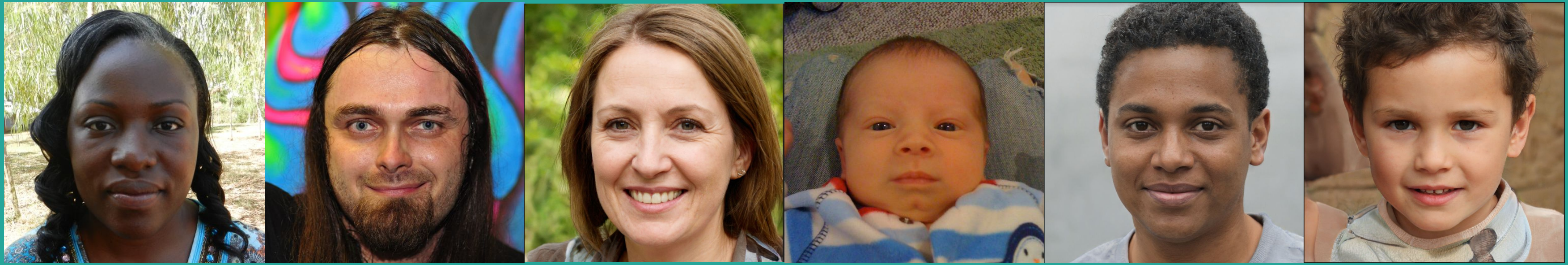


Exploring StyleGAN

CSC 528 - Computer Vision

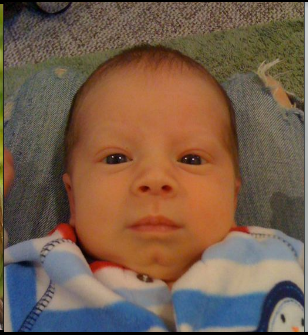
Alex Teboul

Which faces are real?

