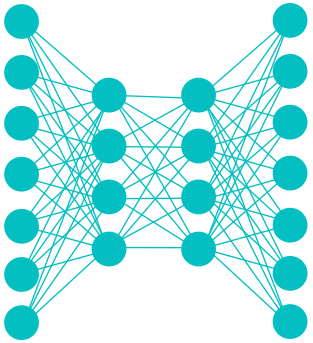
Lecture Notes for

Neural Networks and Machine Learning

Holy GAN-Zooks



Logistics and Agenda

- Logistics
  - Student Paper Presentation next week: AlphaFold
    - Joel, Ayesh, Jack
- Agenda
  - Lightning Round for GANs:
    - CycleGAN
    - Using GANs for Boosting Classifiers
    - Text-to-image Synthesis
    - StyleGAN
    - StyleClip
    - If time: final project Town Hall

Last Time

$$\frac{1}{m}\sum_{i=1}^{m} f(g(z^{(i)}))$$

Maximize g,
freeze weights of critic
No change

- Theorem: a function is 1-Lipschitz if and only if its gradient has a norm less than or equal to one.

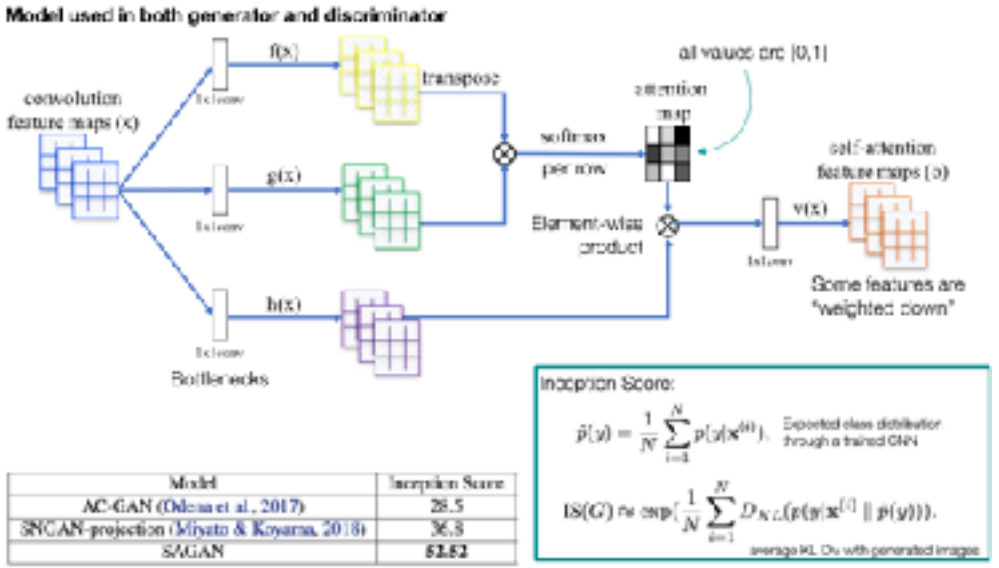
Maximize f
freeze generator weights,
incentivize critic gradient norm to be one

Choose large lambda
like lambda = 10

$$\frac{1}{m}\sum_{i=1}^{m} f(x_{real}^{(i)}) - f(g(z^{(i)})) + \lambda \frac{1}{W}\sum_{i=1}^{W} \left(\|\nabla f(\hat{x}^{(i)})\|_2 - 1\right)^2$$

where for ϵ in U[0,1] $\quad \hat{x}^{(i)} = \epsilon \cdot x_{real}^{(i)} + (1-\epsilon)\cdot g(z^{(i)})$

randomly mix together real and fake images



Model	Inception Score
AC-GAN (Odena et al., 2017)	28.5
SNGAN-projection (Miyato & Kyoama, 2018)	36.8
SAGAN	**52.52**

Inception Score:

$$\tilde{p}(y) = \frac{1}{N}\sum_{i=1}^{N} p(y|x^{(i)}),$$ Expected class distribution through a trained CNN

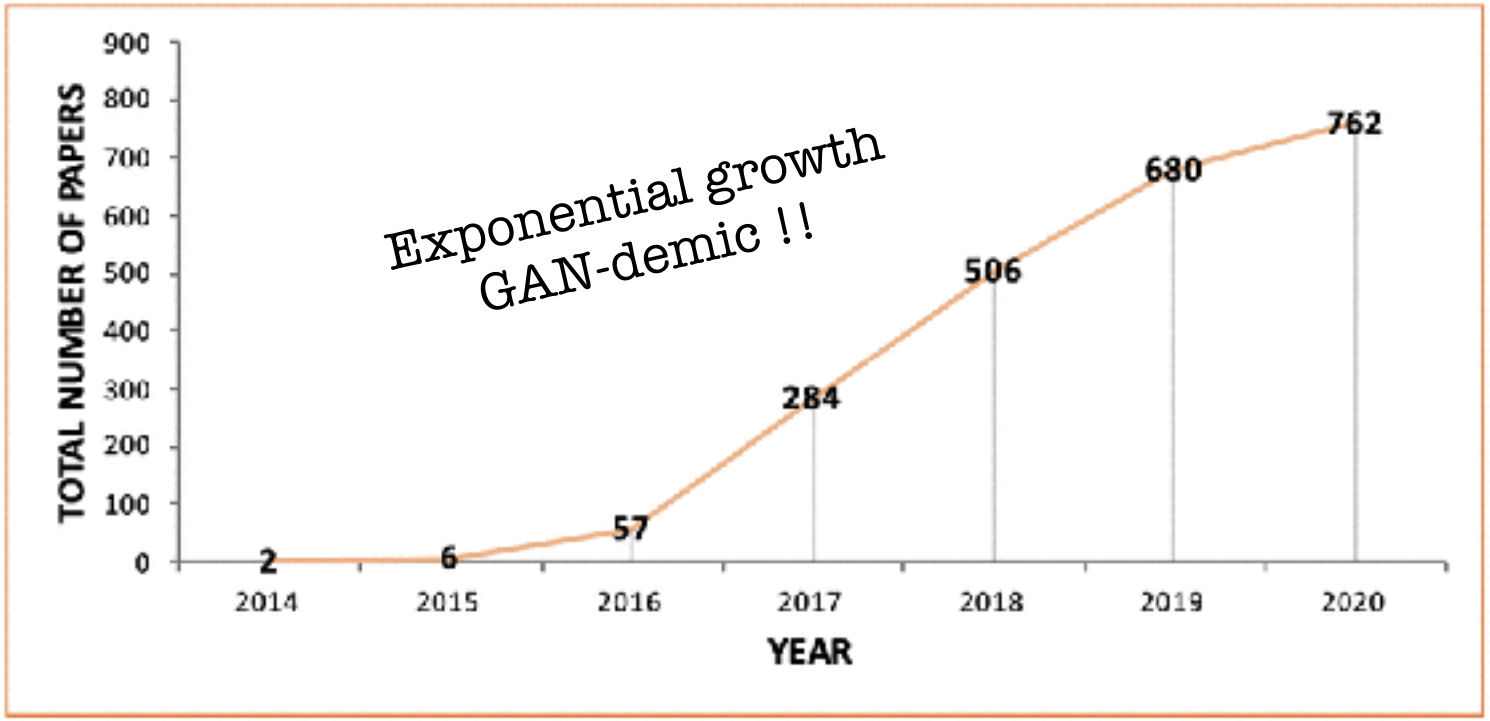
$$\mathrm{IS}(G) = \exp\left(\frac{1}{N}\sum_{i=1}^{N} D_{KL}(p(y|x^{(i)}) \,\|\, p(y))\right).$$

average KL Div with generated images

- Update discriminator twice as often as generator
- Large batch size: 1024 or 2048
- Use skip connections in model architecture, starting from z
- Use LOTS of filters: 150% more filters than related work
- **Truncation trick**: during training, use wider sampling than during evaluation
- Use hinge loss: $\frac{1}{m}\sum_{i=1}^{m} f(x_{real}^{(i)}) \cdot f(g(z^{(i)}))$
- Use moving average of weights: $W_k = \sum_i \gamma^i \underbrace{W_{k-i}}_{\text{past}}$

Example GANs, Abridged

Cumulative Number of GAN Papers, by Year



ABC-GAN — ABC-GAN: Adap
ABC-GAN — GANs for LIFE:
AC-GAN — Conditional Image
acGAN — Face Aging With C
ACGAN — Coverless Informa
acGAN — On-line Adaptative
ACtuAL — ACtuAL: Actor-Criti
AdaGAN — AdaGAN: Boostin
Adaptive GAN — Customizing
AdvEntuRe — AdvEntuRe: Ad
AdvGAN — Generating adver
AE-GAN — AE-GAN: adversa
AE-OT — Latent Space Optim
AEGAN — Learning Inverse M
AF-DCGAN — AF-DCGAN: A
AffGAN — Amortised MAP Inf
AIM — Generating Informative
AL-CGAN — Learning to Gen
ALI — Adversarially Learned I
AlignGAN — AlignGAN: Learn
AlphaGAN — AlphaGAN: Gen
AM-GAN — Activation Maximi
AmbientGAN — AmbientGAN
AMC-GAN — Video Predictio
AnoGAN — Unsupervised An
APD — Adversarial Distillation
APE-GAN — APE-GAN: Adve
ARAE — Adversarially Regula
ARDA — Adversarial Represe
ARIGAN — ARIGAN: Synthet
ArtGAN — ArtGAN: Artwork S
ASDL-GAN — Automatic Steq
ATA-GAN — Attention-Aware
Attention-GAN — Attention-G
AttGAN — Arbitrary Facial Att
AttnGAN — AttnGAN: Fine-Gr
AVID — AVID: Adversarial Vis

https://github.com/hindupuravinash/the-gan-zoo

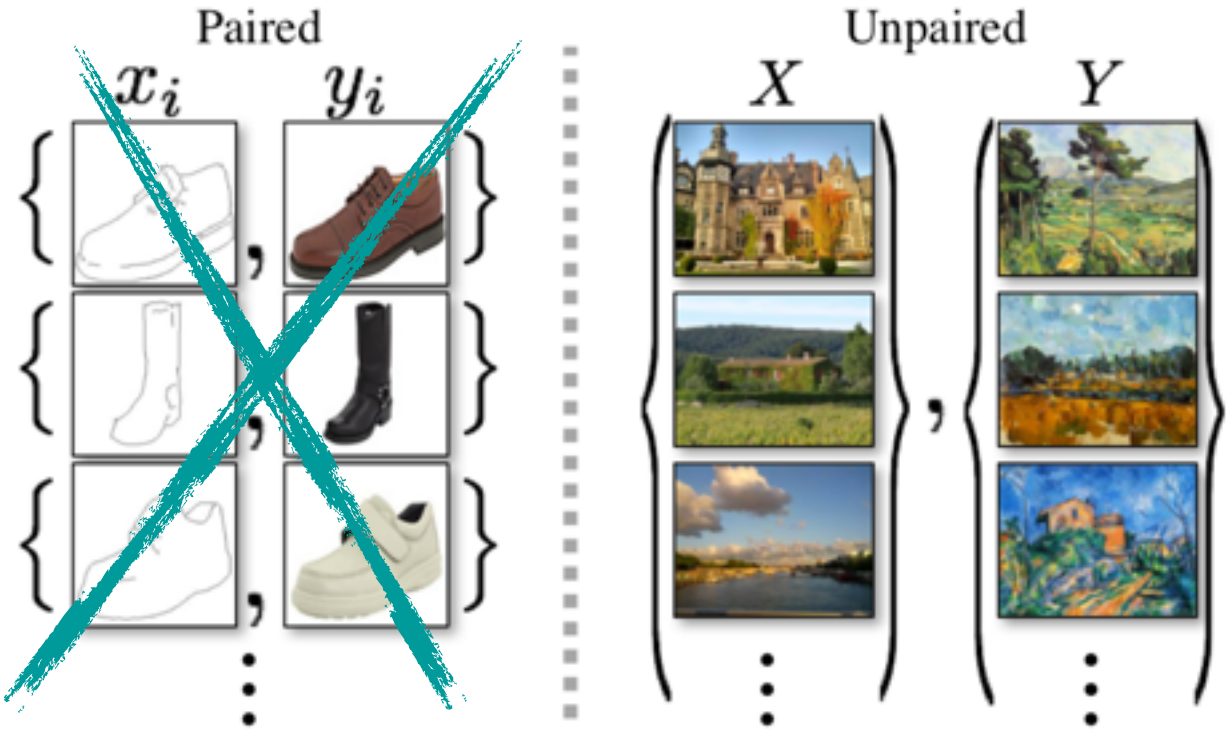
CycleGAN

Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks

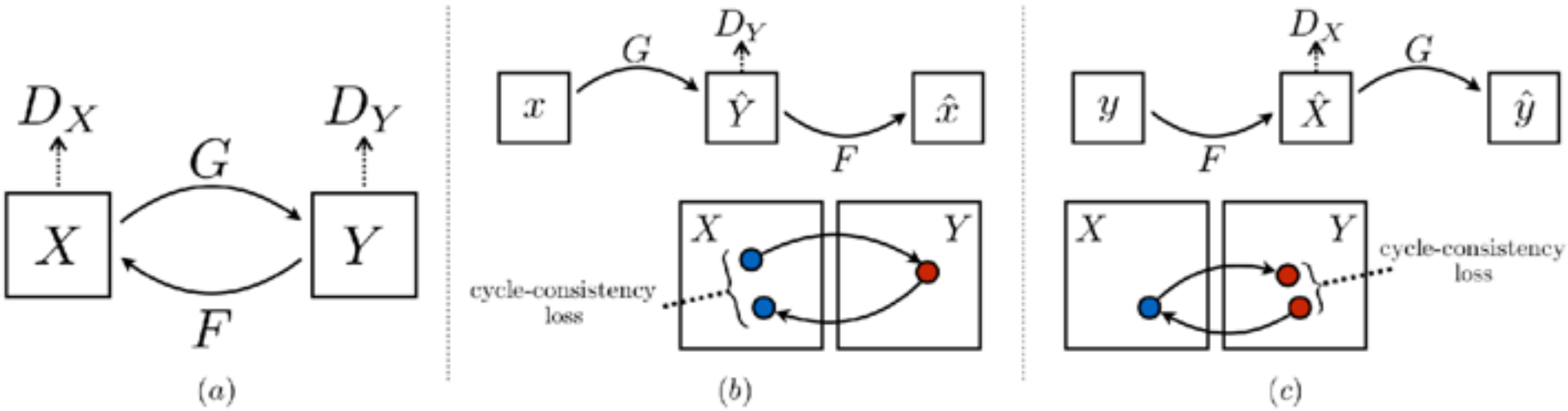
Jun-Yan Zhu* Taesung Park* Phillip Isola Alexei A. Efros
Berkeley AI Research (BAIR) laboratory, UC Berkeley

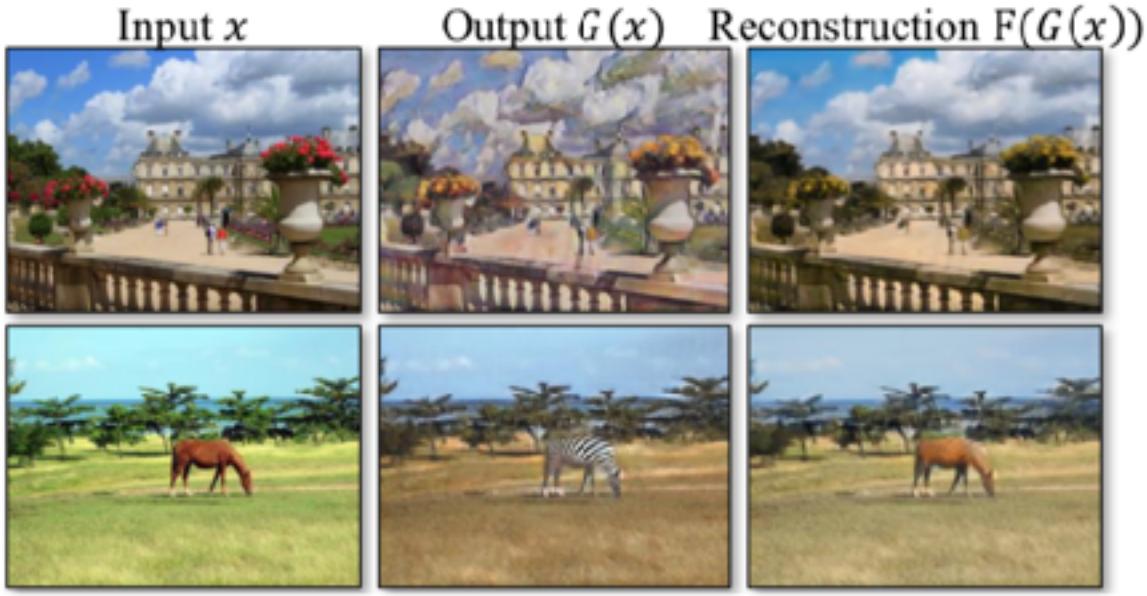
Unpaired Cycles

- Idea: Try to find specialized unpaired translations that are consistent between domains



