Comprehension and exploration of a high-performance generative model: the StyleGAN

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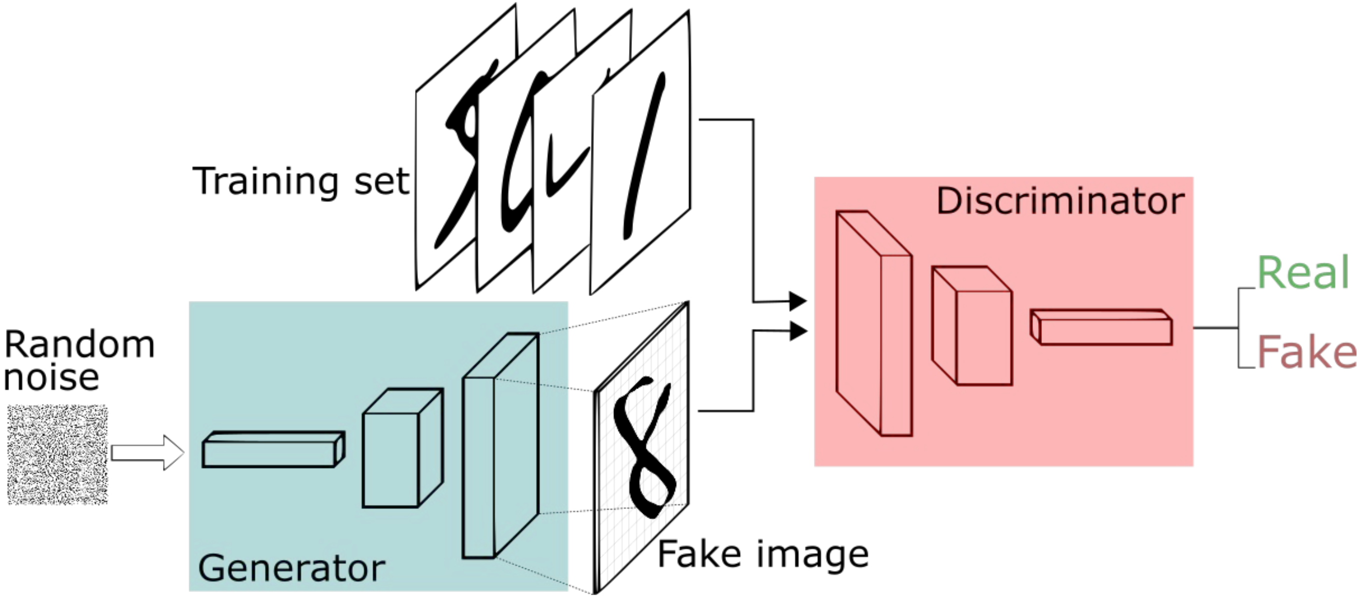
Table of Contents

Theoretical framework:

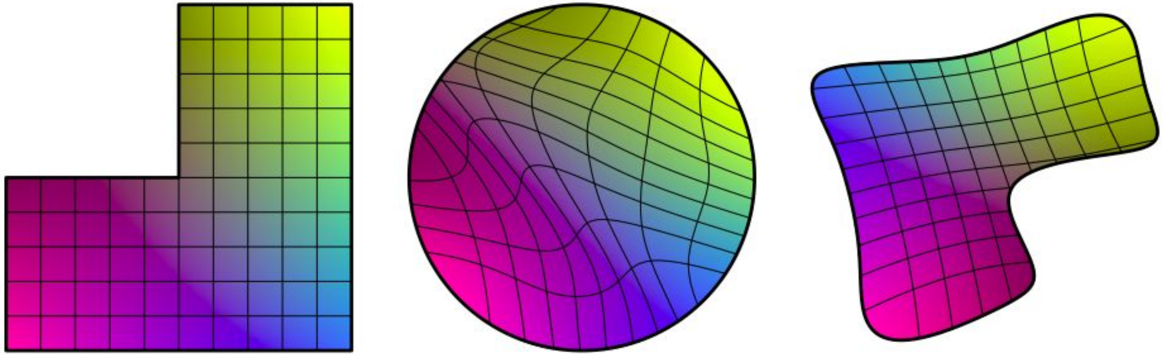
GANs and StyleGAN

Generative Adversarial Networks (2014)



