GANs and their species

IE643 - Lecture 17

October 7, 2022.

1. GAN
   - Training Strategies
   - Conditional GAN
2. Disco GAN

GAN

Generative Adversarial Nets

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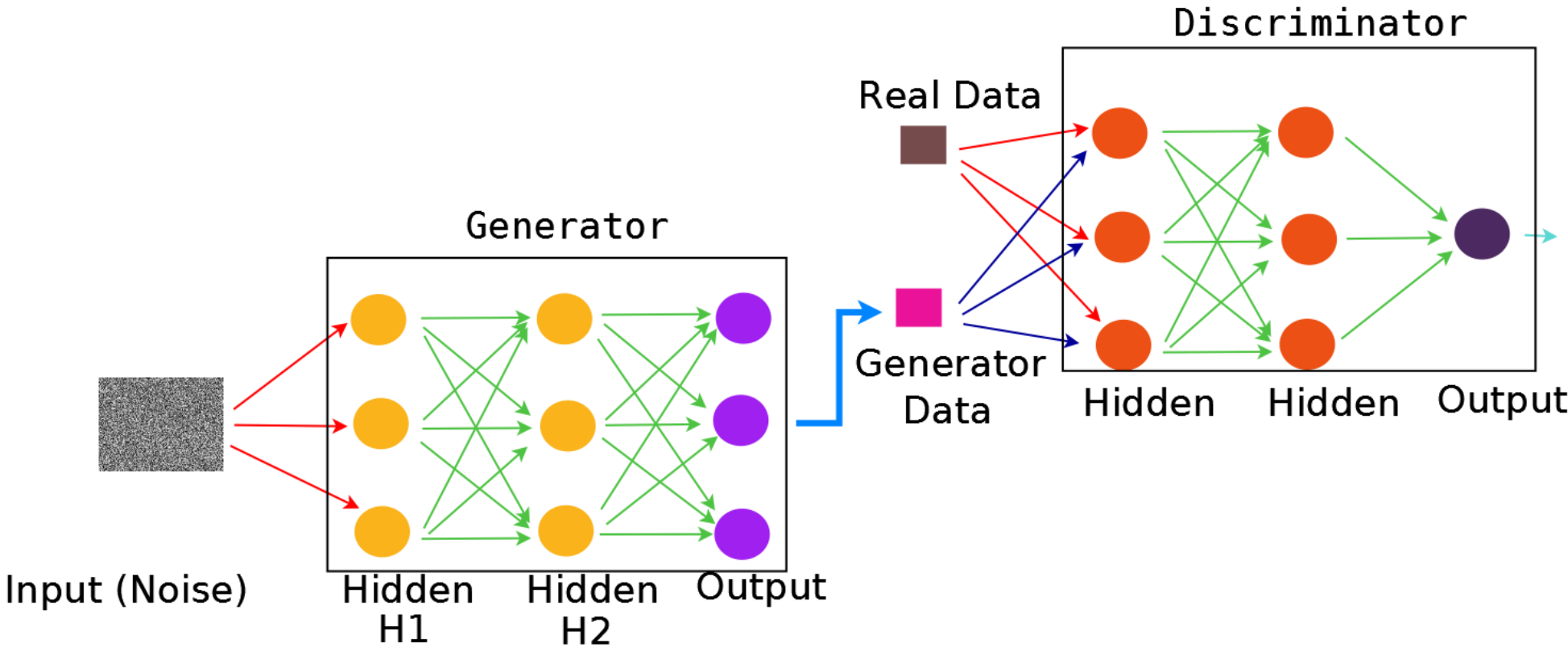
Sherjil Ozair,† Aaron Courville, Yoshua Bengio‡

GAN


Discriminator
Real Data
Generator
Generator Data
Input (Noise)
Hidden H1
Hidden H2
Output
Hidden
Hidden
Output

GAN

- Discriminator component D
- Generator component G

GAN

- Aim of Discriminator component D:
  - Maximize likelihood of real data from distribution p_{data}
  - Minimize likelihood of fake data $G(z)$ obtained through generator G, where z comes from noise distribution p_{noise}.

GAN

- Objective of Discriminator component D: (straightforward)

$$\max_{\theta_d} \; \mathbb{E}_{x \sim p_{data}} \log D_{\theta_d}(x) + \mathbb{E}_{z \sim p_{noise}} \log(1 - D_{\theta_d}(G(z))).$$

Assumption: $D(x)$ is a probability (or likelihood)

GAN

- Aim of Generator component G:
  - Fool the discriminator by providing $G(z)$ as if it comes from p_{data}.
  - How to do that?

GAN

- Aim of Generator component G:
  - Fool the discriminator by providing $G(z)$ as if it comes from p_{data}.
  - How to do that?
- Idea:

$$\min_{\theta_g} \mathbb{E}_{z \sim p_{noise}} \log(1 - D_{\theta_d}(G_{\theta_g}(z))).$$

GAN

- Overall Objective of GAN:

$$\max_{\theta_d} \left[\mathbb{E}_{x \sim p_{data}} \log D_{\theta_d}(x) + \min_{\theta_g} \mathbb{E}_{z \sim p_{noise}} \log(1 - D_{\theta_d}(G_{\theta_g}(z))) \right].$$

GAN

- Overall Objective of GAN (seems to be):

$$\max_{\theta_d} \left[\mathbb{E}_{x \sim p_{data}} \log D_{\theta_d}(x) + \min_{\theta_g} \mathbb{E}_{z \sim p_{noise}} \log(1 - D_{\theta_d}(G_{\theta_g}(z))) \right].$$

- Looks like a max-min problem

GAN

- Overall Objective of GAN (used in paper):

$$\min_{\theta_g}\max_{\theta_d} \left[\mathbb{E}_{x\sim p_{data}} \log D_{\theta_d}(x) + \mathbb{E}_{z\sim p_{noise}} \log(1 - D_{\theta_d}(G_{\theta_g}(z)))\right].$$

- This is a min-max problem

GAN

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.

