MSBA 434: Advanced Workshop on Machine Learning

Lecture 4: Generative Adversarial Networks

UCLA Anderson

2019

Danylo Vashchilenko

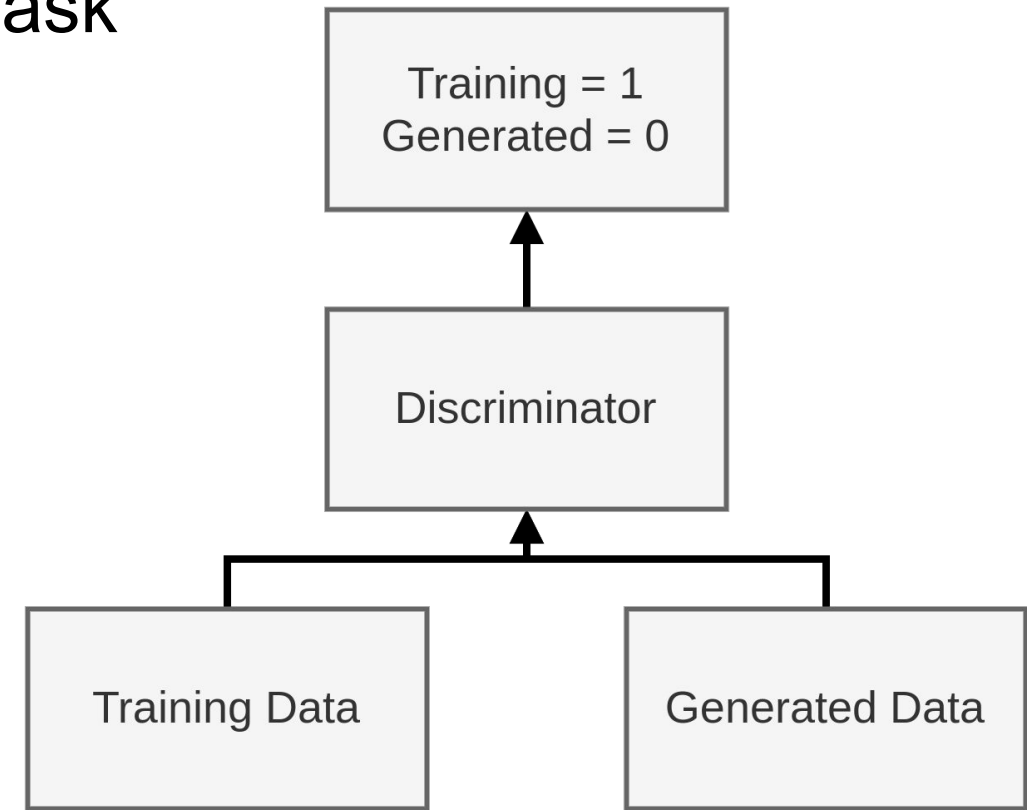
Agenda

1. Adversarial Training
2. Case Study: DCGAN
3. Case Study: SRGAN

4. Case Study: BigGAN
5. Assignment 4

6. Case Study: PGN
7. Case Study: StackGAN
8. Other Generative Tasks

Discriminator Task



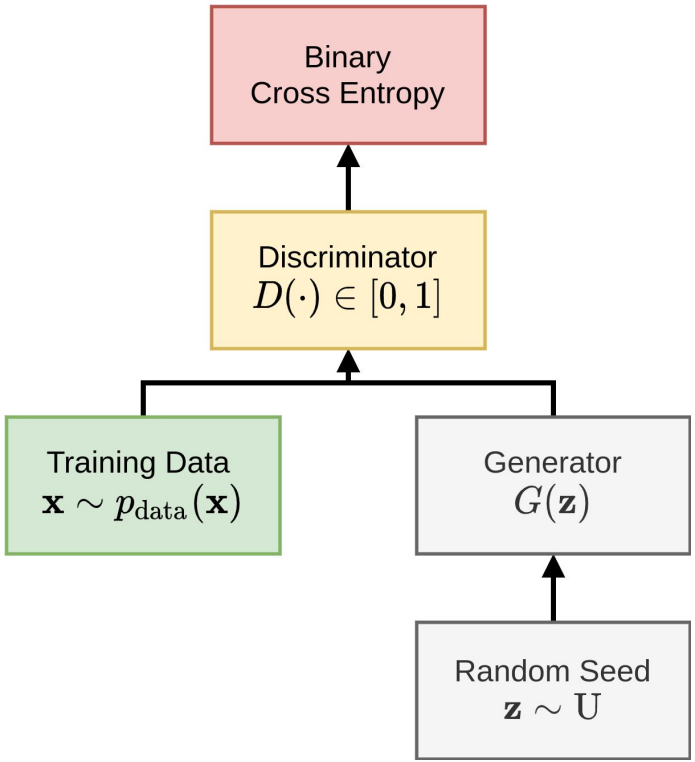
Goodfellow, I., et al. (2014)

Discriminator Training

Discriminator given a batch of examples from training data and the generator's output.

Cost is the average binary cross-entropy across the batch:

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



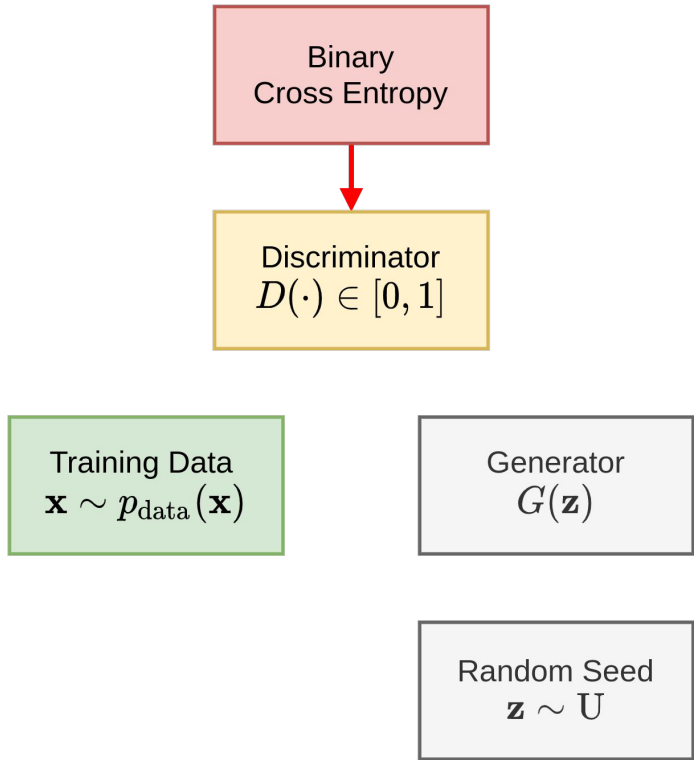
Goodfellow, I., et al. (2014)

Discriminator Training

Discriminator given a batch of examples from training data and the generator's output.

Cost is the average binary cross-entropy across the batch:

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



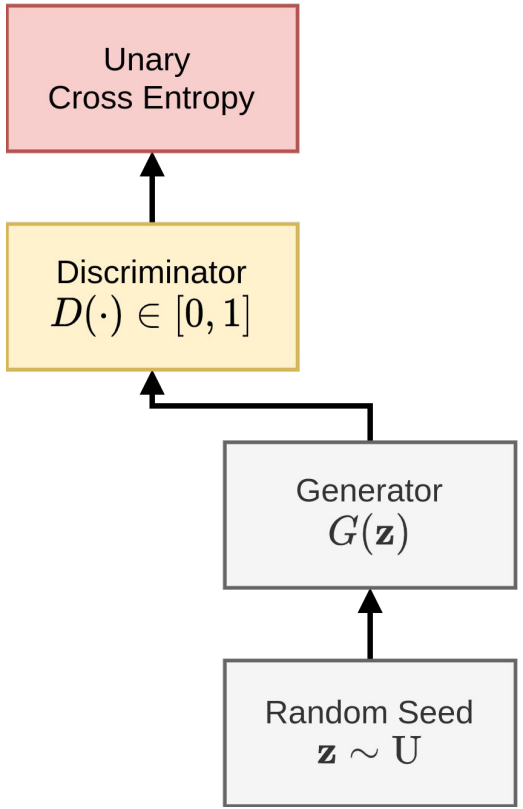
Goodfellow, I., et al. (2014)

Generator Training

The discriminator is given a batch of examples from the generator's output, so it should always output 0.

The generator's cost goes up when the discriminator thinks the samples are coming from the generator:

$$C_G = -\frac{1}{m}\sum_{i=1}^{m}\left[\log\left(D(G(\mathbf{z}^{(i)}))\right)\right]$$



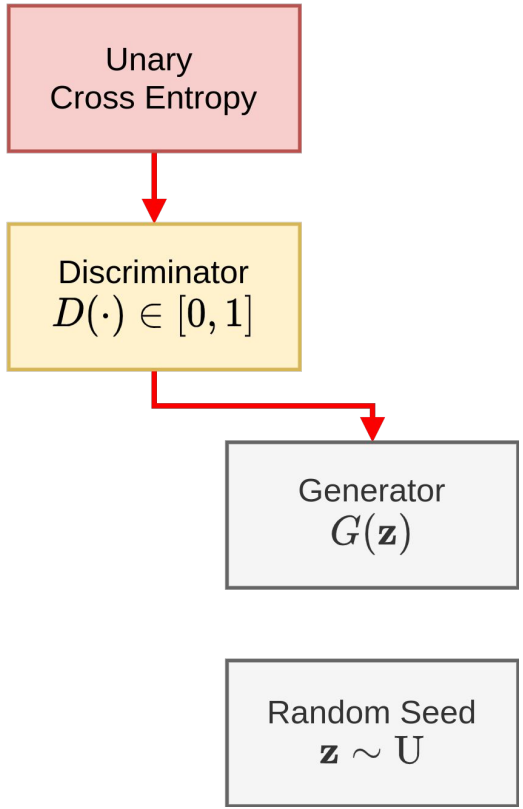
Goodfellow, I., et al. (2014)

Generator Training

The discriminator is given a batch of examples from the generator's output, so it should always output 0.