1

2

3

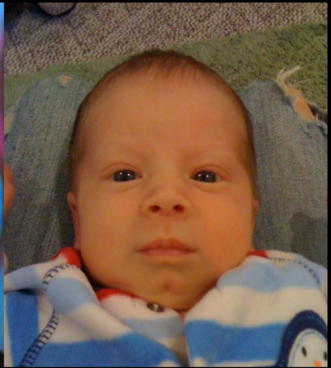


4

5

6

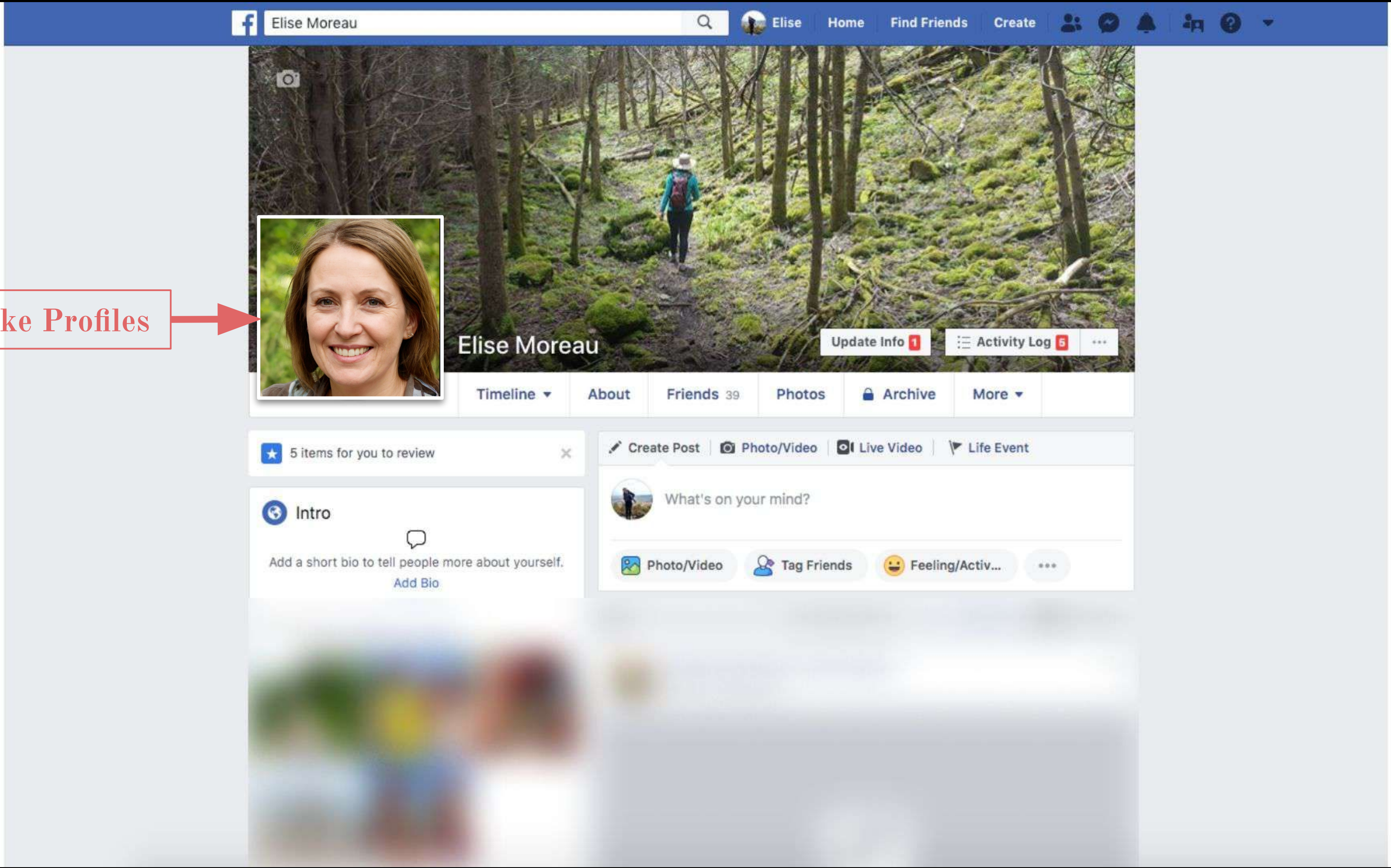
Real


Fake



Fake Profiles



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

Tero Karras
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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

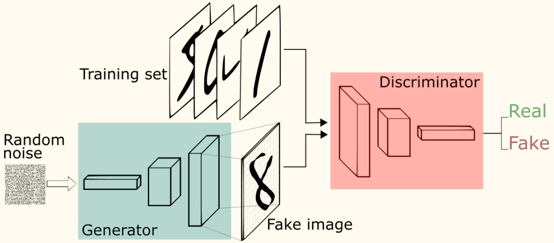
1. 70,000 high quality images
2. Wide Variations in:
   a. Age
   b. Sex
   c. Race
   d. Pose
   e. Facial Distortions:
      i. Glasses
      ii. Makeup

FFHQ Dataset

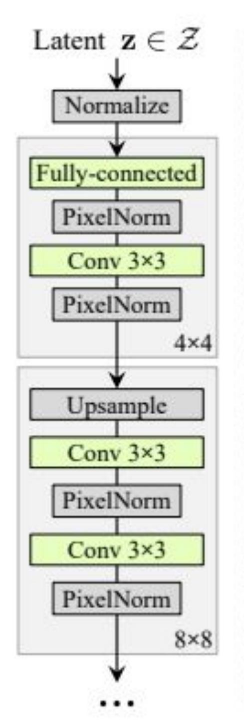
1.a

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



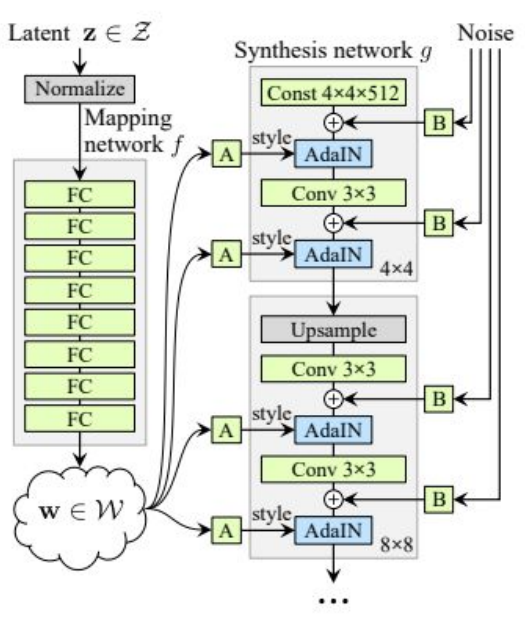
(a) Traditional

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 Guassian 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



