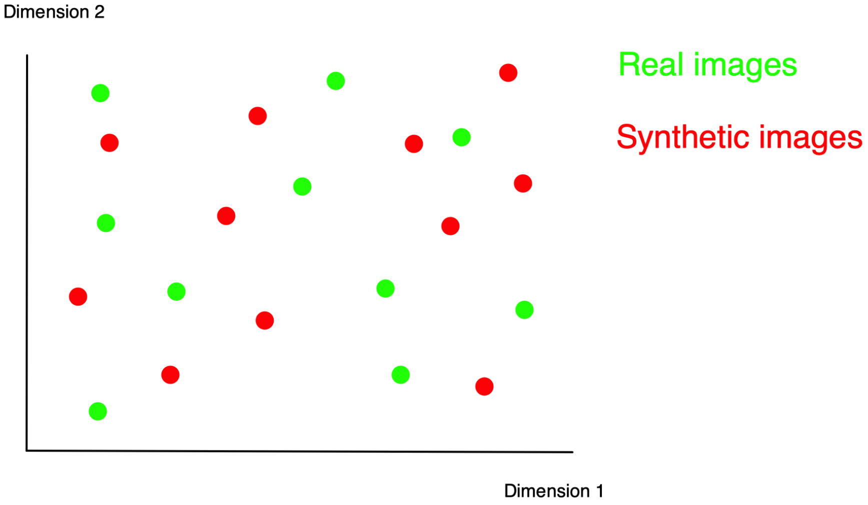
GANS FOR DATA AUGMENTATION

Omniglot DAGAN Augmented Classification		
Experiment ID	**Samples Per Class**	**Test Accuracy**
Omni_5_Standard	5	0.689904
Omni_5_DAGAN_Augmented	5	**0.821314**
Omni_10_Standard	10	0.794071
Omni_10_DAGAN_Augmented	10	**0.862179**
Omni_15_Standard	15	0.819712
Omni_15_DAGAN_Augmented	15	**0.874199**
EMNIST DAGAN Augmented Classification		
Experiment ID	**Samples Per Class**	**Test Accuracy**
EMNIST_Standard	15	0.739353
EMNIST_DAGAN_Augmented	15	**0.760701**
EMNIST_Standard	25	0.783539
EMNIST_DAGAN_Augmented	25	**0.802598**
EMNIST_Standard	50	0.815055
EMNIST_DAGAN_Augmented	50	**0.827832**
EMNIST_Standard	100	0.837787
EMNIST_DAGAN_Augmented	100	**0.848009**
Face DAGAN Augmented Classification		
Experiment ID	**Samples Per Class**	**Test Accuracy**
VGG-Face_Standard	5	0.0446948
VGG-Face_DAGAN_Augmented	5	**0.125969**
VGG-Face_Standard	15	0.39329
VGG-Face_DAGAN_Augmented	15	**0.429385**
VGG-Face_Standard	25	0.579942
VGG-Face_DAGAN_Augmented	25	**0.584666**

Table 1: Vanilla Classification Results: All results are averages over 5 independent runs. The DAGAN augmentation improves the classifier performance in all cases. Test accuracy is the result on the test cases in the test domain

Antoniou, A., Storkey, A., Edwards, H., Data Augmentation Generative Adversarial Networks, arXiv:1711.04340

DATA AUGMENTATION - LOW DIM PLOT



How to evaluate GANs

- No objective loss function is used when training GANs
- Not so easy to say how good a GAN is,
  hard to compare different GAN architectures / configurations
- Want to compare GANs in terms of image quality, diversity
- Manual / visual evaluation;
  synthesize images and let humans evaluate them
  - Subjective, can lead to biased results
  - What is a realistic image in a certain domain?
  - Time consuming
  - Low reproducibility

Qualitative GAN generator evaluation

- Qualitative ways to evaluate a GAN generator
  - Look at nearest neighbours in training set
  - Rapid scene categorization
  - Rating and preference judgment
  - Evaluating mode drop and mode collapse
  - Investigating and visualizing the internals of network
- Borji, A. (2019). Pros and cons of GAN evaluation measures. Computer Vision and Image Understanding, 179, 41-65.