The generator's cost is the unary cross entropy, which penalizes the discriminator predicting 0:

$$C_G = -\frac{1}{m}\sum_{i=1}^{m}\left[\log\left(D(G(\mathbf{z}^{(i)}))\right)\right]$$



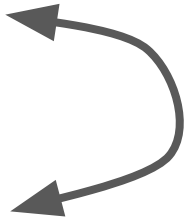
Goodfellow, I., et al. (2014)

Training Procedure

1. Sample a batch of training and generated data
2. Train the discriminator for several steps

3. Sample a batch of noise
4. Train the generator

5. Repeat steps 1-4 until convergence.



Training one component at a time

Goodfellow, I., et al. (2014)

Combined Training

$$V(D,G) = \mathop{\mathbb{E}}_{\mathbf{x}}\left[\log D(\mathbf{x})\right] + \mathop{\mathbb{E}}_{\mathbf{z}}\left[\log\left(1 - D(G(\mathbf{z}))\right)\right]$$

Rewards true positives

Rewards true negatives

$$\min_G \max_D V(D,G)$$

$$G(\mathbf{z}) \rightarrow p_{\text{data}}(\mathbf{x})$$

$$D(G(\mathbf{z})) \rightarrow 0.5$$

Goodfellow, I., et al. (2014)

Generator Output

BigGAN - Brock, A., et al. (2019)

StyleGAN2 - Karras et al (2019)

Ryan Hover

https://arthurfindelair.com/thisnightskydoesnotexist/

GAN Zoo

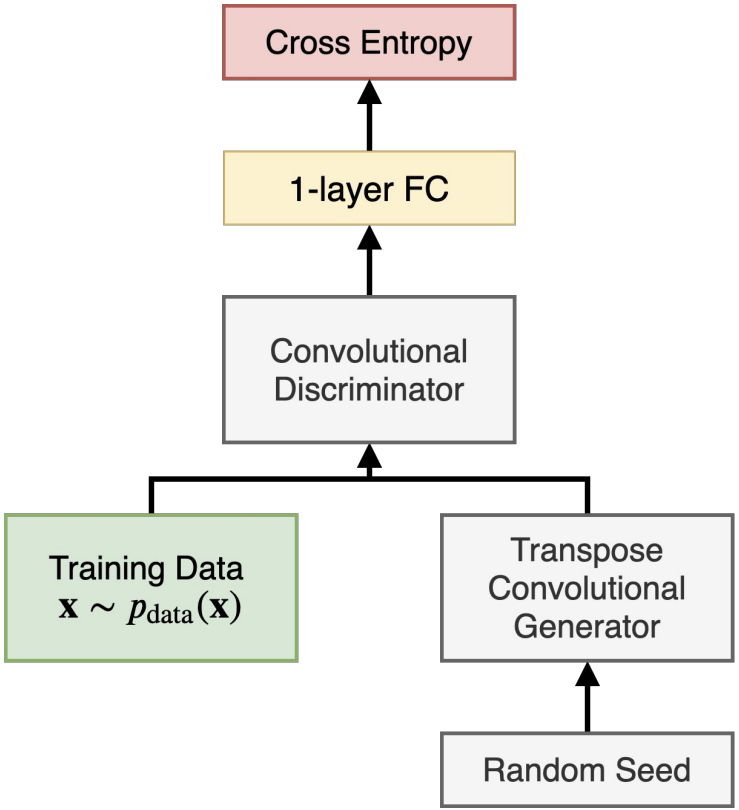
Source: https://github.com/hindupuravinash/the-gan-zoo

Case Study: Deep Convolutional GAN

Convolutional Discriminator
Strides instead of pooling

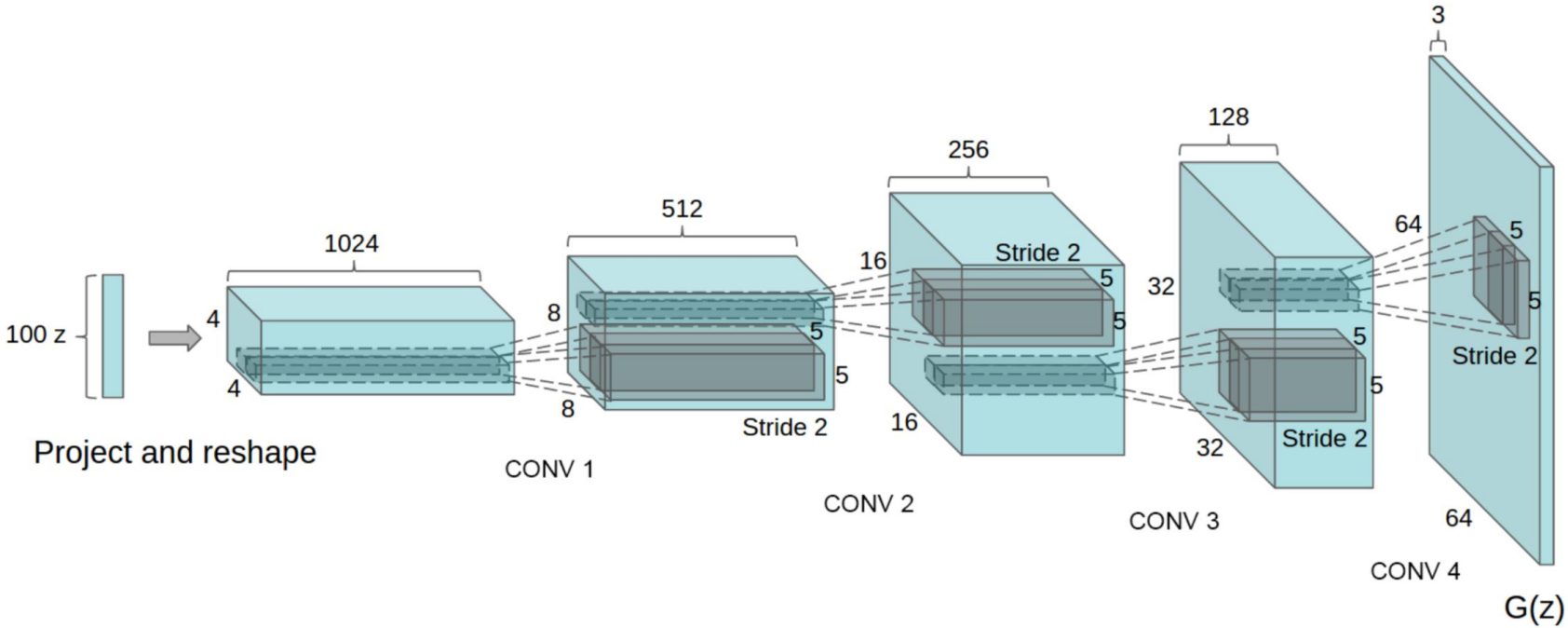
Global average instead of deep FC classifier

Convolutional Generator
Transpose convolutions



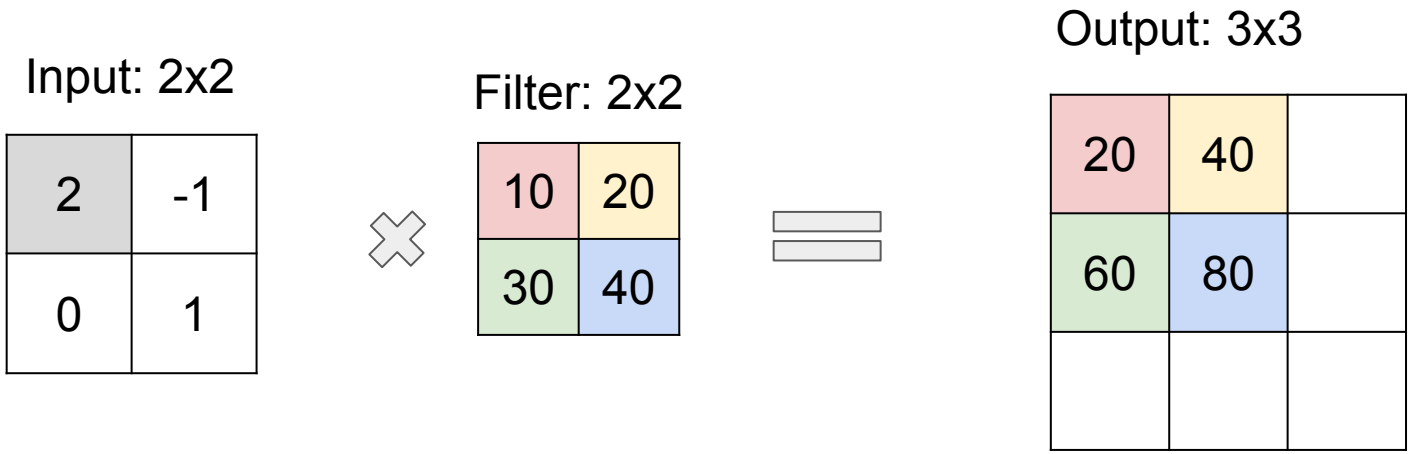
Radford, A., et al. (2016)

DCGAN: Generator



Radford, A., et al. (2016)

