



Exploring StyleGAN

CSC 528 - Computer Vision
Alex Teboul

Which faces are real?



1



2



3



4



5



6

Real



Fake





Elise Moreau

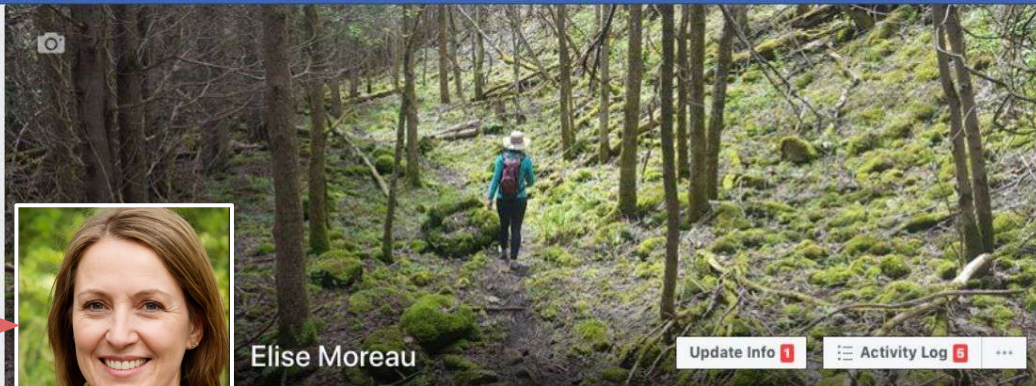


Elise

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Create



Elise Moreau

Update Info

Activity Log

...

Timeline ▾

About

Friends 39

Photos

Archive

More ▾



5 items for you to review



Intro



Add a short bio to tell people more about yourself.

[Add Bio](#)



What's on your mind?



Photo/Video



Tag Friends



Feeling/Activ...



Today's Presentation:

1. StyleGAN Paper Reviews

- a. A Style-Based Generator Architecture for Generative Adversarial Networks*
- b. Analyzing and Improving the Image Quality of StyleGAN*

2. Google Colab - Code Example to Play With

3. Real vs. Fake Faces Survey

4. Next Steps for the Paper

1.a

A Style-Based Generator Architecture for Generative Adversarial Networks

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- March 29, 2019
- Introduces Flickr-Faces-HQ, FFHQ Dataset - Higher Quality/Wider Variation
- Proposes StyleGAN, a variation on traditional GANs for face generation:
 - Adopt techniques from style-transfer learning into a GAN architecture.
 - Automatically learned, unsupervised separation of:
 - High-level attributes (ex. pose)
 - Stochastic variation in the generated images (e.g., freckles, hair)
 - Control of the generated images

1.a A New High Dataset

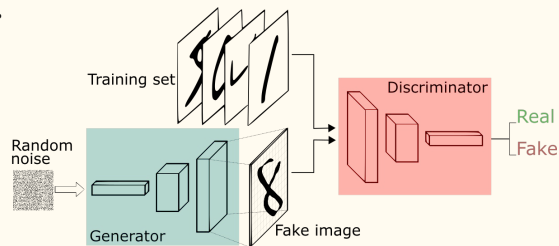
1. 70,000 high quality images
2. Wide Variations in:
 - a. Age
 - b. Sex
 - c. Race
 - d. Pose
 - e. Facial Distortions:
 - i. Glasses
 - ii. Makeup

FFHQ Dataset

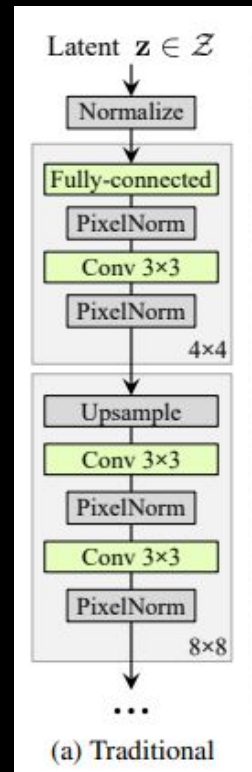


Traditional GAN

1. Traditionally, a generator architecture gets a random noise sample as an input, here referred to as z .
2. That z vector is then fed through multiple upsampling and convolutional layers, until you get an image.
3. In this case, the researchers at NVIDIA also make use of another technique they refer to as progressive growing of GANs.
4. The generator and discriminator start using low res, 4x4 and progressively go to higher res.



