CYCLEGANS-TRANSLATING IMAGES

SNT SUMMER PROJECT 2024

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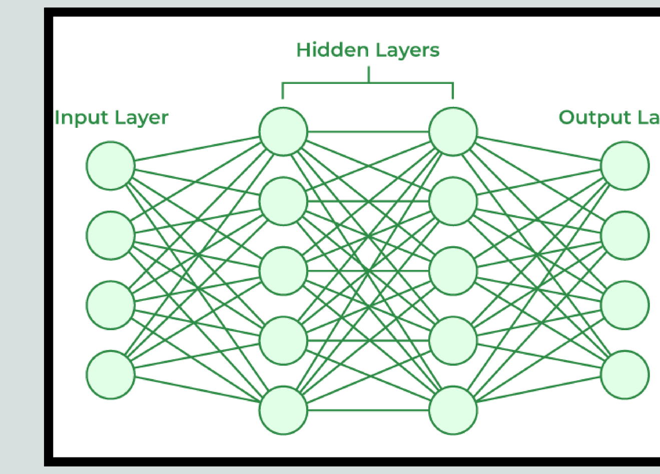
INTRODUCTION AND OBJECTIVE

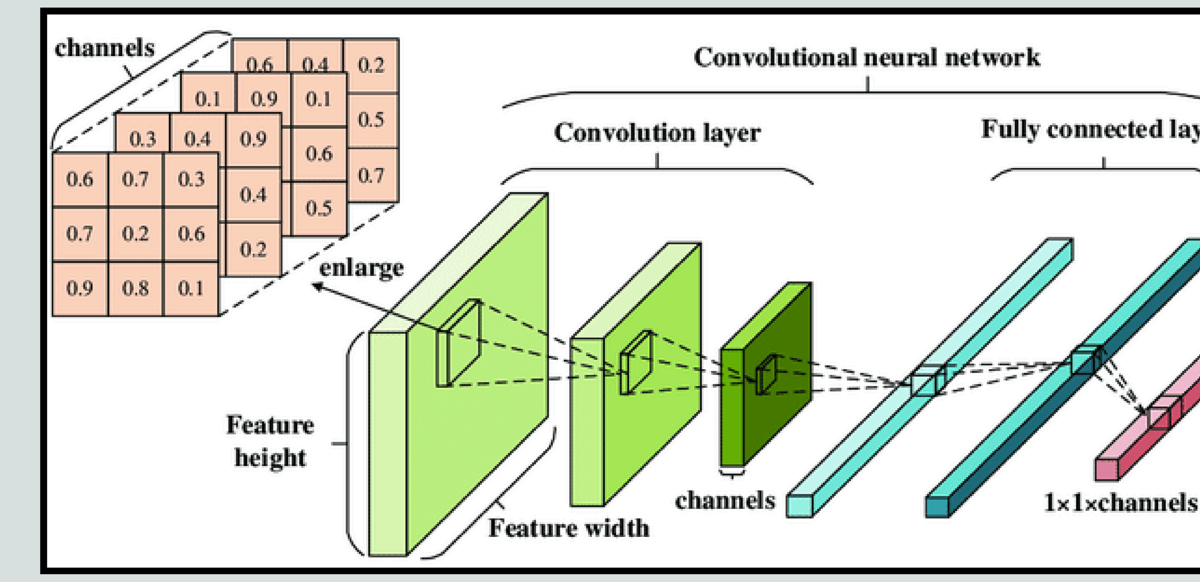
CycleGANs (Cycle-Consistent Generative Adversarial Networks) represent a remarkable breakthrough in the field of image-to-image translation. The primary objective of CycleGANs project is to perform high-quality image-to-image translation without relying on paired datasets. Traditional GANs (Generative Adversarial Networks) require a large dataset of corresponding images between the source and target domains, which is often impractical or impossible to obtain. CycleGANs address this limitation by using unpaired image data, making them extremely versatile and applicable to a wide range of tasks such as style transfer, photo enhancement, and domain adaptation.