Defining Cycle Consistency





"Generator" is actual an encoding transformation network

- goes from image to image
- NOT latent to image
- NOT image to latent

Adding to the loss function

- Have two discriminator losses for two auto encoders:

$$\mathcal{L}_{\text{GAN}}(G, D_Y, X, Y) = \mathbb{E}_{y \sim p_{\text{data}}(y)}[\log D_Y(y)] + \mathbb{E}_{x \sim p_{\text{data}}(x)}[\log(1 - D_Y(G(x))],$$

- Enforce cycle consistency and self consistency:

$$\mathcal{L}_{\text{cyc}}(G, F) = \mathbb{E}_{x \sim p_{\text{data}}(x)}[\|F(G(x)) - x\|_1] + \mathbb{E}_{y \sim p_{\text{data}}(y)}[\|G(F(y)) - y\|_1].$$

$$\mathcal{L}_{\text{identity}}(G, F) = \mathbb{E}_{y \sim p_{\text{data}}(y)}[\|G(y) - y\|_1] + \mathbb{E}_{x \sim p_{\text{data}}(x)}[\|F(x) - x\|_1]$$

- Put it all together:

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

Training Notes

Training details We apply two techniques from recent works to stabilize our model training procedure. First, for $\mathcal{L}_{\text{GAN}}$ (Equation 1), we replace the negative log likelihood objective by a least-squares loss [35]. This loss is more stable during training and generates higher quality results. In particular, for a GAN loss $\mathcal{L}_{\text{GAN}}(G, D, X, Y)$, we train the G to minimize $\mathbb{E}_{x \sim p_{\text{data}}(x)}[(D(G(x)) - 1)^2]$ and train the D to minimize $\mathbb{E}_{y \sim p_{\text{data}}(y)}[(D(y) - 1)^2] + \mathbb{E}_{x \sim p_{\text{data}}(x)}[D(G(x))^2]$.

Second, to reduce model oscillation [15], we follow nators using a history of generated images rather than the ones produced by the latest generators. We keep an image buffer that stores the 50 previously created images.

For all the experiments, we set $\lambda = 10$ in Equation 3. We use the Adam solver [26] with a batch size of 1. All networks were trained from scratch with a learning rate of 0.0002. We keep the same learning rate for the first 100 epochs and linearly decay the rate to zero over the next 100 epochs. Please see the appendix (Section 7) for more details about the datasets, architectures, and training procedures.

So, not using Entropy?

Yes! Experience Replay!

Linear learning rate decay.

Show me the Code!

Disciminators

```
# Build and compile the discriminators
self.d_A = self.build_discriminator()
self.d_B = self.build_discriminator()
self.d_A.compile(loss='mse',
    optimizer=optimizer,
    metrics=['accuracy'])
self.d_B.compile(loss='mse',
    optimizer=optimizer,
    metrics=['accuracy'])
```

Cycle Producers

```
# Translate images to the other domain
fake_B = self.g_AB(img_A)
fake_A = self.g_BA(img_B)
# Translate images back to original domain
reconstr_A = self.g_BA(fake_B)
reconstr_B = self.g_AB(fake_A)
# Identity mapping of images
img_A_id = self.g_BA(img_A)
img_B_id = self.g_AB(img_B)
```

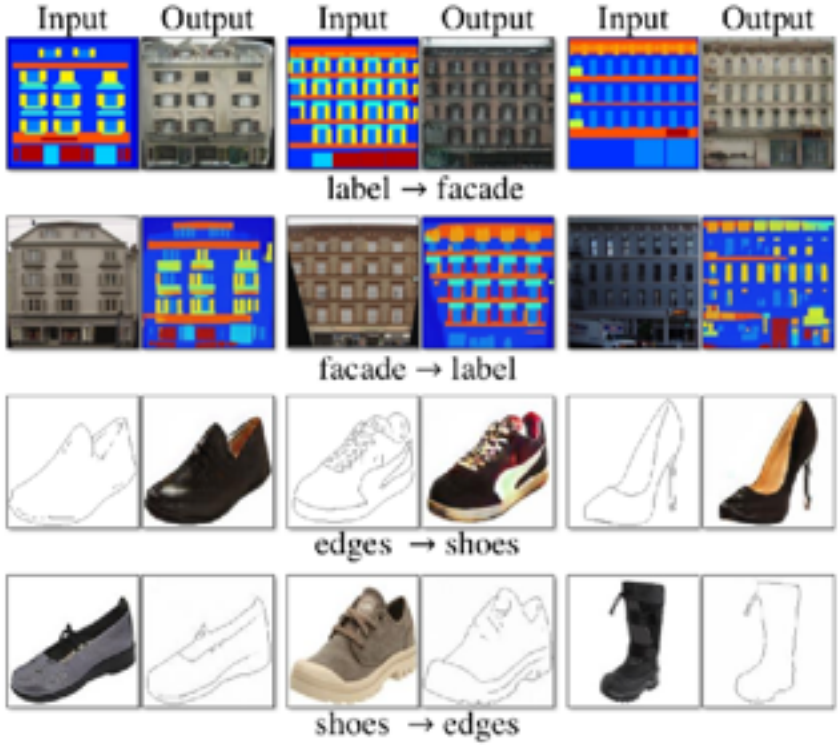
```
# Combined model trains generators to fool discriminators
self.combined = Model(inputs=[img_A, img_B],
                      outputs=[ valid_A, valid_B,
                                reconstr_A, reconstr_B,
                                img_A_id, img_B_id ])
self.combined.compile(loss=['mse', 'mse',
                            'mae', 'mae',
                            'mae', 'mae'],
                      loss_weights=[  1, 1,
                                      self.lambda_cycle, self.lambda_cycle,
                                      self.lambda_id, self.lambda_id ],
                      optimizer=optimizer)
```

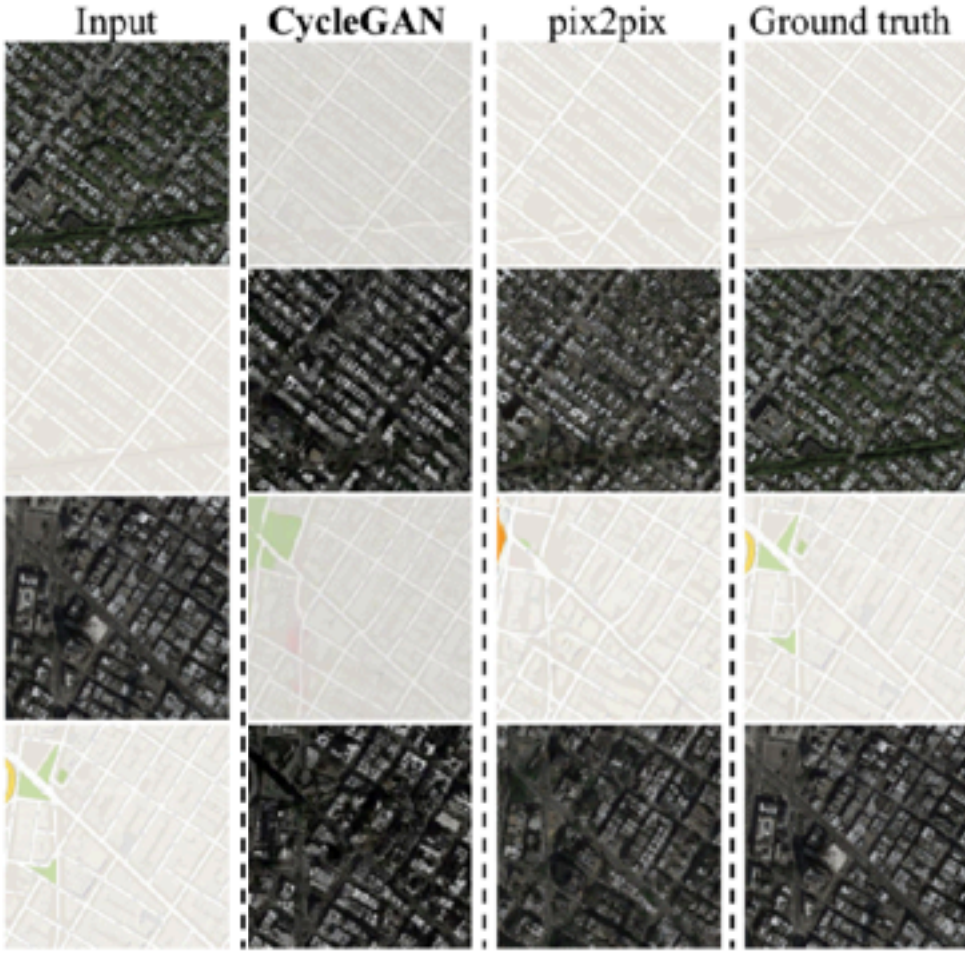
discriminator MSE, 0,1
cycle consistency
self consistency

https://github.com/eriklindernoren/Keras-GAN/blob/master/cyclegan/cyclegan.py

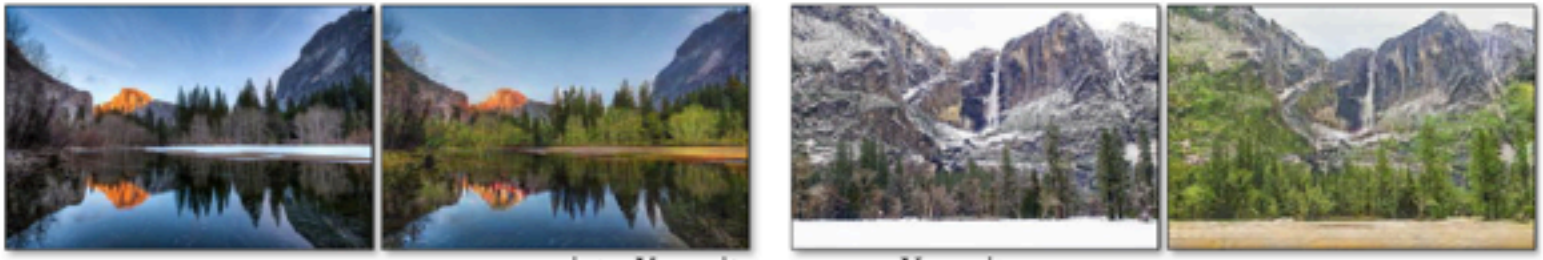
Results


Input
CycleGAN
pix2pix
Ground truth


Input
Output
Input
Output
Input
Output
label → facade
facade → label
edges → shoes
shoes → edges