StyleGAN Architecture

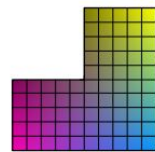
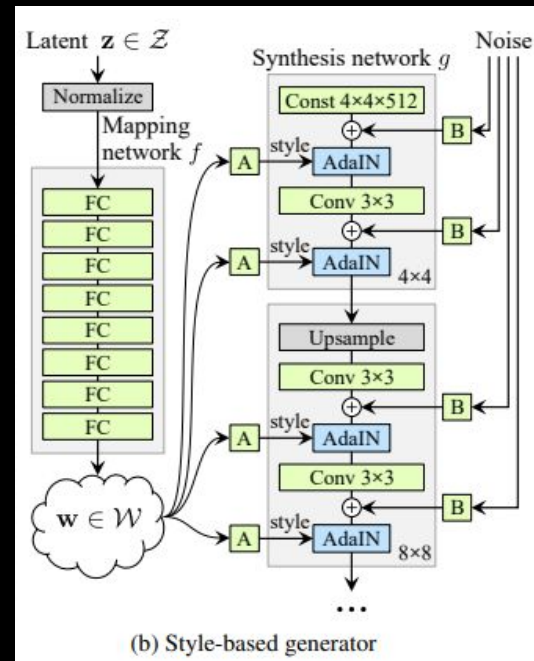


1.a StyleGAN

1. StyleGAN is slightly different. Initially, the noise vector z goes into a mapping network f and transforms it into a different vector W .
2. W does not have to be Gaussian anymore.
3. Now the generator architecture starts with a constant vector, that is optimized during training.
4. The output of the mapping layer W is plugged into multiple layers of the synthesis network using blending layers called AdaIN.
5. Noise is also added in throughout these layers.

*Benefit of this W mapping layer is strange distortions don't happen as frequently from features with unequal distributions.

FFHQ Dataset



(a) Distribution of features in training set



(b) Mapping from \mathcal{Z} to features



(c) Mapping from \mathcal{W} to features

1.b

Analyzing and Improving the Image Quality of StyleGAN

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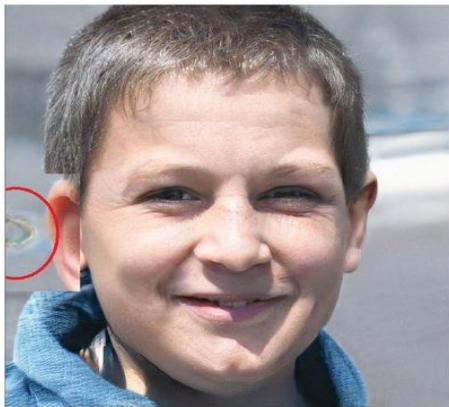
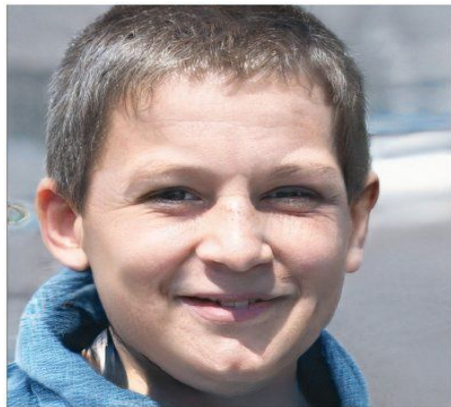
Miika Aittala
NVIDIA

Janne Hellsten
NVIDIA

Jaakko Lehtinen
NVIDIA and Aalto University

Timo Aila
NVIDIA

- March 23, 2020
- Improves the model, in terms of existing distribution quality metrics as well as perceived image quality. Specifically addresses artifacts with a model architecture change.