Evaluating mode drop and mode collapse

- GANs often fail to model the entire data distribution
- Mode collapse; many input noise vectors are mapped to the same synthetic image (i.e. low diversity of the synthetic images)
- Mode drop; some modes of the data distribution are ignored
- May be hard to detect mode collapse for GANs trained on a large number of real images, easier for synthetic datasets
- A mode is considered lost if there is no sample in the generated test data within a certain standard deviations from the center of that mode

Evaluating mode drop and mode collapse

- For real datasets, train GAN using a well balanced dataset (equal number of samples from each class)
- Train a multi-class classifier using the same dataset
- Generate images from GAN, use classifier to obtain labels
- Is the distribution of synthetic images also uniform?

Evaluating mode drop and mode collapse

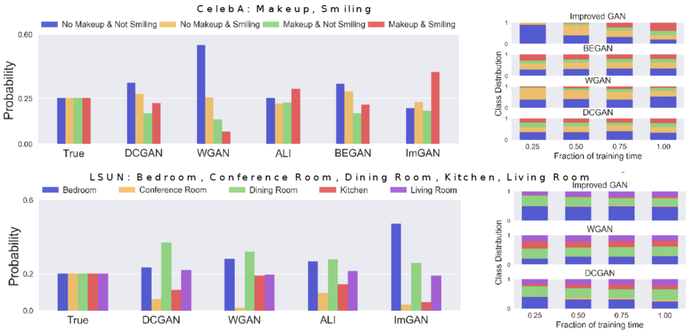


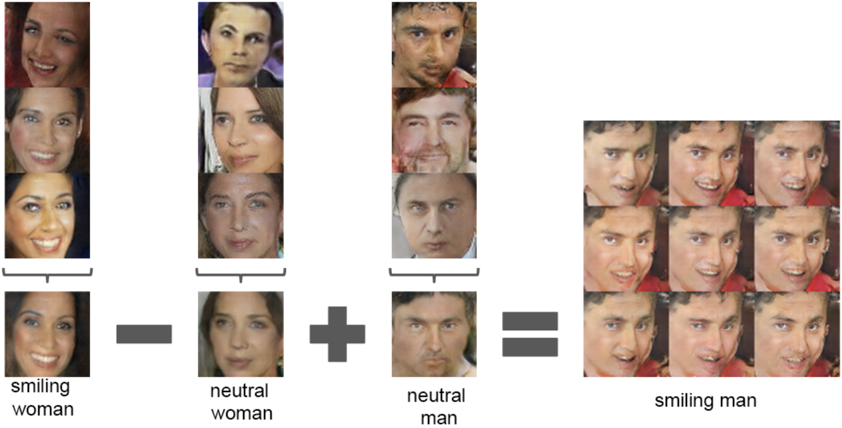
Figure 18: Illustration of mode collapse in GANs trained on select subsets of CelebA and LSUN datasets using the technique in [42]. Left panel shows the relative distribution of modes in samples drawn from the GANs, and compares is to the true data distribution (leftmost plots). Right panel shows the evolution of class distributions in different GANs over the course of training. It can be seen that these GANs introduce covariate shift through mode collapse. Figure compiled from [42].

S. Santurkar, L. Schmidt, A. Madry, A classification-based study of covariate shift in GAN distributions, in: International Conference on Machine Learning, 2018, pp. 4487–4496

Investigating and visualizing the internals of networks

- Understand the latent space; what does each dimension of the noise vector mean?
- Disentangled representations. "Disentanglement" regards the alignment of "semantic" visual concepts to axes in the latent space. Some tests can check the existence of semantically meaningful directions in the latent space, meaning that varying the seed along those directions leads to predictable changes (e.g. changes in facial hair, or pose).
- Perform arithmetic on noise vectors
- Smiling woman - neutral woman + neutral man = smiling man

INVESTIGATING AND VISUALIZING THE INTERNALS OF NETWORKS



Radford, A., Metz, L., & Chintala, S. (2015). Unsupervised representation learning with deep convolutional generative adversarial networks. arXiv:1511.06434.