Input
CycleGAN
pix2pix
Ground truth

Fun Results



winter Yosemite → summer Yosemite

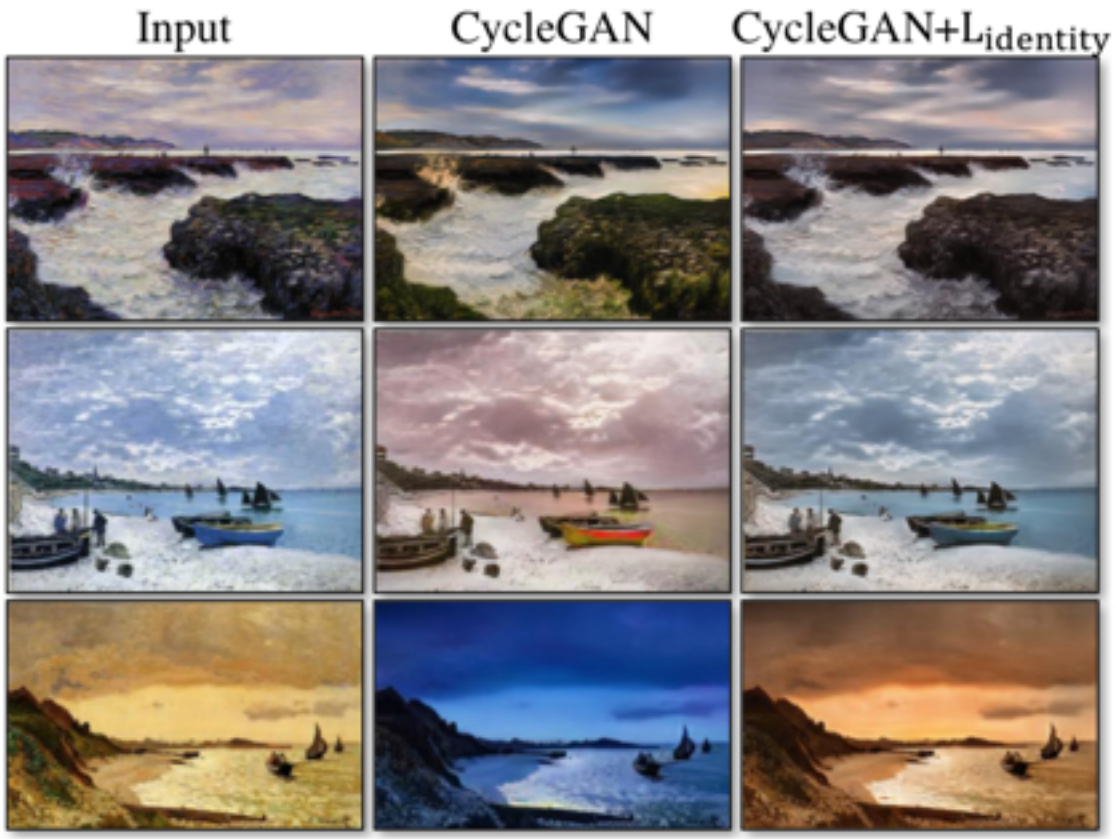
summer Yosemite → winter Yosemite

apple → orange

orange → apple

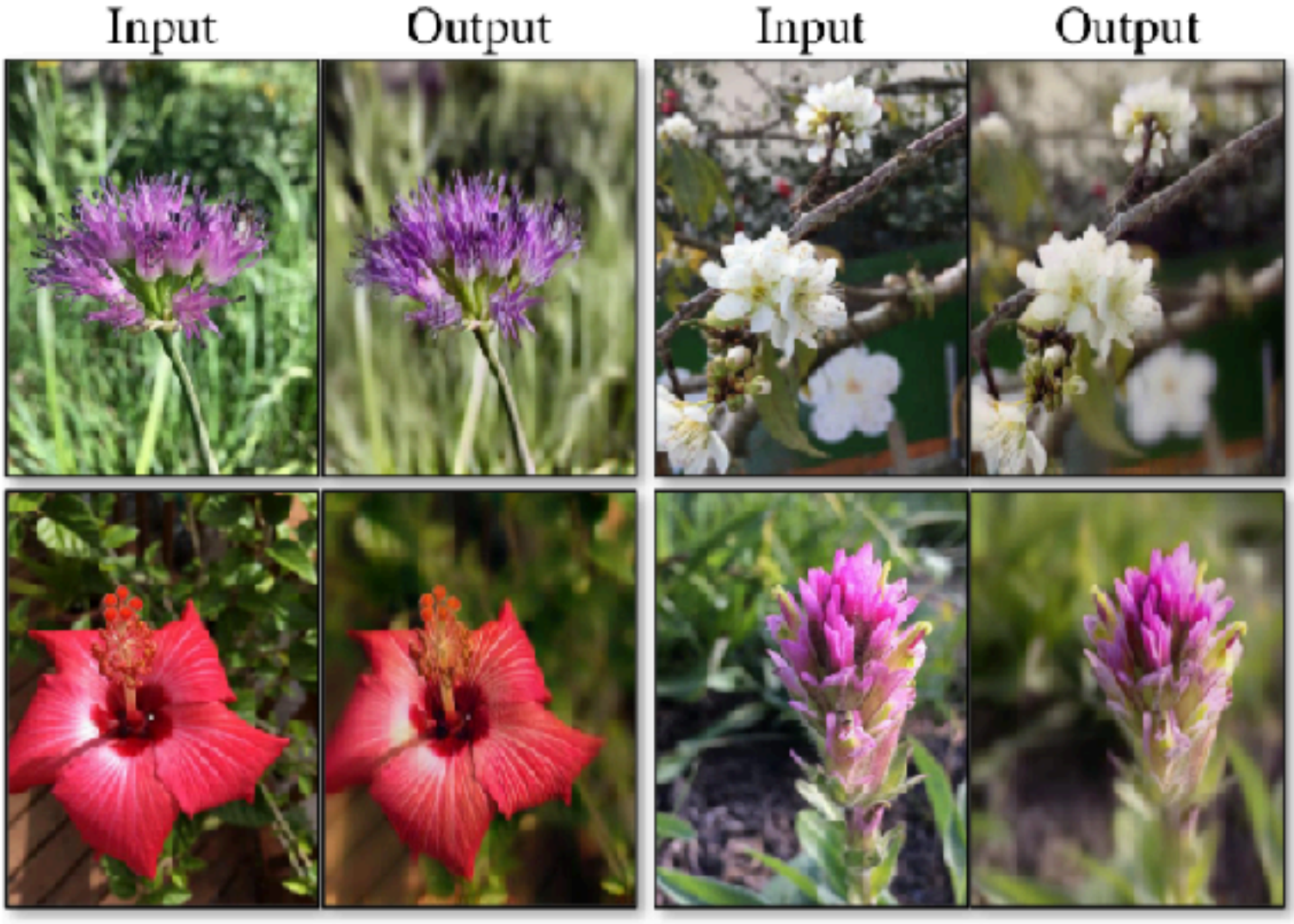
Results: Fixing Hue Changes

- Self consistency is mostly about preserving color



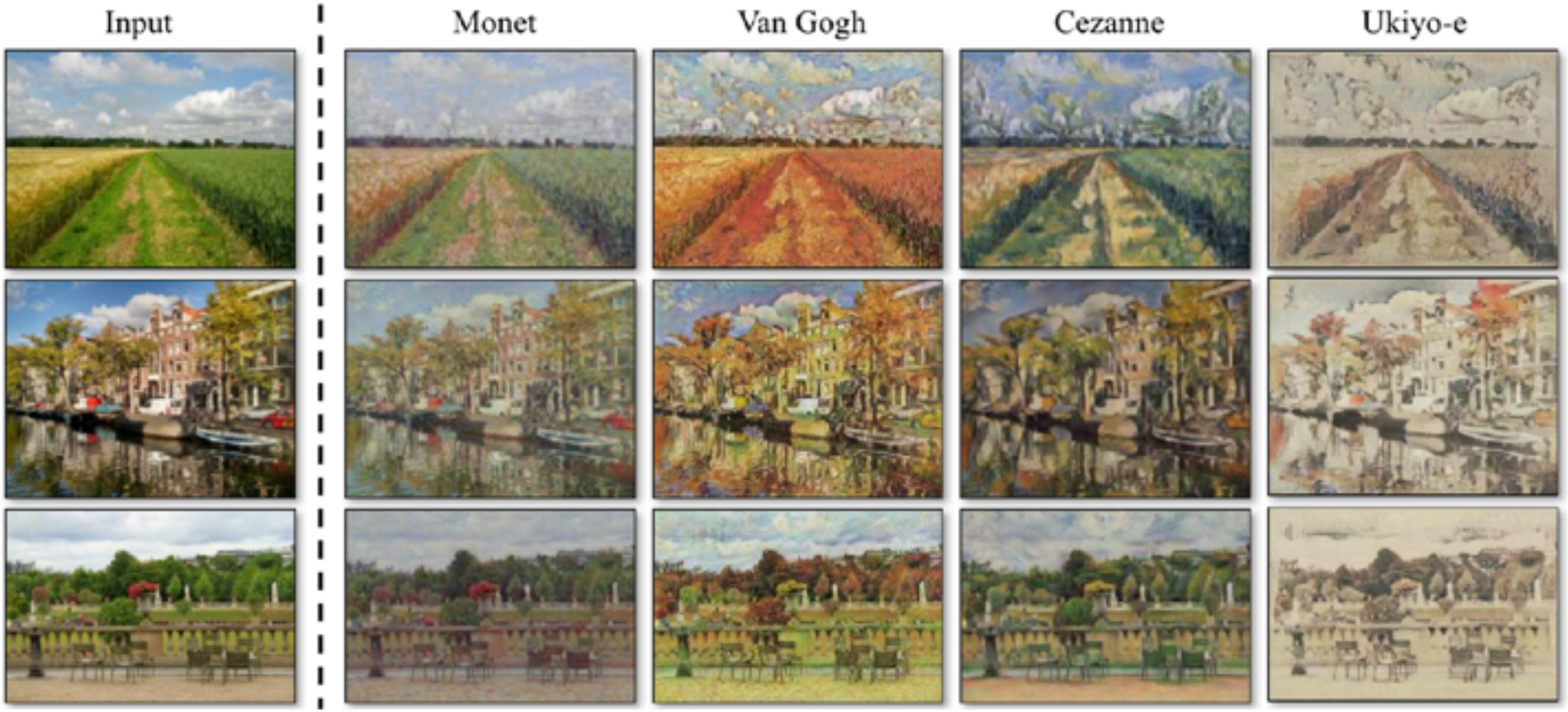
$$\mathcal{L}_{\text{identity}}(G, F) = \mathbb{E}_{y \sim p_{\text{data}}(y)}[\|G(y) - y\|_1] + \mathbb{E}_{x \sim p_{\text{data}}(x)}[\|F(x) - x\|_1]$$

Image Enhancement

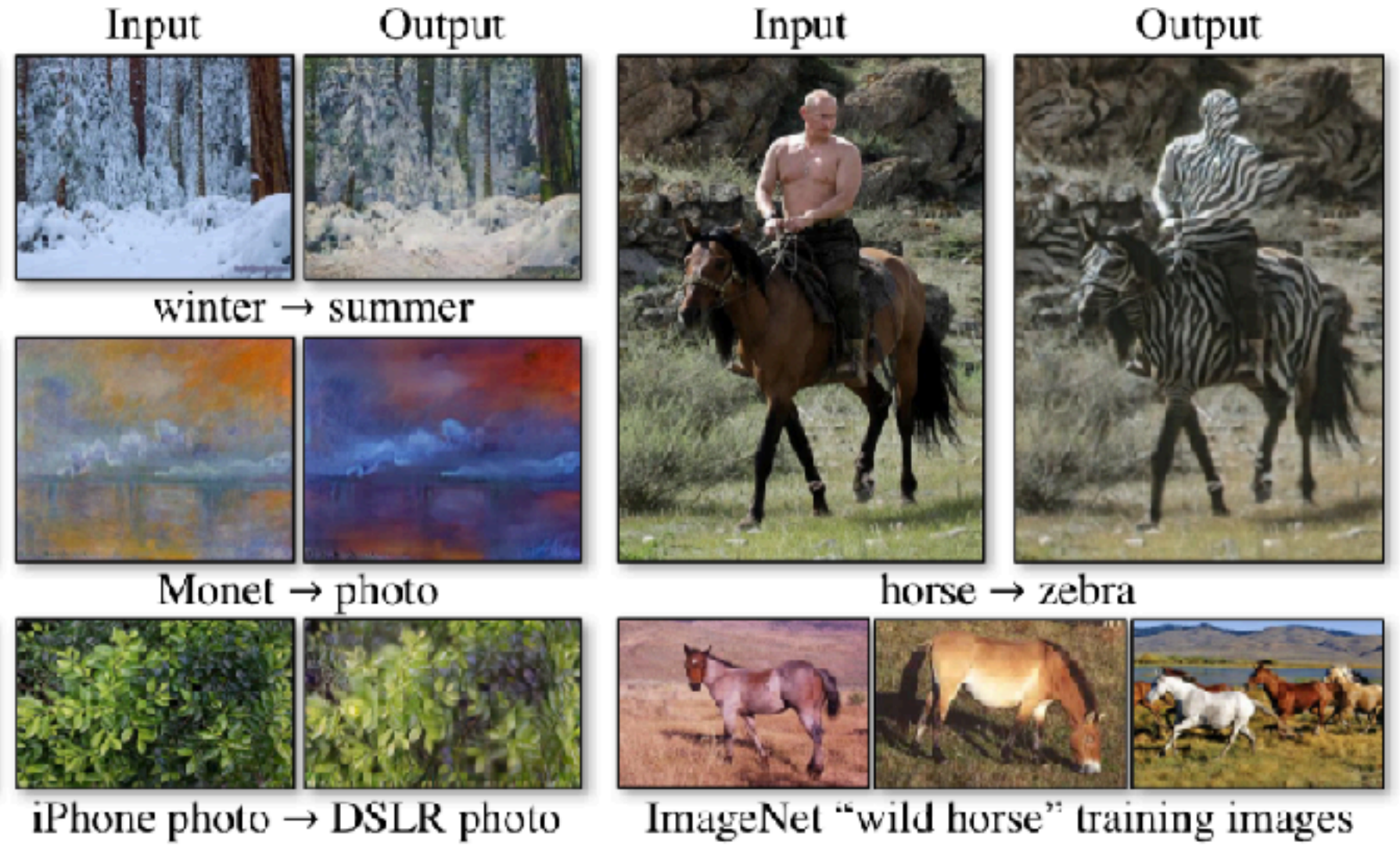


Map from iPhone Images to DSLR Photos

Full Circle: Back to Style Transfer



They can't all be gold

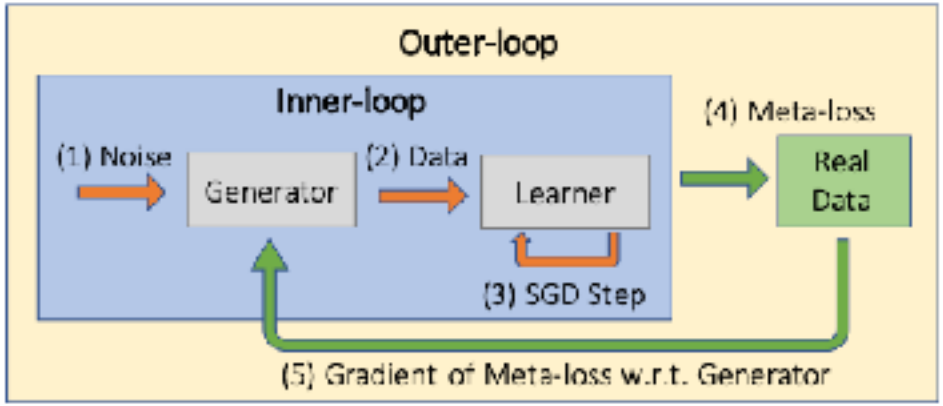


Generative Teaching Networks

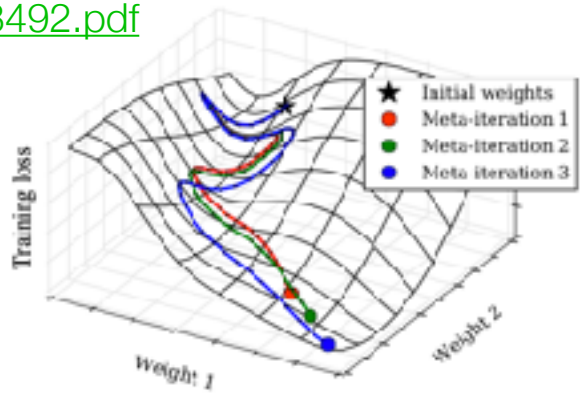
how-to-GAN

Generative Teaching Networks

- Train a network on generated examples
- Update generator, re-init learners, and repeat

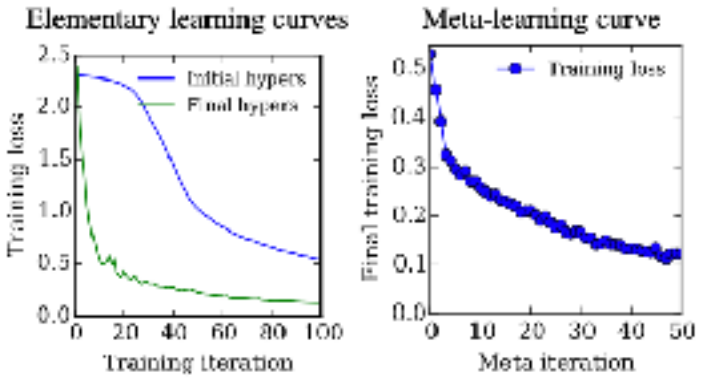


meta-gradients: https://arxiv.org/pdf/1502.03492.pdf



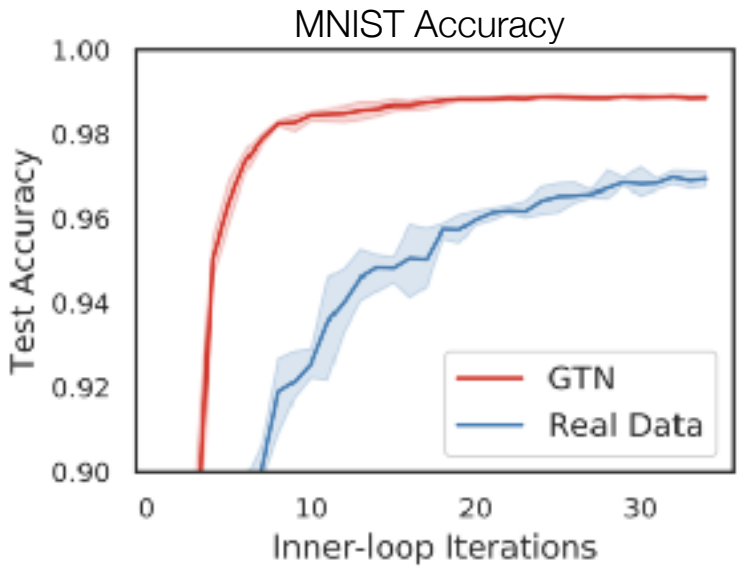
Generator: given a class, provide an image.
Also provide **hyper-params** for SGD like learning rate, momentum scaling, etc. AND architecture params: num conv layers, num filters
Goal: Provide examples to train learner as quickly and as accurately as possible
Hyper-parameters are therefore selected through back-propagation techniques…

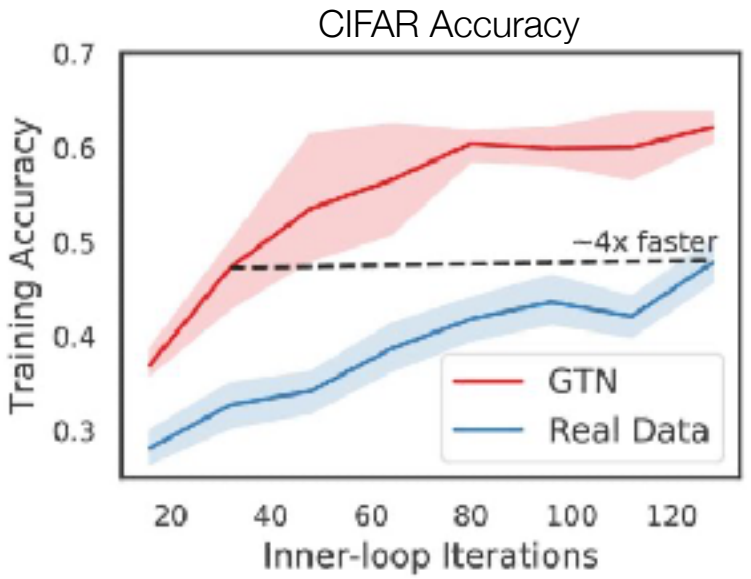
MUST USE SPECTRAL NORM



Felipe Petroski Such, Aditya Rawal, Joel Lehman, Kenneth O. Stanley, and Jeff Clune. Generative Teaching Networks, 2020 https://arxiv.org/pdf/1912.07768.pdf

Generative Teaching Networks





Felipe Petroski Such, Aditya Rawal, Joel Lehman, Kenneth O. Stanley, and Jeff Clune. Generative Teaching Networks, 2020 https://arxiv.org/pdf/1912.07768.pdf