ANN and CNN

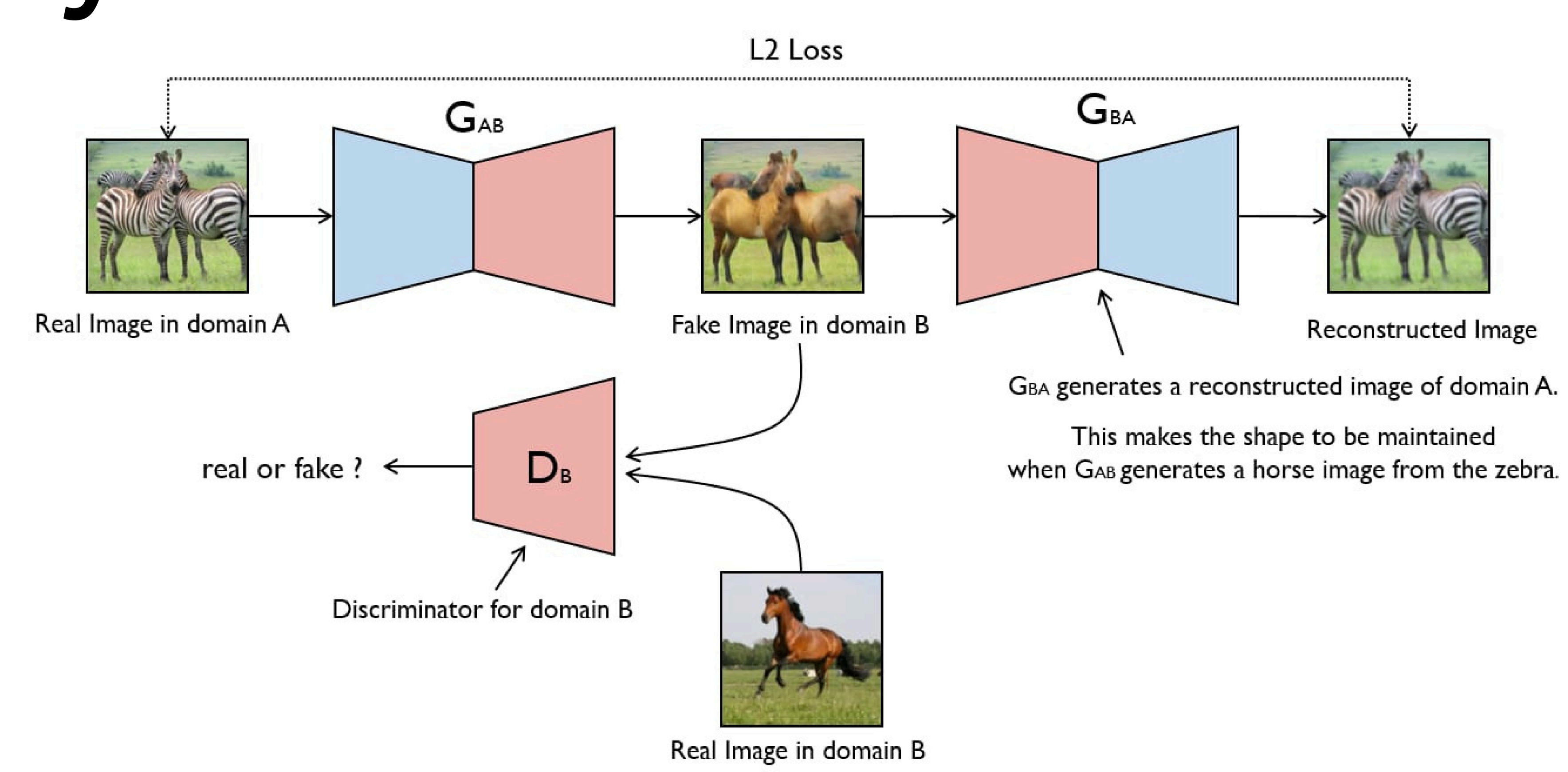
Like the human brain, Artificial Neural Networks (ANNs) and Convolutional Neural Networks (CNNs) use layered structures to learn. ANNs excel at finding patterns in tabular data through densely connected layers, similar to how neurons connect in the brain. CNNs, inspired by the visual cortex, specialize in image recognition with these dense layers, but also leverage convolutional layers to extract intricate details from images. During the training time they use Backpropagation or similar optimization algorithm to optimize weights and biases to minimize error.