Investigating and visualizing the internals of networks

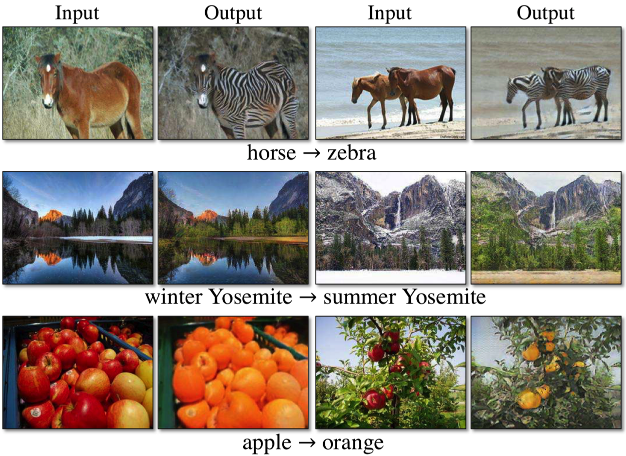
- Space continuity, given two noise vectors z_1, z_2 interpolate between z_1 and z_2, check resulting images
- If the "interpolated" images are reasonable, the model can produce new images, has not only memorized training images
- 

  Figure 20: Top: Interpolations on z_r between real images at 128×128 resolution (from BEGAN [124]). These images were not part of the training data. The first and last columns contain the real images to be represented and interpolated. The images immediately next to them are their corresponding approximations while the images in between are the results of linear interpolation in z_r.
- A. Odena, C. Olah, J. Shlens, Conditional image synthesis with auxiliary classifier GANs, arXiv:1610.09585

IMAGE-TO-IMAGE GAN (CONDITIONAL GANS)

- Noise-to-image GAN: synthesize image from noise (latent vector)
- Image-to-image GAN: synthesize type A image from type B image
- Image-to-image GANs are normally much easier to train, since you start from an image and not from noise

IMAGE-TO-IMAGE GAN (CONDITIONAL GANS)



Zhu et al., Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks, ICCV, 2017

APPLICATIONS - DAY TO NIGHT

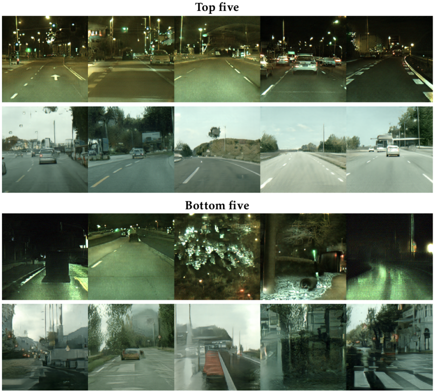


Figure 5.15: *Synthetic results from the CycleGAN baseline model on 256x256 pixel images. The model is trained using the large day and night dataset. Top and bottom results are from city and open road street view environments.*

S. Karlsson, P. Welander, Generative Adversarial Networks for Image-to-Image Translation on Street View and MR Images, LIU-IMT-TFK-A—18/554—SE, 2018