GAN

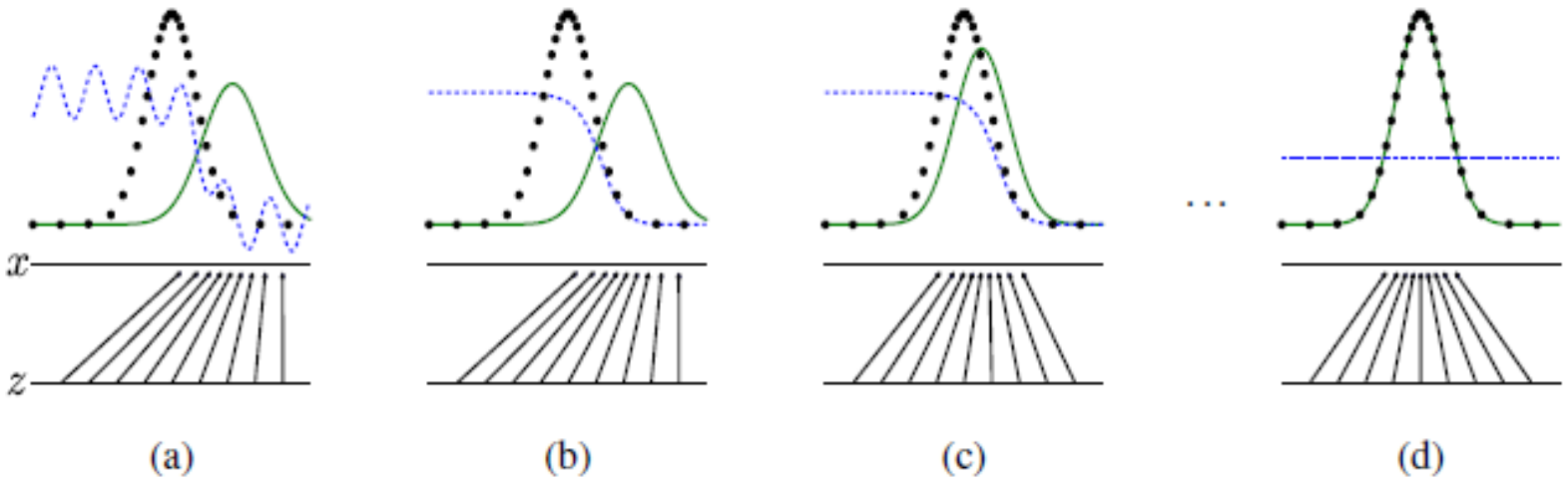


Figure 1: Generative adversarial nets are trained by simultaneously updating the discriminative distribution (D, blue, dashed line) so that it discriminates between samples from the data generating distribution (black, dotted line) p_x from those of the generative distribution p_g (G) (green, solid line). The lower horizontal line is the domain from which z is sampled, in this case uniformly. The horizontal line above is part of the domain of x. The upward arrows show how the mapping $x = G(z)$ 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 $D^*(x) = \frac{p_{\text{data}}(x)}{p_{\text{data}}(x)+p_g(x)}$. (c) After an update to G, gradient of D has guided $G(z)$ 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. $D(x) = \frac{1}{2}$.

GAN

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)

GAN

Figure 3: Digits obtained by linearly interpolating between coordinates in z space of the full model.

GAN - Mode Collapse Problem

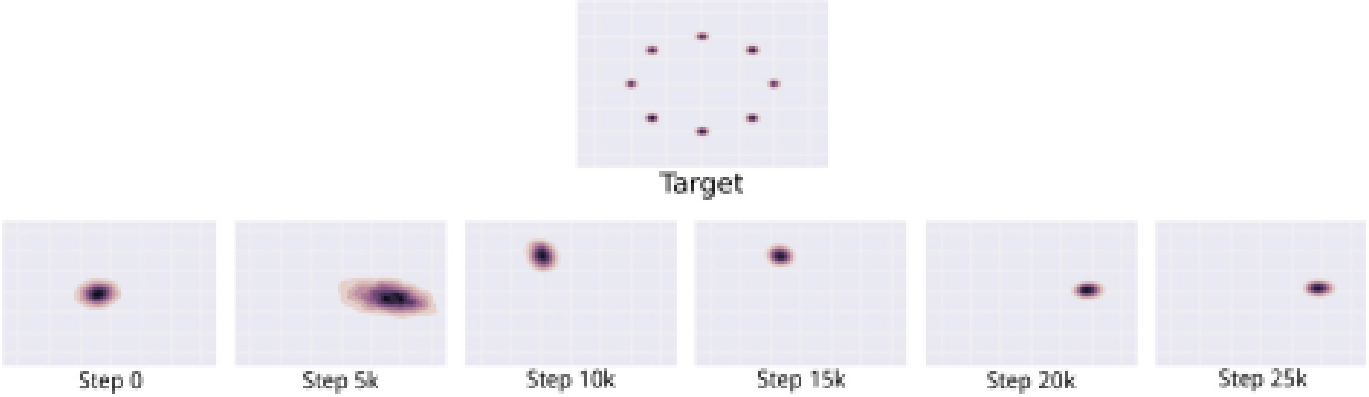


Figure 22: An illustration of the mode collapse problem on a two-dimensional toy dataset. In the top row, we see the target distribution p_{data} that the model should learn. It is a mixture of Gaussians in a two-dimensional space. In the lower row, we see a series of different distributions learned over time as the GAN is trained. Rather than converging to a distribution containing all of the modes in the training set, the generator only ever produces a single mode at a time, cycling between different modes as the discriminator learns to reject each one. Images from Metz *et al.* (2016).

