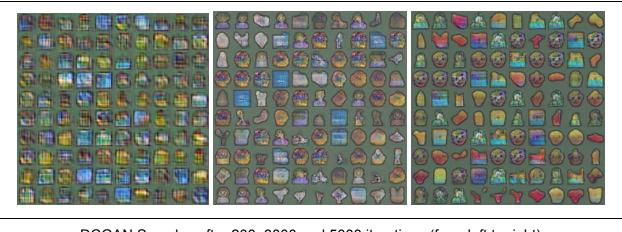
## Part 1

1. The general equation describing the input dimension and output dimension of a convolution is given by  $W_2 = \frac{W_1 - F}{s} + 1$ , where W1 is the input dimension, F is the filter size, s is the stride, and W2 is the output dimension. Let p be the amount of padding.  $W_1/2 = \frac{W_1 + 2p - F}{s} + 1$ . Setting F = 5, s = 2, then p = 3/2.



DCGAN Samples after 200, 3000 and 5000 iterations (from left to right)

As seen, the generated samples improve by taking on more familiar shapes of emoticons and then eventually adding details and more vivid coloring.

## Part 2

1.



Figure: Apple->Windows (left) and Windows->Apple (right) for 200 iterations (top) and 5000 iterations (bottom). Cycle lambda was set to 0.15.

2. Below are samples of the GAN with the same settings, only using different seeds.



Figure: Apple->Windows (left) and Windows->Apple (right) for 200 iterations (top) and 5000 iterations (bottom), with a different seed set. Cycle lambda was set to 0.15.

Interestingly, the colors changed with a different seed. The reason is because a new seed shuffles the images. The gradient is a stochastic gradient and so the neural nets probably entered a different local minimum.

## 3. Below are samples of the cycle gan with lambda set to 0, 0.05, 1 and 100.



Figure: Apple->Windows (left) and Windows->Apple (right) for 200 iterations (top) and 5000 iterations (bottom), with a different seed set. The cycle lambda was set to 0.



Figure: Apple->Windows (left) and Windows->Apple (right) for 200 iterations (top) and 5000 iterations (bottom), with a different seed set. The cycle lambda was set to 0.05



Figure: Apple->Windows (left) and Windows->Apple (right) for 200 iterations (top) and 5000 iterations (bottom), with a different seed set. A high cycle lambda was set (1).



Figure: Apple->Windows (left) and Windows->Apple (right) for 200 iterations (top) and 5000 iterations (bottom), with a different seed set. A very high cycle lambda was set (100).

When lambda was 0, the translations are incoherent but vaguely familiar to the input. The reason is because the generators only aimed to fool the discriminator. As expected, as the cycle lambda increased, the neural net focused on the reconstruction loss. The translations with lambda=0.05 proved to be closer to the original image but still maintained style transfer. As

lambda further increased, the generators only focused on reconstructions. The best way to reconstruct would be for the generator to simply output the original image. The translations are thus much more similar to the original image and maintain it's qualities, but also qualitatively have a worse style transfer (similar color pallette, shape, etc). One can then see that it saturates; the output between lambda=1 and lambda=100 does not change. The reason is because the generators reach capacity and all the loss is from the reconstruction error resulting from the encoding in the bottleneck of the generators.