1.b

Analyzing and Improving the Image Quality of StyleGAN

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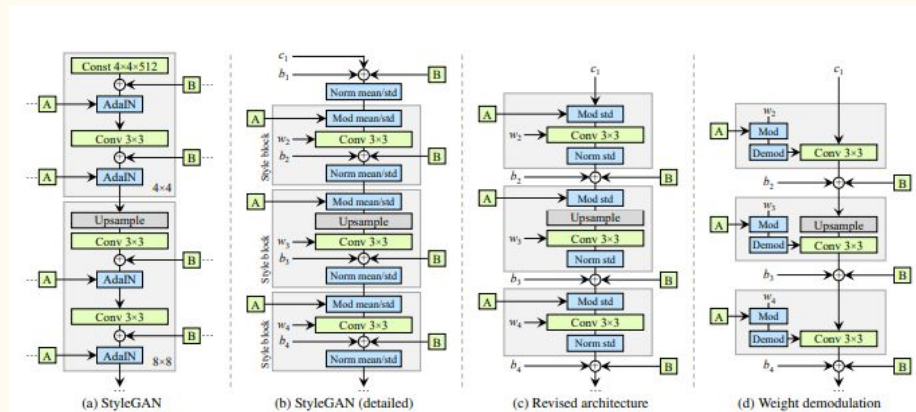
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Timo Aila
NVIDIA

- March 23, 2020
- Redesign the normalization used in the generator, which removes the artifacts.
- Modify model design s.t. training start by focusing on low-resolution images and then progressively shifts focus to higher and higher resolutions — without changing the network topology during training



Google Colab Code Example

Real vs. Fake Faces Survey:

Exploring NVIDIA StyleGAN2: Real vs. Fake Faces

Section 1 of 2

Exploring NVIDIA StyleGAN2: Real vs. Fake

In this Google Form, you will be presented with images of faces. Some images are pictures of real faces and others are generated by a style-based Generative Adversarial Network, developed by a team at NVIDIA.


My hope is to collect data on how well people can tell the real images apart from the fake, computer generated images. It is more important than ever to inform the general public about these techniques, as we are increasingly influenced in digital spaces by both real and fake content.

Email address *


Valid email address

This form is collecting email addresses. [Change settings](#)

Example of a StyleGAN2 Generated image, used as a Facebook profile picture. (This person does not exist)



In the survey, you will be asked "Is this a real person? For the example below, the answer would be "True"

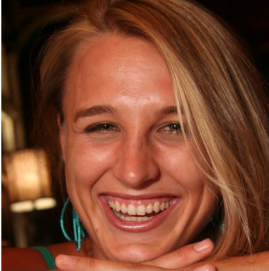


Section 2 of 2

Survey: Is this a real person?

Mark the image as True if you believe it is a picture of a real person - mark the image as False if you believe it was generated by the StyleGAN2 model. 40 Questions total.

1. Is this a real person?



☐ True
☐ False

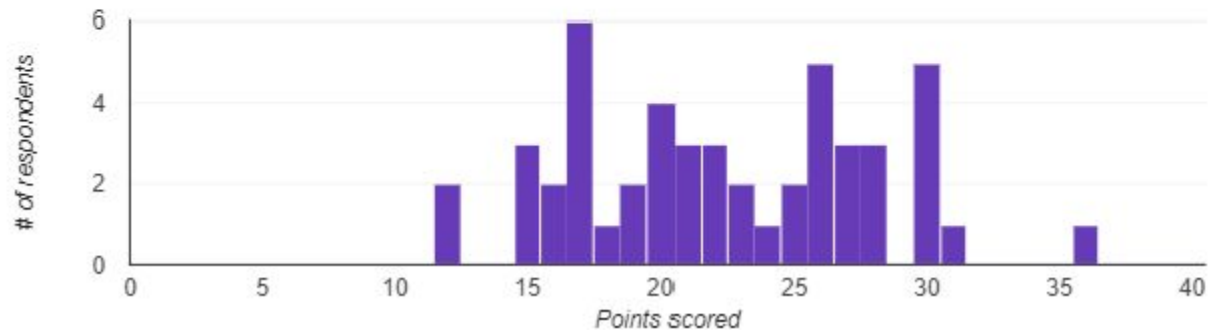
Survey Results (49 responses)