GAN Training

UNSUPERVISED REPRESENTATION LEARNING WITH DEEP CONVOLUTIONAL GENERATIVE ADVERSARIAL NETWORKS

Alec Radford & Luke Metz
Soumith Chintala

DCGAN

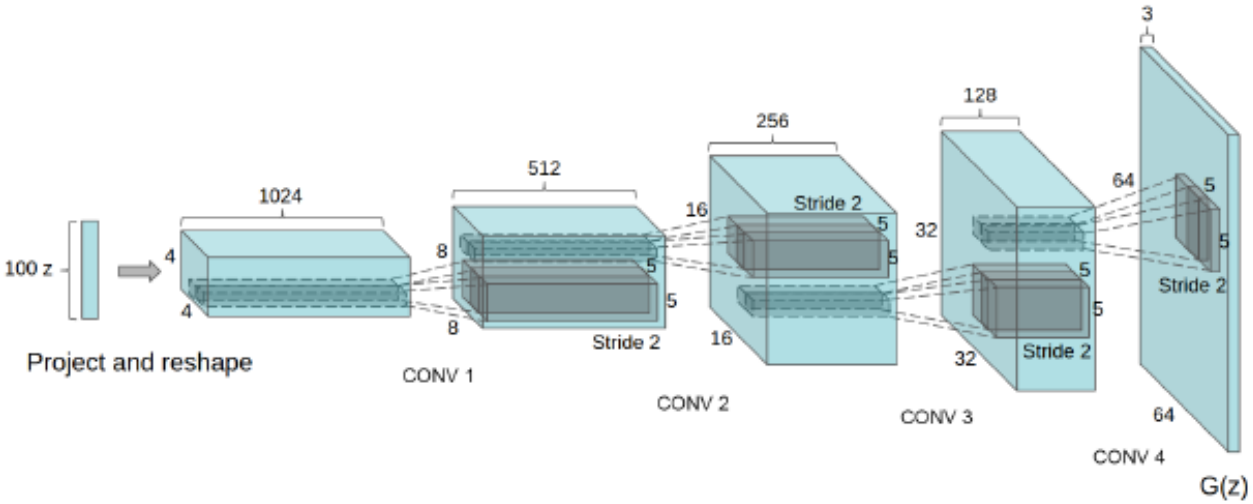


Figure 1: DCGAN generator used for LSUN scene modeling. A 100 dimensional uniform distribution Z is projected to a small spatial extent convolutional representation with many feature maps. A series of four fractionally-strided convolutions (in some recent papers, these are wrongly called deconvolutions)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

DCGAN Training

Architecture guidelines for stable Deep Convolutional GANs

- Replace any pooling layers with strided convolutions (discriminator) and fractional-strided convolutions (generator).
- Use batchnorm in both the generator and the discriminator.
- Remove fully connected hidden layers for deeper architectures.
- Use ReLU activation in generator for all layers except for the output, which uses Tanh.
- Use LeakyReLU activation in the discriminator for all layers.

DCGAN Training

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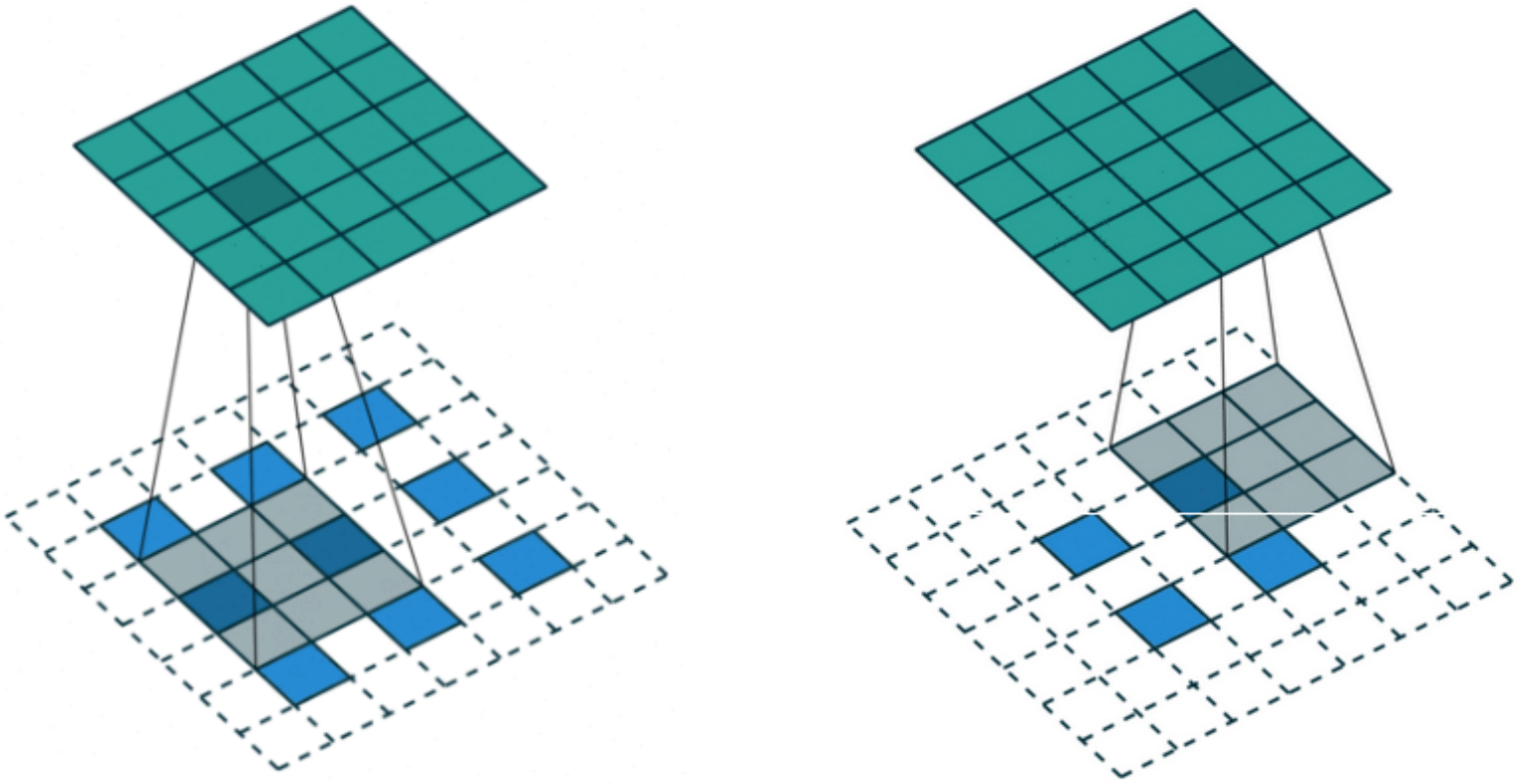
???

