CS 403/603 Machine Leaning Project Report
Image Denoising using AutoEnocoders

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Abstract

In this project, we implement an image denoising method which can be generally used in all kinds of noisy images. We achieve denoising process by adding Gaussian noise to raw images and then feed them into AutoEncoder to learn its core representations(raw images itself or high-level representations).We use pre-trained classifier to test the quality of the representations with the classification accuracy. Our result shows that in task-specific classification neuron networks, the performance of the network with noisy input images is far below the pre-processing images that using denoising AutoEncoder.

Introduction

Image is the object that stores and reflects visual perception. Images are also important information carriers today. Acquisition channel and artificial editing are the two main ways that corrupt observed images. The goal of image restoration techniques is to restore the original image from a noisy observation of it. Image denoising is common image restoration problems that are useful by to many industrial and scientific applications. Image denoising problems arise when an image is corrupted by additive white Gaussian noise which is common result of many acquisition channels. The white Gaussian noise can be harmful to many image applications. Hence, it is of great importance to remove Gaussian noise from images. This Report focuses on image denoising. Some approaches have been focus on the denoising process. The common ideas of these approaches is to transfer image signals to an alternative domain where they can be more easily separated from the noise . With the development of deep artificial neuron networks, end-to-end denoising process can be achieved. In this paper, we use Convolutional AutoEncoders to achieve image denoising.

Related work

Image denoising is a kind of feature representation extraction process. A good denoising algorithm should not just work well on removing all kinds of noises, but also should work effectively. Deep neuron networks is powerful in some image classification task nowadays, however, some noise of input images can change its performance. Some research such as 'One pixel attack for fooling deep neural networks from another aspect states the importance of image denoising. In order to emphasize the performance of input images' quality, we also feed raw images, noisy images and denoised images to certain classification neuron networks.

Data set

In order to see whether our algorithm extract the core information of an image, we use the MNIST dataset , which contains 60000 training images and 10000 testing images. It is a data set of small square 28×28 pixel gray scale images of handwritten single digits between 0 and 9.

Methods

Auto-encoding is a data compression algorithm that have both the compression and decompression functions. Auto-Encoder has there main properties that are data-specific, lossy and can learn core representations automatically from input examples without any supervision signals. Hence, it belongs to unsupervised learning . Moreover, in the content of Auto-Encoder nowadays, both the encoder and decoder are generally neuron networks. To be specific, Auto-encoder is data-specific for the network can only be used to compress data similar to what they have been trained on, so this structure is task-specific. Auto-encoder is also lossy, which means that the output can have poor performance sometimes. Autoencoder is learned automatically from data examples and it is a end-to-end training process.
In our case, To be specific, we use convolution neuron networks (CNN) ReLU activation and Maxpooling of Tensorflow in encoder network. We use deconvolution neuron networks (a special CNN structure), ReLu activation and and Maxpooling of TensorFlow in decoder network. Besides, batch normalization are used in both encoder and decoder network. As Auto-Encoder network can achieve image compression from its the hidden neurons' output, because the hidden layer can learn a compressed feature representation for the input data. We also can achieve decompression by the output layer because the output value size is the same of the input.

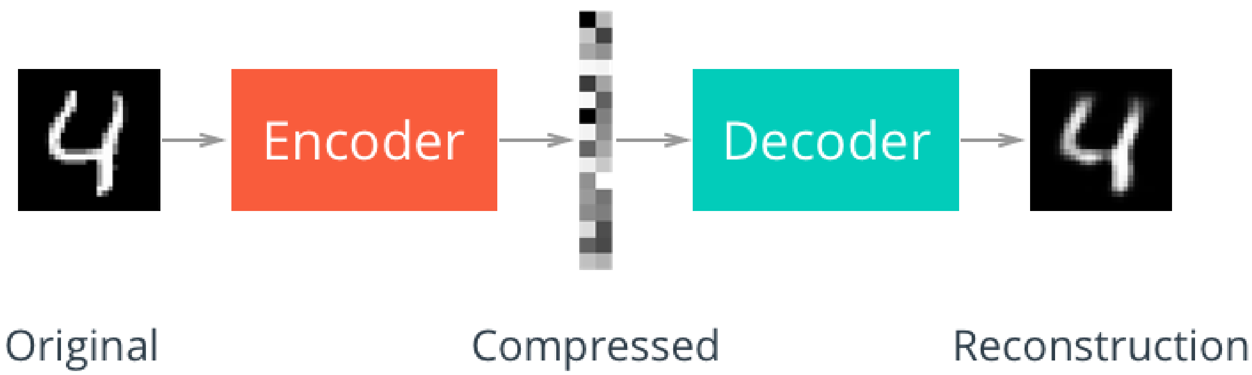
Encoder part:
x=Conv2D(32,(3,3),activation='relu',padding='same')(input _img)
x=MaxPooling2D((2,2),padding='same')(x)
x=Conv2D(32,(3,3),activation='relu',padding='same')(x)
encoded=MaxPooling2D((2,2),padding='same')(x)

