Generative Adversarial Networks

Generative Adversarial Networks (GANs), are an approach to generative modeling using deep learning methods, such as convolutional neural networks.
Generative modeling is an unsupervised learning task in machine learning that involves automatically discovering and learning the regularities or patterns in input data in such a way that the model can be used to generate or output new examples that plausibly could have been drawn from the original dataset.
the idea of generative models, stepping over the supervised vs. unsupervised learning paradigms and discriminative vs. generative modeling.
The GAN model architecture involves two sub-models: a **generator model** for generating new examples and a **discriminator model** for classifying whether generated examples are real, from the domain, or fake, generated by the generator model.

- **Generator**. Model that is used to generate new plausible examples from the problem domain.
- **Discriminator**. Model that is used to classify examples as real (*from the domain*) or fake (*generated*).

GANs typically work with image data and use Convolutional Neural Networks, or CNNs, as the generator and discriminator models.The reason for this may be both because the first description of the technique was in the field of computer vision and used CNNs and image data, and because of the remarkable progress that has been seen in recent years using CNNs more generally to achieve state-of-the-art results on a suite of computer vision tasks such as object detection and face recognition.
the ability to visually assess the quality of the generated output, that has both led to the focus of computer vision applications with CNNs and on the massive leaps in the capability of GANs as compared to other generative models, deep learning based or otherwise.

One of the many major advancements in the use of deep learning methods in domains such as computer vision is a technique called data augmentation. Data augmentation results in better performing models, both increasing model skill and providing a regularizing effect, reducing generalization error. Successful generative modeling provides an alternative and potentially more domain-specific approach for data augmentation.

The most compelling application of GANs is in conditional GANs for tasks that require the generation of new examples. Here, three main examples:

- **Image Super-Resolution**. The ability to generate high-resolution versions of input images.

- **Creating Art**. The ability to create new and artistic images, sketches, painting, and more.
- **Image-to-Image Translation**. The ability to translate photographs across domains, such as day to night, summer to winter, and more.

Some techniques for data augmentation.

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