Text to Image Synthesis with GANs

Generative Adversarial Text to Image Synthesis

Scott Reed, Zeynep Akata, Xinchen Yan, Lajanugen Logeswaran
Bernt Schiele, Honglak Lee

REEDSCOT[1], AKATA[2], XCYAN[1], LLAJAN[1]
SCHIELE[2],HONGLAK[1]

[1] University of Michigan, Ann Arbor, MI, USA (UMICH.EDU)
[2] Max Planck Institute for Informatics, Saarbrücken, Germany (MPI-INF.MPG.DE)

Correspondence Images/Text Features

- Need a correspondence function for text and image representations:

Delta is the 0,1 loss

$$\frac{1}{N}\sum_{n=1}^{N}\Delta(y_n, f_v(v_n)) + \Delta(y_n, f_t(t_n))$$

classify image — classify text

Image Embed — Text Embed

sampled from text for class y

$$f_v(v) = \arg\max_{y\in\mathcal{Y}} \mathbb{E}_{t\sim\mathcal{T}(y)}[\phi(v)^T\varphi(t))]$$

sampled from images for class y

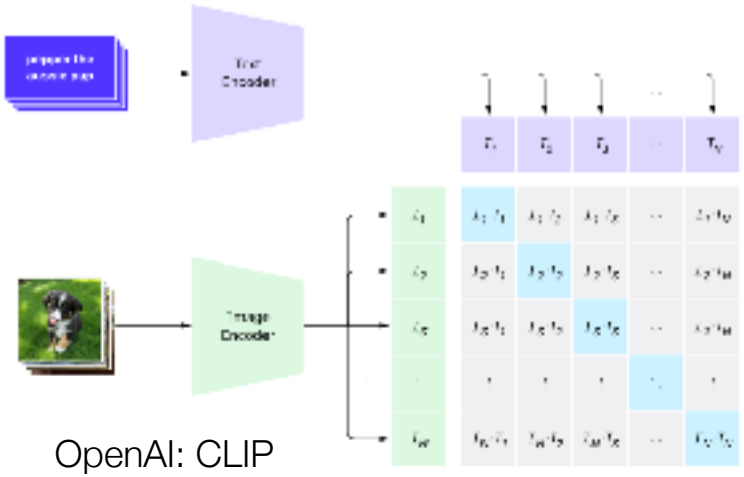
$$f_t(t) = \arg\max_{y\in\mathcal{Y}} \mathbb{E}_{v\sim\mathcal{V}(y)}[\phi(v)^T\varphi(t))]$$

text description * image description

When text and image match, these products should be large, else smaller. Therefore f_v and f_t will learn to make similar text and image features.

$$\mathbb{E}_{t_1,t_2\sim p_{data}}[\log(1 - D(G(z, \beta t_1 + (1-\beta)t_2)))]$$

Can also add to loss function by interpolating text descriptors of the same class



OpenAI: CLIP

Architecture

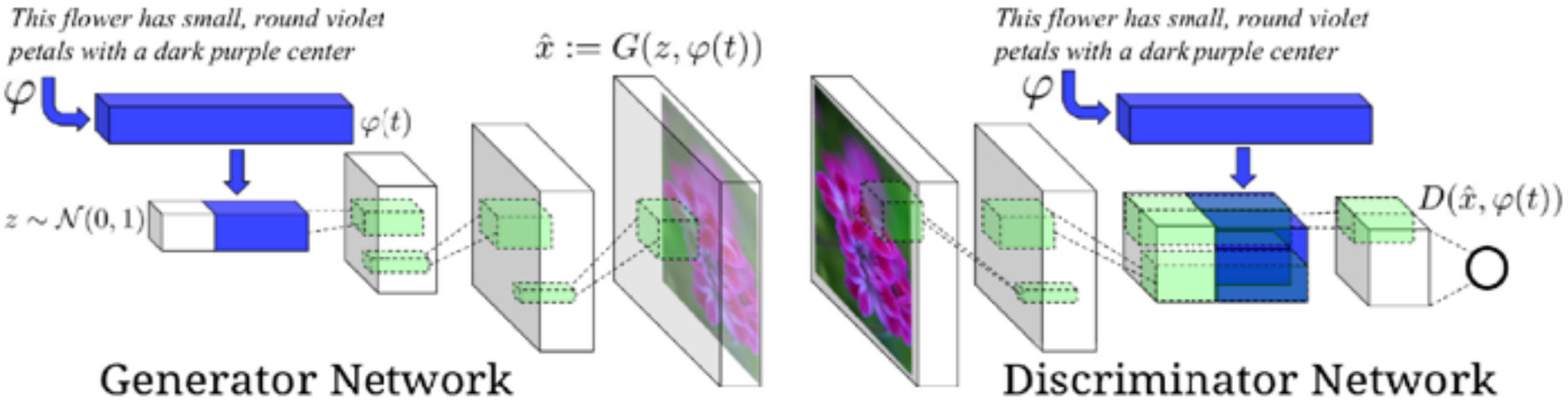


Figure 2. Our text-conditional convolutional GAN architecture. Text encoding $\varphi(t)$ is used by both generator and discriminator. It is projected to a lower-dimensions and depth concatenated with image feature maps for further stages of convolutional processing.

Algorithm 1 GAN-CLS training algorithm with step size α, using minibatch SGD for simplicity.

Input: minibatch images x, matching text t, mismatching $\hat{t}$, number of training batch steps S
for $n = 1$ **to** S **do**
  $h \leftarrow \varphi(t)$ {Encode matching text description}
  $\hat{h} \leftarrow \varphi(\hat{t})$ {Encode mis-matching text description}
  $z \sim \mathcal{N}(0, 1)^Z$ {Draw sample of random noise}
  $\hat{x} \leftarrow G(z, h)$ {Forward through generator}
  $s_r \leftarrow D(x, h)$ {real image, right text}
  $s_w \leftarrow D(x, \hat{h})$ {real image, wrong text}
  $s_f \leftarrow D(\hat{x}, h)$ {fake image, right text}
  $\mathcal{L}_D \leftarrow \log(s_r) + (\log(1 - s_w) + \log(1 - s_f))/2$
  $D \leftarrow D - \alpha \partial \mathcal{L}_D / \partial D$ {Update discriminator}
  $\mathcal{L}_G \leftarrow \log(s_f)$
  $G \leftarrow G - \alpha \partial \mathcal{L}_G / \partial G$ {Update generator}
end for

Results Not Satisfying

- So we need more processing!
- Add attention!

AttnGAN: Fine-Grained Text to Image Generation with Attentional Generative Adversarial Networks

Tao Xu*[1], Pengchuan Zhang[2], Qiuyuan Huang[2],
Han Zhang[3], Zhe Gan[4], Xiaolei Huang[1], Xiaodong He[2]

[1]Lehigh University [2]Microsoft Research [3]Rutgers University [4]Duke University
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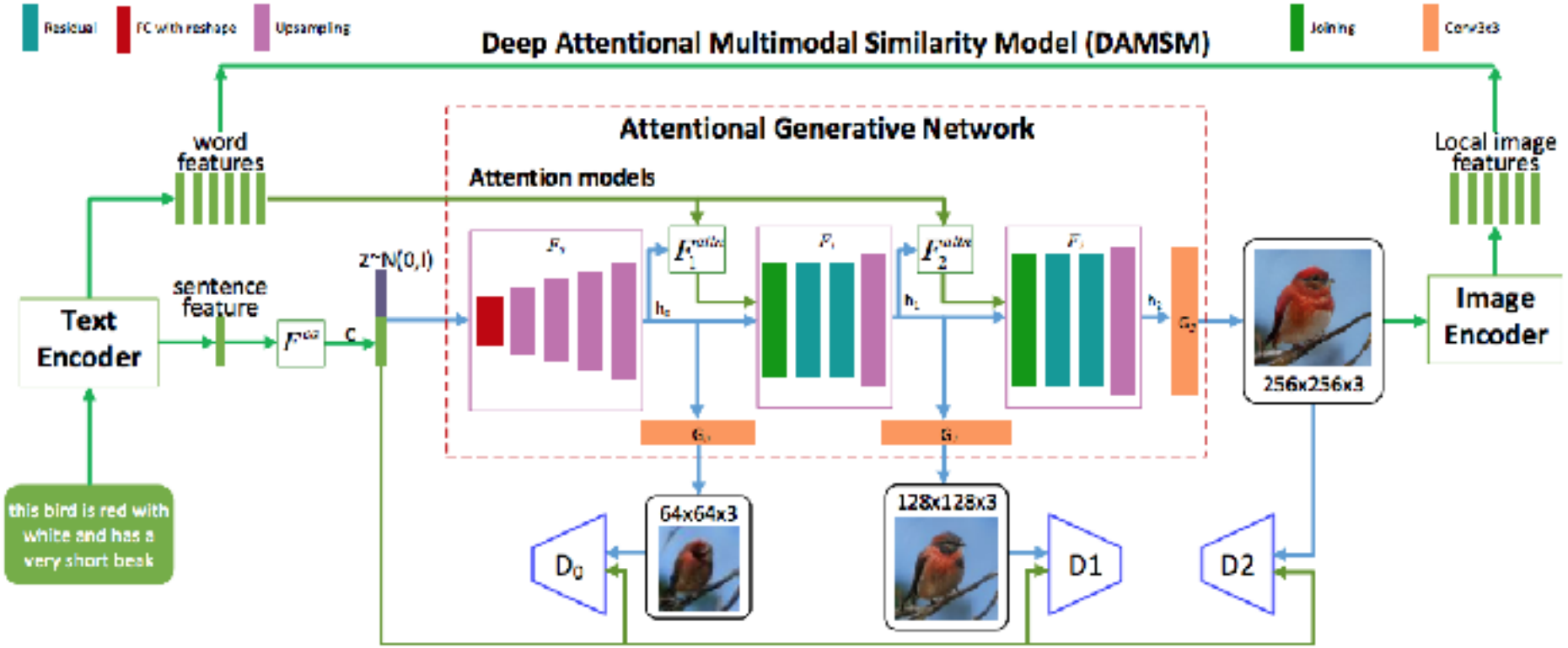
han.zhang@cs.rutgers.edu, zhe.gan@duke.edu

New Process is Similar



Progressive Growing of Size and Multiple Discriminators

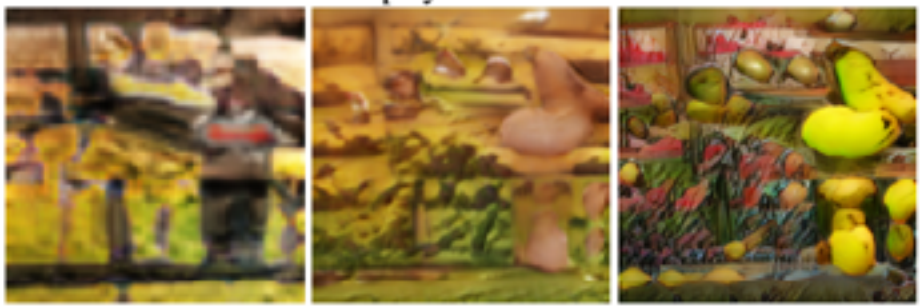
Results are more satisfying!

the bird has a yellow crown and a black eyering that is round

this bird has a green crown black primaries and a white belly

a photo of a homemade swirly pasta with broccoli carrots and onions

a fruit stand display with bananas and kiwi

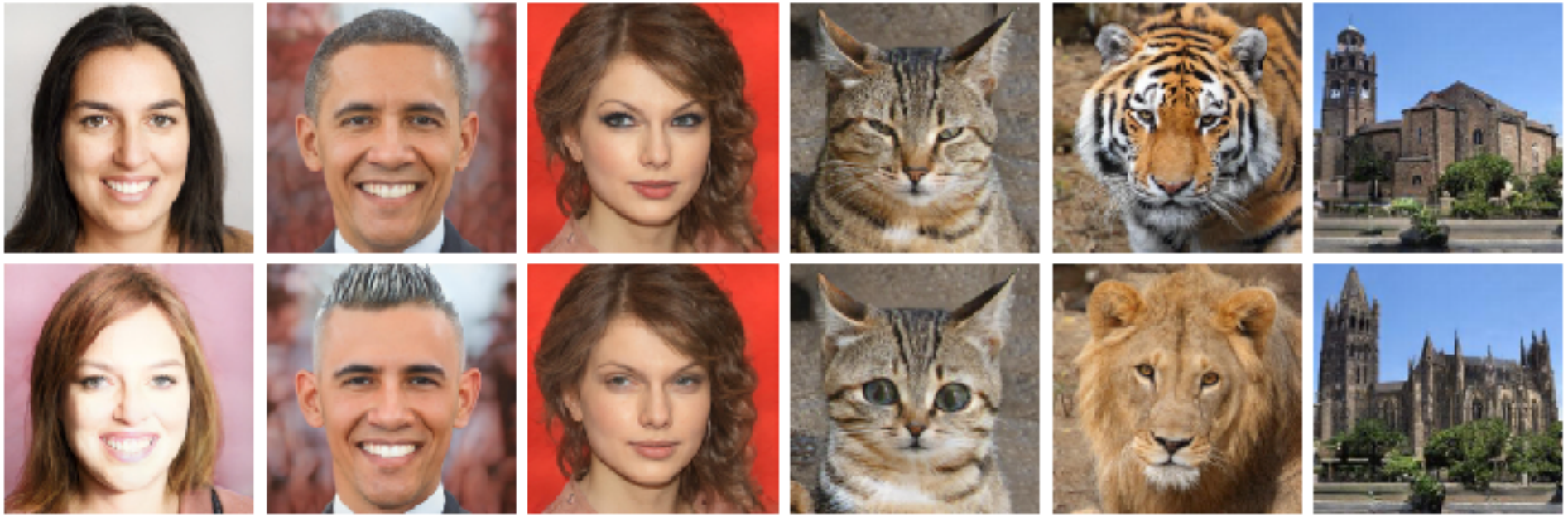


this bird has wings that are black and has a white belly

this bird has wings that are red and has a yellow belly

this bird has wings that are blue and has a red belly

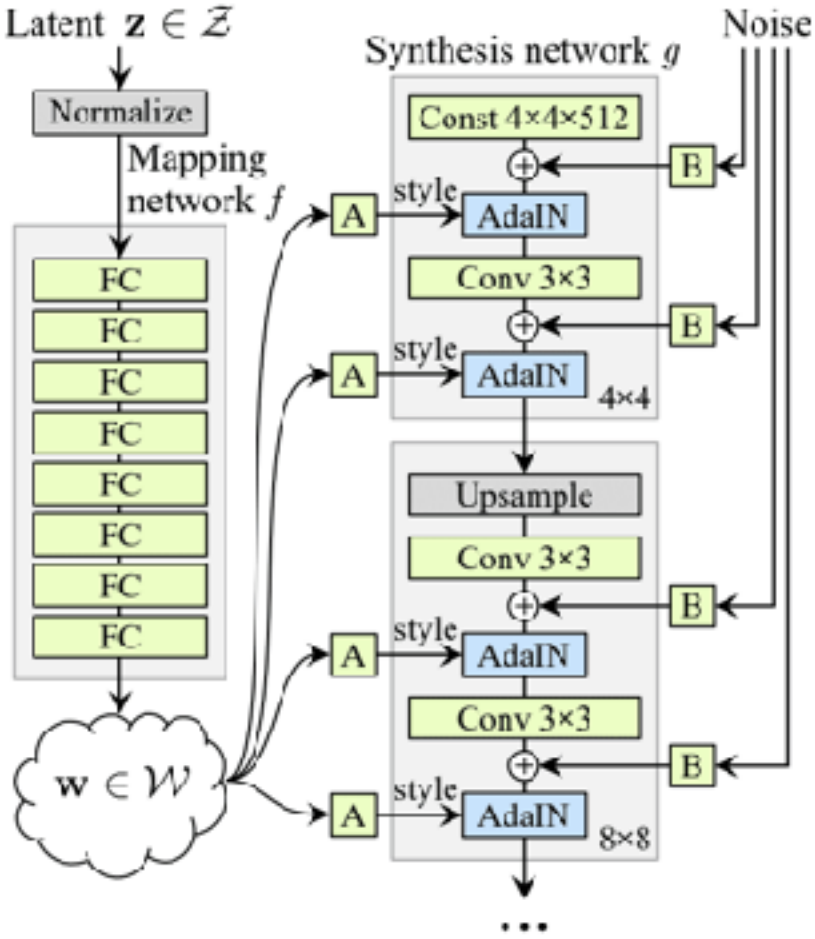
StyleGAN 3.0 and StyleCLIP



https://arxiv.org/abs/2103.17249

StyleGAN

- Progressive Growing
- Bilinear Upsampling
- Noise added everywhere!
  - But start with constant 4x4x512
- Adaptive Input Normalization



A Style-Based Generator Architecture for Generative Adversarial Networks

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Timo Aila
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https://arxiv.org/pdf/1812.04948.pdf

Figure 10. Uncurated set of images produced by our style-based generator (config F) with the LSUN BEDROOM dataset at 256^2. FID computed for 50K images was 2.65.