Transpose Convolution



Transpose Convolution

Input: 2x2

2	-1
0	1

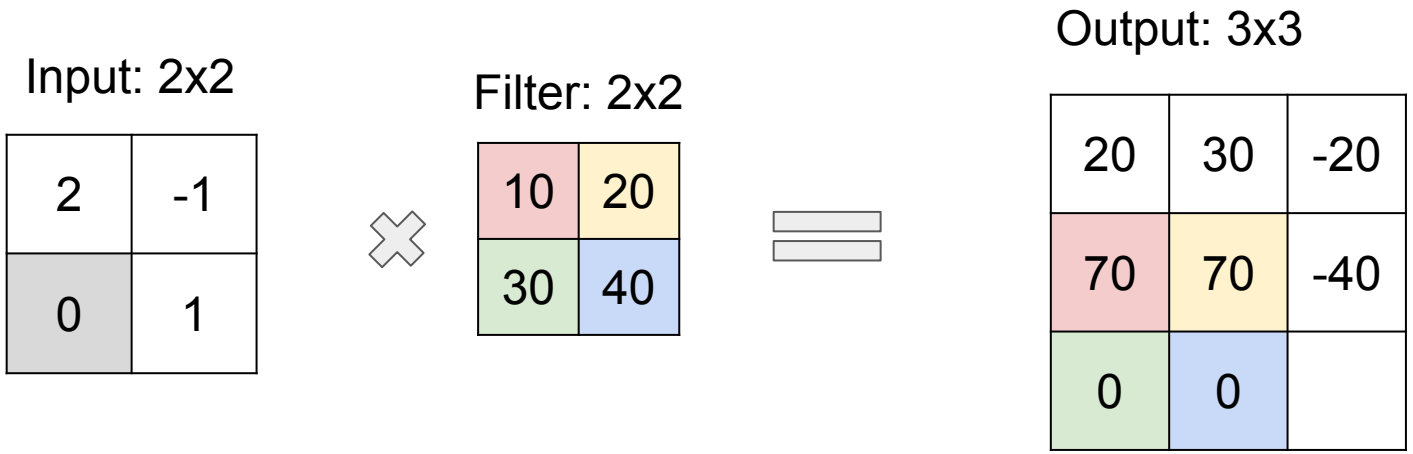
Filter: 2x2

10	20
30	40

Output: 3x3

20	30	-20
60	50	-40

Transpose Convolution



Transpose Convolution

Input: 2x2

2	-1
0	1

Filter: 2x2

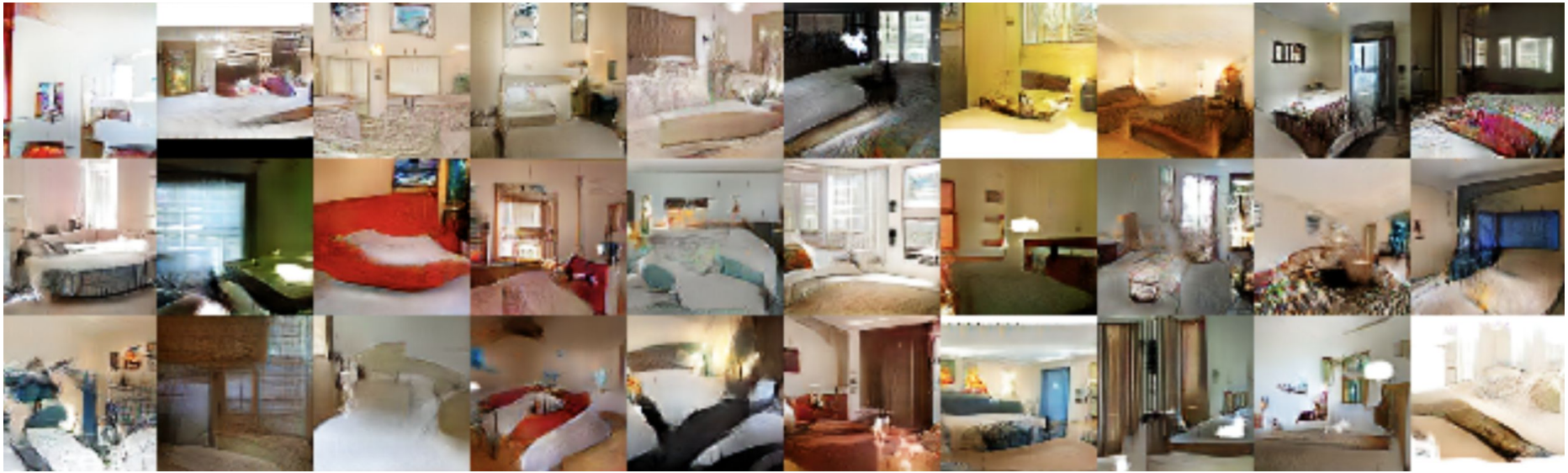
10	20
30	40

Output: 3x3

20	30	-20
70	80	-30
0	30	40

Also called fractionally-strided convolution.
Linear algebra details: https://arxiv.org/pdf/1603.07285.pdf

DCGAN: Generated Samples



Trained on LSUN bedroom images.

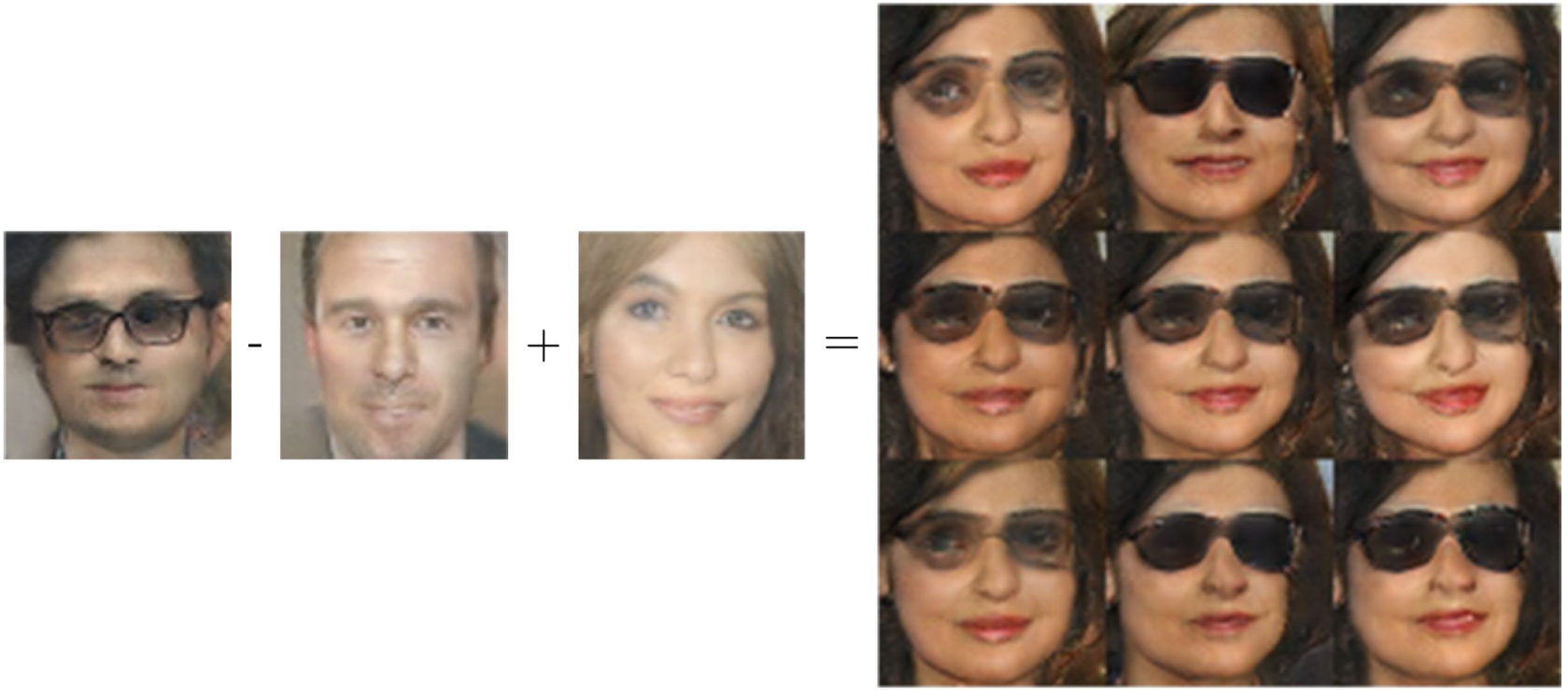
Radford, A., et al. (2016)

DCGAN: Latent Space

Interpolation between **z** vectors with and without windows in the generated image.

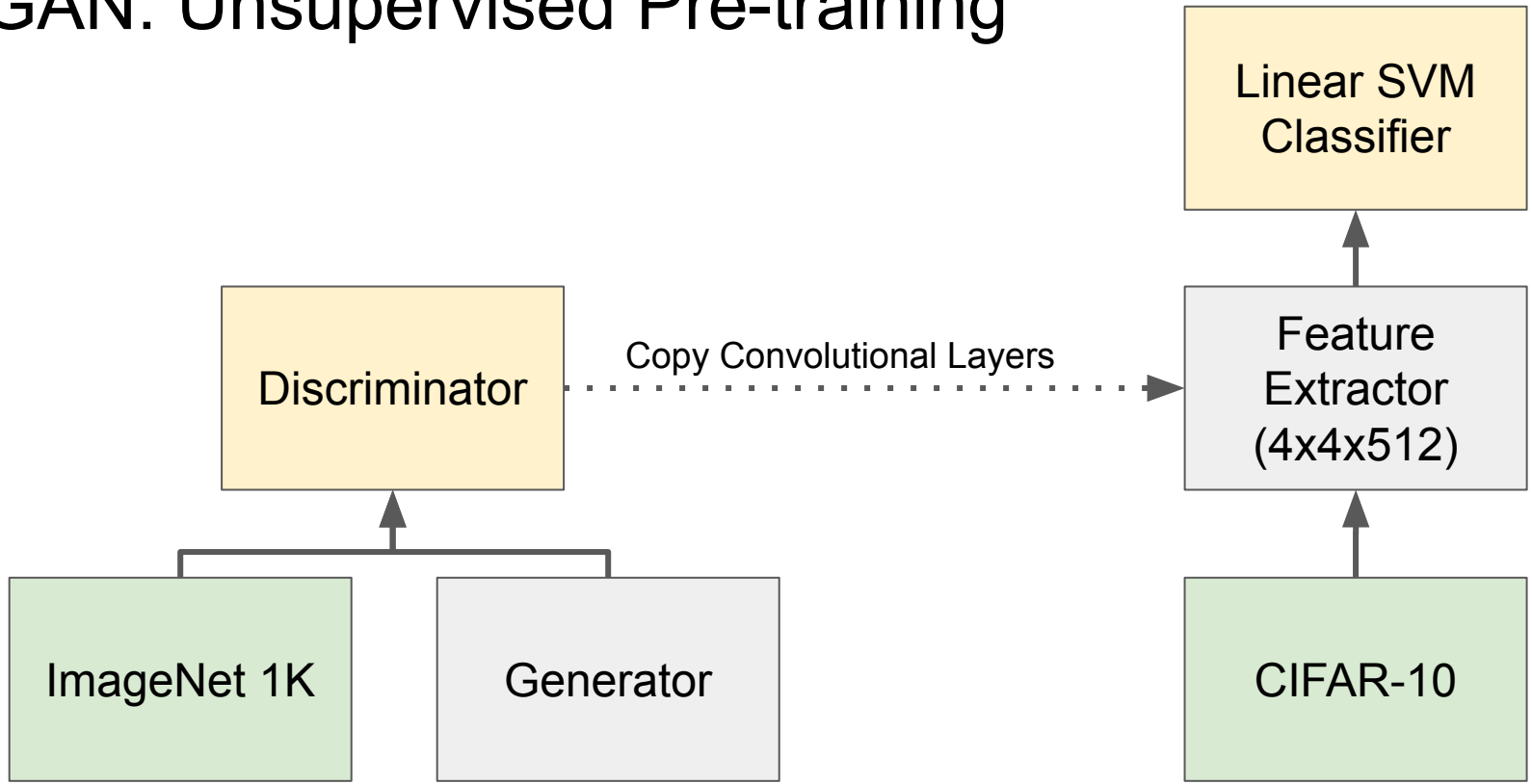
Radford, A., et al. (2016)