Concept images



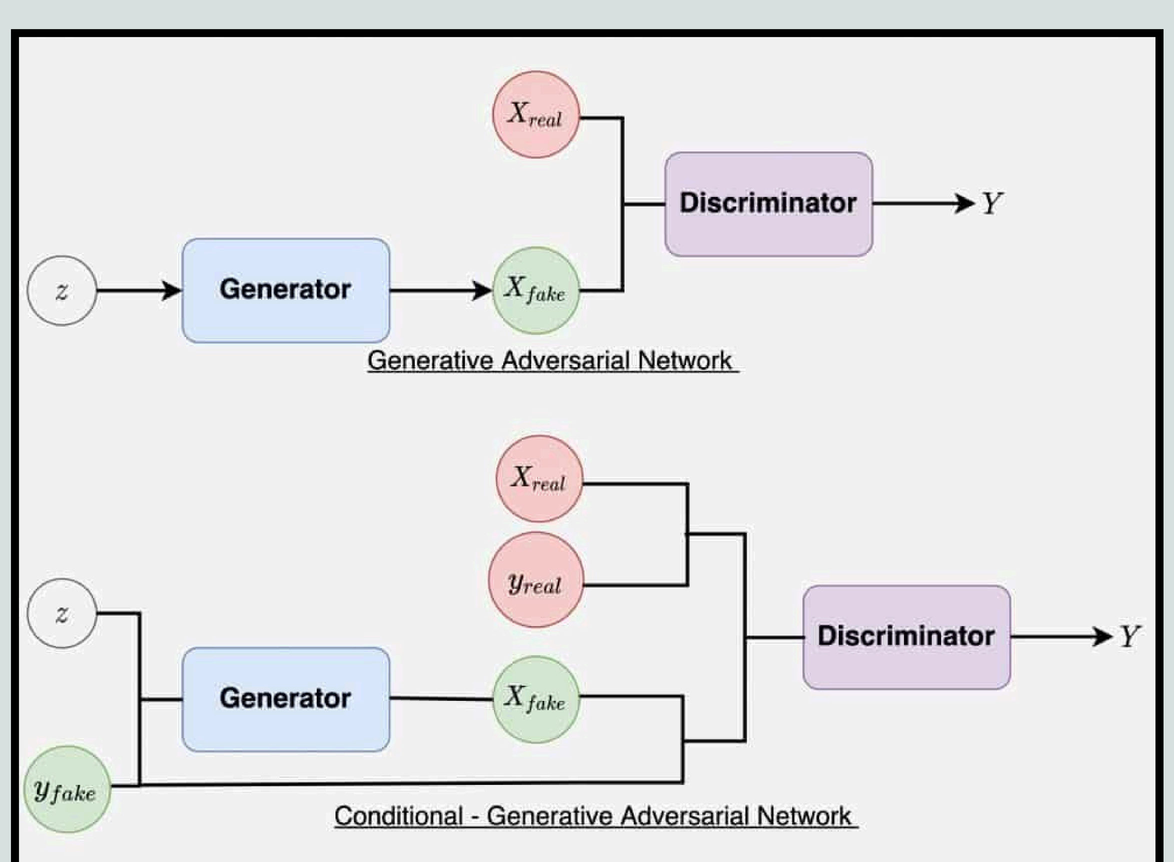


CycleGAN



CycleGAN is used to transfer characteristic of one image to another or can map the distribution of images to another. In CycleGAN we treat the problem as an image reconstruction problem. We first take an image input and using the generator to convert into the reconstructed image. Then we reverse this process from reconstructed image to original image using a generator. Then we calculate the mean squared error loss between real and reconstructed image. The most important feature of CycleGAN is that it can do this image translation on an unpaired image where no relation exists between the input image and output image.

Concept images



GANs

A DCGAN has a Generator and a Discriminator that compete to create realistic images. The Generator turns random noise into images, and the Discriminator classifies images as real or fake. Through training, the Generator improves at creating images that fool the Discriminator, resulting in highly realistic images.

We've implemented several advanced GAN techniques, including DCGAN, Pix2Pix, Conditional GAN, and PatchGAN. These implementations have enabled us to explore a range of image generation and translation tasks.

CONCLUSION

This summer project has been a comprehensive journey through the fundamental and advanced techniques in machine learning and deep learning. We began with the basics of Python and NumPy, progressed through regression techniques including linear and logistic regression, explored k-means clustering, and implemented neural networks from scratch. From there, we delved into convolutional neural networks (CNNs) and advanced models such as DCGANs, CGANs, Pix2Pix, and CycleGANs. This project provided an invaluable learning experience, offering a deep dive into the intricacies of machine learning and deep learning, and building a strong foundation for future endeavors in this field.

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