Decoder part:

x = decoder_conv1(encoded)
x = decoder_upsamp1(x)
x = decoder_conv2(x)
x = decoder_upsamp2(x)
decoder_output = decoder_conv3(x)

We are aiming to get noiseless images. To achieve that, we first add white Gaussian noise to original images. We treat these noise-added images as the input of AutoEncoder and the desired output from decoder are the original images (images that have no added white Gaussian noise). We use this denoising method because we think that the added white noise are not parts of the core representations of the input images. So those added noise will be filtered by the encoder and the compressed representations have no noise information, thus the output of decoder should be clean and noiseless images.

As we want to use the output from the AutoEncoder to form an images , the network should produce positive output. Hence, we adding ReLU activation at the last the output layer of decoder, which can also accelerating the training speed. Instead of using SGD optimizer , we choose to use Adam optimizer that can adjust the learning rate on each weight parameter, which guarantees effective training.



Experiment

We use MNIST dataset to train our Denoising AutoEncoder. We train the AutoEncoder with a 128 batch size input noisy images for 50 epochs. We get the noisy images by manually adding some random Gaussian noise to the input images. By trying to get the output images as the origin noiseless images, we get our denoised images in Fig 1. As we can see through the results, the denoised images quality is very good and is almost the same with the noiseless images.

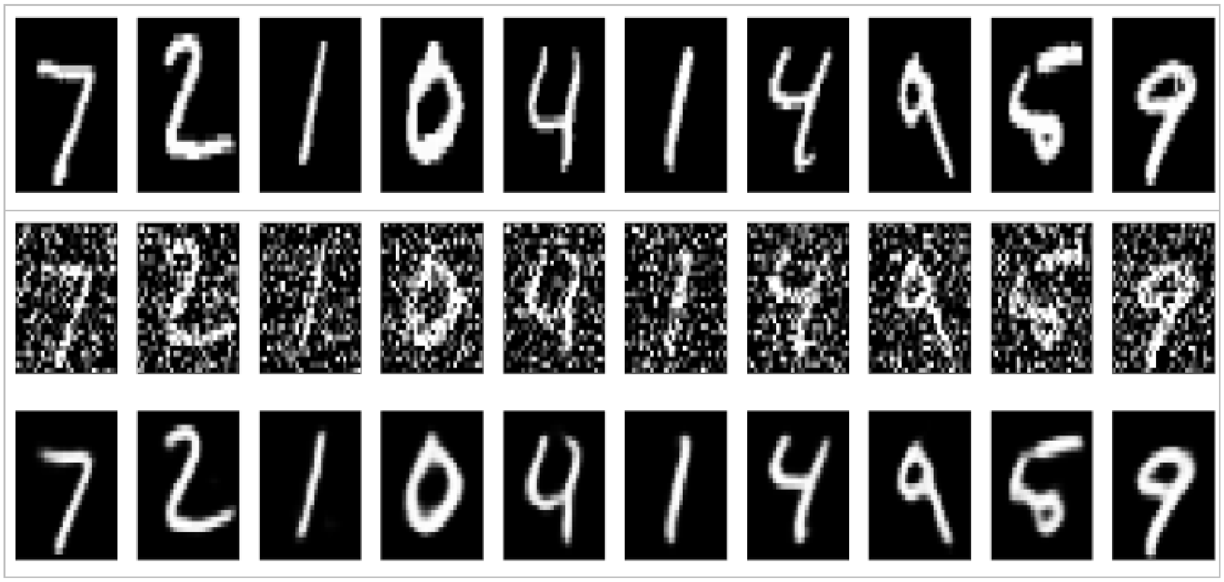


Figure 1: Result.