DCGAN: Latent Space



Radford, A., et al. (2016)

DCGAN: Unsupervised Pre-training



Radford, A., et al. (2016)

Case Study: SuperResolution GAN

Supervised Task

Given a low-resolution image, reconstruct the high-resolution image.

Prior Art

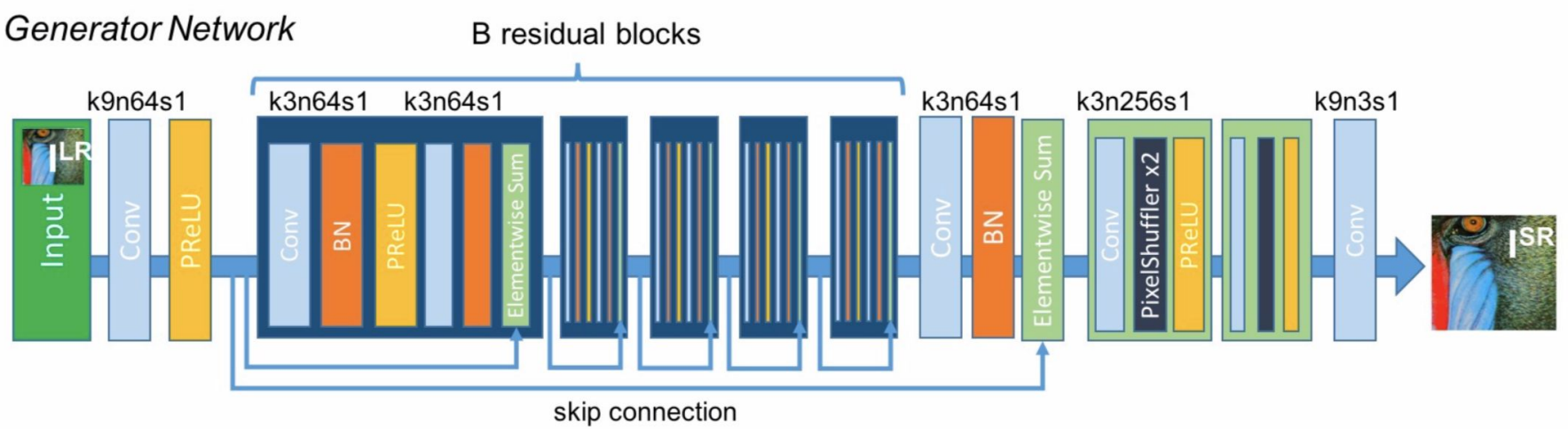
Residual Transpose CNN with MSE loss has shown great performance on this task but the reconstructions are blurry.

Bicubic

Original

Ledig, C., et al. (2017)

SRGAN: Generator CNN



Similar to ResNet, but uses Transposed Convolutions to increase the spatial dimensions.

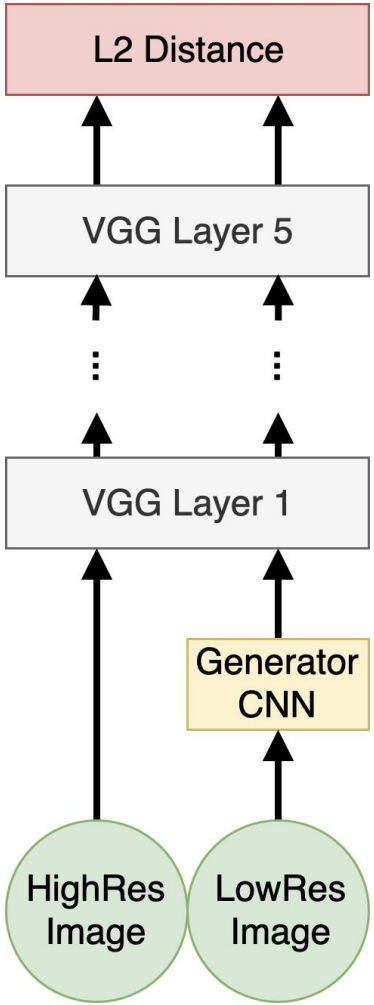
Ledig, C., et al. (2017)

SRGAN: VGG Loss

Comparison of reconstructed vs the original image is done using pre-trained VGG19.

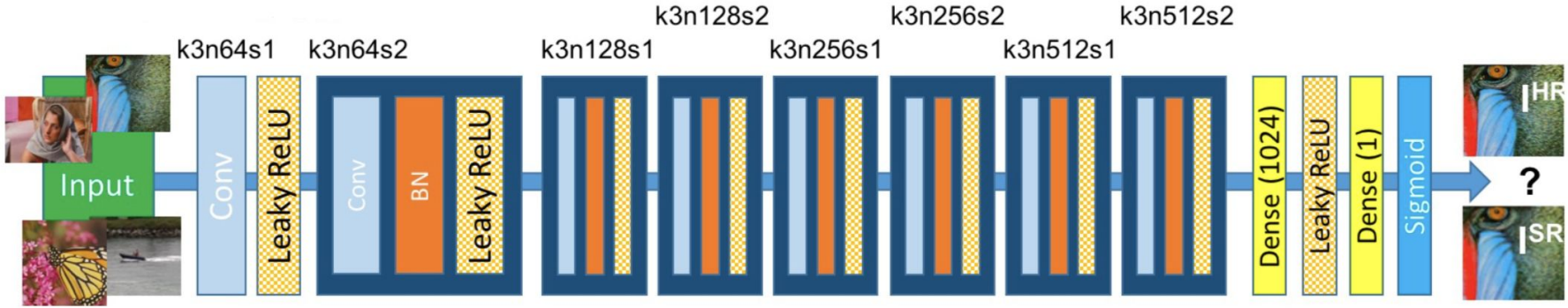
Both images go through several convolutional layers of VGG19, and the final activation volumes are compared.

The loss is the L2 distance between the activation volumes of the reconstruction vs the original image.



Ledig, C., et al. (2017)

SRGAN: Discriminator CNN



1. Fully-convolutional CNN
2. MLP Classifier
3. Binary Cross Entropy.

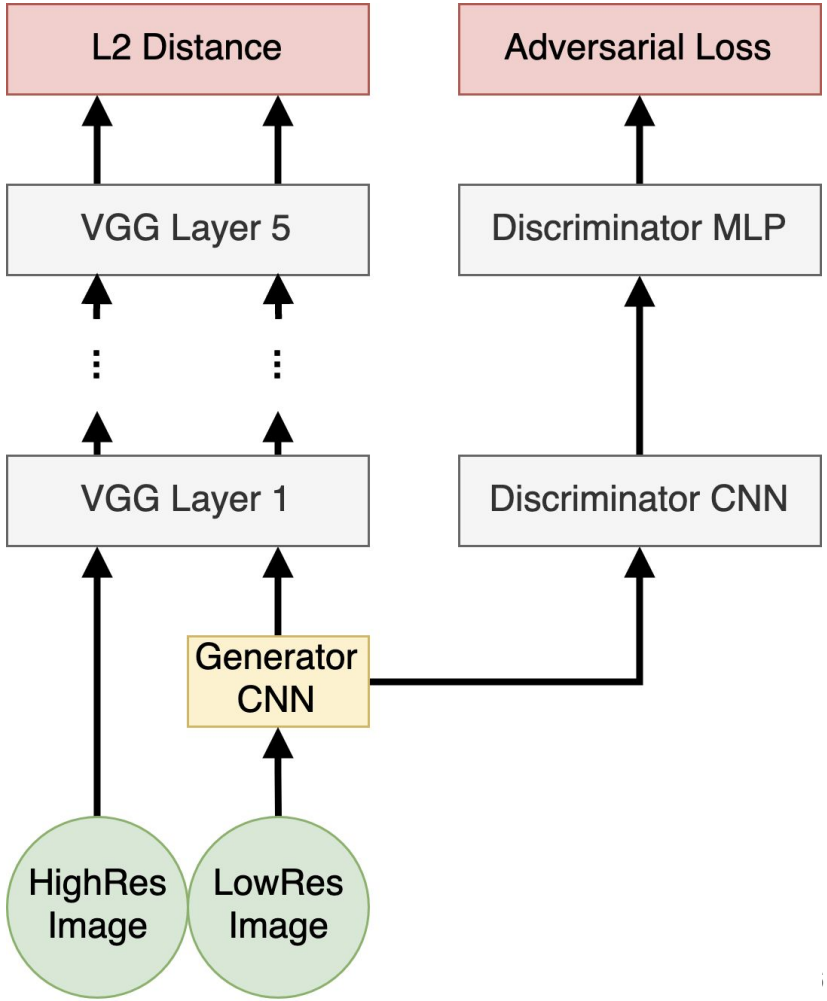
Ledig, C., et al. (2017)

SRGAN: Forward Pass

Dual Loss

Weighted sum of Adversarial Loss and VGG Activation Loss

Authors find the AL+VGG combo to work better than individual losses or MSE.