Average
22.45 / 40 points

Median
22 / 40 points

Range
12 - 36 points

Total points distribution

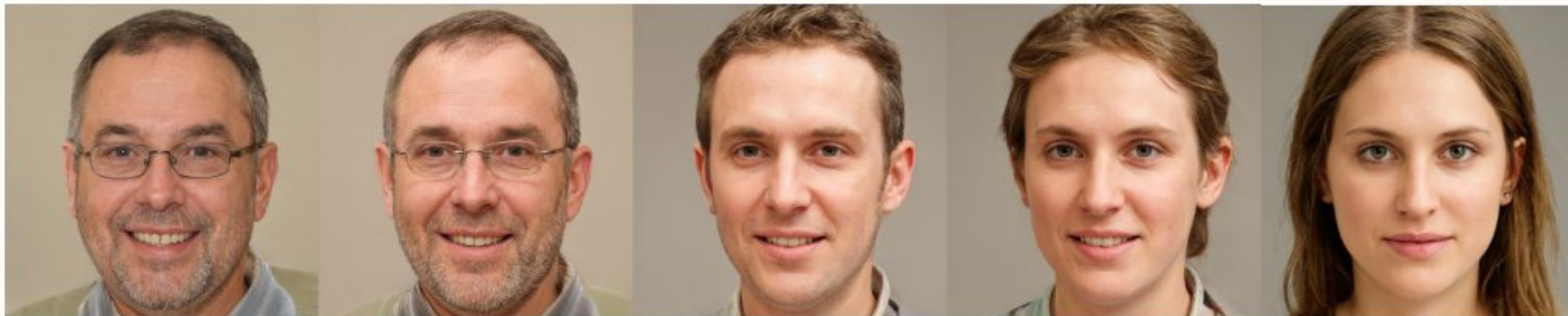


Next Steps for the Paper

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Next Steps for the Paper

1. Manipulations of the Latent Space for Face Editing



“Male”

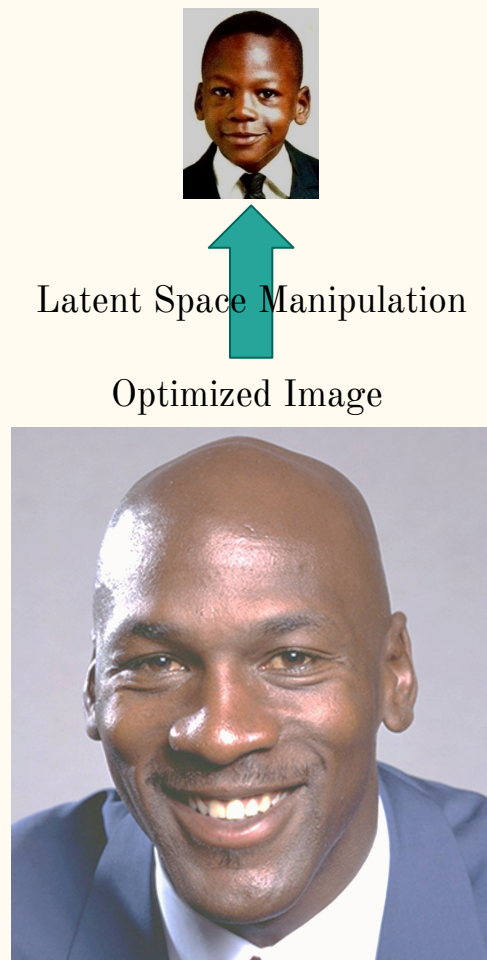
Many steps in latent space

“Female”

*A different challenge for Query Images (ex. using your own face)

Next Steps for the Paper

1. Using Query Images



References

StyleGAN Papers:

- [A Style-Based Generator Architecture for Generative Adversarial Networks](#)
- [Analyzing and Improving the Image Quality of StyleGAN](#)
- [Interpreting the Latent Space of GANs for Semantic Face Editing](#)
- [Image2StyleGAN: How to Embed Images Into the StyleGAN Latent Space?](#)