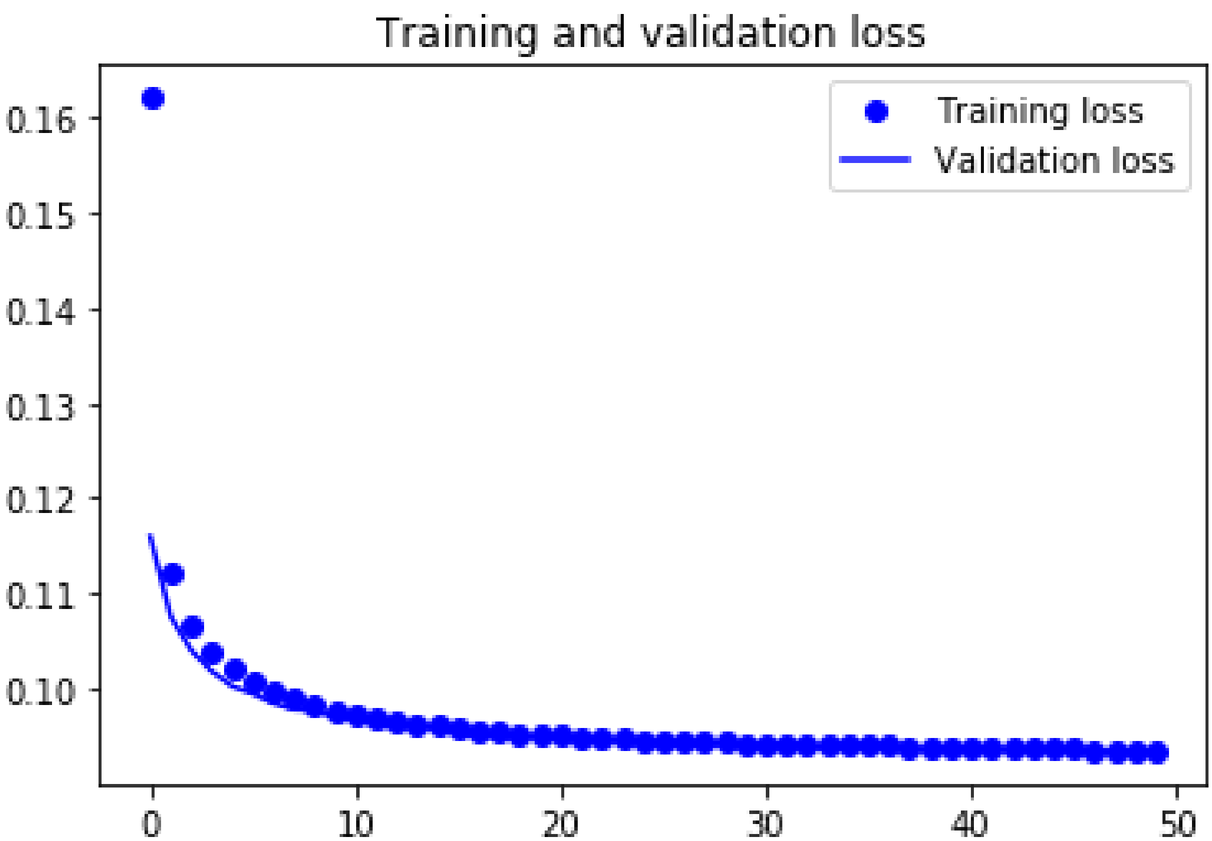


Figure 2: Epoch vs loss.

Conclusion

We have shown that we can achieve effective image denoising with the method of AutoEncoder network by just feeding noisy images to AutoEncoder and make sure that the output images are similar as the origin noiseless images. This method guarantees that we don't need to do much images preprocessing work and can get the denoised images just from the AutoEncoder. Though the process of encoder is a lossy compression, our method can guarantees the representations generated by encoder have less or no noise in it. Our experiments also shows even little noise of the input images will greatly influence the accuracy of certain neuron network classifier. Moreover, in our cases, the noise is just white Gaussian noise. From its denoising principle, we can see that if we can measure the added noise, this denoising method can be used in removing all kind of digital noise.

References

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