# How image quality is improved progressively:



### Further Improvements in StyleGAN:

- 1. Style Mixing
- 2. Stochastic Variation

Adding per pixel noise will help in better understanding of the minute textures in the images This created amazing results where a single image is released from two types of latent codes w1 and w2 from z1 and z2.

Prevents the network to memorise the features that are correlated





#### **Style Mixing:**

Generator thinks of an image as a collection of "styles" where each style controls the effects at a particular scale :

- Coarse styles → pose, hair, face shape
- Middle styles —> facial features, eyes
- Fine styles —> color scheme

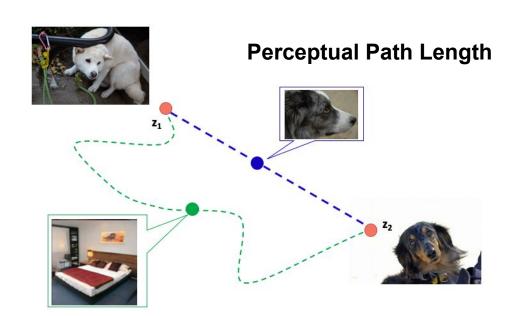


### **Disentanglement Studies:**

it is true that if we had latent codes of each of the face features we would be able to control the features in the image and come up with a completely different representation

- 1. Perceptual Path Length
- Linear Separability (Known already)

This will find the distance between feature maps visually. If separating the images far off and we observe a drastic change, this means the feature maps are entangled. Suppose removing the hair feature removes ears also, then we need to take care of it as removing hair shall not remove ears.



#### **Conclusion and Misc. Takeouts:**

- 1. StyleGAN Allows a control over the features in the image.
- 2. Major changes from previous tools is AdaIN and Mapping Network.
- 3. Advantages over ProGAN: <u>Now you can easily manipulate entangled features</u>. <u>High quality and realistic images are generated</u>.
- 4. **Limitation**: Check for the blue line in the image. Smile is not changing wrt the Face Movement



## **Small Comparisons:**

Conditional GAN (Exploiting the given	These GANS use extra laber information and result in better quality images and are able to control now generated
labels and preserving class identities in	images will look. cGANs learn to produce better images by exploiting the information fed to the model.
early stages)	
Cycle GAN (For unplared data)	CycleGAN is an extension to the GAN for image-to-image translation without paired image data. That means that

examples of the target image are not required as is the case with conditional GANs. This we have briefly covered in

class **PROGAN** (Improving images PROGan is a change to the architecture and training of GAN models that involves progressively increasing the model progressively and increasing depth of depth during the training process. starting from a low resolution, we add new layers that model increasingly fine details

GANS) as training progresses. **StyleGAN** (Idea is to grab features from latent code and reducing the load on generator, which now focuses on constant latent

code)

StyleGAN2. This article explores changes made in... | by Connor Shorten | Towards Data Science https://towardsdatascience.com/stylegan2-ace6d3da405d

Which Face is Real? Applying StyleGAN to Create Fake People - Exxact https://blog.exxactcorp.com/which-face-is-real-applying-stylegan-to-create-fake-people/

References

https://medium.com/analytics-vidhya/from-gan-basic-to-stylegan2-680add7abe82

From GAN basic to StyleGAN2. This post describes GAN basic... | by Akihiro FUJII | Analytics Vidhya | Medium

Can anyone inform me please about the advantages and limitations of Generative Adversarial Networks (GANs)? https://www.researchgate.net/post/Can-anyone-inform-me-please-about-the-advantages-and-limitations-of-Generative-Adversarial-Networks-GANs

StyleGAN: Use machine learning to generate and customize realistic images | by Jamshed Khan | Heartbeat https://heartbeat.fritz.ai/stylegans-use-machine-learning-to-generate-and-customize-realistic-images-c943388dc672

Which Face is Real? https://www.kdnuggets.com/2019/04/which-face-real-stylegan.html#:~:text=Generative%20models%20have%20a%20limitation,the%20differences%20in%20the%20photogr aphs.

Introduction to Generative Adversarial Networks (GANs): Types, and Applications, and Implementation | by Derrick Mwiti | Heartbeat https://heartbeat.fritz.ai/introduction-to-generative-adversarial-networks-gans-35ef44f21193

GANs vs. Autoencoders: Comparison of Deep Generative Models | by Matthew Stewart, PhD Researcher | Towards Data Science

6 GAN Architectures You Really Should Know - neptune.ai https://neptune.ai/blog/6-gan-architectures

3 different types of generative adversarial networks (GANs) and how they work | Packt Hub https://hub.packtpub.com/3-different-types-of-generative-adversarial-networks-gans-and-how-they-work/

https://towardsdatascience.com/gans-vs-autoencoders-comparison-of-deep-generative-models-985cf15936ea

[StyleGAN] A Style-Based Generator Architecture for GANs, part 1 (algorithm review) | TDLS - YouTube

https://www.youtube.com/watch?v=SPI5uGCnxlc&ab channel=MLExplained-AggregateIntellect-AI.SCIENCE

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A Gentle Introduction to StyleGAN the Style Generative Adversarial Network https://machinelearningmastery.com/introduction-to-style-generative-adversarial-network-stylegan/