In [1]:
```
# imports
import tensorflow as tf
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
# draw plots in notebook not new window
```

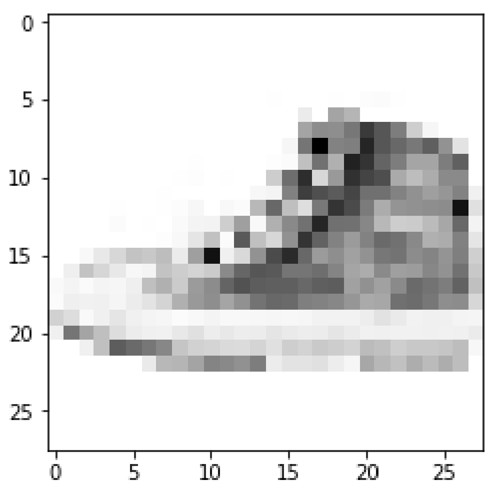
In [37]:
```
# load data
from tensorflow.examples.tutorials.mnist import input_data
'''
switch for Fashion or Digits Data set
'''
# mn = input_data.read_data_sets("./MNIST_DATA",one_hot=True)
mn = input_data.read_data_sets("./FASHION_DATA",one_hot=True)
```

```
Extracting ./FASHION_DATA/train-images-idx3-ubyte.gz
Extracting ./FASHION_DATA/train-labels-idx1-ubyte.gz
Extracting ./FASHION_DATA/t10k-images-idx3-ubyte.gz
Extracting ./FASHION_DATA/t10k-labels-idx1-ubyte.gz
```

In [38]:
```
print('shape of image is: ', mn.train.images[0].shape)          # image
 is a long flat vector
# plt.imshow(mn.train.images[23].reshape(28,28), cmap="Greys")     # ref
ormat long flat img vector in to 28x28 square img
plt.imshow(mn.train.images[2].reshape(28,28), cmap="Greys")     # reform
at long flat img vector in to 28x28 square img
```

```
shape of image is:  (784,)
```

Out[38]:
```
<matplotlib.image.AxesImage at 0x11db6d6a0>
```



In [4]:
```
# define generator/faker net with own var_scope
def gen(z, reuse=None, extra_layer=0):
    '''
    input: takes random seed z
    outputs: a 784 pixel img vector
    '''
    with tf.variable_scope('gen', reuse=reuse):
        leaky_relu_const = 0.01 # using RELU (sparse activation) causes
 instability, use leaky relu
        hid1 = tf.layers.dense(inputs=z, units=128)
        hid1 = tf.maximum(leaky_relu_const*hid1, hid1)
        hid2 = tf.layers.dense(inputs=hid1, units=128)
        hid2 = tf.maximum(leaky_relu_const*hid2, hid2)
        if extra_layer:
            hid3 = tf.layers.dense(inputs=hid2, units=256)
            hid3 = tf.maximum(leaky_relu_const*hid3, hid3)
            outl = tf.layers.dense(hid3, units=784, activation=tf.nn.tan
h)
        else:
            outl = tf.layers.dense(hid2, units=784, activation=tf.nn.tan
h)
        return outl
```

In [5]:
```
# define descriminator/judge net with own var_scope
def judge(x, reuse=None, extra_layer=0):
    '''
    input: a 784 pixel img vector (either generated by the faker or a re
al example from MNIST)
    output: tuple (Boolean (0 or 1) where 1 = image is real (MNIST) and
 not generated, prediction proability)
    '''
    with tf.variable_scope('jud', reuse=reuse):
        hid1 = tf.layers.dense(inputs=x, units=128)
        leaky_relu_const = 0.01
        hid1 = tf.maximum(leaky_relu_const*hid1, hid1)
        hid2 = tf.layers.dense(inputs=hid1, units=128)
        hid2 = tf.maximum(leaky_relu_const*hid2, hid2)
        if extra_layer:
            hid3 = tf.layers.dense(inputs=hid2, units=256)
            hid3 = tf.maximum(leaky_relu_const*hid3, hid3)
            logits = tf.layers.dense(hid3, units=1)
        else:
            logits = tf.layers.dense(hid2, units=1)
        outl = tf.sigmoid(logits)
        return outl, logits
```