General model of a GAN. Source:
https://wiki.pathmind.com/generative-adversarial-network-gan

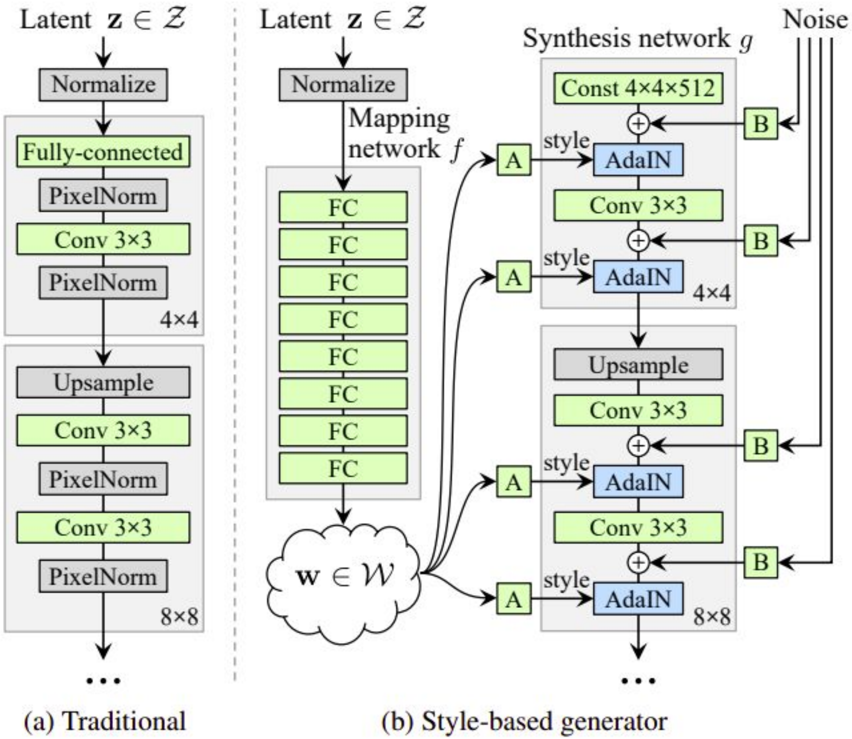
StyleGAN - Motivation (2018)



(a) Distribution of features in training set (b) Mapping from $\mathcal{Z}$ to features (c) Mapping from $\mathcal{W}$ to features

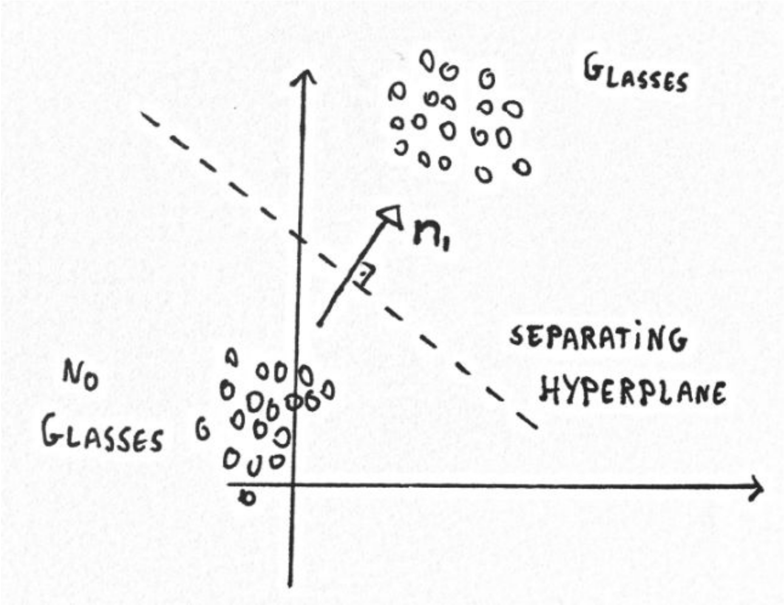
Mapping directly from input space Z to features may generate problems on features space

StyleGAN (2018) Architecture



Stylegan (2018) architecture compared to traditional GAN architecture. Source: Karras et al.