APPLICATIONS - MR TO CT

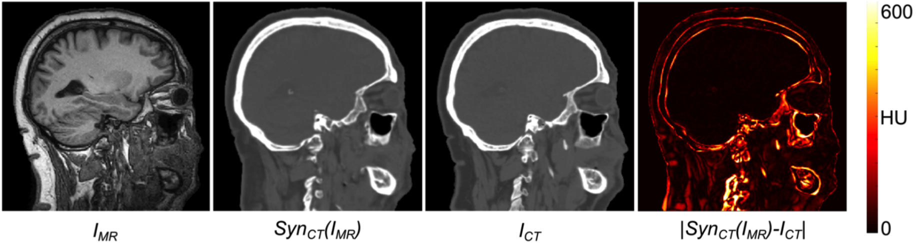


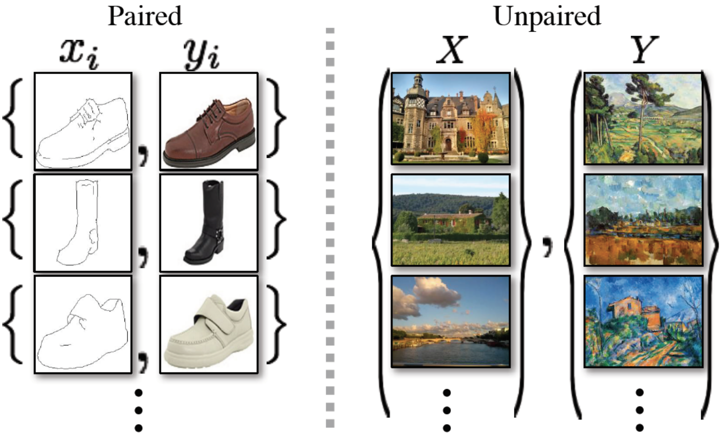
Fig. 4: *From left to right* Input MR image, synthesized CT image, reference real CT image, and absolute error between real and synthesized CT image.

Wolterink et al., Deep MR to CT synthesis using unpaired data. International Workshop on Simulation and Synthesis in Medical Imaging, 2017

SUPERVISED VS UNSUPERVISED GANS

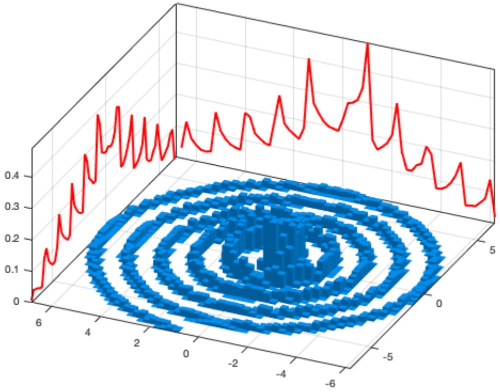
- We have images from two domains, X & Y
- We can train a GAN to convert from domain X to domain Y
  - If we have every image represented in both domains (x1; y1); (x2; y2); we can train a *supervised* GAN, which learns from the joint distribution of the data in both domains
  - If we have unmatched images in both domains (x1; ?); (?; y2); we can train an *unsupervised* GAN, which learns from the marginal distributions of the data in both domains.

PAIRED AND UNPAIRED DATA



Zhu et al., Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks, ICCV, 2017

SUPERVISED VS UNSUPERVISED GANS

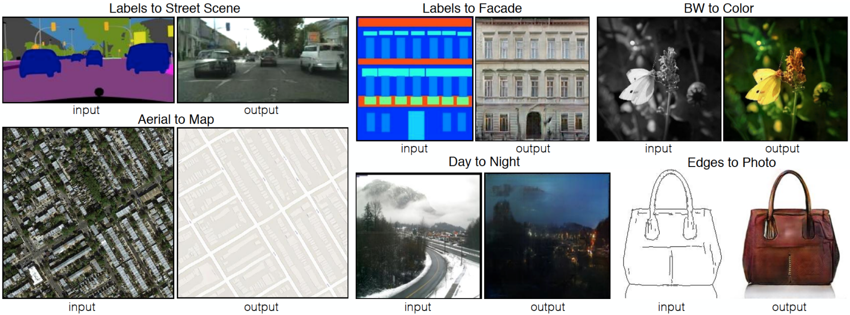


Supervised GAN: Learn the blue distribution
from paired examples from the blue distribution

Unsupervised GAN: Learn the blue distribution
from examples from the red distributions

PAIRED TRAINING - PIX2PIX

- Given images in two domains, X and Y, the GAN learns to convert an image in domain X to domain Y
- Drawback: We need paired (and registered) training images



Isola et al., Image-to-Image Translation with Conditional Adversarial Networks, CVPR, 2017

unpaired training - CycleGAN

- Unsupervised image-to-image translation is more difficult
- Learning a joint distribution from marginal distributions is a vastly underdetermined problem, need regularization.
- One solution: CycleGAN. Learn transformations in both directions $X \leftrightarrow Y$ and impose a consistency constraint in forward-backward conversion
- $$\begin{cases} x_i \to \widehat{y}_i \to \widetilde{x}_i \approx x_i \\ y_i \to \widehat{x}_i \to \widetilde{y}_i \approx y_i \end{cases}$$