In [6]:
```
# define placeholders
extra_layer=False # use 1 for fashion, 0 for MNIST
real_img = tf.placeholder(tf.float32, shape=[None, 784])
z= tf.placeholder(tf.float32, shape=[None, 100])  # random seed for the
 faker


G = gen(z, extra_layer=extra_layer) # initate a faker
```

In [7]:
```
JoutReal, JlogitsReal = judge(real_img, extra_layer=extra_layer)  # this
 is a tensorFlow node, this version takes in real MNIST images
JoutFake, JlogitsFake = judge(G, reuse=True, extra_layer=extra_layer) #
 this is a tensorFlow node, this version takes in faked images
```

In [8]:
```
# losses: how "off" was the model?
def lossfunc (logitsin, yin):
    '''
    for each 0/1 prediction, calculate the error, and return the average
 for the batch
    '''
    return tf.reduce_mean(tf.nn.sigmoid_cross_entropy_with_logits(logits
=logitsin, labels=yin))
```

In [9]:
```
# define labels (either 0 or 1 because we know if the image is a fake or
 real MNIST data)
JlossReal = lossfunc(JlogitsReal, tf.ones_like(JlogitsReal)*0.90)
'''
tf.ones_like(JlogitsReal)*0.9 is applying a smoothing factor to real ima
ges (lablel = 1)
so the model genearlize better
'''
JlossFake = lossfunc(JlogitsFake, tf.zeros_like(JlogitsFake))
Jloss = JlossReal + JlossFake # overall error for the judge-net

'''
overall error for the faker net, it doesn't care about loss on real MNIS
T images
is labeled 1 (a lil counter-intuitive maybe):
- but since if the judge thinks the image is real, it'll output value
 "1"
- then the generator won, we want to label genenerator images with 1
(other wise we would be punishing the generator for it's sucess)
'''
Gloss=lossfunc(JlogitsFake, tf.ones_like(JlogitsFake))
```

In [10]:
```
# define visualizer function

skip = 5

def visualize_sample(imgarray, pos, greyscale=0):
    img = imgarray.reshape(28,28)
    fig = plt.figure()
    fig.suptitle("after {} epochs".format(pos), fontsize=14, fontweight=
'bold')
    if greyscale == 1:
        plt.imshow(img, cmap='Greys')
    else:
        plt.imshow(img)
```

In [11]:

```
# define pipeline parameters

batchsz=100 # number of images processed before we make a update
rounds = 256 # number of times we train over the whole data-set
samples = [] # a array to store the random samples at each epoch
lr = 0.001 # learning rate

# define what to optimize
allvars = tf.trainable_variables()
jvars = [var for var in allvars if 'jud' in var.name]
gvars = [var for var in allvars if 'gen' in var.name]

jtrain = tf.train.AdamOptimizer(lr).minimize(Jloss, var_list=jvars) # tr
ain judge only
gtrain = tf.train.AdamOptimizer(lr).minimize(Gloss, var_list=gvars) # tr
ain generator only

init = tf.global_variables_initializer()
```

In [36]:

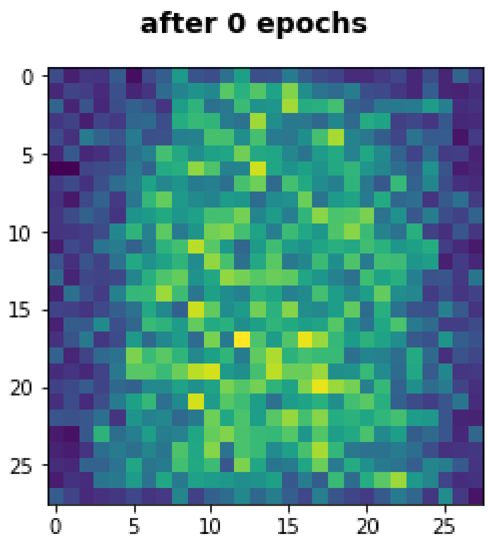
```
with tf.Session() as sess:
    sess.run(init)
    for e in range(rounds):
        nbatch = mn.train.num_examples // batchsz
        # train the network for 1 batch (there are # of Images/Bach_size
 batches in each epoch)
        for i in range(nbatch):
            batch = mn.train.next_batch(batchsz) # get the next batch of
 training data
            batchimgs = batch[0].reshape((batchsz, 784))
            batchimgs = batchimgs * 2 - 1 # adjust values for tanh activ
ation, batch imgs are pre-normalized
            batch_z = np.random.uniform(-1,1,size=(batchsz,100)) # gener
ate random seed batch for faker
            sess.run(jtrain, feed_dict={real_img: batchimgs, z: batch_z
}) # train one batch on judge
            sess.run(gtrain, feed_dict={z:batch_z}) # train one batch on
 faker
        print("on epoch {}".format(e))
        samplez = np.random.uniform(-1,1,size=(1,100))  # make random se
ed vector for sampling
        fakeimg = sess.run(gen(z, reuse=True, extra_layer=extra_layer),
feed_dict={z: samplez}) # make fake images
        samples.extend(fakeimg)
```