(b) Style-based generator

(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

Tero Karras, NVIDIA
Samuli Laine, NVIDIA
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

Tero Karras
NVIDIA

Samuli Laine
NVIDIA

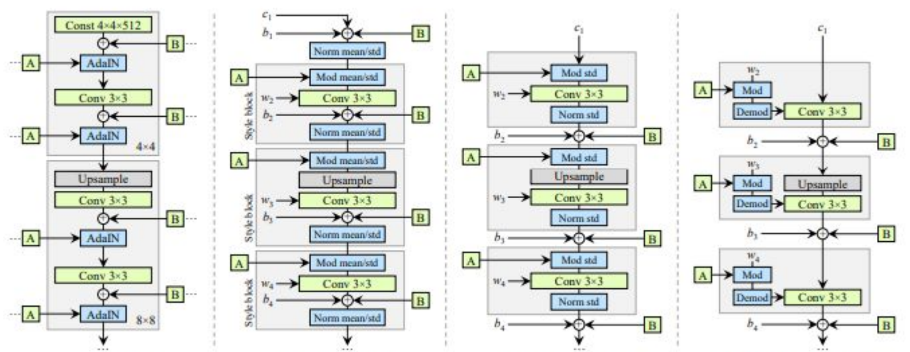
Miika Aittala
NVIDIA

Janne Hellsten
NVIDIA

Jaakko Lehtinen
NVIDIA and Aalto University

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

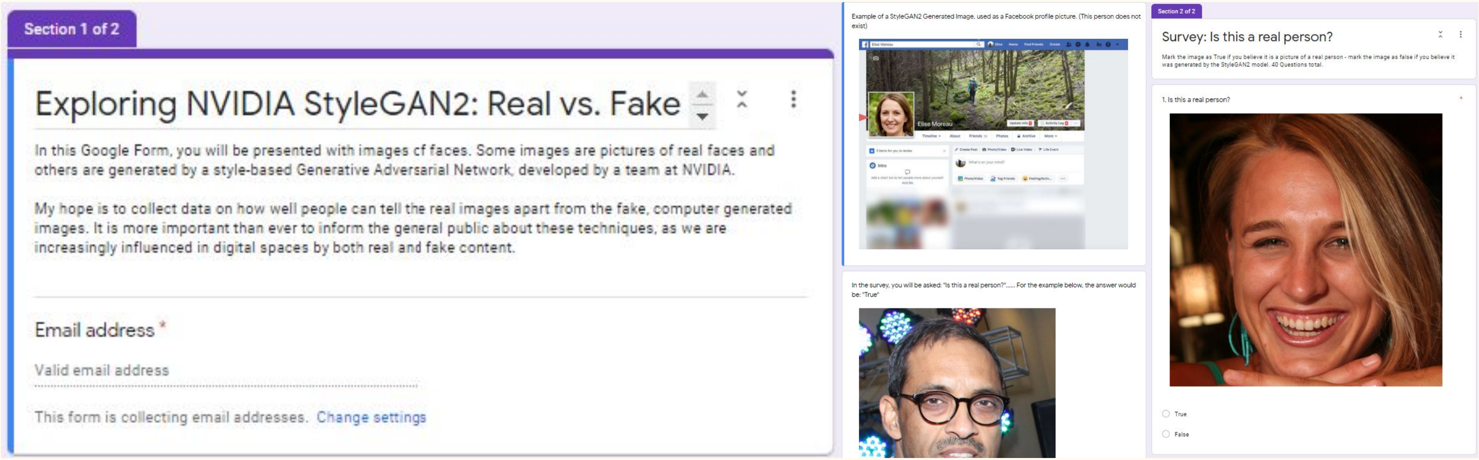


(a) StyleGAN (b) StyleGAN (detailed) (c) Revised architecture (d) Weight demodulation

