Visual Explanations for Convolutional Neural Networks via Latent Traversal of Generative Adversarial Networks (Student Abstract)

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Abstract

Lack of explainability in artificial intelligence, specifically deep neural networks, remains a bottleneck for implementing models in practice. Popular techniques such as Gradient-weighted Class Activation Mapping (Grad-CAM) provide a coarse map of salient features in an image, which rarely tells the whole story of what a convolutional neural network (CNN) learned. Using COVID-19 chest X-rays, we present a method for interpreting what a CNN has learned by utilizing Generative Adversarial Networks (GANs). Our GAN framework disentangles lung structure from COVID-19 features. Using this GAN, we can visualize the transition of a pair of COVID negative lungs in a chest radiograph to a COVID positive pair by interpolating in the latent space of the GAN, which provides fine-grained visualization of how the CNN responds to varying features within the lungs.

Introduction

Interpreting convolutional neural networks (CNNs) has gained significant relevance with the surge of deep learning-enabled COVID detection models. However, many of these models have been found to be biased and misled by validation and visualization techniques such as Grad-CAM (DeGrave, Janizek, and Lee 2021; Selvaraju et al. 2017). Generative Adversarial Networks (GANs) show promise in feature visualization as they have gained considerable popularity in generating photo-realistic images (Goodfellow et al. 2014). A GAN's generator learns to transform points from a low-dimensional manifold known as the *latent space* into an image via a vector of randomly sampled numbers. After training, it can be observed how one image morphs into another by linearly interpolating between the two images' corresponding latent vectors. This provides the basis for our proposed method of feature visualization.

Methods

Our method first relies on a pre-trained classifier that we wish to visualize. We specifically use a VGG16 model trained to $\sim 75\%$ accuracy on a private COVID chest X-ray dataset of 128x128 grayscale images. The GAN framework is inspired by the Auxiliary-Classifier GAN (Odena, Olah, and Shlens 2017), except we decouple the classifier from the discriminator, and employ a different latent vector scheme (see Figure 1). The generator carries out supervised disentanglement by taking in a latent vector z_1 that corresponds to lung structure, and a class information vector z_2. The vector z_1 is sampled from a spherical normal distribution. The z_2 sampling scheme relies on the intuition that COVID manifestations are not deterministic: the same pair of healthy lungs will retain their lung structure even with COVID, but COVID features can present in many ways within the lungs. Thus, when the class is COVID-negative (class = 0), z_2 is a vector of zeros, otherwise (class = 1) it is drawn from the spherical normal distribution to represent a continuous manifold of COVID features.

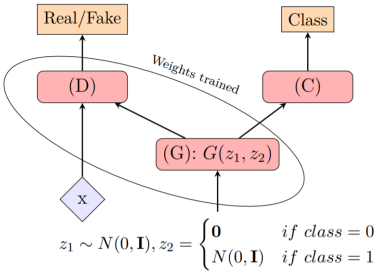

Figure 1: Generator (G) takes in structural latent vector z_1 and class latent vector z_2 to produce fake chest X-rays fed into the discriminator, along with real samples x. The classifier (C) provides feedback for generating class-discriminable images.

During training, the following objective is optimized:

$$\begin{aligned} \min_G \max_D & \mathop{\mathbb{E}}_{x \sim p_x} [\log D(x)] \\ & + \mathop{\mathbb{E}}_{z_1 \sim p_{z_1}, y \sim p_y} [\log(1 - D(G(z_1, y)))] \\ & - \mathop{\mathbb{E}}_{z_1 \sim p_{z_1}, y \sim p_y} [\log(p_c(y|G(z_1, y)))] \end{aligned} \quad (1)$$

The first two terms correspond to the typical min-max game between the generator G and discriminator D, where x corresponds to data observations, z_1 is the structural latent vector, and y is the class that is encoded in the z_2 vector. The third term relates to the generator learning to create images

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that the classifier C can correctly classify as COVID negative or positive. In this formulation, the generator is trained with the discriminator to produce high-fidelity images, while getting feedback from the frozen classifier to incorporate class-specific features. It has been shown that minimizing this third term roughly approximates the KL divergence between the classifier's learned distribution $p_c(y|x)$ and the generator's $p_g(y|x)$ (Gong et al. 2019). Thus, the generator provides a representation of what the classifier has learned.