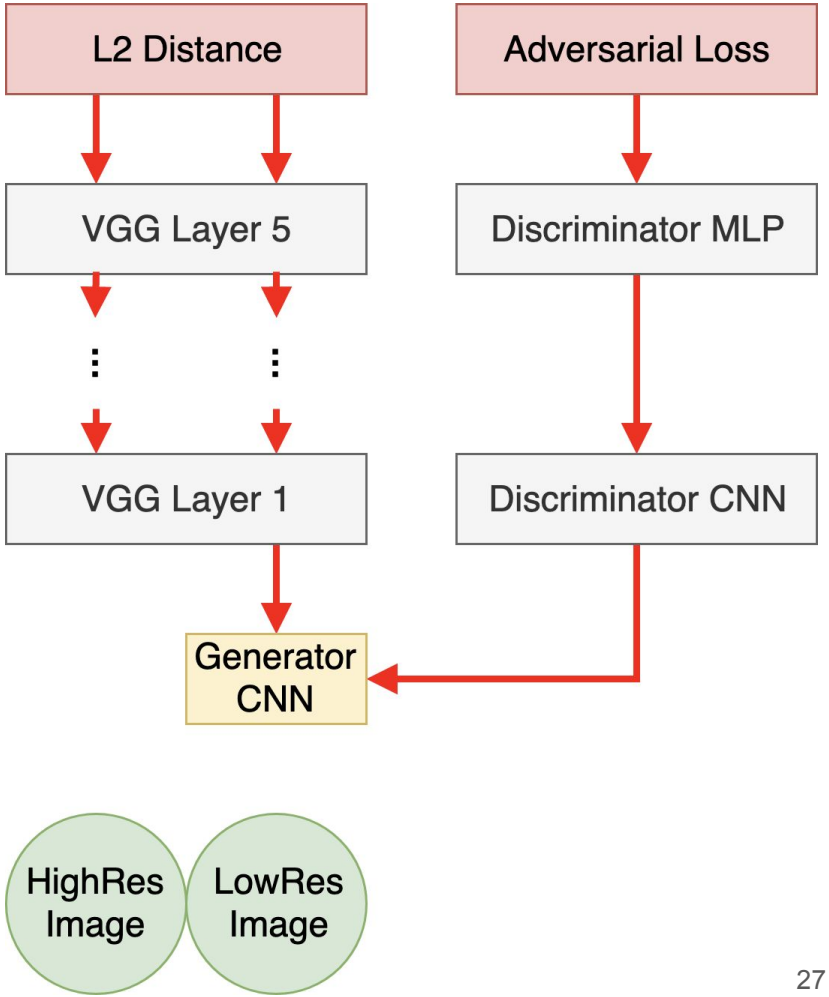
Ledig, C., et al. (2017)

SRGAN: Backprop

Dual Loss

Weighted sum of Adversarial Loss and VGG Activation Loss

Authors find the AL+VGG combo to work better than individual losses or MSE.



Ledig, C., et al. (2017)

SRGAN: Examples

Bicubic

MSE

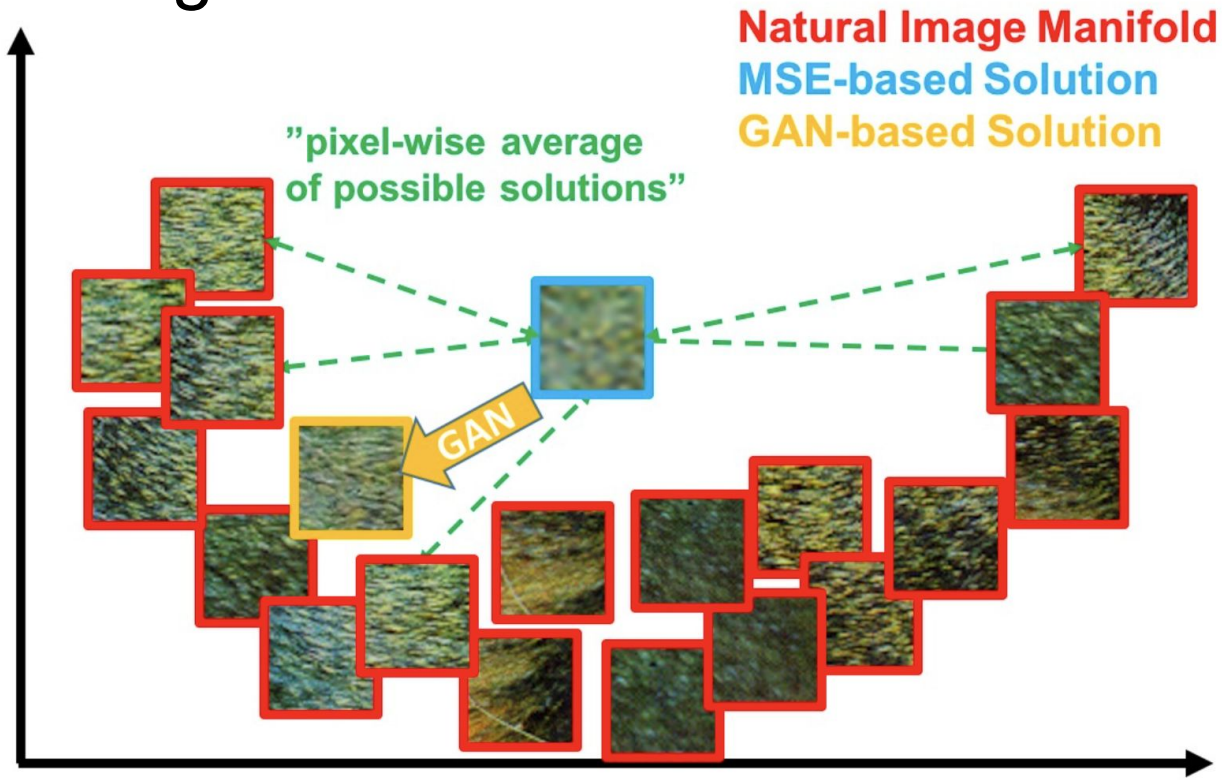
VGG+AL

Original

Ledig, C., et al. (2017)

SRGAN: What's wrong with MSE?

A mean is often a bad approximator of any of the samples from multi-modal distributions.



Ledig, C., et al. (2017)

Case Study: BigGAN

Which one of these images is real?

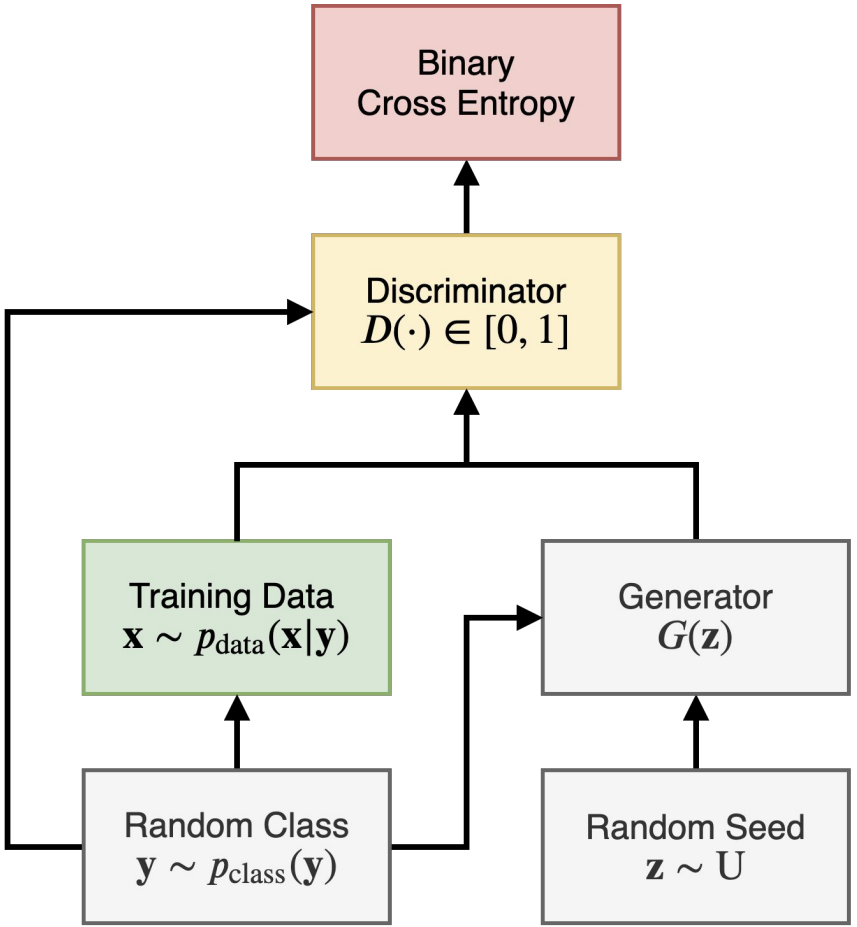
Brock, A., et al. (2019) / USDA (2014)

