- For image translation with unpaired data, the task was to find a mapping G between 2 distributions. There will be infinite such mappings. As the function is under-constrained, it was coupled with an inverse mapping F so that F(G(x)) = x.
- Direct adversarial loss training may lead to instability. The 2 mappings can induce target distribution by giving diff outputs for the same set of input images.So using the constraint that any 2 images must be cycle consistent, we can simultaneously train both mappings.
- 2 adversarial discriminators are used to ensure that generated image distribution matched target domain distribution. Cycle consistency loss ensures that both mappings are in sync with each other.
- L1 distance was used as loss for both forward and backward cycle consistency losses. Adversarial loss was used but gave worse results.
- It can be seen as training 2 adversarial autoencoders with target domain distribution as the intermediate bottleneck.
- Generator architecture:
    - 3 Convolutional layers
    - Residual blocks
    - 2 Fractionally strided conv layers with stride ½
    - 1 conv to convert to RGB image
- Discriminator architecture used 70x70 Patch GAN (https://paperswithcode.com/method/patchgan#:~:text=PatchGAN%20is%20a%20type%20of,scale%20of%20local%20image%20patches.&text=of%20%24D%24.-,Such%20a%20discriminator%20effectively%20models%20the%20image%20as%20a%20Markov,more%20than%20a%20patch%20diameter.).
- Stable training
    - Replacing logloss by L2 loss
    - Using history of generated images instead of latest images
- Identity mapping loss helps to preserve same coloration.
- Successful in cases that require color and texture change.
- Failures
    - Geometrical changes
    - Changes in distribution