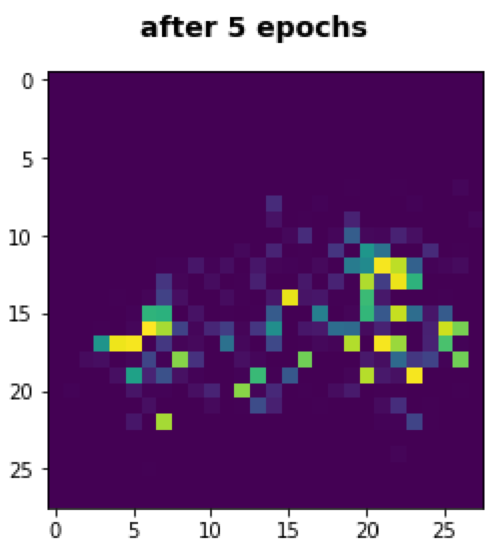
In [44]:
```
'''
code to save and load results
uncomment to (switch) save the appropriate sample vector file
'''



'''
np.save('./samples_250t', samples)
'''
# res = np.load('./samples_250t_1.npy')


'''
np.save('./samples_250t_FASHION2', samples)
'''

res = np.load('./samples_250t_FASHION2.npy') # './samples_250_FASHION.np
y'

loaded_samples = res # res
```

In [45]:

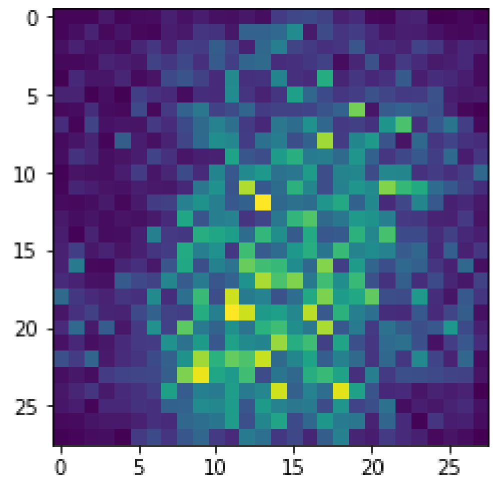
```
for pos, imgs in enumerate(loaded_samples):
    if pos%skip ==0 or pos==250-1 :
            visualize_sample(imgs, pos)
```

```
/Users/mengningshang/Desktop/Dev_Env/carAI/CarND-Alexnet-Feature-Extrac
tion/wcd-ml-b2/lib/python3.6/site-packages/matplotlib/pyplot.py:524: Ru
ntimeWarning: More than 20 figures have been opened. Figures created th
rough the pyplot interface (`matplotlib.pyplot.figure`) are retained un
til explicitly closed and may consume too much memory. (To control this
warning, see the rcParam `figure.max_open_warning`).
  max_open_warning, RuntimeWarning)
```