After training, the generator can be leveraged to explain the classifier. Given a COVID-positive image x, the latent vectors can be reconstructed by optimizing:

$$\arg\min_{z_1,z_2} \text{MSE}(G(z_1, z_2), x) + \text{BCE}(C(G(z_1, z_2)), C(x)) \tag{2}$$

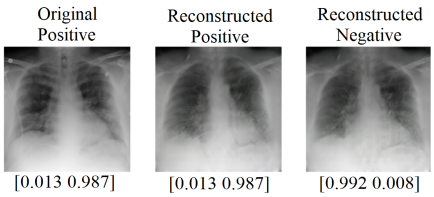
The latent vectors z_1 and z_2 are found via gradient descent. The objective is to minimize the mean-squared error between the generated image and the ground-truth in addition to the binary cross-entropy between the classifier's output on both images. These two terms can be balanced with constant coefficients. After z_1 and z_2 are found, we can rely on the sampling scheme for z_2, changing it to $\overrightarrow{0}$ to convert the COVID-positive lungs to COVID-negative.

Finally, we traverse the latent space to visualize how the classifier's output changes with the interior lung pathology. We interpolate through the latent vector z_2 with steps n at a rate of λ while keeping the lung structure constant with z_1 by looking at the outputs of $G(z_1, \overrightarrow{0} + n\lambda z_2)$, for $n = 1, 2, ...$

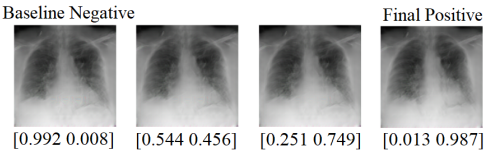
Experiments and Results

After training the generator for 1000 epochs, we evaluate how well z_2 maps to COVID features. We generate 4 samples from the same lung structure z_1, generating 1 COVID negative lung with $z_2 = \overrightarrow{0}$ and 3 positive with $z_2 \sim N(0, \mathbf{I})$. This is repeated 1000 times, and all samples are fed into the classifier. The classifier's predictions match the class fed into the generator with $91.15\% \pm 0.09$ accuracy. Given that random guessing would yield 50%, the z_2 sampling scheme seems to consistently incorporate COVID features as per the classifier.

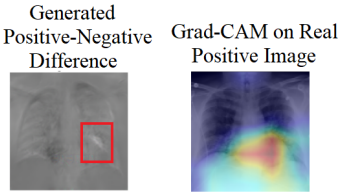
When interpolating through the z_2 latent space between pairs of COVID negative and positive lungs with the same z_1, the classifier's softmax probability for COVID positive monotonically increases as z_2 moves away from $\overrightarrow{0}$, which suggests that the z_2 latent space is structured such that $\overrightarrow{0}$ corresponds to the mean of a highly dense COVID negative probability region. This can be exploited in feature visualization. After reconstructing the COVID positive image and its negative pair with high confidence (as seen in Figure 2a), we can observe the softmax probabilities over the outputs as we morph the negative image into a positive (Figure 2b). Thus, the images across the decision boundary can be observed as the classifier's prediction changes. Compared to Grad-CAM (Figure 2c), traversing through the latent space provides more fine grained feature visualization and holds more explaining power.



(a) Reconstructing an original, real COVID positive image and turning it into negative with the generator.



(b) Interpolating through the latent space between the reconstructed pair of lungs with COVID and without.



(c) Pixel-wise difference between the last and first images in the latent interpolation highlights salient, changing regions. Compare against Grad-CAM to the right.

Figure 2: Running through the proposed feature visualization pipeline. Classifier's softmax outputs are below each example.

This framework can inspire applications beyond chest radiographs, particularly situations that reflect spatially distributed intensity profiles; from satellite images to electron microscopy and medical imaging datasets. Observing structural changes via latent interpolation can provide insight into how the classifier responds to these changing features.

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