DCGAN Training

Fractional Convolutions:



https://github.com/vdumoulin/conv_arithmetic

DCGAN Results

Figure 2: Generated bedrooms after one training pass through the dataset. Theoretically, the model could learn to memorize training examples, but this is experimentally unlikely as we train with a small learning rate and minibatch SGD. We are aware of no prior empirical evidence demonstrating memorization with SGD and a small learning rate.

DCGAN Results

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.

DCGAN Results

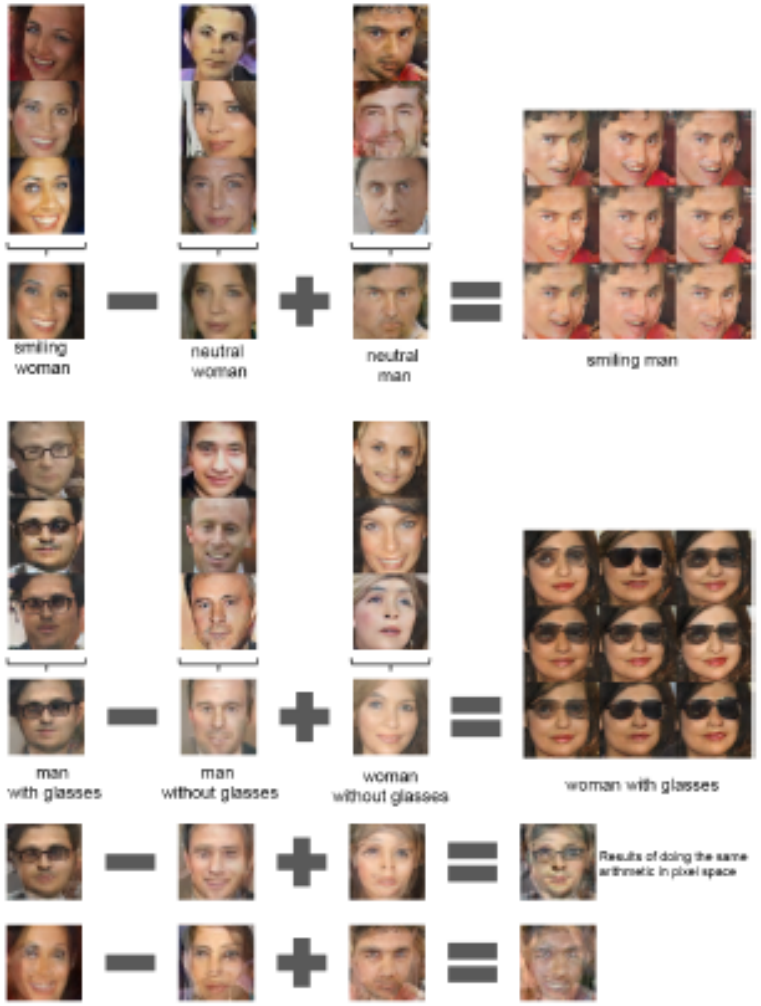


Figure 7: Vector arithmetic for visual concepts. For each column, the Z vectors of samples are averaged. Arithmetic was then performed on the mean vectors creating a new vector Y. The center sample on the right hand side is produce by feeding Y as input to the generator. To demonstrate the interpolation capabilities of the generator, uniform noise sampled with scale +-0.25 was added to Y to produce the 8 other samples. Applying arithmetic in the input space (bottom two examples) results in noisy overlap due to misalignment.

DCGAN Results

Figure 8: A "turn" vector was created from four averaged samples of faces looking left vs looking right. By adding interpolations along this axis to random samples we were able to reliably transform their pose.

DCGAN Results

Figure 10: More face generations from our Face DCGAN.

GAN Training - More strategies

Improved Techniques for Training GANs

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GAN Training - More strategies

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- Some more heuristics proposed !

GAN Training - More strategies

Figure 6: Samples generated from the ImageNet dataset. *(Left)* Samples generated by a DCGAN. *(Right)* Samples generated using the techniques proposed in this work. The new techniques enable GANs to learn recognizable features of animals, such as fur, eyes, and noses, but these features are not correctly combined to form an animal with realistic anatomical structure.