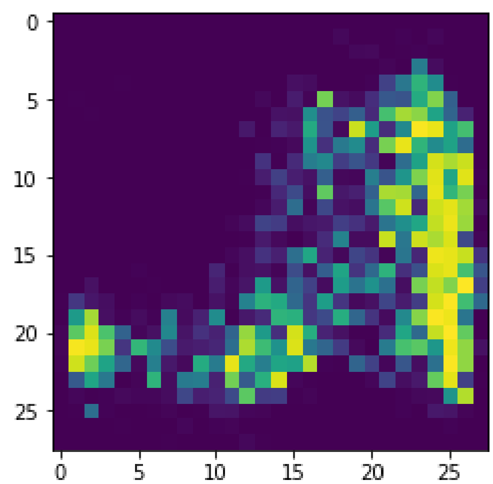




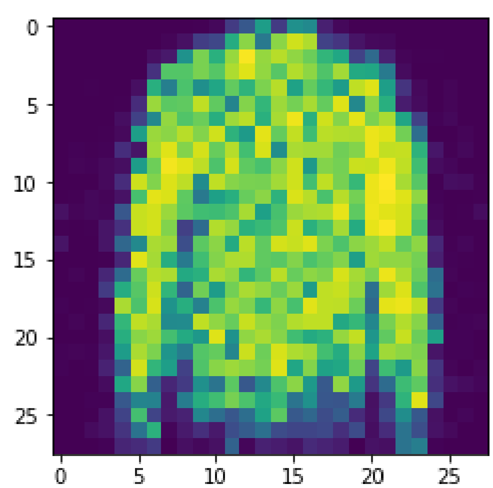
after 10 epochs



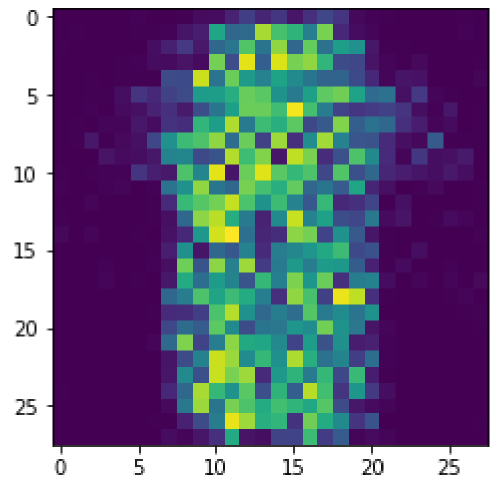
after 15 epochs



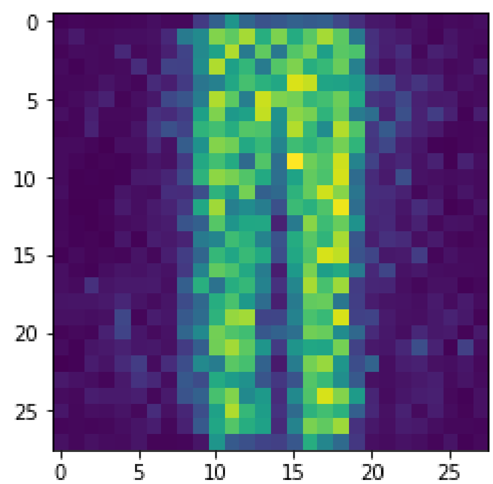
after 20 epochs



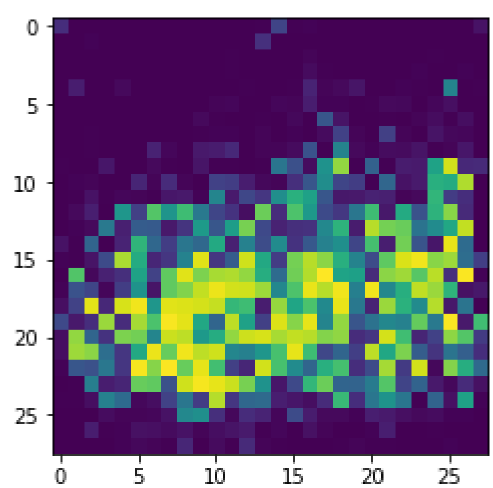
after 25 epochs



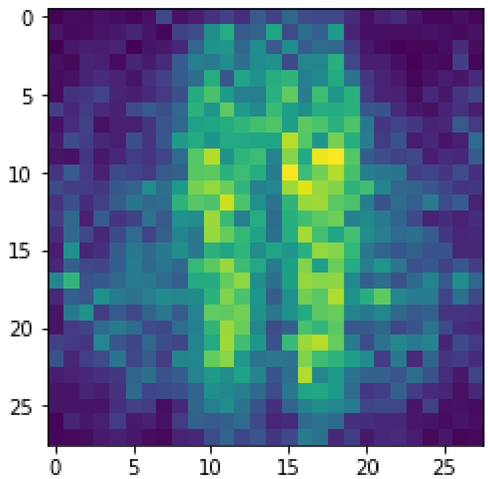