Loss functions for training

- Mappings $G : X -> Y$ and $F : Y -> X$, discriminators D_X and D_Y
- Adversarial loss function (GAN), L_{GAN}

  $$L_{GAN}(G, D_Y, X, Y) = E\left[logD_Y(y)\right] + E\left[log(1 - D_Y(G(x))\right]$$

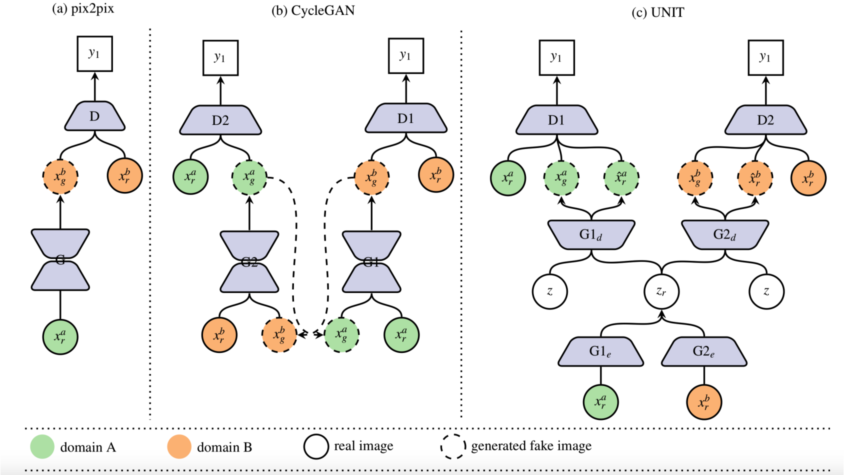
- Cycle consistency loss function (CycleGAN), L_{cyc}

  $$L_{cyc}(G, F) = E\left[||F(G(x)) - x||_1\right] + E\left[||G(F(y)) - y||_1\right]$$

- Full loss function for CycleGAN

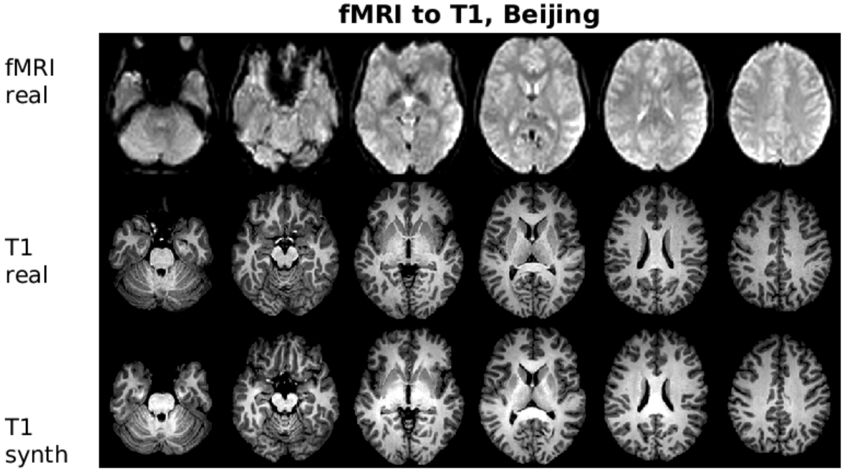
  $$L(G, F, D_X, D_Y) = \\ L_{GAN}(G, D_Y, X, Y) + L_{GAN}(F, D_X, Y, X) + \lambda L_{cyc}(G, F)$$

PIX2PIX VS CYCLEGAN VS UNIT



Yi, X., Walia, E., & Babyn, P. (2018). Generative adversarial network in medical imaging: A review. Medical Image Analysis

CycleGAN - 3D



Abramian, D., & Eklund, A. (2019). Generating fMRI volumes from T1-weighted volumes using 3D CycleGAN. arXiv:1907.08533.