BigGAN

Class-conditional generation

High-resolution images
512 x 512

Quality vs diversity trade-off
via noise truncation



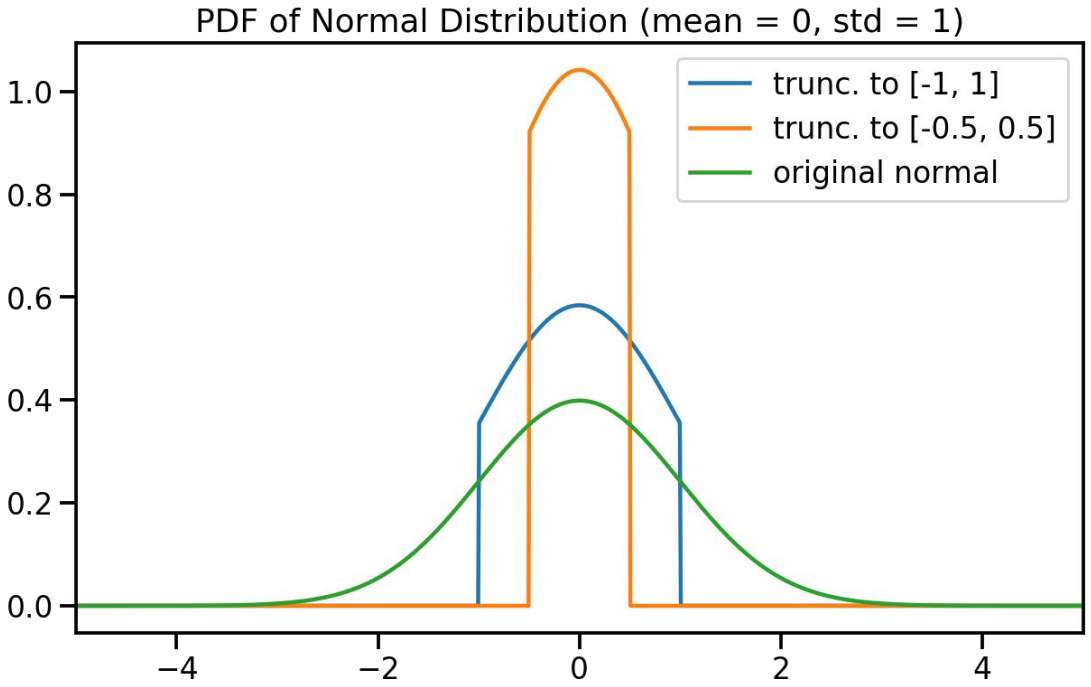
Brock, A., et al. (2019)

BigGAN: Noise Truncation

Properties of symmetrically truncated normal distribution:

1. excludes low-probability events
2. preserves mean
3. lowers variance

Enables trade-off of diversity for quality.



Brock, A., et al. (2019)

BigGAN: Diversity

Larger noise space allows to generate diverse sets of same-class images.

Since low-probability noise was less frequently checked by the discriminator, its quality is lower.

Diversity and quality are a trade off.

Brock, A., et al. (2019)

BigGAN: Class Interpolation

1. Randomly choose a noise vector

2. Choose two classes
   (terrier and tiger in this example)

3. Linearly interpolate
   one-hot-encoded class vectors

4. Feed the constant-noise vector, and
   the class vectors to the generator.

Brock, A., et al. (2019)

iPod to ice cream

Train to golf cart

Demo

BigGAN.ipynb

Assignment 4

1. BigGAN model
   a. Optional reading: https://arxiv.org/abs/1809.11096

2. Explore the relationship between truncation and image properties
   a. See the assignment template notebook for details

3. Deliverables:
   a. Jupyter notebook with task solutions
   b. Fully executed and saved with images

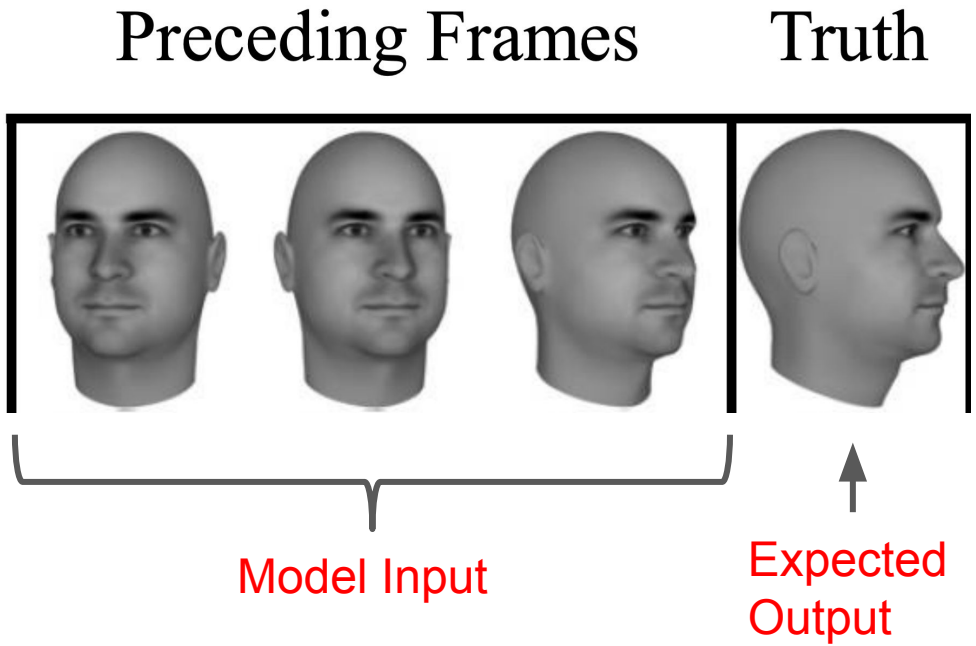
4. Due by EOD 10/25

Case Study: Predictive Generative Network

Task
Predict the next frame in a sequence given last 3 frames

Every sequence has a randomly generated face rotating around Y axis.

Initial angle and angular velocity are random across sequences.



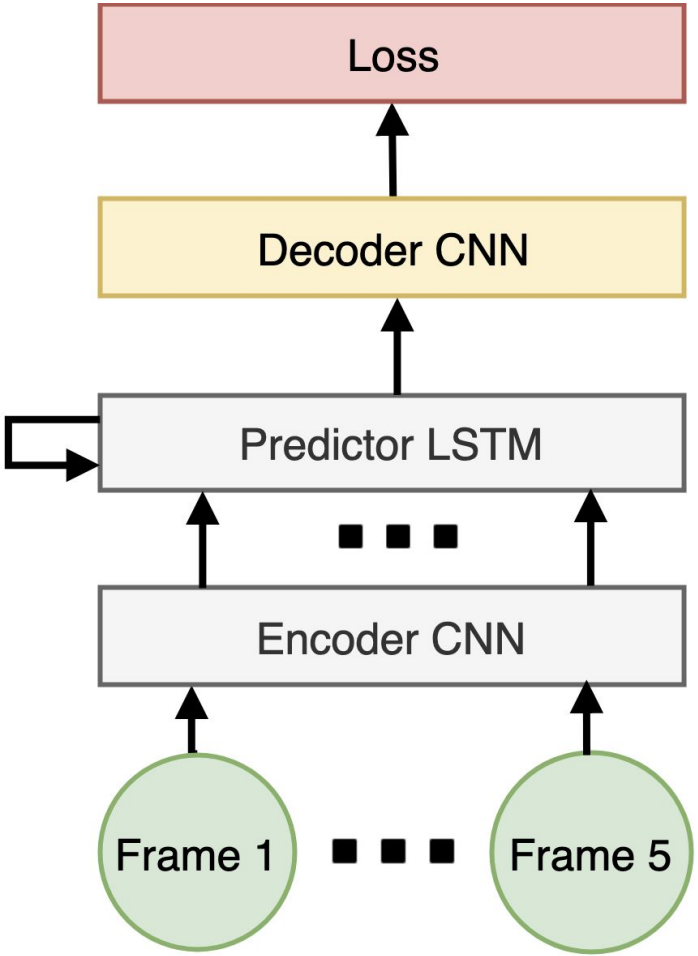
Lotter, W., et al. (2016)

PGN: Generator Model

1. Encoder CNN extracts each frame's features into a low-dimensional encoding.

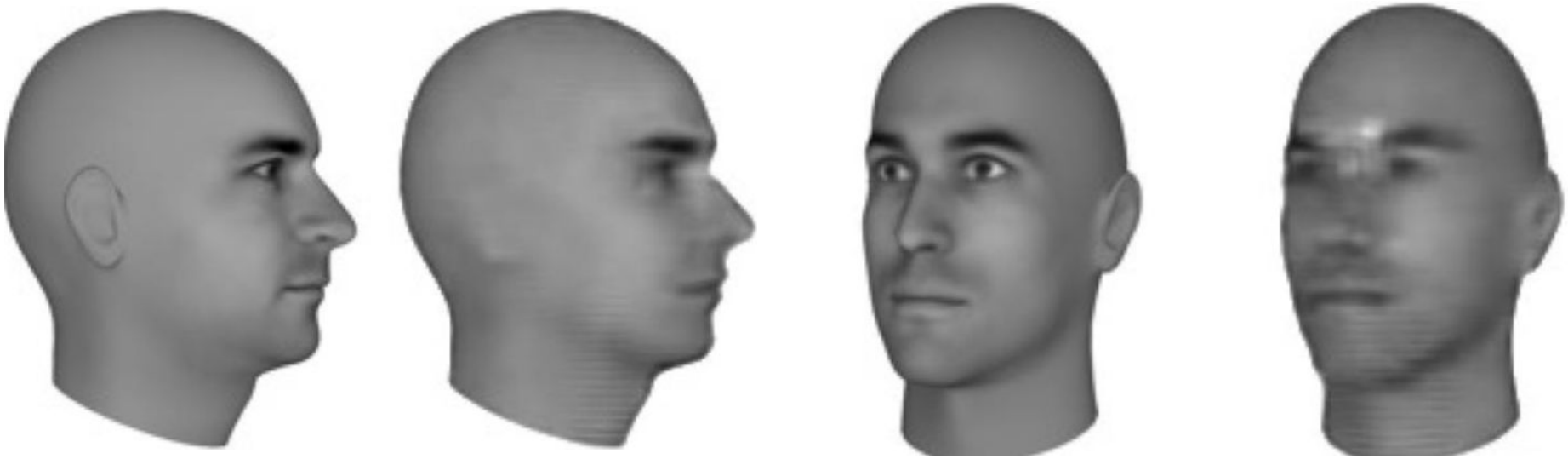
2. Predictor LSTM consumes each encoding sequentially, and produces an encoding for the target frame.