Conditional GAN

Conditional Generative Adversarial Nets

Mehdi Mirza
Simon Osindero

Conditional generative adversarial nets for convolutional face generation

Jon Gauthier

Conditional GAN

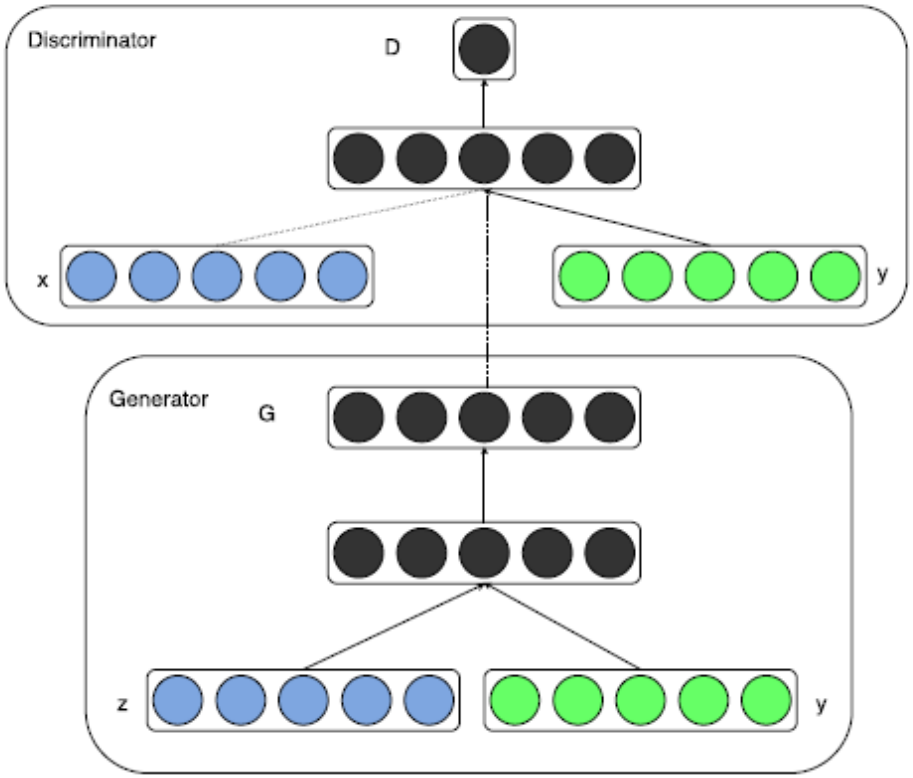
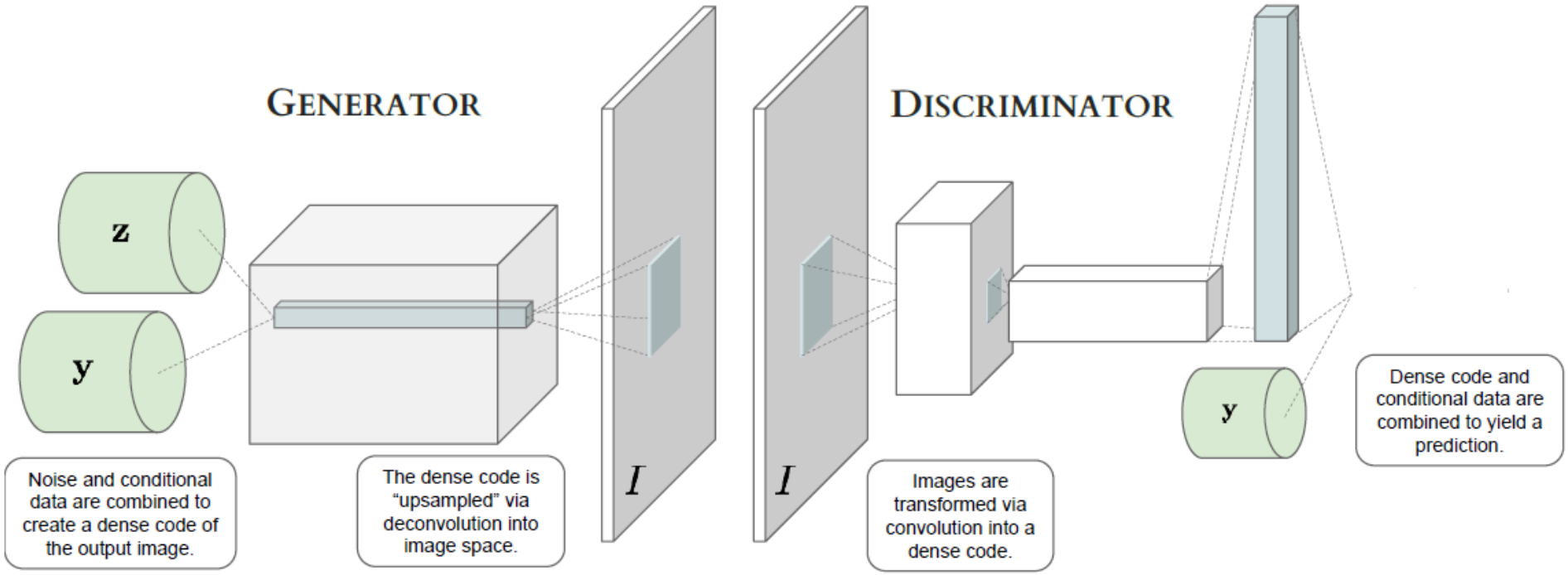


Figure 1: Conditional adversarial net

Conditional GAN



Conditional GAN

- Overall Objective of conditional GAN:

$$\min_{\theta_g}\max_{\theta_d} \left[\mathbb{E}_{(x,y)\sim p_{data}} \log D_{\theta_d}(x,y) + \mathbb{E}_{y\sim p_y, z\sim p_{noise}} \log(1 - D_{\theta_d}(G_{\theta_g}(z,y),y))\right].$$

