

Restricted Boltzman Machines

What is the effect of different parameters (epochs, learning rate, components) on training the RBM, evaluate the performance visually by reconstructing unseen test images.

The number of epochs is the amount of times that the network is trained on the training data. The more epochs are used, the longer training will take. If the incorrect amount of epochs is used it will lead to under-training or over-training.

The learning rate is the extent to which the update of hidden and visible units affects the weights vector. For RBMs it is recommended to keep this quite small.

The number of components is the number of hidden units used. If more hiddenunits are used it takes longer to train the RBM. If the incorrect amount of components is used it will lead to underfitting or overfitting. Visually there is very little difference between 5, 10 and 20 components.

Change the number of Gibbs sampling steps, can you explain the result?

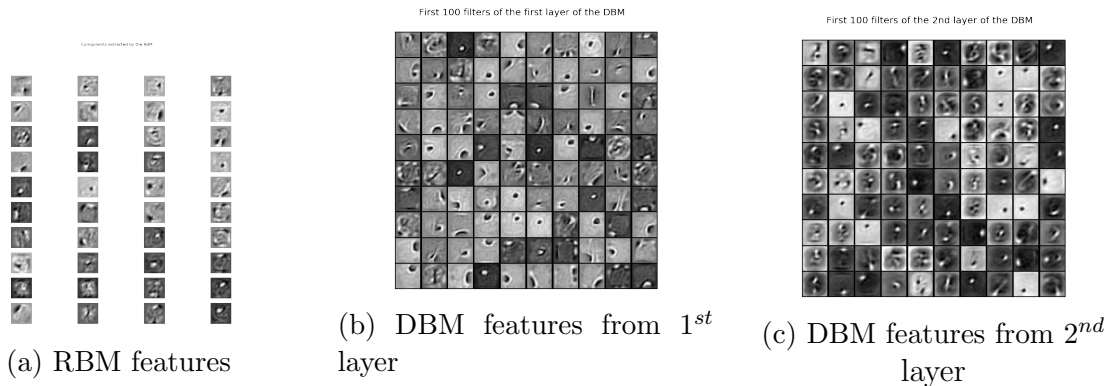
Changing the number of Gibbs sampling steps changes how many times the visible and hidden vectors will update.

What is the role of the number of hidden units, learning rate and number of iterations on the performance. How many rows can you remove such that reconstruction is still possible?

The **number of hidden units** determines the amount of features that the network can learn, therefore if there aren't enough hidden units the RBM will not be able to reconstruct the image accurately.

Again, the **learning rate** the degree of which the change in visible and hidden units affects the weights. It is found that to reconstruct the images one should keep this number small and use a large **number of iterations**.

Deep Boltzman machines



These features can, in a sense to be viewed as a set of filters. By using a deeper Boltzman machine it is possible to obtain more complex feature extraction. It can be seen that the features in the first hidden layer of the DBM are less complex to those in the second. It appears that simpler features are extracted first and then using those, the more complex features are constructed.

Sample new images from the DBM. Is the quality better than the RBM from the previous exercise and explain why?

Yes the quality of the images is much better. The DBM is able to take advantage of its structure and use a combination of similar patterns / features to generate more complex pattern representation and thus produce better quality images.(analogous to what stacked autoencoder and CNNs can do)

Deep convolutional generative adversarial networks

Exercise Comment on the loss and accuracy of the generator and discriminator, shown during training and discuss its stability.

The loss and accuracy of both the discriminator and generator are highly unstable and subject to large variations during training. This essentially boils down to how generative adversarial networks operate. As the generator becomes better at creating images, the discriminator becomes better at detecting fakes. In theory GANs should be able to converge when both networks reach a Nash equilibrium. Non convergence is a common problem with GANs whereby the parameters of the model constantly oscillate in an unstable manner during training and fail to converge. G

The **generator loss** is relatively stable around 0.7 ± 0.1 .

The **generator accuracy** fluctuates between 0.3 and 0.6

The **discriminator loss** is relatively stable around 0.7 ± 0.1 .

The **discriminator accuracy** fluctuates between 0.3 and 0.8, becoming slightly more stable as training goes on.

Generative Adversarial Networks

Essentially what this is doing is trying to converge the colour space of each image onto the colour space of the other based on the distance metric between the two distributions.

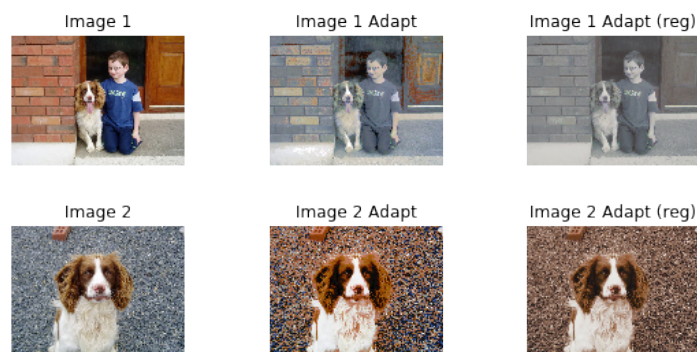


Figure 2: Colour swap

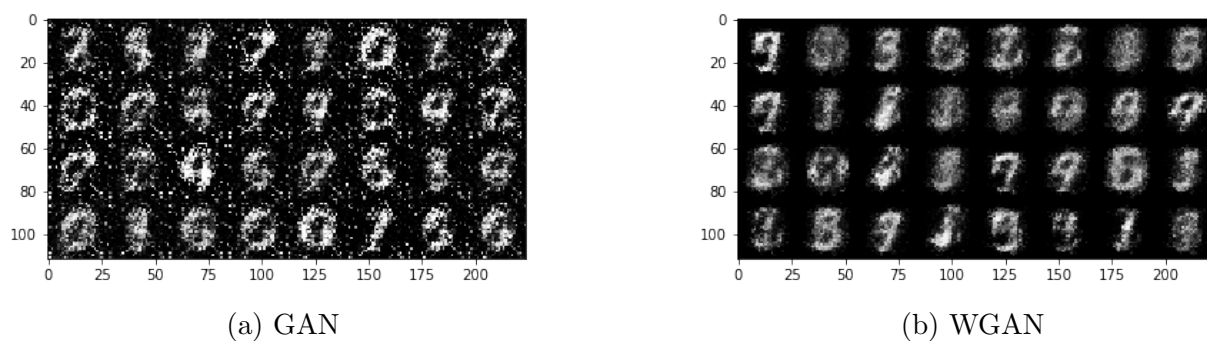


Figure 3: Generated images after 5000 batches of 32 images

The WGAN is more stable during training as the the loss appears to be converging on a value.