Figure 11. Uncurated set of images produced by our style-based generator (config F) with the LSUN CAR dataset at 512×384. FID computed for 50K images was 3.27.

StyleCLIP

- Also add in noise representations from text, guides the latent space…

$$\mathcal{L}_{\text{CLIP}}(w) = D_{\text{CLIP}}(G(w + M_t(w)), t),$$

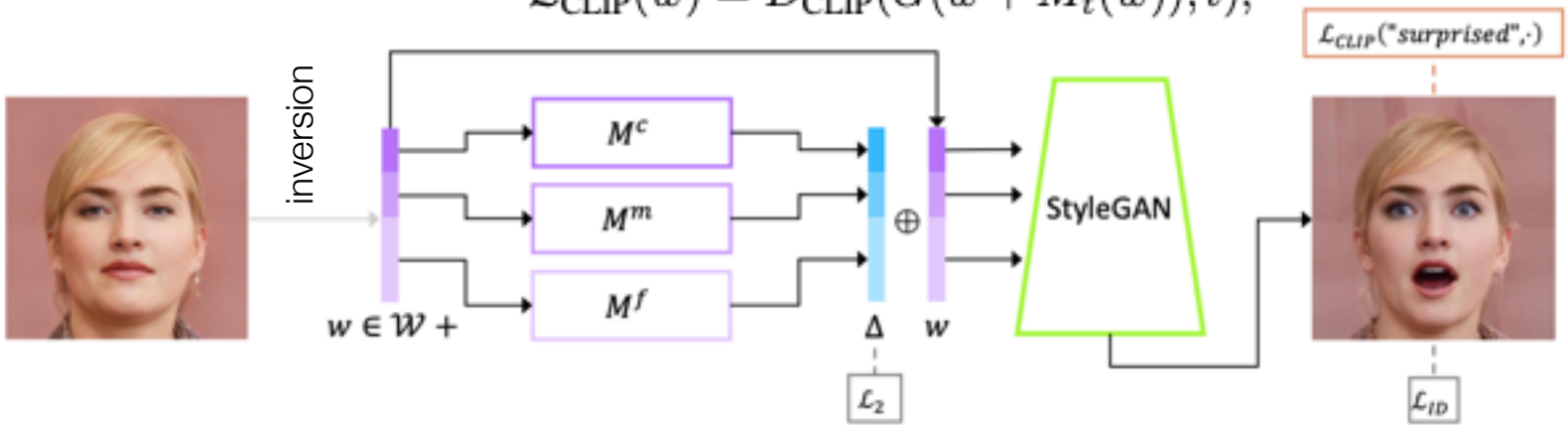
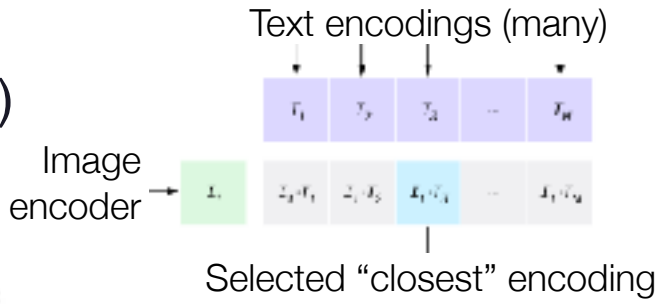


Figure 2. The architecture of our text-guided mapper (using the text prompt "surprised", in this example). The source image (left) is inverted into a latent code w. Three separate mapping functions are trained to generate residuals (in blue) that are added to w to yield the target code, from which a pretrained StyleGAN (in green) generates an image (right), assessed by the CLIP and identity losses.

CLIP: *Contrastive Language–Image Pre-training*
(from OpenAI, trained to match NLP and images)



StyleCLIP: Text-Driven Manipulation of StyleGAN Imagery

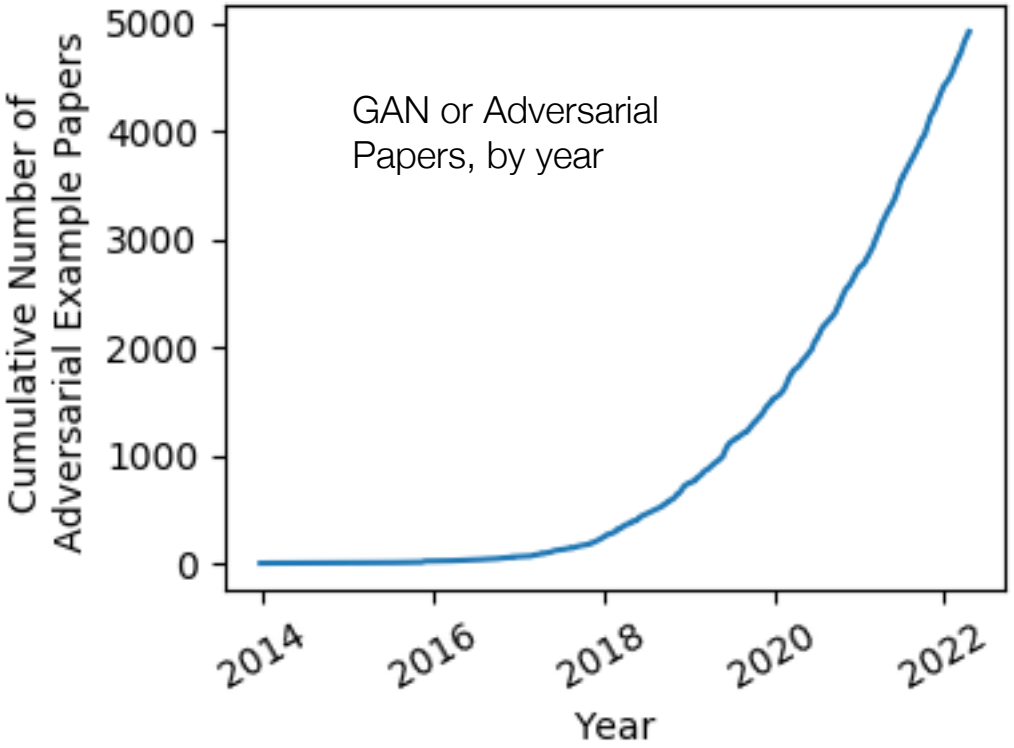
Or Patashnik[†*] Zongze Wu[‡*] Eli Shechtman[§] Daniel Cohen-Or[†] Dani Lischinski[‡]
[‡]Hebrew University of Jerusalem [†]Tel-Aviv University [§]Adobe Research

https://arxiv.org/abs/2103.17249

Figure 3. Edits of real celebrity portraits obtained by latent optimization. The driving text prompt and the $(\lambda_{L2}, \lambda_{ID})$ parameters for each edit are indicated under the corresponding result.

The END!
Lots of open research problems!

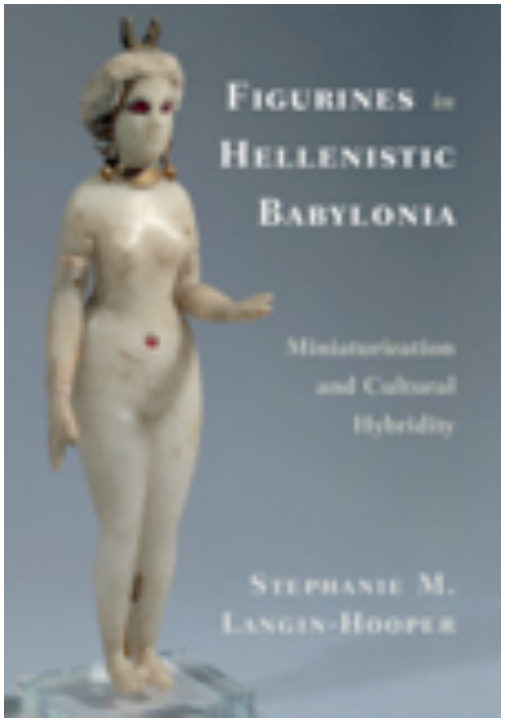
- Look at some of the recent research
- There are so many individuals in the field
- …and so many great applications.



https://nicholas.carlini.com/writing/2019/all-adversarial-example-papers.html

Final Project

One Idea from Professor Stephanie Langin-Hooper
SMU Meadows



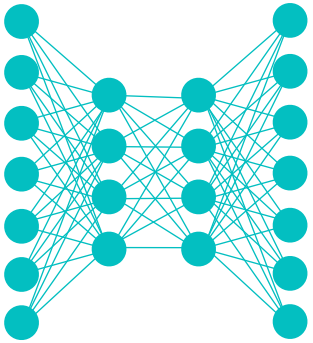
Lecture Notes for

Neural Networks and Machine Learning

Holy GAN-Zooks

Next Time:
Lapan Ch. 1

Reading: None



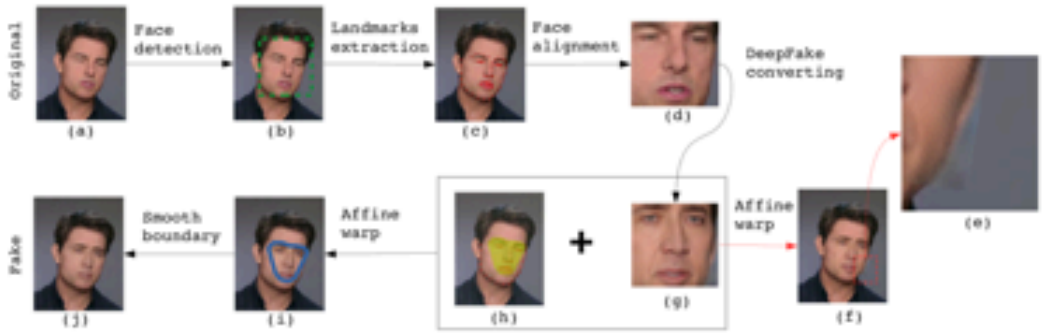
Backup slides

(a) (b) (c)

Figure 1: (a) The input image. (b) The result of face swapping with Nicolas Cage using our method. (c) The result of a manual face swap (source: http://niccageaseveryone.blogspot.com).

"As deepfake technology becomes more advanced and more accessible, it could pose a threat to United States public discourse and national security, with broad and concerning implications for offensive active measured campaigns targeting the United States."

"US lawmakers say AI Deepfakes have the potential to disrupt every facet of our society." US Congressional Letter



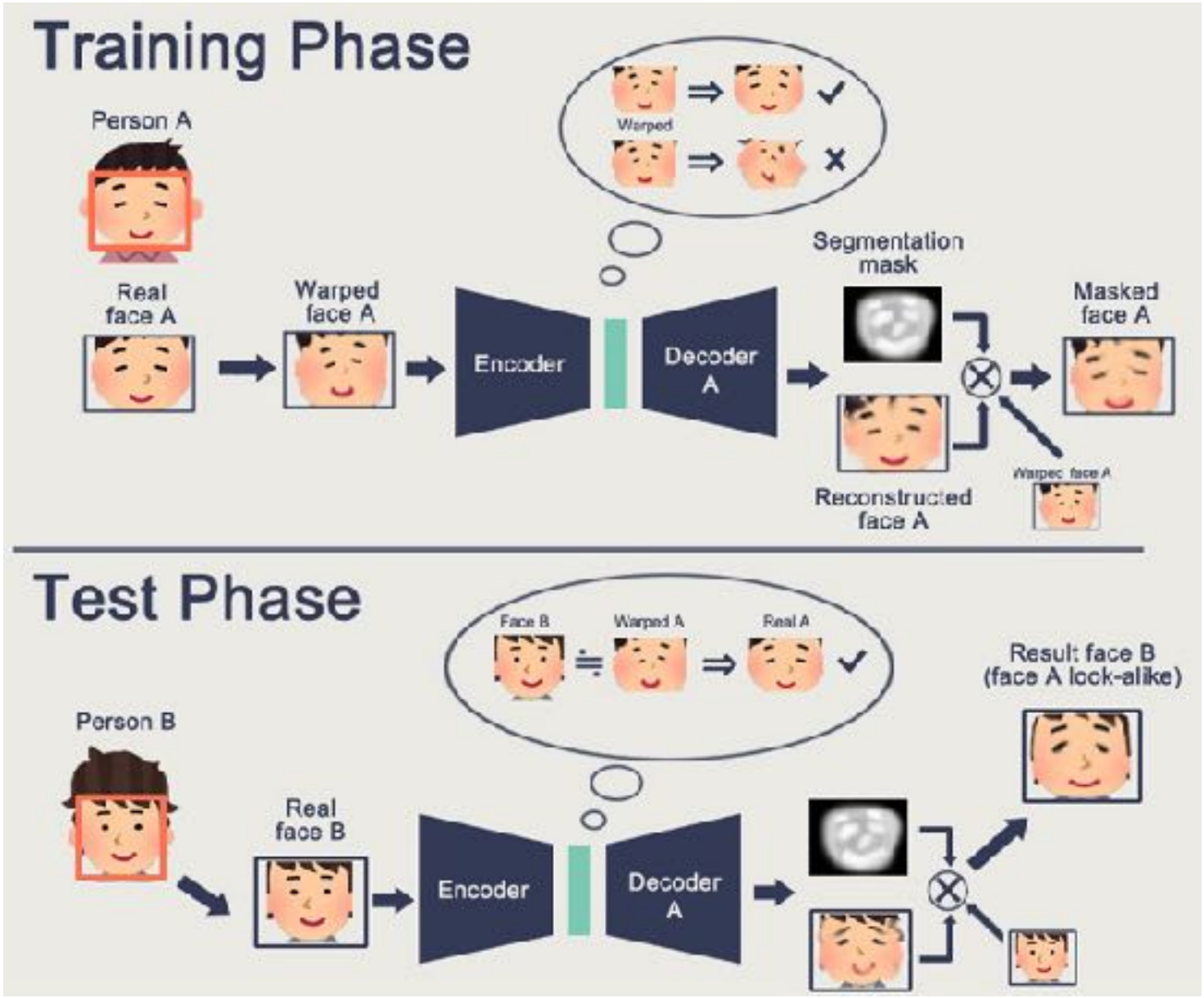
Original

Aligned

Cropped

- 50 different celebrities (from People.com listing)
- Selected celebrity pairs of faces to swap
- Swapped Faces via:
  - Auto-Encoding (Adversarial Network)
  - Pipelining with Convolutional Neural Network
- 1000 – 3000 fake images created per celebrity pair
- 400,000 images for training and evaluation

SMU | Bobby B. Lyle School of Engineering


Training Phase
Person A
Real face A
Warped face A
Encoder
Decoder A
Warped
Segmentation mask
Masked face A
Reconstructed face A
Warped face A
Test Phase
Face B
Warped A
Real A
Person B
Real face B
Encoder
Decoder A
Result: face B (face A look-alike)

Rating Swapped Images

faceface.lyle.smu.edu

- Selected subset of 400 images to rate
- Used paired selection algorithm on website to choose most "needed" image comparison
- Collected **40,000 ratings** from ~200 unique individuals
- **Result**: Sorting of images from most fake to most real

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- https://github.com/fchollet/deep-learning-with-python-notebooks/blob/master/8.5-introduction-to-gans.ipynb
- https://sthalles.github.io/semi-supervised-learning-with-gans/
- https://openai.com/blog/generative-models/#gan
- https://openai.com/blog/glow/
- https://arxiv.org/pdf/1807.03039.pdf
- https://arxiv.org/pdf/1606.03498.pdf
- https://github.com/sthalles/blog-resources/blob/master/semi-supervised/semi-supervised_learning.ipynb
- https://arxiv.org/pdf/1701.07875.pdf
- https://medium.com/@jonathan_hui/gan-wasserstein-gan-wgan-gp-6a1a2aa1b490
- https://medium.com/nurture-ai/keeping-up-with-the-gans-66e89343b46
- Reversible Flow Algorithms (https://arxiv.org/pdf/1807.03039.pdf)