3. Decoder CNN converts the encoding into the target frame.



Lotter, W., et al. (2016)

PGN: Mean Squared Error



Target Prediction Target Prediction

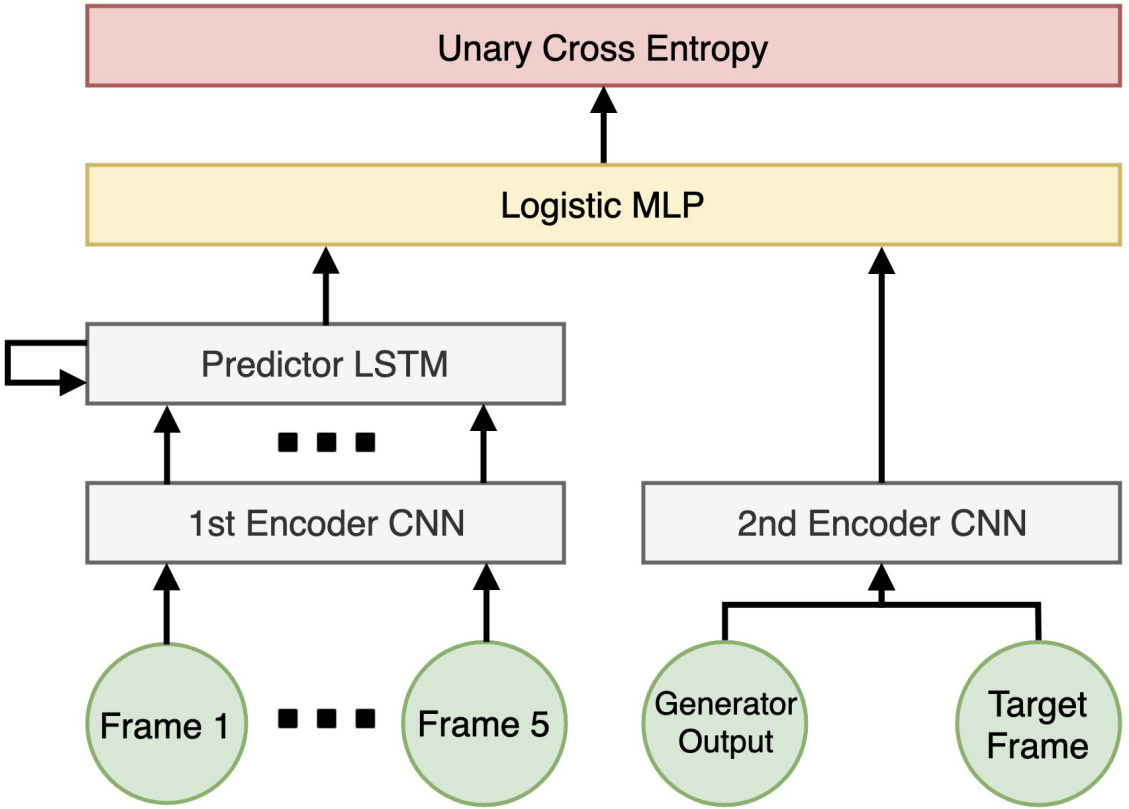
Lotter, W., et al. (2016)

PGN: Discriminator

1st Encoder CNN and Predictor LSTM form conditional expectations about the target frame.

2nd Encoder CNN extracts features from the adversarial input.

Logistic MLP determines whether the adversarial input is the true target frame.



Lotter, W., et al. (2016)

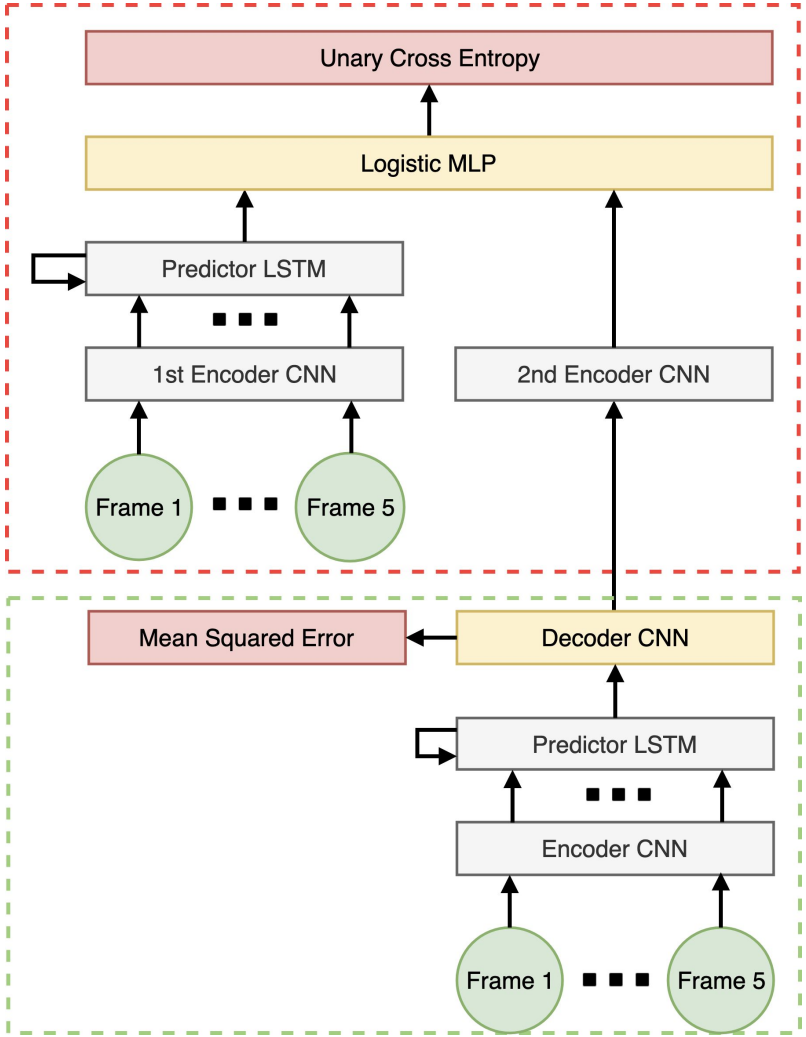
PGN: Generator Training

The generator is trained with dual loss:

- MSE against the target frame
- Adversarial loss

The final cost is a weighted sum of the two losses. Weights are hyperparams.

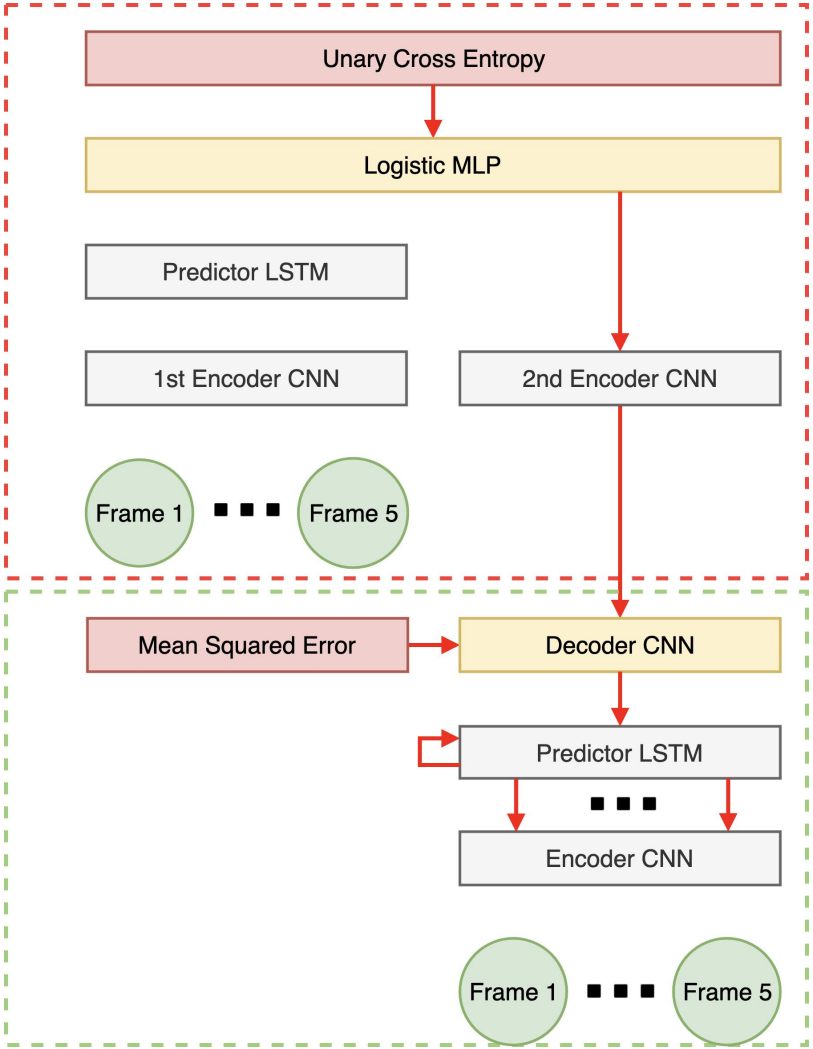
None of the LSTMs or CNNs share parameters across layers.



Lotter, W., et al. (2016)

PGN: Generator Backprop

During backward propagation gradient flows through only a part of the discriminator.

