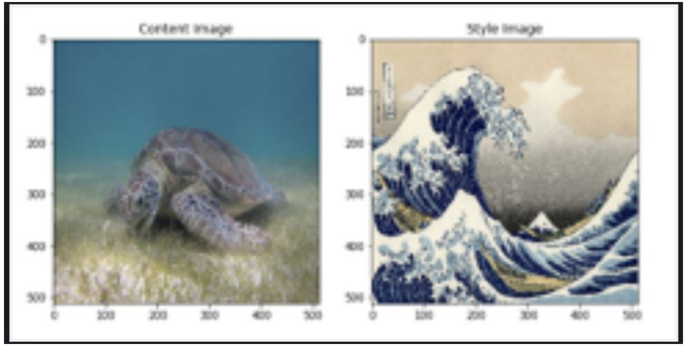
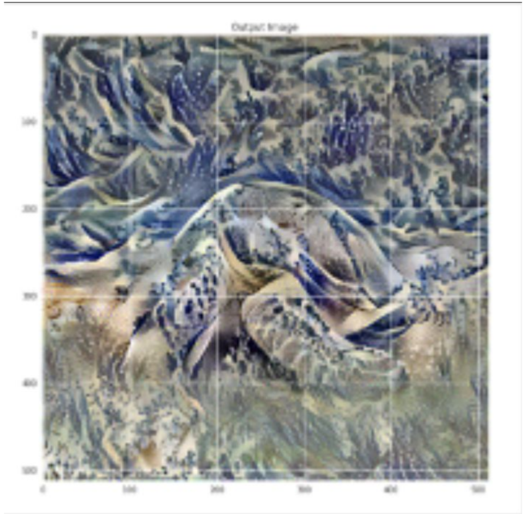
Continuing my friend's talk… Let's connect the dots and see what we have understood so far...

No ownership for any image

What we have learned so far...

- Style Transfer
- Disentanglement
- Interpolation





Claims:

- Separating the latent factors from compact code.
- Interpolation and Disentanglement between features

Principle Idea:

- Reduce the workload of generator.
- Generator sees a processed input.
- Directly controlling the image features.

Why Entanglement?

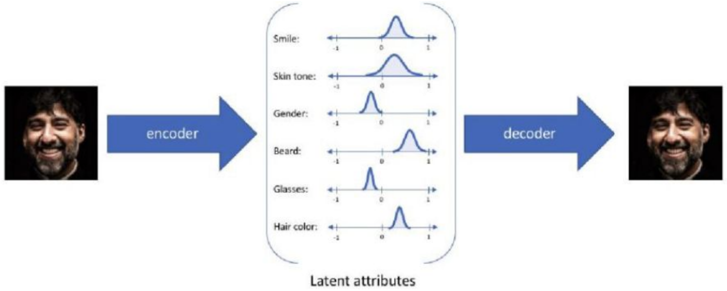
- Previous work mainly focussed to match the generated image to be as close as ground truth. The features are learned directly from the image.
- This brings unavoidable constraints and features gets entangled to one another.

To overcome entanglement:

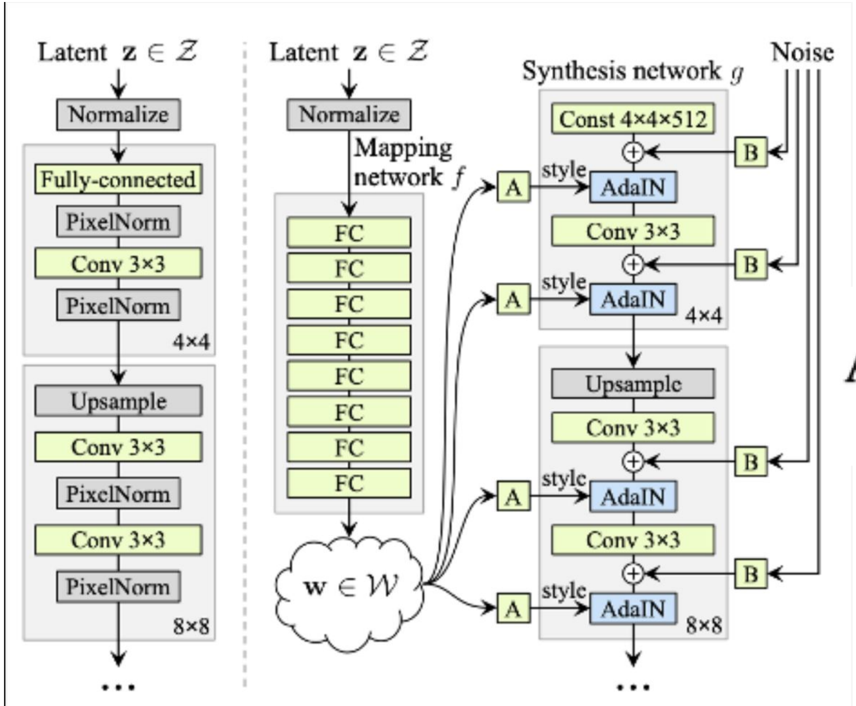
- Break the correlation which is developed inherently and learn a compact code which is constant.
- Allow disentanglement.