InfoGAN

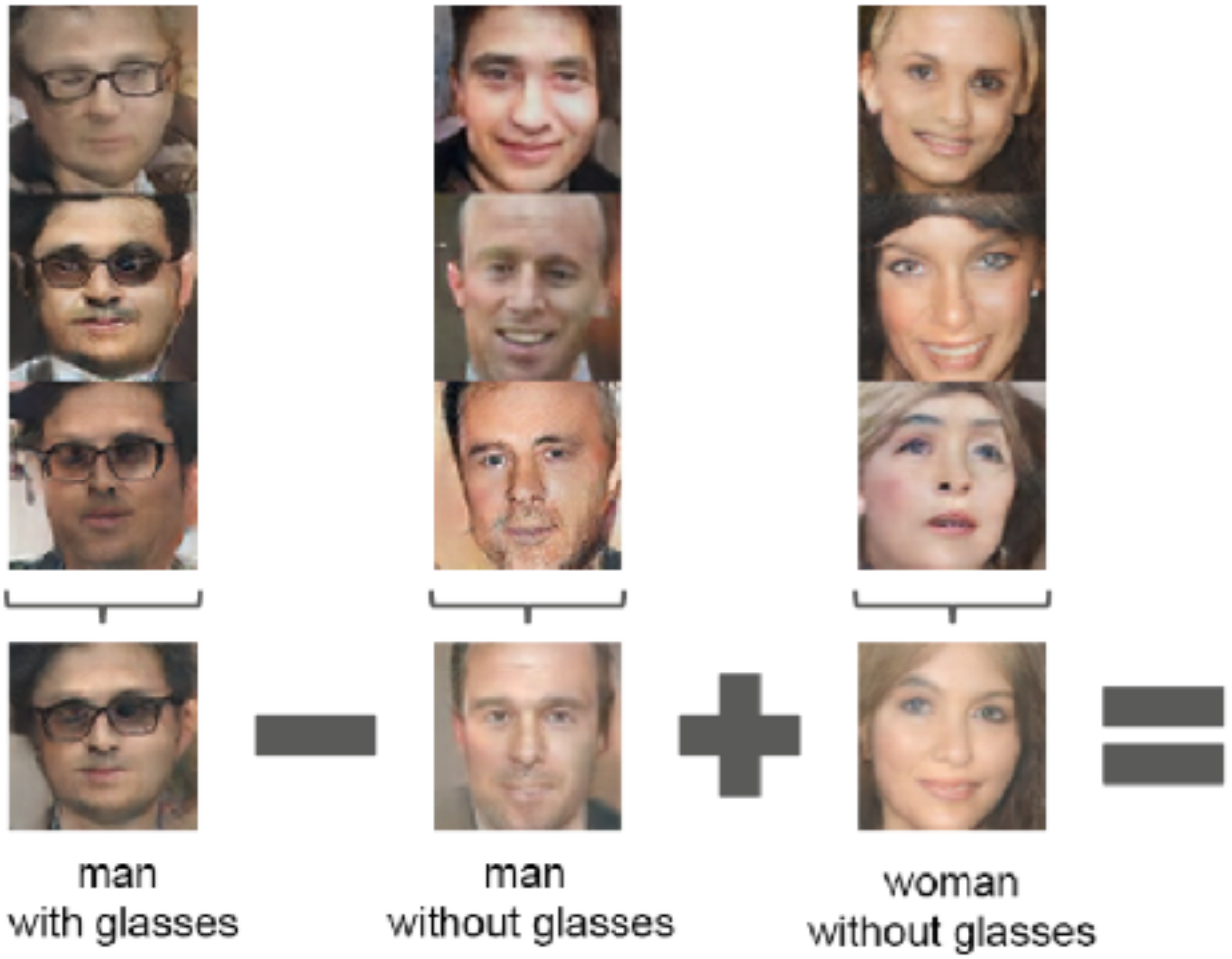
InfoGAN: Interpretable Representation Learning by Information Maximizing Generative Adversarial Nets

Xi Chen[†‡], **Yan Duan**[†‡], **Rein Houthooft**[†‡], **John Schulman**[†‡], **Ilya Sutskever**[‡], **Pieter Abbeel**[†‡]
† UC Berkeley, Department of Electrical Engineering and Computer Sciences
‡ OpenAI

InfoGAN Problem Statement

- We need to disentangle information in the latent space for it to be truly useful
- Disentangling should be ascertained by the ability of the generator to have interpretable latent space axes
- Each axis should have little impact on the other axes, which is not imposed by any GAN structure yet
  - *For example, for a dataset of faces, a useful disentangled representation may allocate a separate set of dimensions for each of the following attributes: facial expression, eye color, hairstyle, presence or absence of eyeglasses, and the identity of the corresponding person.*

How to perform latent space arithmetic?



NOT Systematic!

woman with glasses

Need to find a bunch of these

Need to find a bunch of these

Need to find a bunch of these

To generate all these

The InfoGAN Money Back Guarantee

However, many domains naturally decompose into a set of semantically meaningful factors of variation. For instance, when generating images from the MNIST dataset, it would be ideal if the model automatically chose to allocate a discrete random variable to represent the numerical identity of the d… the digit's angle a… ndent and salient, … by simply specify… dependent continuous variables.

Authors: by Maximizing Mutual Information the network will learn to disentangle latent space

- Decompose latent variable representation into
  - z: continuous incompressible noise
  - c: latent code, hopefully learns semantic features
- We want mutual information of c and $G(z,c)$ to be large
- Using standard entropy definition: $I(X;Y)=H(X)-H(X|Y)$
- New Loss Function: $\min_G \max_D V_I(D,G) = V(D,G) - \lambda I(c;G(z,c))$

Regular GAN Loss — MI Loss

Maximizing Mutual Information

- You guessed it, Mutual Informaiton with P is intractable to compute!
- So let's dust off our approximation pants and put some ELBO grease into this
- Variational Inference Maximization, Assume there is an approximation of P from Q:

$$
\begin{aligned}
I(c; G(z,c)) &= H(c) - H(c|G(z,c)) \\
&= \mathbb{E}_{x\sim G(z,c)}[\mathbb{E}_{c'\sim P(c|x)}[\log P(c'|x)]] + H(c) \\
&= \mathbb{E}_{x\sim G(z,c)}[\underbrace{D_{\mathrm{KL}}(P(\cdot|x) \parallel Q(\cdot|x))}_{\text{make Q close to P } \geq 0} + \mathbb{E}_{c'\sim P(c|x)}[\log Q(c'|x)]] + H(c) \\
&\geq \mathbb{E}_{x\sim G(z,c)}[\mathbb{E}_{c'\sim P(c|x)}[\log Q(c'|x)]] + H(c)
\end{aligned}
$$

Expand Def. of Conditional Entropy

Insert Q Approximation (Variational)

sample from Q

Define a Lower Bound to Maximize because we don't like other terms…

Lemma 5.1 *For random variables X, Y and function $f(x,y)$ under suitable regularity conditions:* $\mathbb{E}_{x\sim X, y\sim Y|x}[f(x,y)] = \mathbb{E}_{x\sim X, y\sim Y|x, x'\sim X|y}[f(x',y)]$.

Maximizing Mutual Information (kinda)

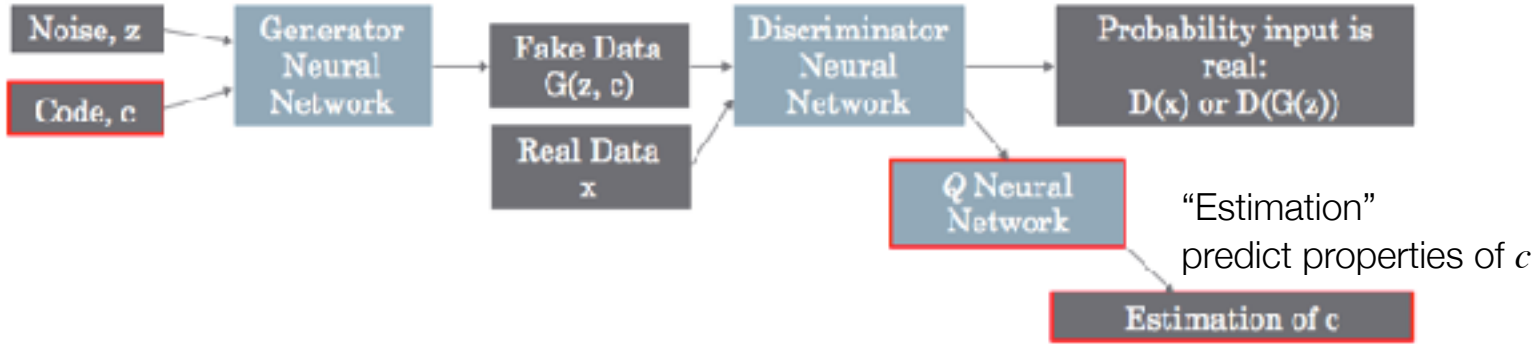
$$I(c; G(z,c)) \geq \mathbb{E}_{x \sim G(z,c)}[\mathbb{E}_{c' \sim P(c|x)}[\log Q(c'|x)]] + H(c)$$

Lemma 5.1 *For random variables X, Y and function $f(x, y)$ under suitable regularity conditions:* $\mathbb{E}_{x \sim X, y \sim Y|x}[f(x,y)] = \mathbb{E}_{x \sim X, y \sim Y|x, x' \sim X|y}[f(x', y)]$.

$$\begin{aligned} L_I(G,Q) &= E_{c \sim P(c), x \sim G(z,c)}[\log Q(c|x)] + H(c) \\ &= E_{x \sim G(z,c)}[\mathbb{E}_{c' \sim P(c|x)}[\log Q(c'|x)]] + H(c) \\ &\leq I(c; G(z,c)) \end{aligned}$$

Re-parameterize:
Q will be good if we can measure c from the Generator network

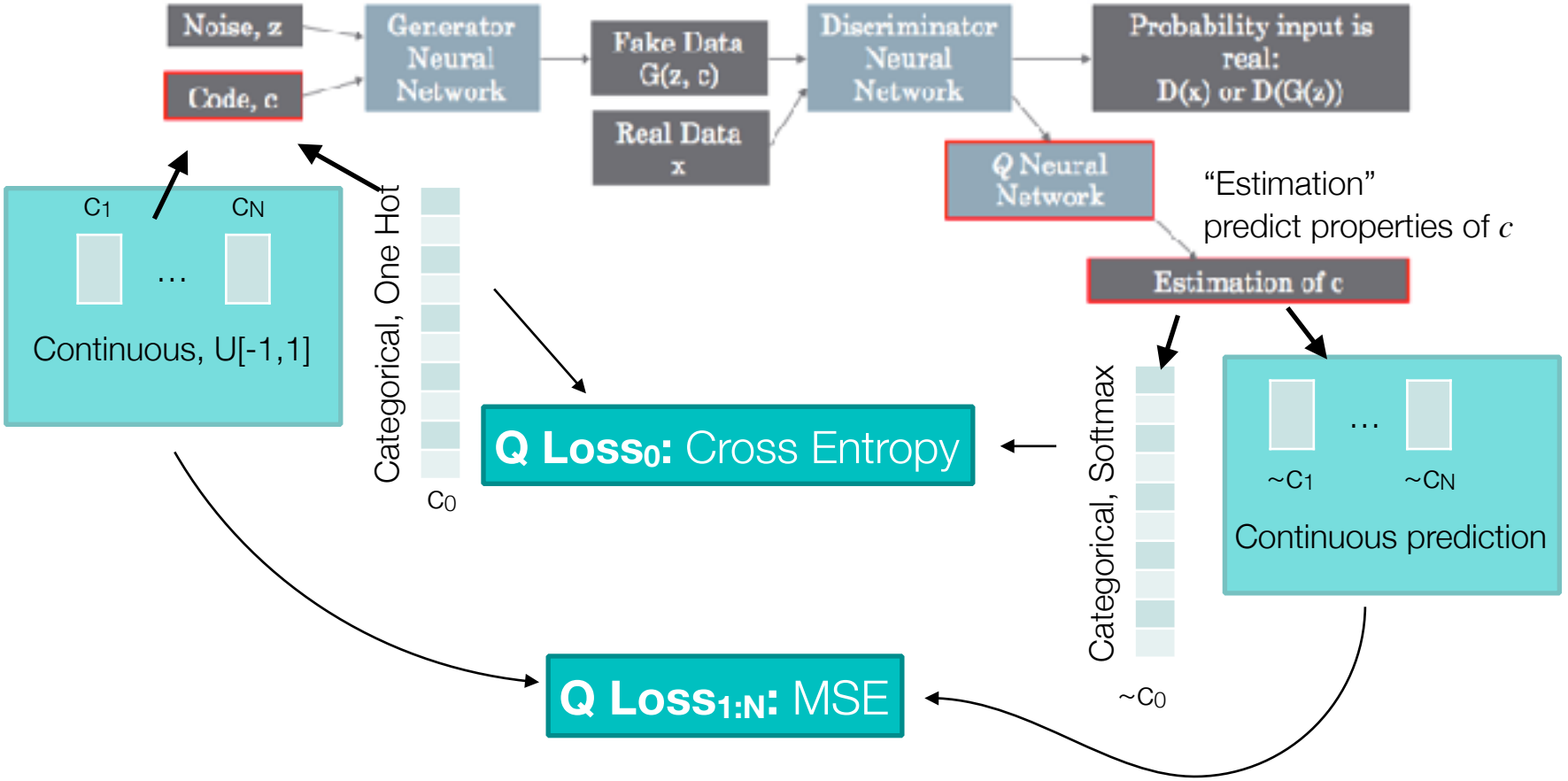
New Objective Function Becomes: $\min_{G,Q} \max_{D} V_{\text{InfoGAN}}(D,G,Q) = V(D,G) - \lambda L_I(G,Q)$



"Estimation"
predict properties of c

https://towardsdatascience.com/infogan-generative-adversarial-networks-part-iii-380c0c6712cd

Measuring Latent Codes in Loss



Intuition: If the generator starts to use these codes and variables semantically, then the Q network (and therefore the discriminator) can start learning to predict these semantics. By learning these semantics, the generator is incentivized to produce disentangled, meaningful features from the codes.