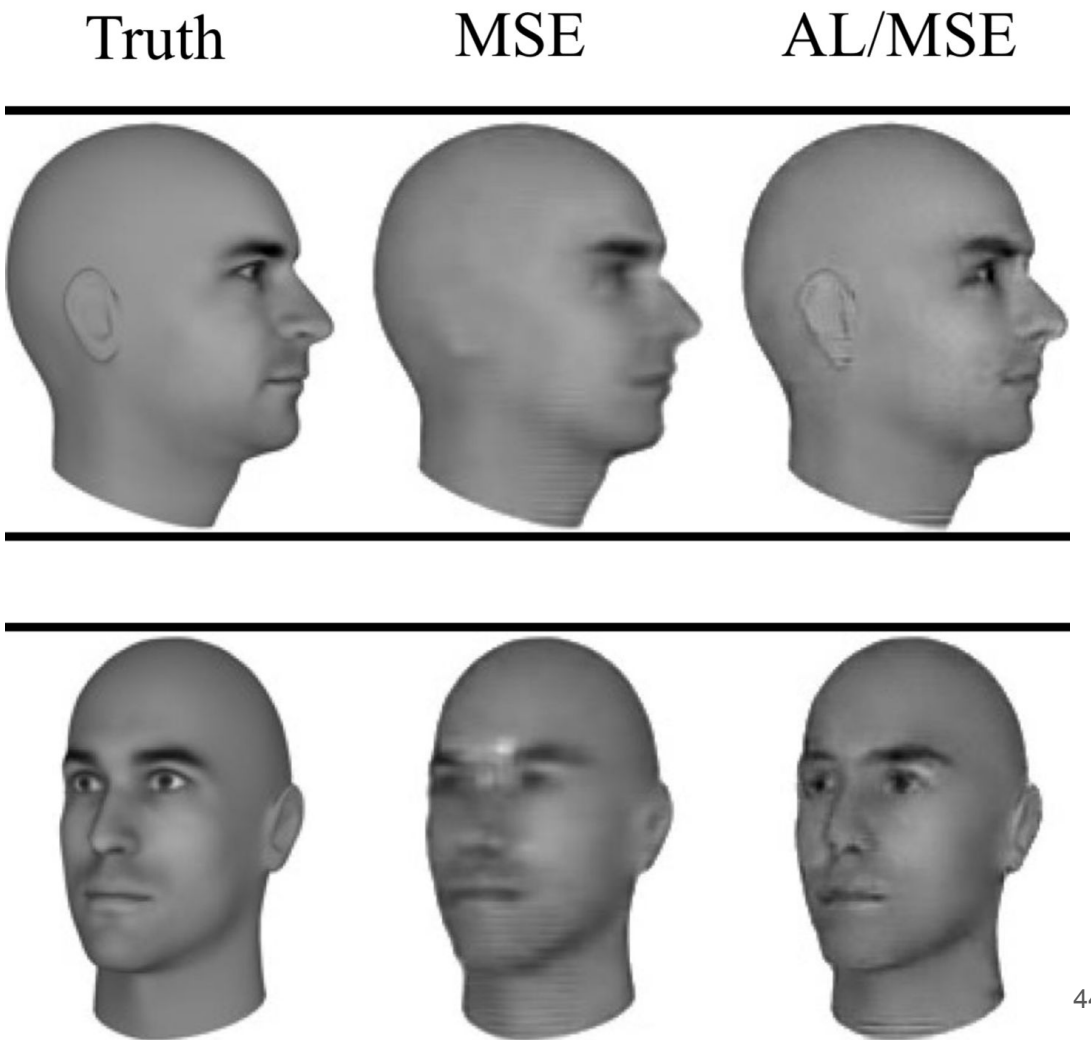


Lotter, W., et al. (2016)

PGN: Dual Loss

Model trained with Dual Loss outputs sharp frames which more closely resemble the target frames.

Read the paper for more predictive task examples.



Lotter, W., et al. (2016)

Text to Synthetic Image

this small bird has a pink breast and crown, and black primaries and secondaries.

this magnificent fellow is almost all black with a red crest, and white cheek patch.

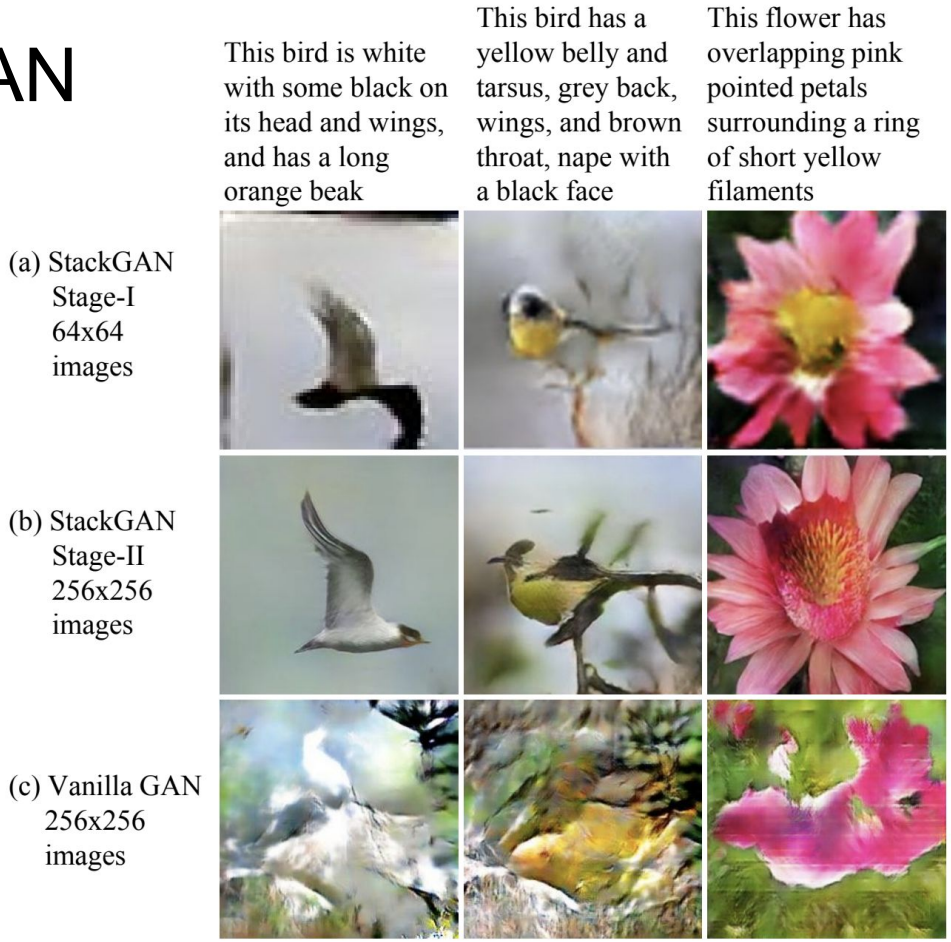
Reed, S., et al. (2016)

Case Study: StackGAN

Multi-stage generator/discriminator:

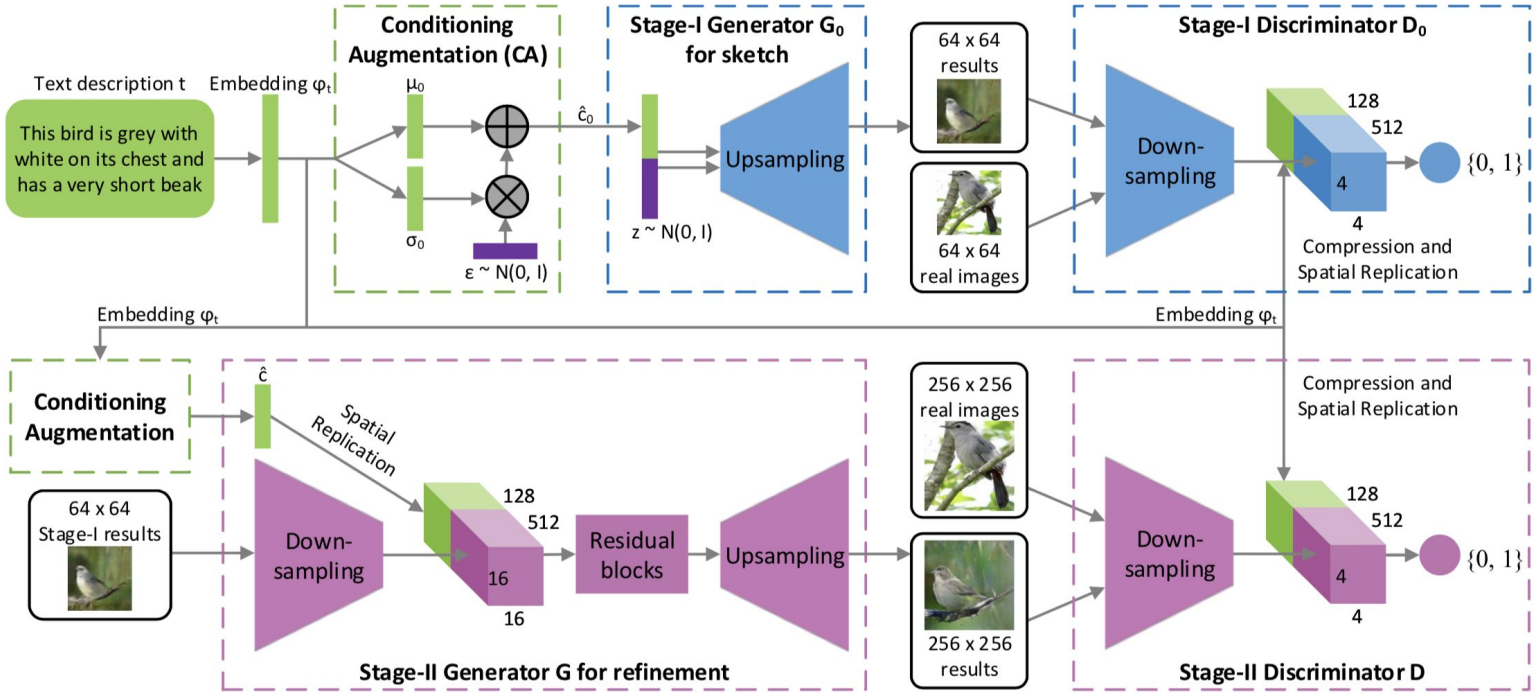
1. High-level sketch
2. Fine details

Embeddings for text conditioning but no recurrent layers



Zhang, H., et al. (2016)

StackGAN: Architecture



Zhang, H., et al. (2016)

References

1. Generative Adversarial Nets (Goodfellow, I., et al. 2014)
2. Generative Adversarial Text to Image Synthesis (Redd, S., et al., 2016)
3. Large Scale GAN Training for High Fidelity Natural Images Synthesis (Brock, A., et al., 2019)
4. NIPS 2016 Tutorial: Generative Adversarial Networks (Goodfellow, I., 2016)
5. Photo-Realistic Single Image Super-Resolution Using a Generative Adversarial Network (Ledig, C., et al., 2017)
6. StackGAN: Text to Photo-realistic Image Synthesis with Stacked Generative Adversarial Networks (Zhang, H., et al., 2017)
7. Unsupervised Learning of Visual Structure using Predictive Generative Networks (Lotter, W., et al., 2016)
8. Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks (Radford, A., Metz, L., 2016)

Thank you

Final Q&A Time