Conditional GAN

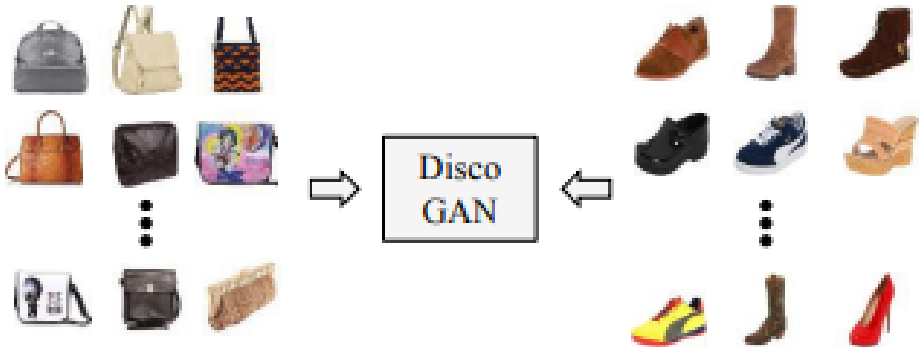
Figure 7: Results of constant additive shifts along particular axes of the conditional data $\mathbf{y}$. (Full details of this shift are given in Section 4.3.1.) Row 1: randomly sampled images from the generator. Row 2: constant additive shift along the SENIOR axis; faces visibly age in the resulting samples. Row 3: constant additive shift along the MOUTHOPEN axis; faces open mouths / smile.

Disco GAN

Learning to Discover Cross-Domain Relations with Generative Adversarial Networks

Taeksoo Kim [1] Moonsu Cha [1] Hyunsoo Kim [1] Jung Kwon Lee [1] Jiwon Kim [1]

Disco GAN



(a) Learning cross-domain relations **without any extra label**

(b) Handbag images (input) & **Generated** shoe images (output)

(c) Shoe images (input) & **Generated** handbag images (output)

Disco GAN

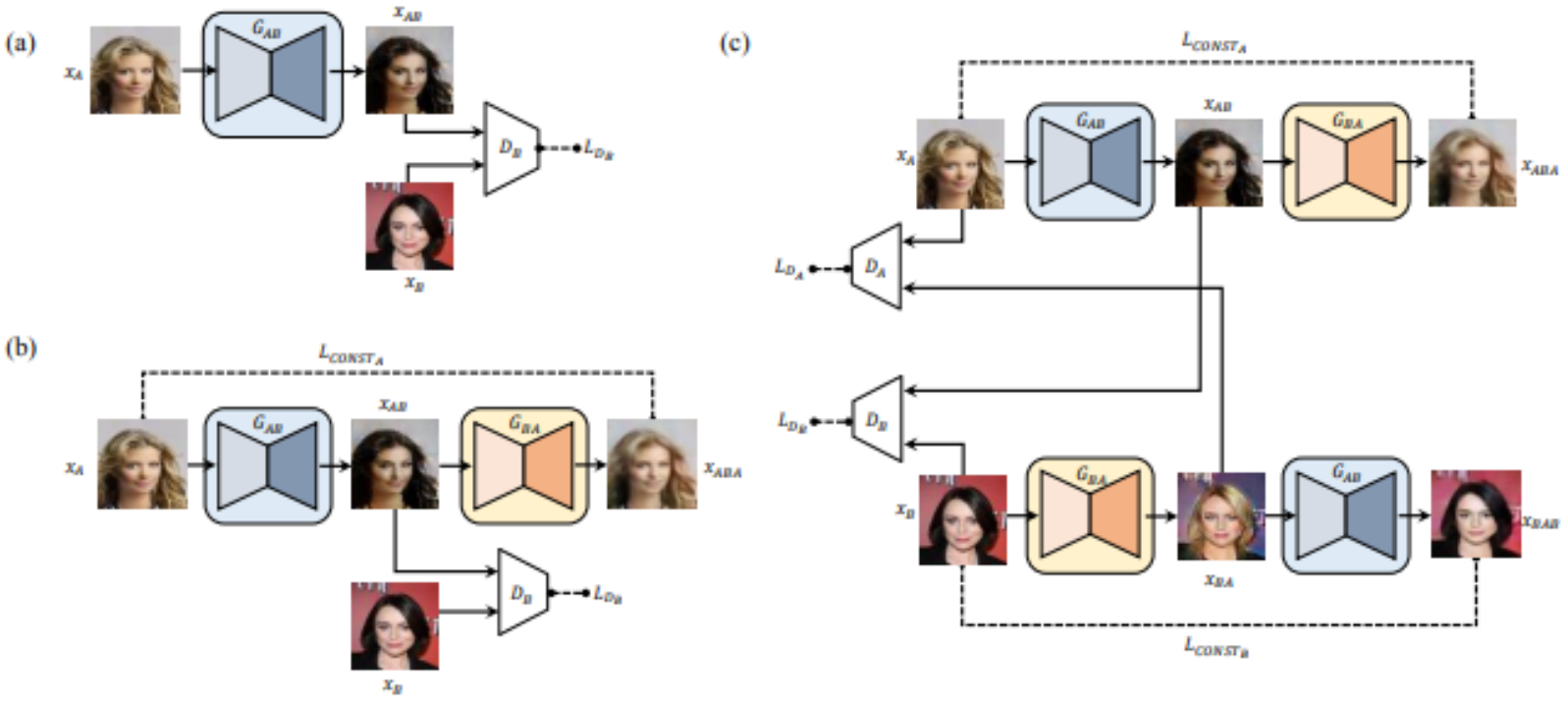
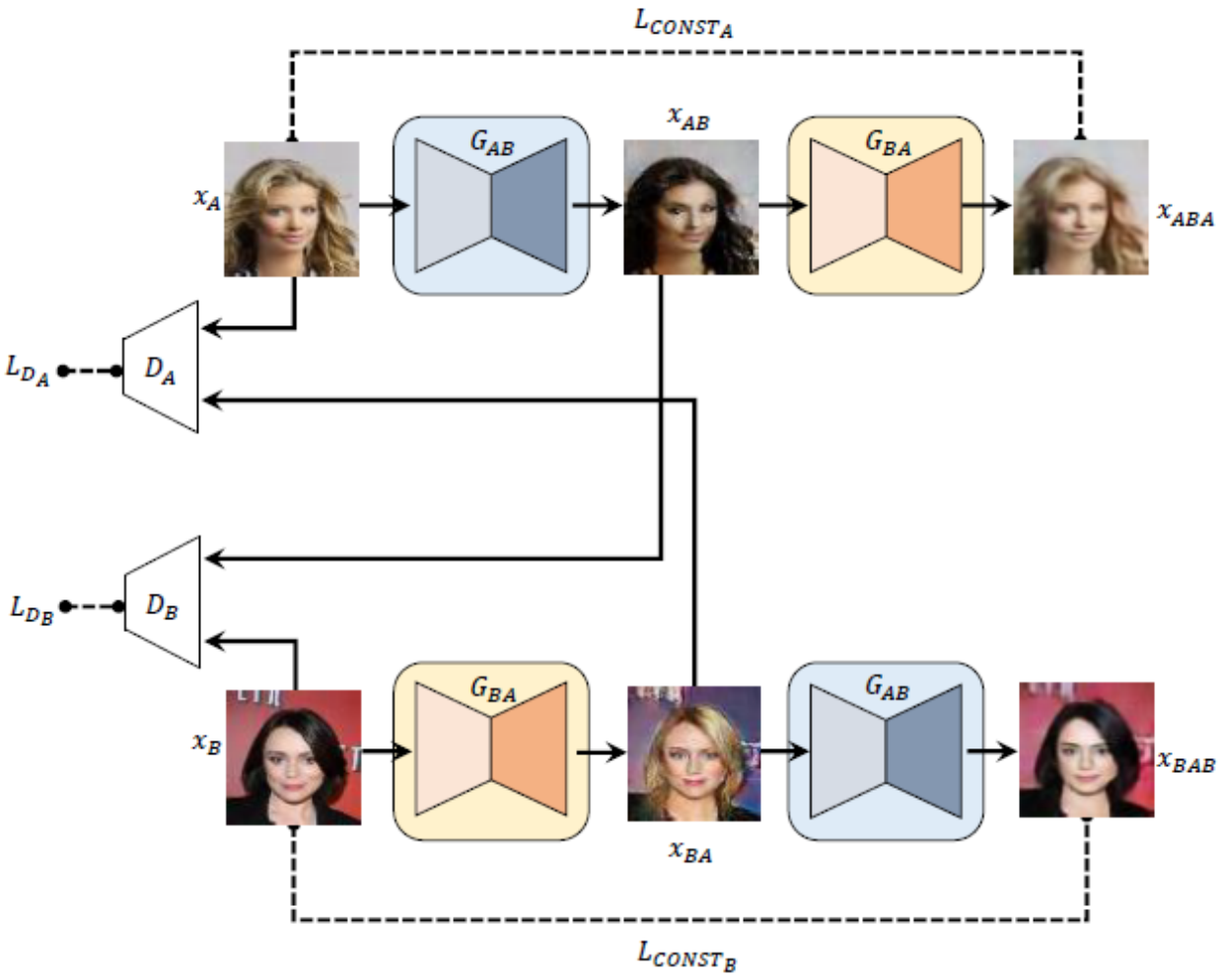