How entanglement gets developed...

- Recall what we have studied in class.
- Gr and Dr models
- Pr(Observation) = Pr (Synthetic Observation)
- Nash Equilibrium
- Same with VAE (matching Probabilities)
- This is where features gets entangled with each other



Quick relook to architecture and Properties:



(a) Traditional (b) Style-based generator

mapping network is introduced in the Style Gan which extracts the features already for the generator.

$$\mathrm{AdaIN}(\mathbf{x}_i, \mathbf{y}) = \mathbf{y}_{s,i} \frac{\mathbf{x}_i - \mu(\mathbf{x}_i)}{\sigma(\mathbf{x}_i)} + \mathbf{y}_{b,i},$$

latent vector W which is also called as intermediate controls generator with Adaptive Instance Normalisation

A quick comparison with ProGAN:

- Quality of Generated Images
- How ProGan works?
- Why not ProGAN?

Improvement is StyleGAN...

Demerits of ProGAN:

attempt to tweak anything changes the whole distribution of the image quality

Do not learn any face specific features and Features are learned as if it is mugging up the information.

Further Improvements:

1. **Style Mixing**
2. **Stochastic Variation**

This created amazing results where a single image is released from two types of latent codes w1 and w2 from z1 and z2.

Adding per pixel noise will help in better understanding of the minute textures in the images

Prevents the network to memorise the features that are correlated

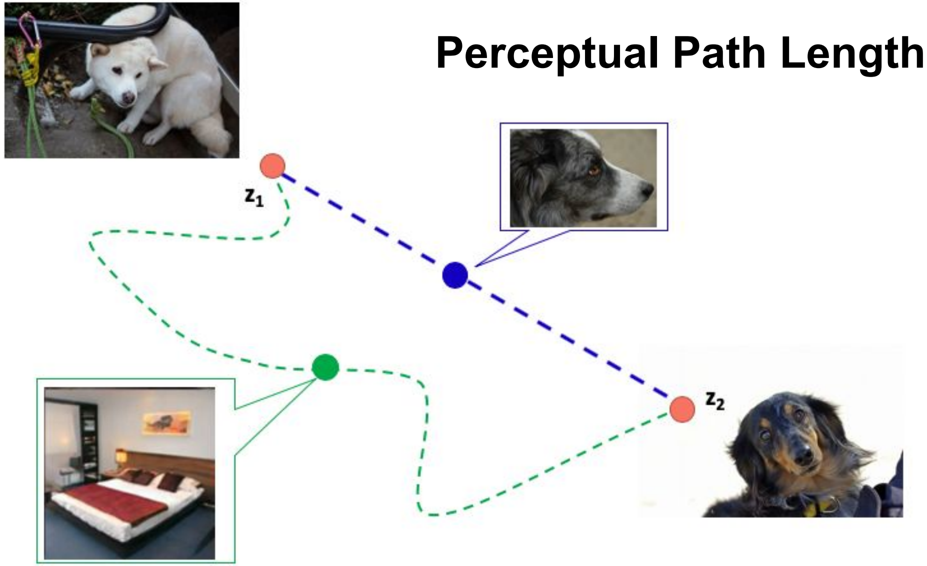
https://youtu.be/kSLJriaOumA

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**
2. **Linear Separability (Known already)**

Perceptual Path Length



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 : *Now you can easily manipulate entangled features. High quality and realistic images are generated.*
4. **Limitation**: Check for the blue line in the image. Smile is not changing wrt the Face Movement

If time permits:

Conditional GAN (Exploiting the given labels and preserving class identities in early stages)	These GANs use extra label information and result in better quality images and are able to control how generated images will look. cGANs learn to produce better images by exploiting the information fed to the model.
Cycle GAN (For unpiared 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 progressively and increasing depth of GANS)	PROGan is a change to the architecture and training of GAN models that involves progressively increasing the model depth during the training process. *starting from a low resolution, we add new layers that model increasingly fine details 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)

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