Implementation: D and Q

```
# define the standalone discriminator model
def define_discriminator(n_cat, in_shape=(28,28,1)):
	# weight initialization
	init = RandomNormal(stddev=0.02)
	# image input
	in_image = Input(shape=in_shape)
	# downsample to 14x14
	d = Conv2D(64, (4,4), strides=(2,2), padding='same', kernel_initializer=init)(in_image)
	d = LeakyReLU(alpha=0.1)(d)
	# downsample to 7x7
	d = Conv2D(128, (4,4), strides=(2,2), padding='same', kernel_initializer=init)(d)
	d = LeakyReLU(alpha=0.1)(d)
	d = BatchNormalization()(d)
	# normal
	d = Conv2D(256, (4,4), padding='same', kernel_initializer=init)(d)
	d = LeakyReLU(alpha=0.1)(d)
	d = BatchNormalization()(d)
	# flatten feature maps
	d = Flatten()(d)
	# real/fake output
	out_classifier = Dense(1, activation='sigmoid')(d)
	# define d model
	d_model = Model(in_image, out_classifier)
	# compile d model
	d_model.compile(loss='binary_crossentropy', optimizer=Adam(lr=0.0002, beta_1=0.5))
	# create q model layers
	q = Dense(128)(d)
	q = BatchNormalization()(q)
	q = LeakyReLU(alpha=0.1)(q)
	# q model output
	out_codes = Dense(n_cat, activation='softmax')(q)
	# define q model
	q_model = Model(in_image, out_codes)
	return d_model, q_model
```

https://machinelearningmastery.com/how-to-develop-an-information-maximizing-generative-adversarial-network-infogan-in-keras/

Implementation: G and Q Trained

```
# define the combined discriminator, generator and q network model
def define_gan(g_model, d_model, q_model):
	# make weights in the discriminator (some shared with the q model) as not trainable
	d_model.trainable = False
	# connect g outputs to d inputs
	d_output = d_model(g_model.output)
	# connect g outputs to q inputs
	q_output = q_model(g_model.output)
	# define composite model
	model = Model(g_model.input, [d_output, q_output])
	# compile model
	opt = Adam(lr=0.0002, beta_1=0.5)
	model.compile(loss=['binary_crossentropy', 'categorical_crossentropy'], optimizer=opt)
	return model
```

Q network will update with generator
(for variables not shared with discriminator)

```
# generate points in latent space as input for the generator
def generate_latent_points(latent_dim, n_cat, n_samples):
	# generate points in the latent space
	z_latent = randn(latent_dim * n_samples)
	# reshape into a batch of inputs for the network
	z_latent = z_latent.reshape(n_samples, latent_dim)
	# generate categorical codes
	cat_codes = randint(0, n_cat, n_samples)
	# one hot encode
	cat_codes = to_categorical(cat_codes, num_classes=n_cat)
	# concatenate latent points and control codes
	z_input = hstack((z_latent, cat_codes))
	return [z_input, cat_codes]
```

Only uses codes, not continuous “c” vars

Input to generator and labels for Q network returned (repeats “c”)

https://machinelearningmastery.com/how-to-develop-an-information-maximizing-generative-adversarial-network-infogan-in-keras/

Implementation: Training

```
# train the generator and discriminator
def train(g_model, d_model, gan_model, dataset, latent_dim, n_cat, n_epochs=100, n_batch=64):
	# calculate the number of batches per training epoch
	bat_per_epo = int(dataset.shape[0] / n_batch)
	# calculate the number of training iterations
	n_steps = bat_per_epo * n_epochs
	# calculate the size of half a batch of samples
	half_batch = int(n_batch / 2)
	# manually enumerate epochs
	for i in range(n_steps):
		# get randomly selected ‘real' and ‘fake’ samples
		X_real, y_real = generate_real_samples(dataset, half_batch)
		X_fake, y_fake = generate_fake_samples(g_model, latent_dim, n_cat, half_batch)
		# update discriminator and q model weights
		d_loss1 = d_model.train_on_batch(X_real, y_real)
		d_loss2 = d_model.train_on_batch(X_fake, y_fake)
		# prepare points in latent space as input for the generator
		z_input, cat_codes = generate_latent_points(latent_dim, n_cat, n_batch)
		# create inverted labels for the fake samples
		y_mislead = ones((n_batch, 1))
		# update the g via the d and q error
		_,g_1,g_2 = gan_model.train_on_batch(z_input, [y_mislead, cat_codes])
		# summarize loss on this batch
		print('>%d, d[%.3f,%.3f], g[%.3f] q[%.3f]' % (i+1, d_loss1, d_loss2, g_1, g_2))
		# evaluate the model performance every 'epoch'
		if (i+1) % (bat_per_epo * 10) == 0:
			summarize_performance(i, g_model, gan_model, latent_dim, n_cat)
```

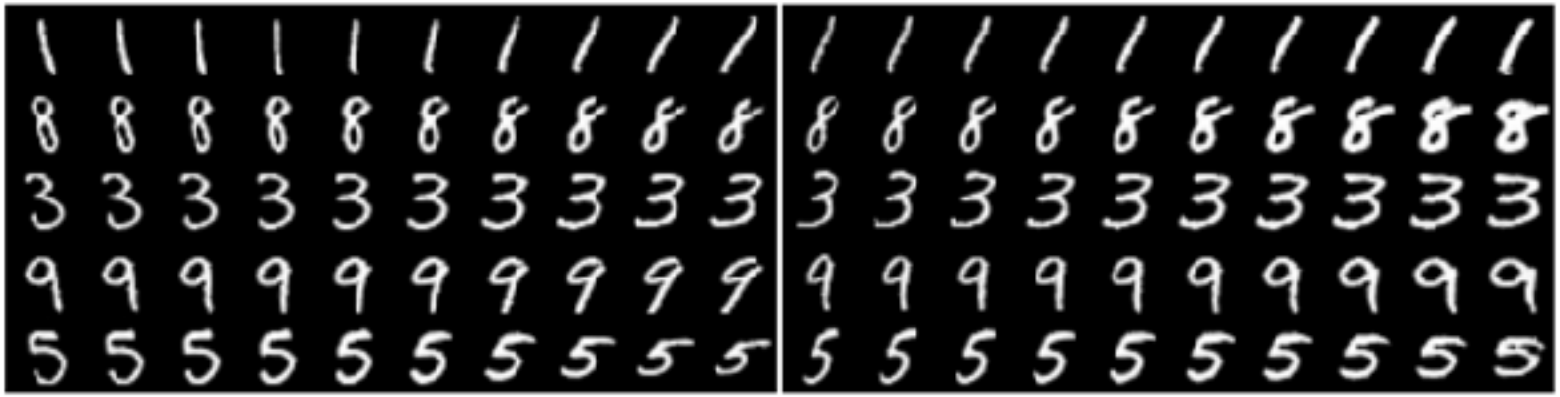
https://machinelearningmastery.com/how-to-develop-an-information-maximizing-generative-adversarial-network-infogan-in-keras/

Did they really disentangle?

c1 = 10 discrete codes with equal probability 0.1
c2 and c3 = uniformly sampled data from -1 to 1

(a) Varying c_1 on InfoGAN (Digit type)

(b) Varying c_1 on regular GAN (No clear meaning)



(c) Varying c_2 from -2 to 2 on InfoGAN (Rotation)

(d) Varying c_3 from -2 to 2 on InfoGAN (Width)

Columns: Hold other variables constant, Rows: Vary named variable

Did they really disentangle?

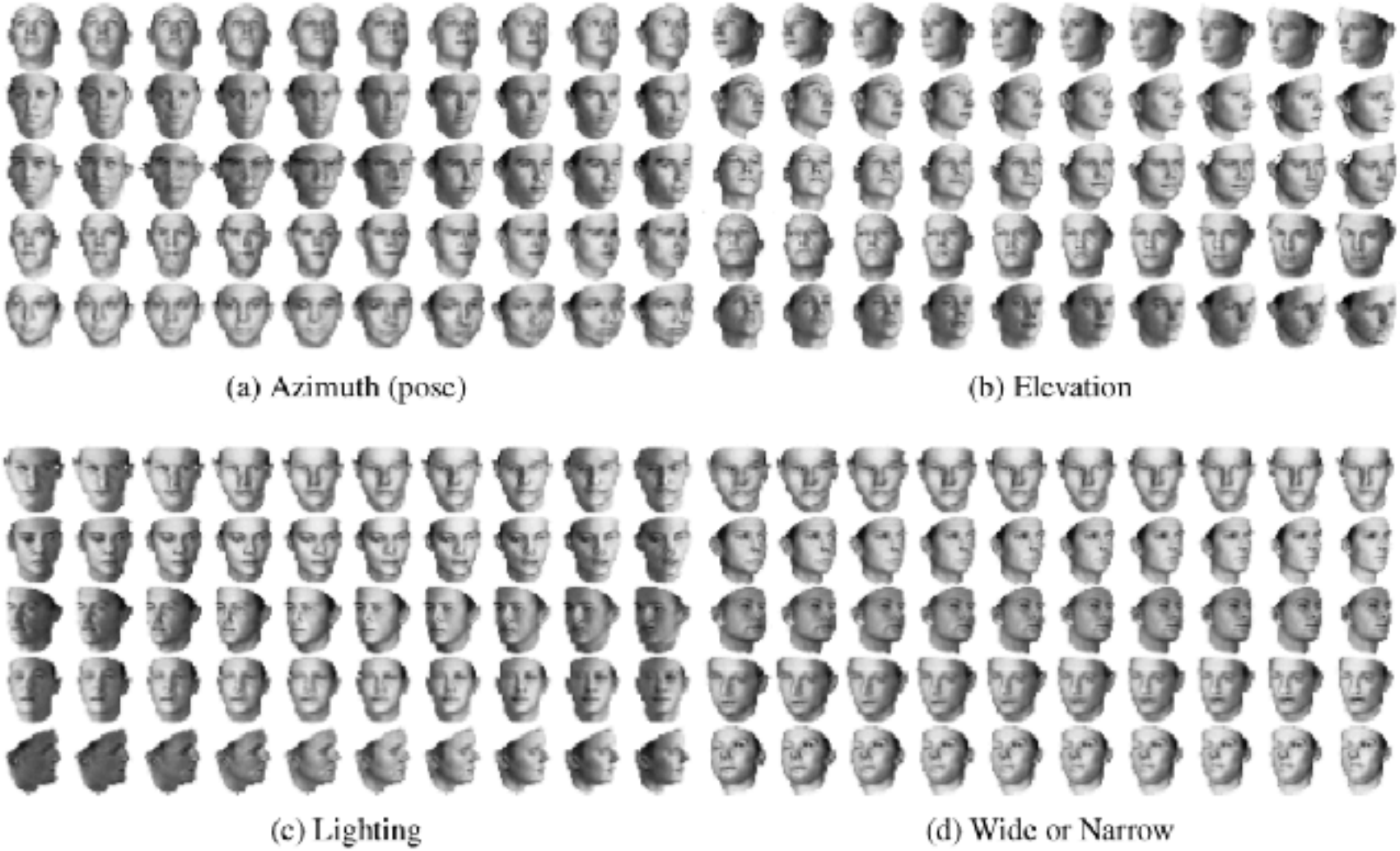


Figure 3: **Manipulating latent codes on 3D Faces:** We show the effect of the learned continuous

Did they really disentangle?

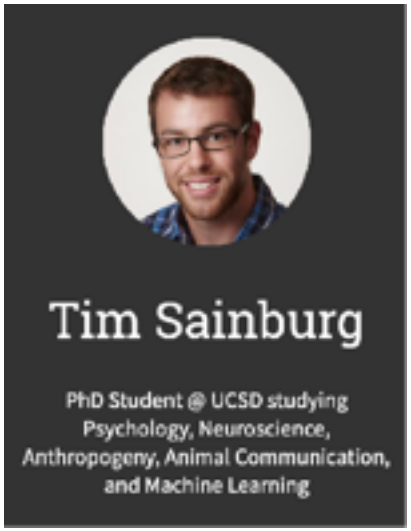
(a) Azimuth (pose)

(b) Presence or absence of glasses

(c) Hair style

(d) Emotion

GAIA



Generative adversarial interpolative autoencoding: adversarial training on latent space interpolations encourage convex latent distributions

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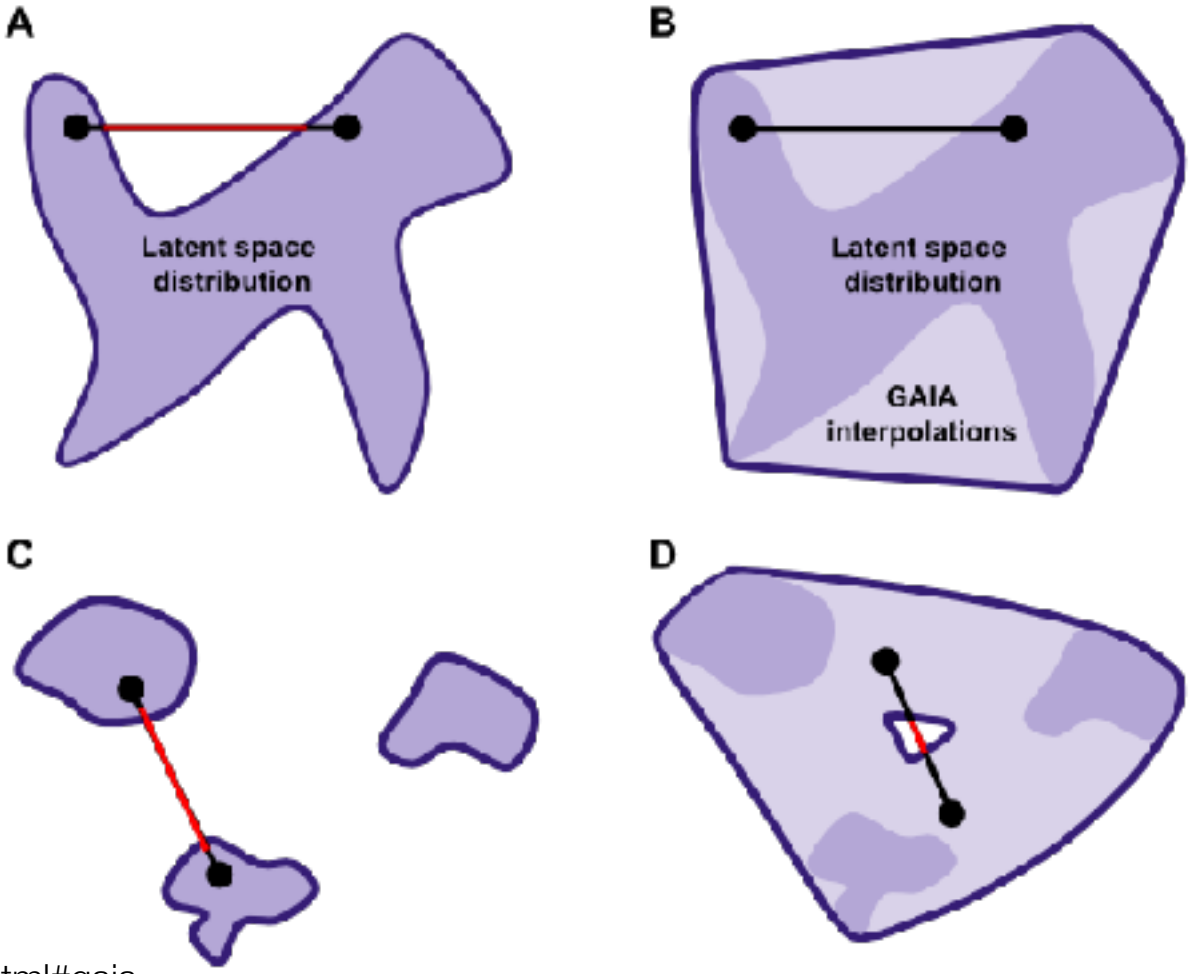
What does GAIA address?

- Explicitly Interpolate to make latent space as **convex** as possible

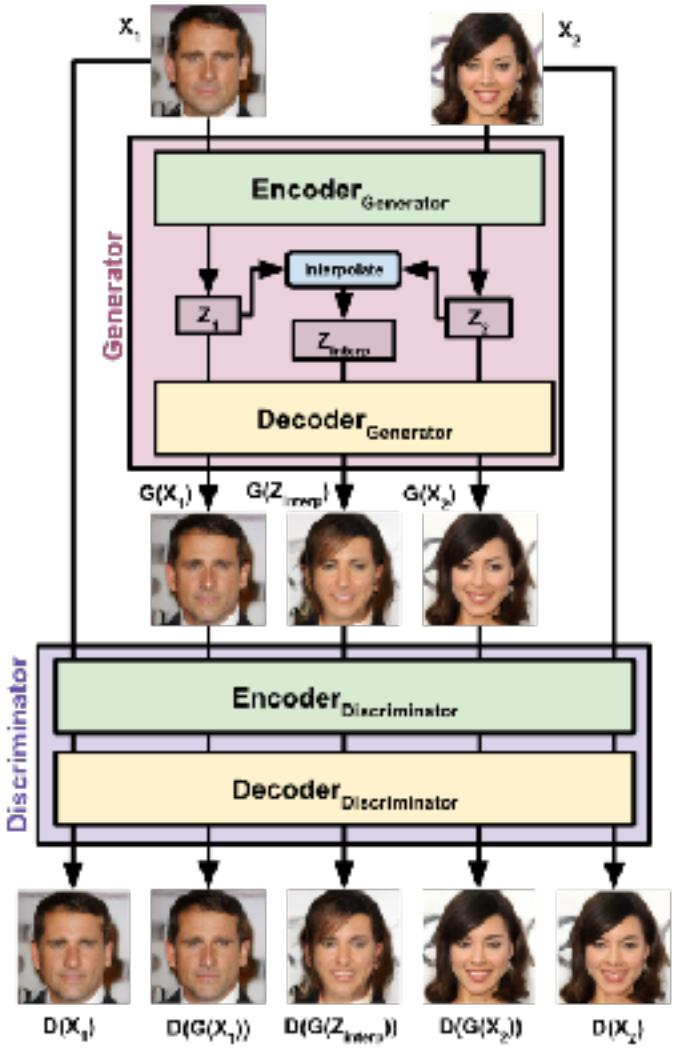


https://timsainburg.com/gaia.html#gaia

How to enforce convexity?

