- ❑ Cycle-Consistent Adversarial Networks (GAN), CoGAN, BiGAN, ALI & SimGAN
- ❑ CycleGAN is designed to translate an image from a source domain X to a target domain Y in the absence of paired examples, i.e. G: X→Y
- ❑ This mapping is highly under-constrained, an inverse mapping F: Y→X is coupled and a cycle consistency loss is introduced to enforce F(G(X))=X (and vice versa)
- ❑ Unpaired training data consists of a source set {xi} (xi∈X) and a target set {yi} (yi∈Y), with no information provided as to which xi matches which yj.
- ❑ CycleGAN seeks to learn to translate between domains without paired input-output examples.
- ❑ Cycle Consistency?
  - ❑ A mapping G: X→Y should be learnt such that the output ^y = G(x), x∈X, is indistinguishable from images y∈Y by an adversary trained to classify ^y apart from y.
  - ❑ There can be infinitely many mappings G. It is difficult to optimize. Standard procedures often lead to the well-known problem of **mode collapse**.
  - ❑ A property should be exploited, i.e. translation should be “cycle consistent”
  - ❑ Mathematically, if we have a translator G: X→Y and another translator F: Y→X, then G and F should be inverses of each other.
  - ❑ A cycle consistency loss is added that encourages F(G(x))≈x and G(F(y))≈y
  - ❑ Combining this loss with adversarial losses on domains X and Y yields our full objective for unpaired image-to-image translation.
- ❑ CycleGAN can be viewed as training two “autoencoders”: learning one autoencoder F○G: X→X jointly with another G○F: Y→Y

- ❏ Cycle-Consistent Adversarial Networks (GAN), CoGAN, BiGAN, ALI & SimGAN
- ❏ What CycleGAN does differently from a standard GAN is that it doesn’t generate images from random noise. It uses a given image to get a different version of that image.
- ❏ Generating a realistic rendering of what a building would look like based on its blueprints.
- ❏ Creating an image of how a location would look in each different season.
- ❏ Changing paintings to be a real image.
- ❏ CycleGAN has been demonstrated on a range of applications including season translation, object transfiguration, style transfer, and generating photos from paintings.

- To improve the quality of SAR images and to reduce the costs of their generation, Dialectical Generative Adversarial Network (Dialectical GAN) is proposed to generate high-quality SAR images. This method is based on the analysis of hierarchical SAR information and the “**dialectical**” structure of GAN frameworks.
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- Cycle-Consistent Adversarial Networks (GAN), CoGAN, BiGAN, ALI & SimGAN
- http://noiselab.ucsd.edu/ECE228-2021/projects/PresentationVideosPPT/32PPT.pdf
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