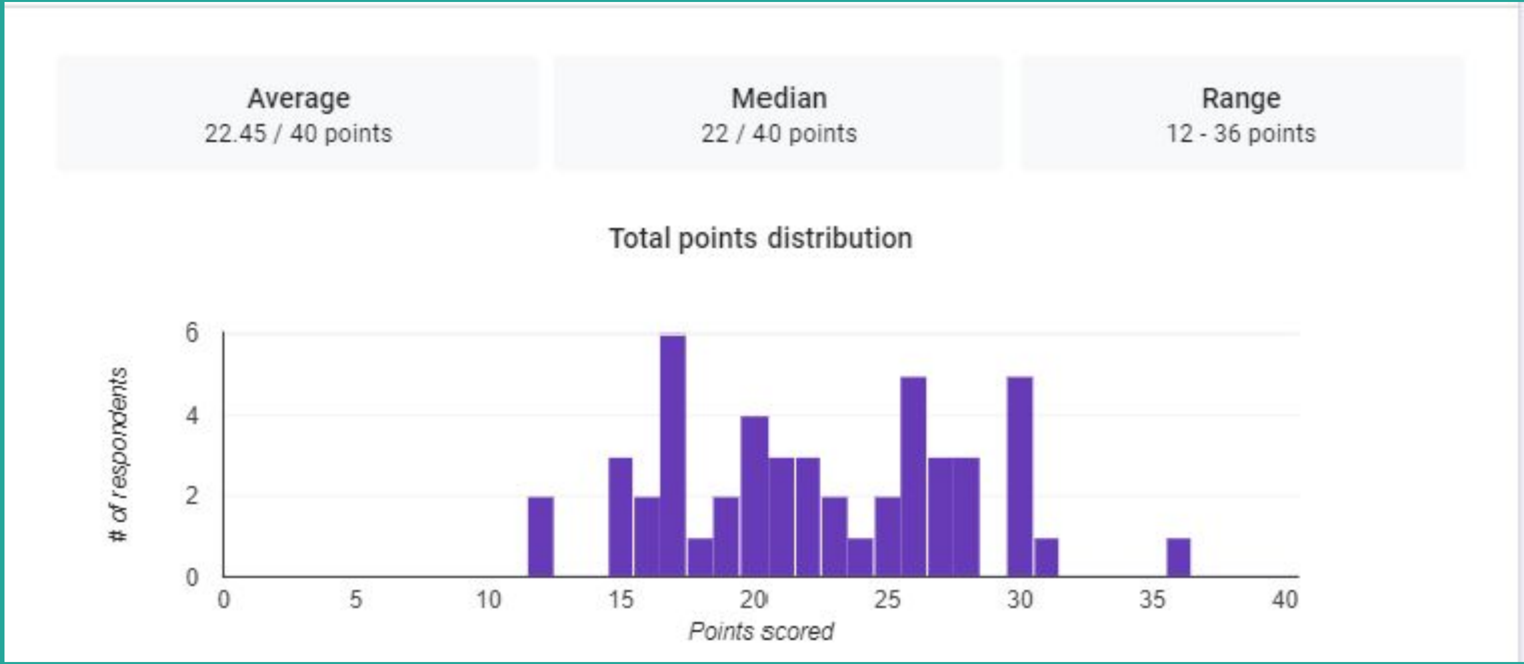
Google Colab Code Example

Real vs. Fake Faces Survey:

Exploring NVIDIA StyleGAN2: Real vs. Fake Faces



Survey Results (49 responses)



Next Steps for the Paper

Next Steps for the Paper

1. Manipulations of the Latent Space for Face Editing

“Male”

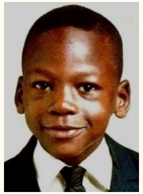
Many steps in latent space

“Female”

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

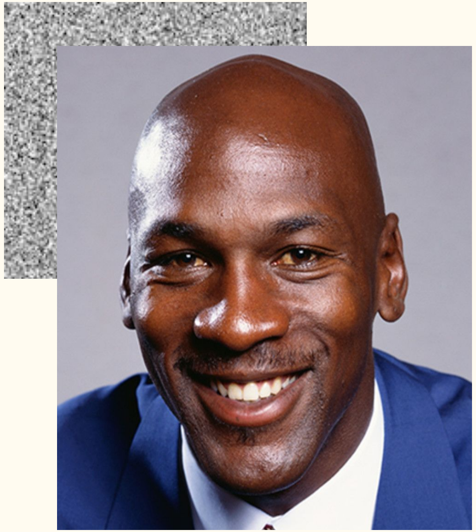
Next Steps for the Paper

1. Using Query Images



Latent Space Manipulation

Query Image



Initial Guess

seed_2079

Optimized Image

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?