Generative Adversarial Networks (GANs)

Generative Adversarial Networks, or GANs for short, 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.

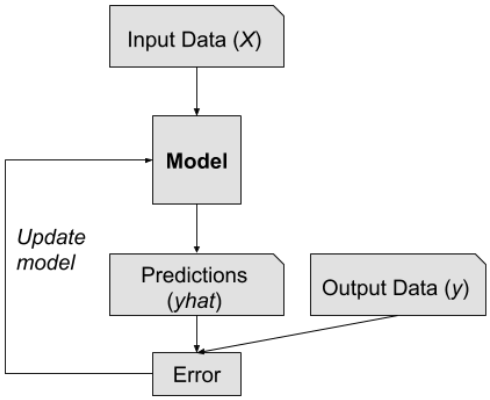
GANs are a clever way of training a generative model by framing the problem as a supervised learning problem with two sub-models: the generator model that we train to generate new examples, and the discriminator model that tries to classify examples as either real (from the domain) or fake (generated). The two models are trained together in a zero-sum game, adversarial, until the discriminator model is fooled about half the time, meaning the generator model is generating plausible examples.

Supervised vs. Unsupervised Learning

A typical machine learning problem involves using a model to make a prediction, e.g. predictive modeling. This requires a training dataset that is used to train a model, comprised of multiple examples, called samples, each with input variables (X) and output class labels (y). A model is trained by showing examples of inputs, having it predict outputs, and correcting the model to make the outputs more like the expected outputs.

In the predictive or supervised learning approach, the goal is to learn a mapping from inputs x to outputs y, given a labeled set of input-output pairs …
— Page 2, Machine Learning: A Probabilistic Perspective, 2012.

This correction of the model is generally referred to as a supervised form of learning or supervised learning. Example of Supervised Learning:



How GANs Work:

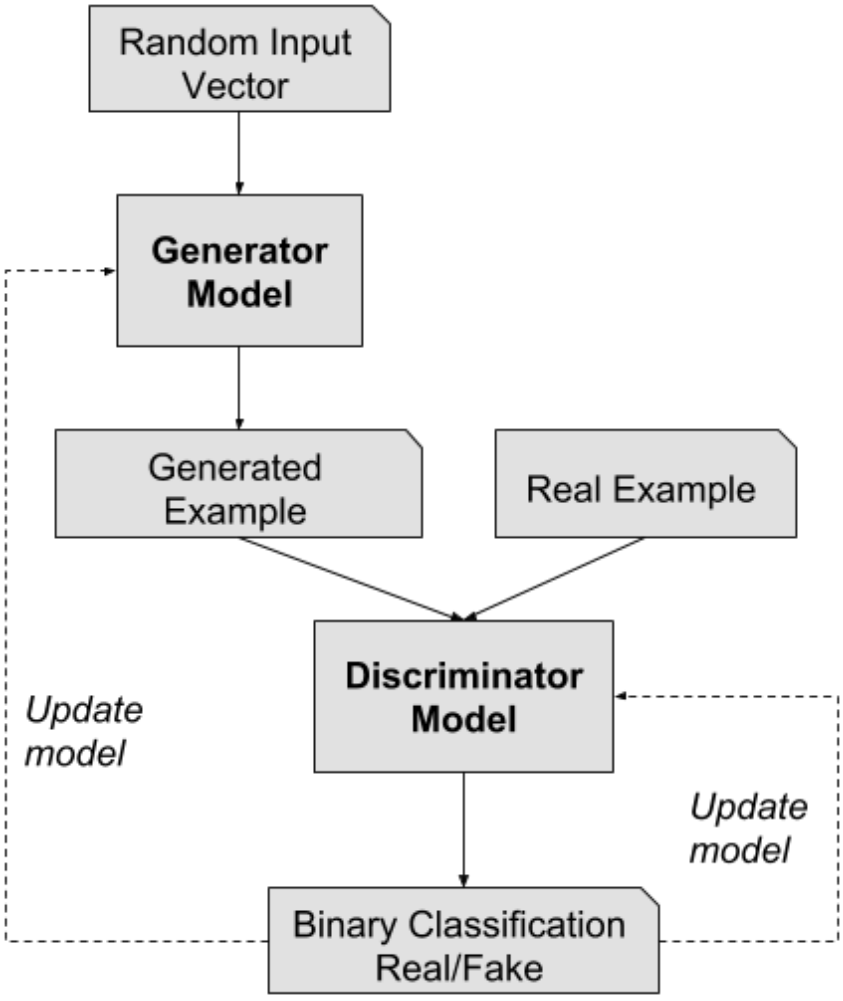
Generative Adversarial Networks, or GANs, are a deep-learning-based generative model.

More generally, GANs are a model architecture for training a generative model, and it is most common to use deep learning models in this architecture.

The GAN architecture was first described in the 2014 paper by Ian Goodfellow, et al. titled "Generative Adversarial Networks."

A standardized approach called Deep Convolutional Generative Adversarial Networks, or DCGAN, that led to more stable models was later formalized by Alec Radford, et al. in the 2015 paper titled "Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks".

General Overview Architecture of Generative Adversarial Networks (GANs):



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

Generative adversarial networks are based on a game theoretic scenario in which the generator network must compete against an adversary. The generator network directly produces samples. Its adversary, the discriminator network, attempts to distinguish between samples drawn from the training data and samples drawn from the generator.
— Page 699, Deep Learning, 2016.

