Module 8: Portfolio Project

Working with a Generative Adversarial Network: Research Write-up

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A Generative Adversarial Networks (GANs) is a neural network architecture that consists of two models that compete with one another throughout training. Goodfellow et. al. explains that through training, they two models are being trained at the same time, which are the “generative model G that captures the data distribution, and a discriminative model D that estimates the probability that a sample came from the training data rather than G” (Goodfellow et. al., 2014, pg. 1). The discriminator is a Convolutional Neural Network (CNN) that determines if the content being provided by the generative model is real data, or content that was created by the generator. The goal of the generator is to maximize the probability that the discriminator makes a mistake, to think that the generated content is a real sample. As a result of training, one model can generate content that it was trained on, and the other can detect if provided data comes from a real dataset or is fabricated. This paper highlights the use cases that GANs can be used for in different industries along with the benefits that GANs could provide.

One of the challenges that the medical industry has when trying to implement AI solutions is how expensive creating medical image datasets are. This is “due to the sensitive nature of the data and the highly specific domain knowledge required to reliably annotate it” (Skandarani et. al., 2023, pg. 2). To overcome the lack of medical image datasets, GANs can be used to generate synthetic examples to be used to train a classifying model. If we had a GAN that was trained on magnetic resonance imaging (MRI) images, which indicate cancer in the image, then theoretically, we could have an endless supply of data samples containing examples of cancer, for our classifying model. This data could be used to help balance out an existing data set of MRI images, so that positive and negative cases balance out more evenly, helping to build a more accurate classifying model.

Automatic Face Recognition (AFR) systems that are being used in social media platforms introduce privacy concerns, as they can automatically identify, process, and tag individuals in photos (Khojaste et. al., 2022, pg. 2). Those who upload images to the platform would like to have their faces undetectable from these AFR systems, while being recognizable by humans. Blurring a face can prevent a user from being identified, but the person could not be identified by a human user. Khojaste et. al. proposes that a GAN can “edit the face regions of the input image in such a way that the faces are still similar to the original ones but not recognizable by the AFR tools” (Khojaste et. al., 2022, pg. 2). The approach that Khojaste took was by identifying and grabbing the face from within the image, used the GAN to transform the face, then merge the transformed face on top of the original location of the face in the photo. By having the face extracted out of the image before sending it through the GAN, it allows it to focus only on the face, rather than the entire image, which would have made it more difficult to process. A more traditional approach to avoid these AFR systems was by blurring out or blacking out a face completely, which is not visually appealing to the human eye. By having a GAN alter the subjects faces in the image, it can help the subjects remain anonymous to the AFR systems, while maintaining the visual integrity of the image.

GANs can also help improve the accuracy of weather prediction, especially for heavy rainfall events. Jeong explains that numerical weather prediction models are “more stable for short- and medium-term forecasting, but the results may deviate from the observed data” (Jeong, 2023, para. 1). By using a GAN with the numerical weather prediction models, it is possible to correct the forecasts to have more accurate representations of where we should expect precipitation. Jeong trained this model “by converting the distribution of its forecast data into the distribution of the observed rainfall data measured using radar” (Jeong, 2023, para. 11).

The GAN model then corrects the data generated from the numerical weather prediction model “by transforming the data distribution of source domain A into the data distribution of target domain B using an adversarial learning process performed by its generator and discriminator networks” (Jeong, 2023, para. 11). As a result, they were able to predict rainfall in the short and medium term more accurately, especially when the rainfall was predicted to be heavy. With the ability to better predict where rainfall will occur, we can better predict where floods can occur, allowing us to respond more effectively, saving lives that could be taken during flooding disasters.

Advertising can make use of GANs to better personalize advertising to the consumer. When a consumer is shopping for makeup, they could be overwhelmed by the numerous options and brands that are in a store, not knowing which products and color of products that would match their skin tone the best. Beauty GAN can transfer a makeup style from a face that is wearing makeup to another face that is not wearing makeup. By doing so, shoppers would not have to try on numerous shades to determine which product works best for them and can eliminate guesswork. The Beauty GAN architecture includes two discriminator networks along with a generator network. Li et. al. explains that the generator network “takes the makeup and anti-makeup face images as inputs and produces a new after-makeup face and an anti-makeup face.” (Li et. al., 2018, pg. 19). The first discriminator “discriminates the generator-generated makeup face image from the real makeup samples dataset” , whereas the second discriminator “discriminates the generator-generated anti-make-up face image from the real non-makeup samples dataset” (Li et. al., 2018, pg. 19). By using this trained Beauty GAN, end users can upload an image of themselves, and have a personalized experience when shopping for makeup online, or have an image taken of themselves in store, and have the GAN show the end user how they would look with different makeup products.

Conclusion

Generative Adversarial Networks consist of a Generator and Discriminator model that compete with one another, where the generator tries to trick the discriminator into predicting that the generated content created by the generator is real. The discriminator’s job is to correctly predict if content is real or fabricated data. In the medical industry, GANs can be used to generate MRI scans that contain signs of cancer. GANs can help generate medical image datasets that are balanced, which can be expensive and time consuming to acquire. GANs have their use cases in meteorology, where it can further enhance the predictions that are currently being used to predict when and where rainfall will occur. GANs can help users who are using social media circumvent Automatic Face Recognition (AFR) systems by altering faces of subject within an image so that they cannot be detected by these AFR systems, while maintaining the visual integrity of the image. GANs can also be used in advertising, to help provide a more personalized experience to shoppers. Shoppers can upload an image of themselves, and have the generator remove any makeup that the shopper could be currently wearing and display how they would look like with various makeup products, effectively allowing the consumer to choose the product that works best for them, without any guesswork involved, or the time-consuming process of trial and error, looking for the best makeup products to use. GANs address a wide array of challenges that different industries face and has the potential to reshape the future of various industries and consumer experiences.

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