Figure 2. Three investigated models. (a) standard GAN (Goodfellow et al., 2014), (b) GAN with a reconstruction loss, (c) our **proposed model (DiscoGAN)** designed to discover relations between two unpaired, unlabeled datasets. Details are described in Section 3.

Disco GAN


L_{CONST_A}
x_A
G_{AB}
x_{AB}
G_{BA}
x_{ABA}
L_{D_A}
D_A
L_{D_B}
D_B
x_B
G_{BA}
x_{BA}
G_{AB}
x_{BAB}
L_{CONST_B}

Disco GAN - Components

- Two domains A and B
- Examples:
  - A = Vehicles B = Mesh Diagrams
  - A = Face Emotions B = Music
  - A = Adult animals B = Cubs
  - A = Actors B = Videos
- Two generators G_{AB} and G_{BA}
- Two discriminators D_A and D_B

Disco GAN - Components

- Generator G_{AB}
  - Randomly sample x_A from A
  - Form $x_{AB} = G_{AB}(x_A)$
  - Get back $x_{ABA} = G_{BA}(x_{AB}) = G_{BA}(G_{AB}(x_A))$
  - Reconstruction loss: $R_{G_{AB}} = \mathbb{E}_{x_A \sim A} d(x_A, x_{ABA})$
  - Discriminator loss: $GAN_{G_{AB}} = \mathbb{E}_{x_A \sim A} \log D_B(G_{AB}(x_A))$
  - Total loss: $L_{G_{AB}} = R_{G_{AB}} + GAN_{G_{AB}}$

Disco GAN - Components

- Generator G_{AB}
  - Randomly sample x_A from A
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  - Total loss: $L_{G_{AB}} = R_{G_{AB}} + GAN_{G_{AB}}$
- Generator G_{BA}
  - Randomly sample x_B from B
  - Form $x_{BA} = G_{BA}(x_B)$
  - Get back $x_{BAB} = G_{AB}(x_{BA}) = G_{AB}(G_{BA}(x_B))$
  - Reconstruction loss: $R_{G_{BA}} = \mathbb{E}_{x_B \sim B} d(x_B, x_{BAB})$
  - Discriminator loss: $GAN_{G_{BA}} = \mathbb{E}_{x_B \sim B} \log D_A(G_{BA}(x_B))$
  - Total loss: $L_{G_{BA}} = R_{G_{BA}} + GAN_{G_{BA}}$