- Change discriminator function entirely
  - Discriminator also auto-encodes an image
  - Maximize **reconstruction error** in generated image for **fake**
  - Minimize **reconstruction error** in generated image for **real**
- Generator takes two images and outputs three
  - Two are simply auto encoded
  - Third Image is interpolated

How to enforce convexity?



Generator: Minimize

$$\mathcal{L}_{Gen} = \|X - D(G(X))\|_1 + \|G(Z_{interp}) - D(G(Z_{interp}))\|_1$$

Discriminator: Minimize

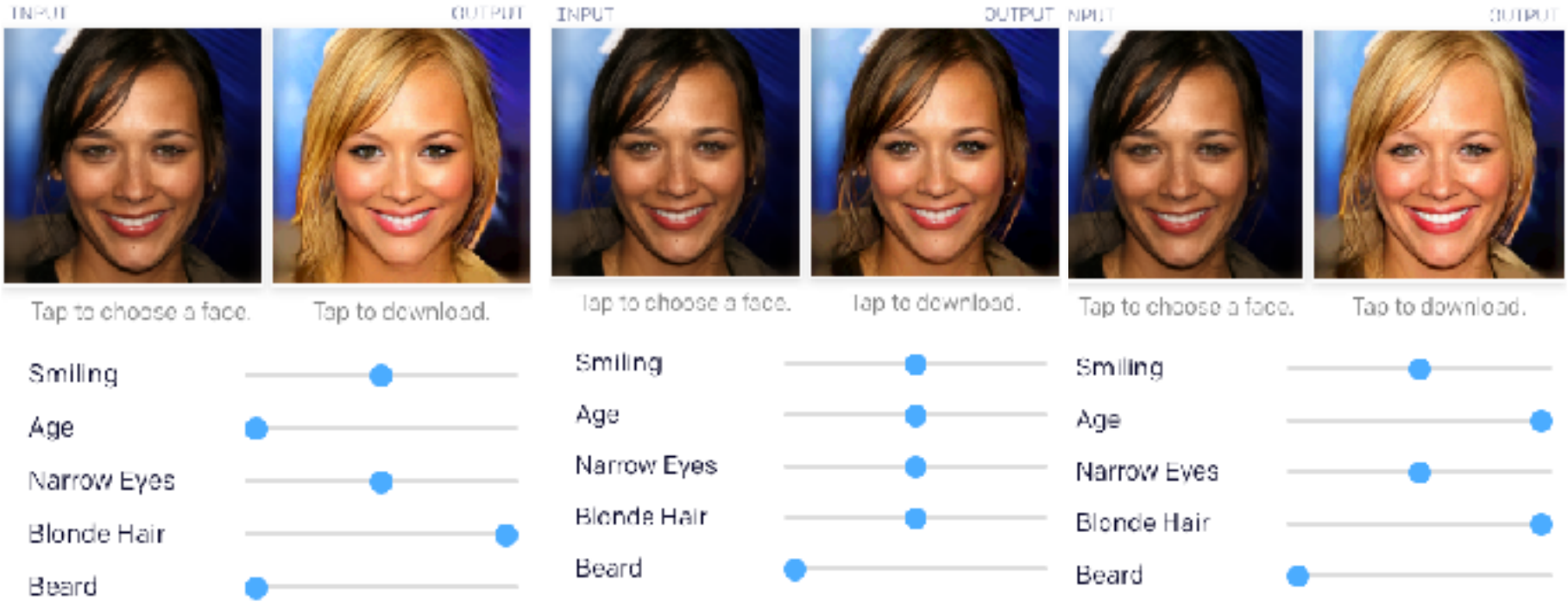
$$\mathcal{L}_{Disc} = \|X - D(X)\|_1 + -\|G(X) - D(G(X))\|_1 + -\|G(Z_{interp}) - D(G(Z_{interp}))\|_1$$

Regularize, for each mini-batch:

$$\mathcal{L}_{dist}(X,Z) = \frac{1}{B}\sum_{i,j}^{B}\left[log_2\left(1 + \frac{(X_i - X_j)^2}{\frac{1}{N}\sum_{i,j}(X_i - X_j)^2}\right) - log_2\left(1 + \frac{(Z_i - Z_j)^2}{\frac{1}{N}\sum_{i,j}(Z_i - Z_j)^2}\right)\right]$$

Results

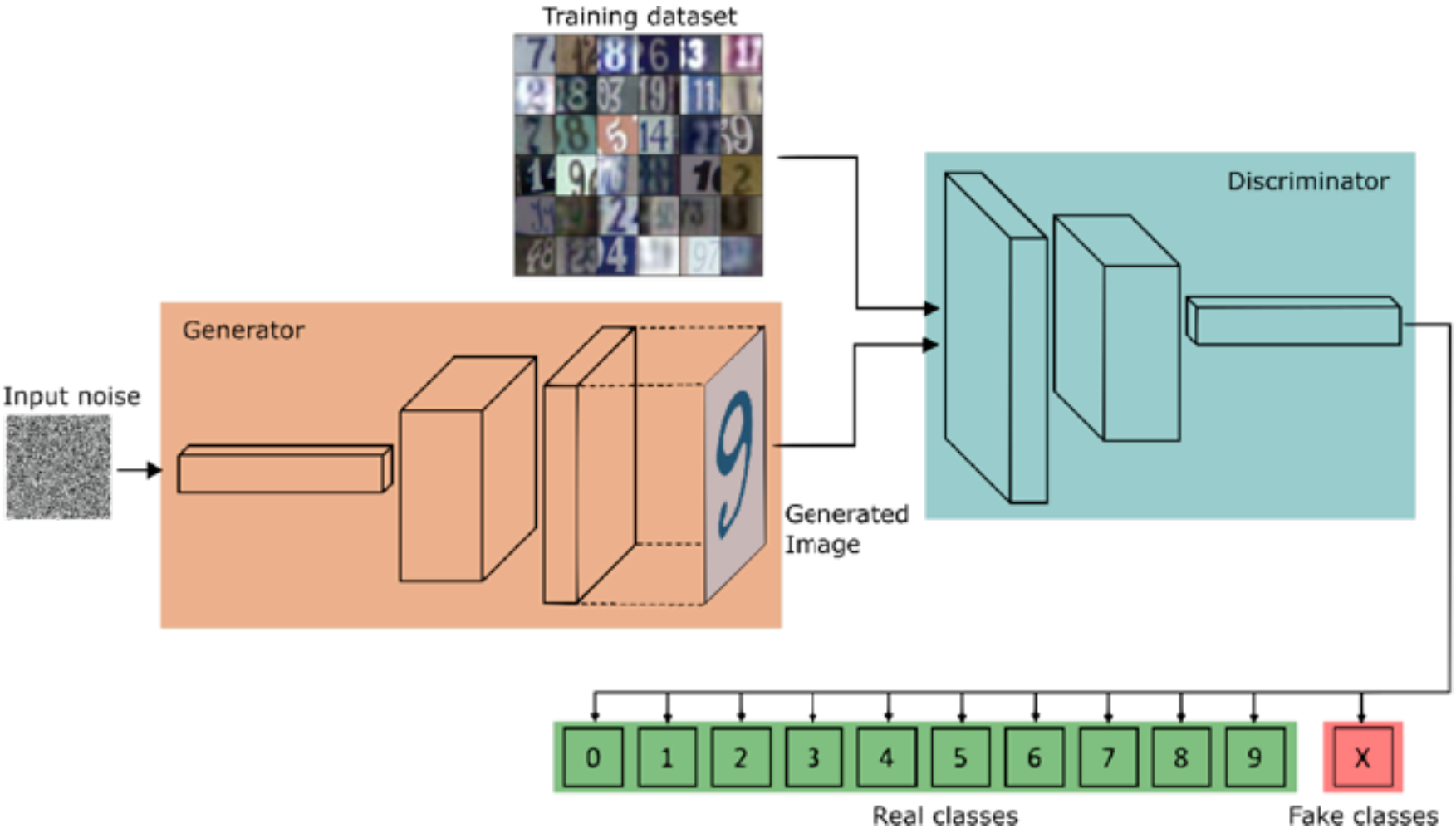
GLOW


INPUT
OUTPUT
Tap to choose a face.
Tap to download.
Smiling
Age
Narrow Eyes
Blonde Hair
Beard
INPUT
OUTPUT
Tap to choose a face.
Tap to download.
Smiling
Age
Narrow Eyes
Blonde Hair
Beard
INPUT
OUTPUT
Tap to choose a face.
Tap to download.
Smiling
Age
Narrow Eyes
Blonde Hair
Beard

Results

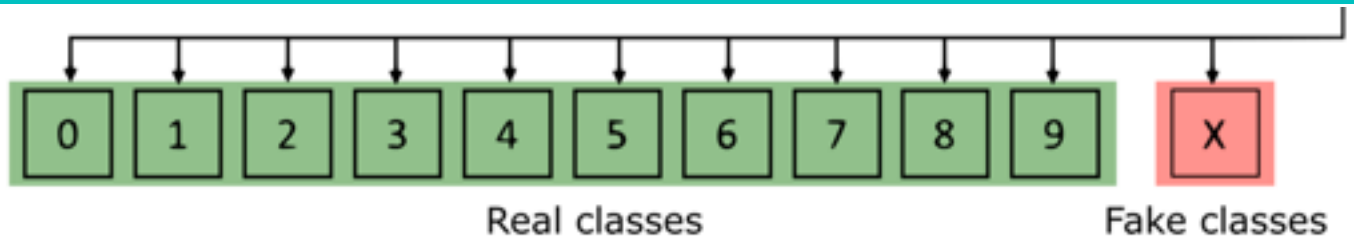

Original
Reconstruction
Young
Old
Male
Female
Bangs
Eyeglasses
Rosy Cheeks
Goatee
Smiling
Pale Skin

Fewer Labels, Still Lots of Data



https://sthalles.github.io/semi-supervised-learning-with-gans/

Minimizing Labels



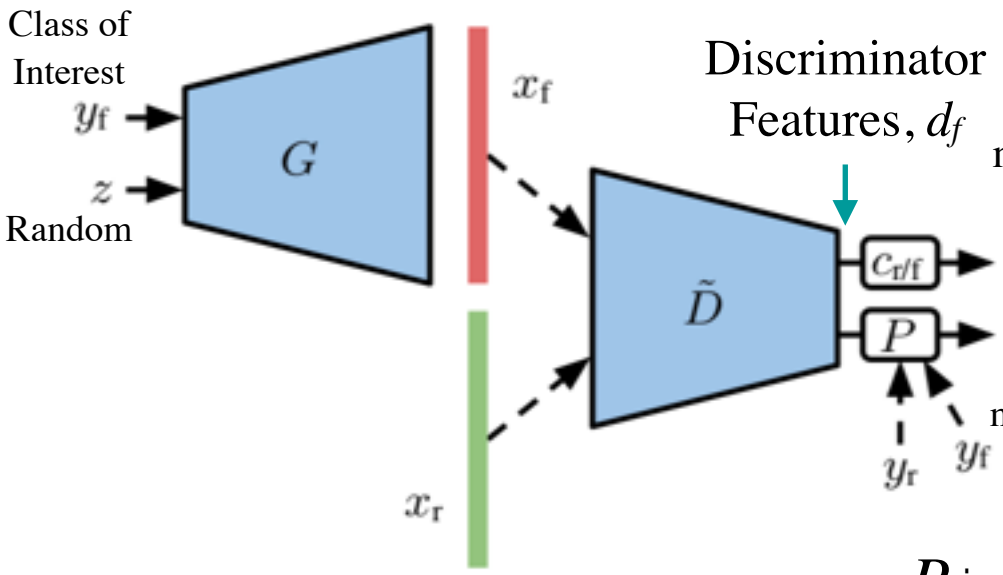
- MNIST Performance
  - 60,000 labels → 1,000 labels
  - 0.6% Error (~SOA)
- SVHN Performance
  - 73,000 labels → 1,000 labels
  - 1.3% Error (~SOA)
- ImageNet
  - 20% Labels (of 1.3M)
  - 10.3% Top-5 Error (slightly worse than SOA)

Need a slightly more complicated loss function

https://arxiv.org/pdf/1903.02271.pdf

Conditional GANs and Self-Supervision

Lucic, Mario, Michael Tschannen, Marvin Ritter, Xiaohua Zhai, Olivier Bachem, and Sylvain Gelly. "High-Fidelity Image Generation With Fewer Labels." *arXiv preprint arXiv:1903.02271* (2019).



$$\max_d \mathbf{E}_{x \leftarrow p_{data}} \left[\log d(x)\right] + \mathbf{E}_{x \leftarrow g(z)} \left[\log(1 - d(x))\right]$$

Traditional Discriminator Loss, Goodfellow

Class Conditioned Discriminator Loss

$$\max_d \mathbf{E}_{x \leftarrow p_{data}} \left[\log \tilde{d}(x_r, y_r)\right] + \mathbf{E}_{x \leftarrow g(z, y_f)} \left[\log(1 - \tilde{d}(x_f, y_f))\right]$$

P is trained using outer product

$$\tilde{d} = d_f^T W y_{enc}$$

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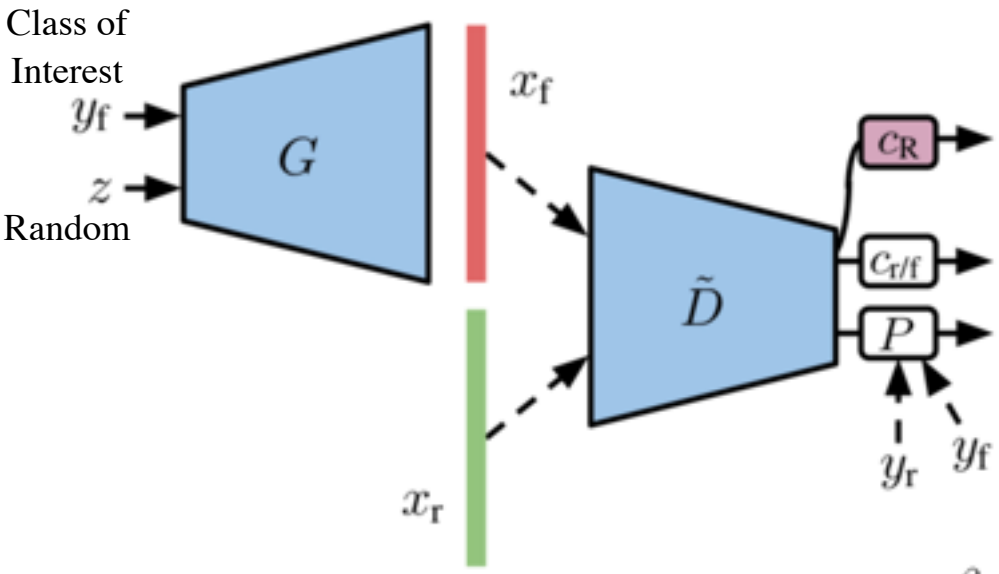

New task, detect rotations in image

All these equations are saying is that they classify rotations from real and fake images.

And… nothing in these equations is meaningful except α, β

$$-\frac{\beta}{|\mathcal{R}|}\sum_{r\in\mathcal{R}}\mathbb{E}_{x\sim p_{\text{data}}(x)}[\log p(c_R(\tilde{D}(x^r)=r)]$$

and

$$-\frac{\alpha}{|\mathcal{R}|}\mathbb{E}_{(z,y)\sim p(z,y)}[\log p(c_R(\tilde{D}(G(z,y)^r)=r)],$$

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Lucic, M… *arXiv preprint*

Cla… Int…

Ran…

Table 3. Top-1 and top-5 error rate (%) on the IMAGENET validation set of $c_{S^2L}(F(x))$ using both self- and semi-supervised losses as described in Section 3.1. While the models are clearly not state-of-the-art compared to the fully supervised IMAGENET classification task, the quality of labels is sufficient to match and in some cases improve the state-of-the-art GAN natural image synthesis.

	LABELS		
METRIC	5%	10%	20%
TOP-1 ERROR	50.08	36.74	29.21
TOP-5 ERROR	26.94	16.04	10.33

And… nothing in these equations is meaningful except α, β

$$\frac{1}{|\mathcal{R}|} \mathbb{E}_{(z,y)\sim p(z,y)} [\log P(c_k(D(G(z,y)))) - \ldots]$$