The Generator Model

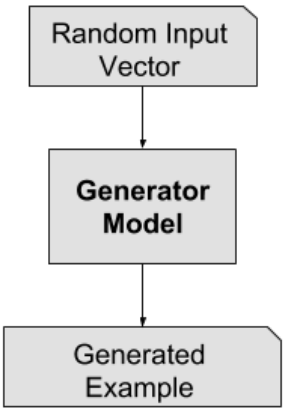
The generator model takes a fixed-length random vector as input and generates a sample in the domain. The vector is drawn from randomly from a Gaussian distribution, and the vector is used to seed the generative process. After training, points in this multidimensional vector space will correspond to points in the problem domain, forming a compressed representation of the data distribution.

This vector space is referred to as a latent space, or a vector space comprised of latent variables. Latent variables, or hidden variables, are those variables that are important for a domain but are not directly observable.

We often refer to latent variables, or a latent space, as a projection or compression of a data distribution. That is, a latent space provides a compression or high-level concepts of the observed raw data such as the input data distribution. In the case of GANs, the generator model applies meaning to points in a chosen latent space, such that new points drawn from the latent space can be provided to the generator model as input and used to generate new and different output examples.

Machine-learning models can learn the statistical latent space of images, music, and stories, and they can then sample from this space, creating new artworks with characteristics similar to those the model has seen in its training data.
— Page 270, Deep Learning with Python, 2017.

After training, the generator model is kept and used to generate new samples.



The Discriminator Model

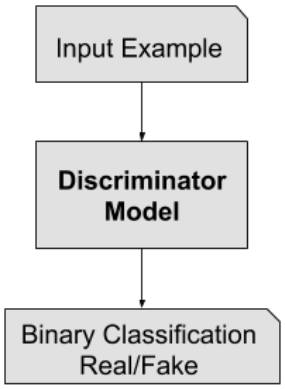
The discriminator model takes an example from the domain as input (real or generated) and predicts a binary class label of real or fake (generated).

The real example comes from the training dataset. The generated examples are output by the generator model.

The discriminator is a normal (and well understood) classification model. After the training process, the discriminator model is discarded as we are interested in the generator. Sometimes, the generator can be repurposed as it has learned to effectively extract features from examples in the problem domain. Some or all of the feature extraction layers can be used in transfer learning applications using the same or similar input data.

We propose that one way to build good image representations is by training Generative Adversarial Networks (GANs), and later reusing parts of the generator and discriminator networks as feature extractors for supervised tasks

— Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks, 2015.



GANs as a Two-Player Game

Generative modeling is an unsupervised learning problem, as we discussed in the previous section, although a clever property of the GAN architecture is that the training of the generative model is framed as a supervised learning problem.

The two models, the generator and discriminator, are trained together. The generator generates a batch of samples, and these, along with real examples from the domain, are provided to the discriminator and classified as real or fake.

The discriminator is then updated to get better at discriminating real and fake samples in the next round, and importantly, the generator is updated based on how well, or not, the generated samples fooled the discriminator.

We can think of the generator as being like a counterfeiter, trying to make fake money, and the discriminator as being like police, trying to allow legitimate money and catch counterfeit money. To succeed in this game, the counterfeiter must learn to make money that is indistinguishable from genuine money, and the generator network must learn to create samples that are drawn from the same distribution as the training data.
— NIPS 2016 Tutorial: Generative Adversarial Networks, 2016.

In this way, the two models are competing against each other, they are adversarial in the game theory sense, and are playing a zero-sum game.

Because the GAN framework can naturally be analyzed with the tools of game theory, we call GANs "adversarial".
— NIPS 2016 Tutorial: Generative Adversarial Networks, 2016.

In this case, zero-sum means that when the discriminator successfully identifies real and fake samples, it is rewarded or no change is needed to the model parameters, whereas the generator is penalized with large updates to model parameters.

Alternately, when the generator fools the discriminator, it is rewarded, or no change is needed to the model parameters, but the discriminator is penalized and its model parameters are updated.

At a limit, the generator generates perfect replicas from the input domain every time, and the discriminator cannot tell the difference and predicts "unsure" (e.g. 50% for real and fake) in every case. This is just an example of an idealized case; we do not need to get to this point to arrive at a useful generator model.

GANs and Convolutional Neural Networks

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.

Modeling image data means that the latent space, the input to the generator, provides a compressed representation of the set of images or photographs used to train the model. It also means that the generator generates new images or photographs, providing an output that can be easily viewed and assessed by developers or users of the model.

It may be this fact above others, 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.

Why Generative Adversarial Networks?

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. It works by creating new, artificial but plausible examples from the input problem domain on which the model is trained.

The techniques are primitive in the case of image data, involving crops, flips, zooms, and other simple transforms of existing images in the training dataset.

Successful generative modeling provides an alternative and potentially more domain-specific approach for data augmentation. In fact, data augmentation is a simplified version of generative modeling, although it is rarely described this way.

In complex domains or domains with a limited amount of data, generative modeling provides a path towards more training for modeling. GANs have seen much success in this use case in domains such as deep reinforcement learning.

There are many research reasons why GANs are interesting, important, and require further study. Ian Goodfellow outlines a number of these in his 2016 conference keynote and associated technical report titled “NIPS 2016 Tutorial: Generative Adversarial Networks.”

Among these reasons, he highlights GANs’ successful ability to model high-dimensional data, handle missing data, and the capacity of GANs to provide multi-modal outputs or multiple plausible answers.

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

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

Perhaps the most compelling reason that GANs are widely studied, developed, and used is because of their success. GANs have been able to generate photos so realistic that humans are unable to tell that they are of objects, scenes, and people that do not exist in real life.

Astonishing is not a sufficient adjective for their capability and success.