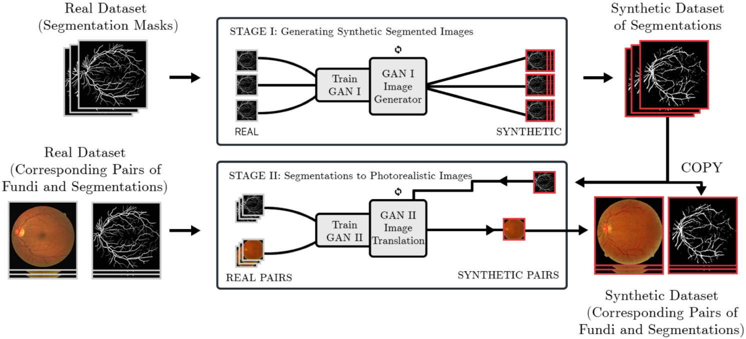
More advanced - combining GANs

- Difficult to synthesize realistic data from scratch (image-to-image GANs are normally easier / more stable to train compared to noise-to-image GANs)
- Use noise-to-image GAN to synthesize object of interest (as a (small) binary image / volume)
- Use image-to-image GAN to transform binary image / volume into a realistic dataset
- For training segmentation networks, we need training images AND (binary) masks

More advanced - combining GANs

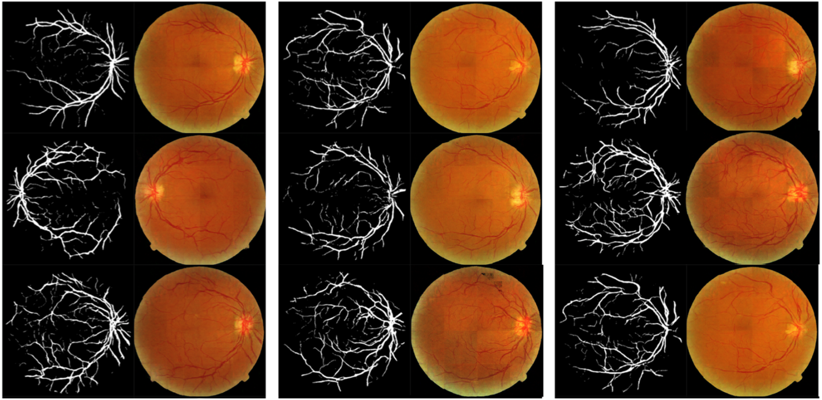
1. Stage-I GAN: Produce segmentation masks that represent the variable geometries of the dataset.
2. Stage-II GAN: Translate the masks produced in Stage-I to photorealistic images.

We illustrate the process with retinal fundi images.



Guibas, J. T., Virdi, T. S., & Li, P. S. Synthetic medical images from dual generative adversarial networks. arXiv:1709.01872.

More advanced - combining GANs

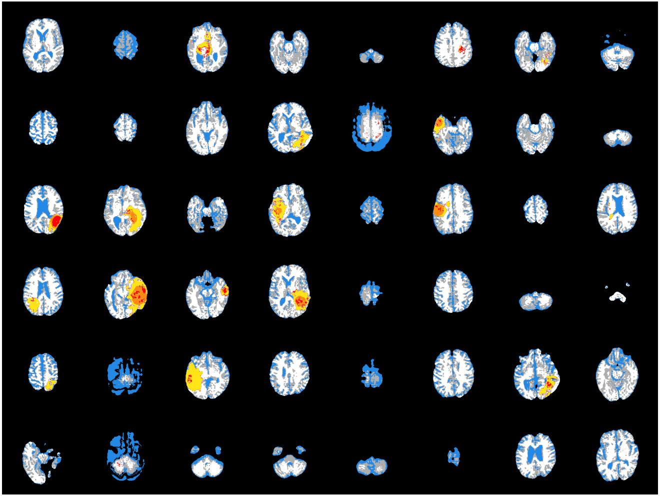


Guibas, J. T., Virdi, T. S., & Li, P. S. Synthetic medical images from dual generative adversarial networks. arXiv:1709.01872.