Disco GAN - Components

- Discriminator D_A
  - Randomly sample x_A from A
  - Compute $L_{D_A}^{real} = \mathbb{E}_{x_A \sim A} \log D_A(x_A)$
  - Obtain input from generator G_{BA}
  - Compute $L_{D_A}^{gen} = \mathbb{E}_{x_A \sim A} \log D_A(G_{BA}(x_B))$
  - Total loss: $L_{D_A} = L_{D_A}^{real} + L_{D_A}^{gen}$.
- Discriminator D_B
  - Randomly sample x_B from B
  - Compute $L_{D_B}^{real} = \mathbb{E}_{x_B \sim B} \log D_B(x_B)$
  - Obtain input from generator G_{AB}
  - Compute $L_{D_B}^{gen} = \mathbb{E}_{x_B \sim B} \log D_B(G_{AB}(x_A))$
  - Total loss: $L_{D_B} = L_{D_B}^{real} + L_{D_B}^{gen}$.

Disco GAN - Components

- Total Generator loss: $L_{Gen} = L_{G_{AB}} + L_{G_{BA}}$
- Total Discriminator loss: $L_{Disc} = L_{D_A} + L_{D_B}$
- Overall loss: $L = L_{Gen} + L_{Disc}$

Disco GAN

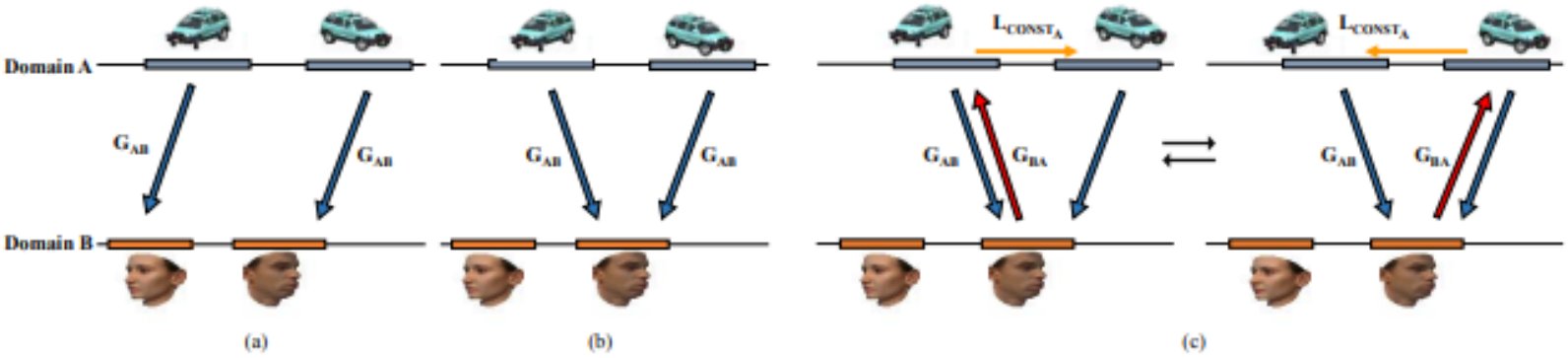

Figure 3. Illustration of our models on simplified one dimensional domains. (a) ideal mapping from domain A to domain B in which the two domain A modes map to two different domain B modes, (b) GAN model failure case, (c) GAN with reconstruction model failure case.

Disco GAN

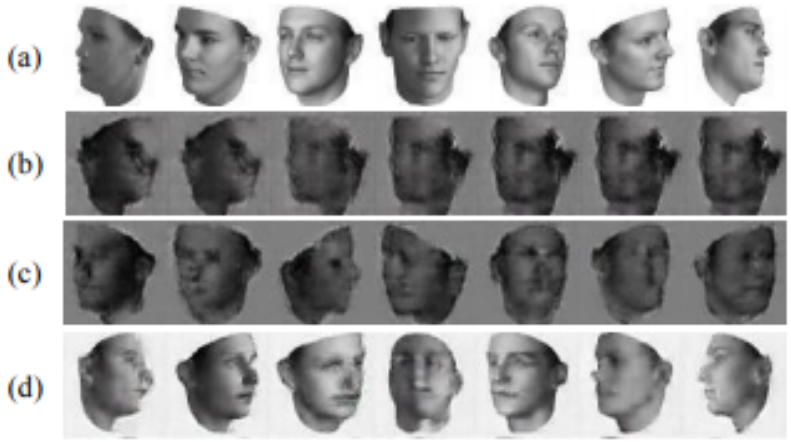

Figure 6. Face to Face translation experiment. (a) input face images from -90° to +90° (b) results from a standard GAN (c) results from GAN with a reconstruction loss (d) results from our DiscoGAN. Here our model generated images in the opposite range, from +90° to -90°.

Disco GAN

Figure 7. (a,b) Translation of gender in Facescrub dataset and CelebA dataset. (c) Blond to black and black to blond hair color conversion in CelebA dataset. (d) Wearing eyeglasses conversion in CelebA dataset (e) Results of applying a sequence of conversion of gender and hair color (left to right) (f) Results of repeatedly applying the same conversions (upper: hair color, lower: gender)

Disco GAN

(a) Chair to Car

(b) Car to Face

Figure 8. Discovering relations of images from visually very different object classes. (a) chair to car translation. DiscoGAN is trained on chair and car images (b) car to face translation. DiscoGAN is trained on car and face images. Our model successfully pairs images with similar orientation.

Disco GAN

Figure 9. Edges to photos experiment. Our model is trained on a set of object sketches and colored images and learns to generate new sketches or photos. (a) colored images of handbags are generated from sketches of handbags, (b) colored images of shoes are generated from sketches of shoes, (c) sketches of handbags are generated from colored images of handbags