Walking in the latent space



Simplified example of a latent space walk

Methodology

Step-by-step

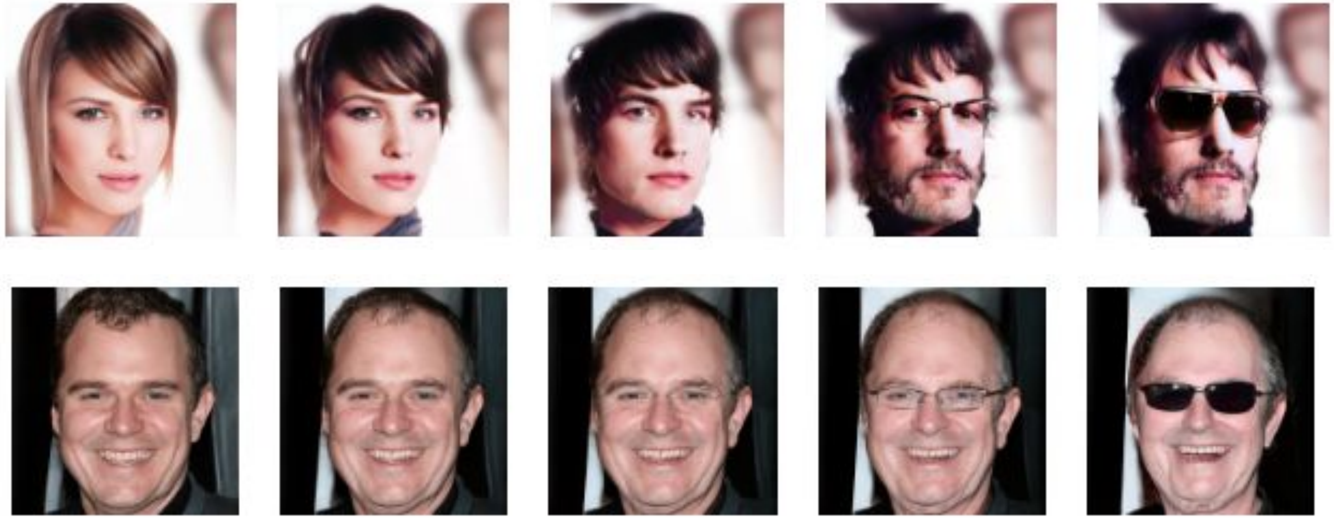
- Dataset CelebA-256
- 3 binary attributes: sex, age and glasses

1. Data in latent space Z (random from a normal distribution)
2. Data in latent space W
3. Generate images
4. Label the generated images
5. Fit a Linear SVC for each attribute
6. Hyperplane and direction of w to navigate towards an attribute

Results

First approach

- Manually selected 120 images of each feature



- Chosen features are correlated

Second approach

- Use classifier to select 1000 images for each feature and not manually select them

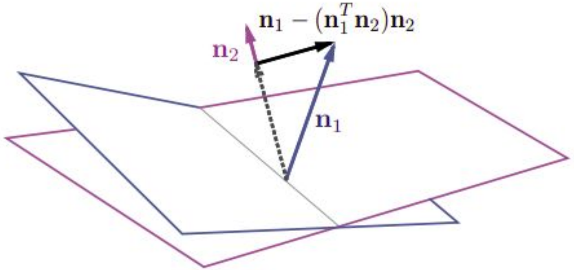
Latent space Z

- Linear SVC in the latent space Z

- Attributes change faster than in W

Latent space Z: attempt to untie different features

- Changes are not relevant



Conclusion

StyleGAN Architecture

- Overall functioning
- Latent Space Z versus Latent Space W
- Obstacles encountered
- Future perspectives

Thank you!