More advanced - combining GANs

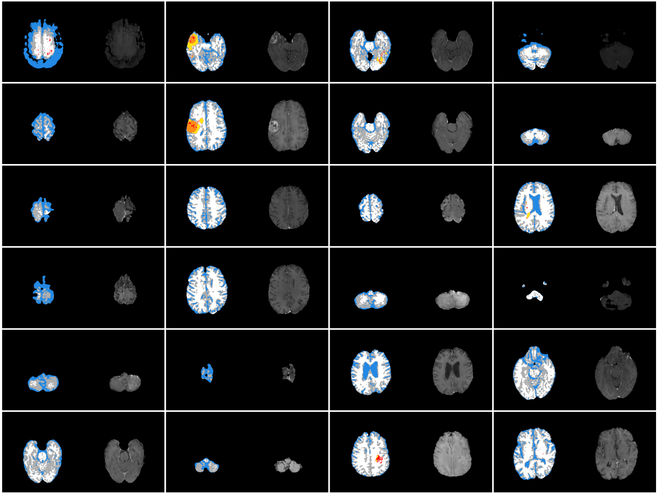
- In this master thesis several CNNs were used
- Progressive growing GAN to synthesize label images (noise to image GAN)
- SPADE to synthesize MR images from label images (image to image GAN)
- U-Net to perform brain tumor segmentation
- Mehdi Foroozandeh, GAN-Based Synthesis of Brain Tumor Segmentation Data: Augmenting a dataset by generating artificial images, LIU-IMT-TFK-A-20/586, 2020

More advanced - combining GANs



Mehdi Foroozandeh, GAN-Based Synthesis of Brain Tumor Segmentation Data: Augmenting a dataset by generating artificial images, LIU-IMT-TFK-A-20/586, 2020

More advanced - combining GANs



Mehdi Foroozandeh, GAN-Based Synthesis of Brain Tumor Segmentation Data: Augmenting a dataset by generating artificial images, LIU-IMT-TFK-A-20/586, 2020

More advanced - combining GANs

	Classes		
Number of training images (real, synthetic)	7	4	2
(26,040, 0), total: 26,040	10.94	6.62	2.49
(26,040, 8,960), total: 35,000	10.92	6.65	**2.48**
(26,040, 23,960), total: 50,000	**10.90**	**6.42**	2.53
(0, 26,040), total: 26,040	42.76	39.11	24.14
(5,208, 0), total: 5,208	16.80	12.90	6.16
(5,208, 4792), total: 10,000	16.44	12.51	6.14
(5,208, 20832), total: 26,040	**16.18**	**12.11**	**5.80**

Table 1. Dice error in percent, calculated over the test set. **Top rows:** training with the full dataset (26,040 images). **Bottom rows:** training with the reduced dataset (5,208 images). The best data configuration in each class has been highlighted in bold, with respect to both the full and reduced datasets.

Mehdi Foroozandeh, GAN-Based Synthesis of Brain Tumor Segmentation Data: Augmenting a dataset by generating artificial images, LIU-IMT-TFK-A-20/586, 2020

Ethical questions

- Synthetic images raise new ethical questions
- Who is the owner of synthetic data?
- Can AI be an author / painter?
- If a GAN is trained on medical images,
  can the synthetic images be seen as anonymized? GDPR?
- Researchers should not fabricate data...
- Will medical doctors accept to work on synthetic images?

Generative AI

Is artificial intelligence set to become art's next medium?

12 December 2018

PHOTOGRAPHS & PRINTS | AUCTION PREVIEW

Main image:

Portrait of Edmond Belamy (detail) created by GAN (Generative Adversarial Network), which will be offered at Christie's on 23-25 October. Image © Obvious

Highlighted sale

Prints & Multiples

AI artwork sells for $432,500 — nearly 45 times its high estimate — as Christie's becomes the first auction house to offer a work of art created by an algorithm

The portrait in its gilt frame depicts a portly gentleman, possibly French and — to judge by his dark frockcoat and plain white collar — a man of the church. The work appears unfinished: the facial features are somewhat indistinct and there are blank areas of canvas. Oddly, the whole composition is displaced slightly to the north-west. A label on the wall states that the sitter is a man named Edmond Belamy, but the giveaway clue as to the origins of the work is the artist's signature at the bottom right. In cursive Gallic script it reads:

$$\min_G \max_D \mathbb{E}_x[\log(D(x))] + \mathbb{E}_z[\log(1 - D(G(z)))]$$

https://www.christies.com/features/A-collaboration-between-two-artists-one-human-one-a-machine-9332-1.aspx