after 30 epochs



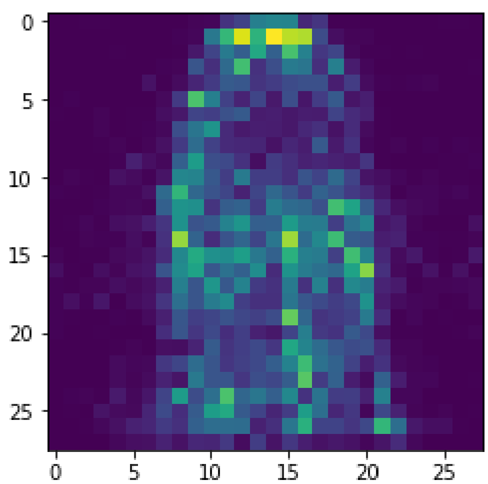
after 35 epochs



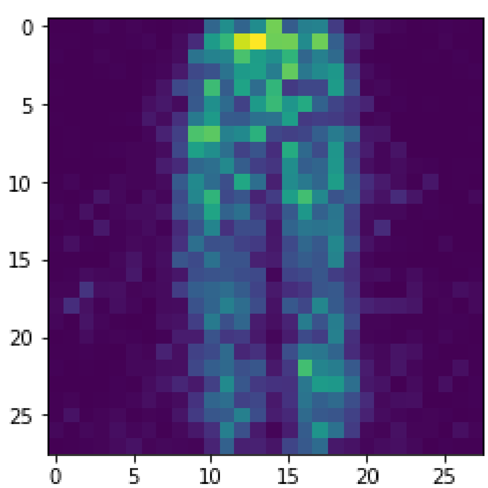
after 40 epochs



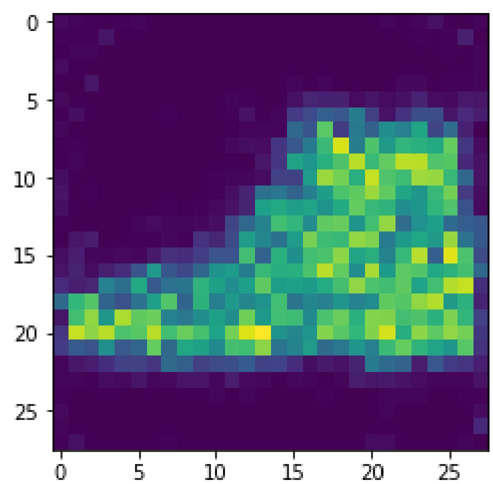
after 45 epochs



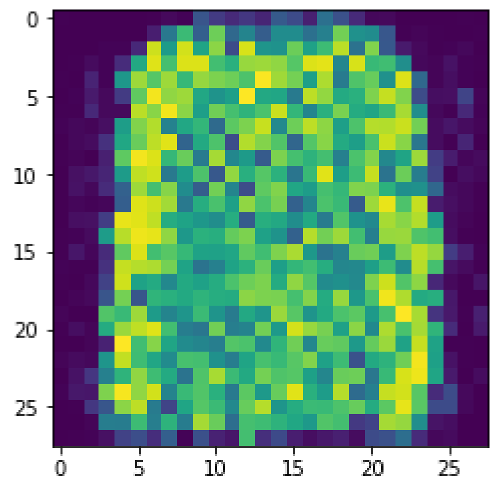
after 50 epochs



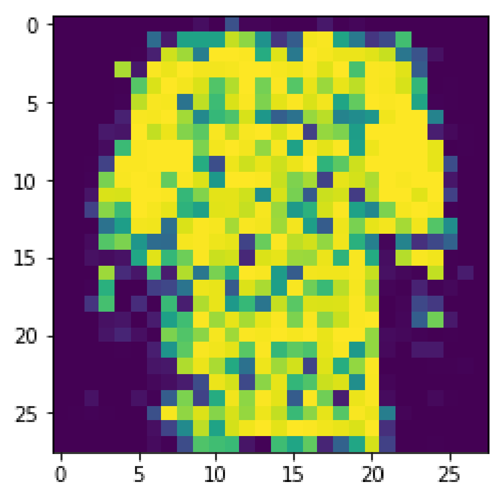
after 55 epochs



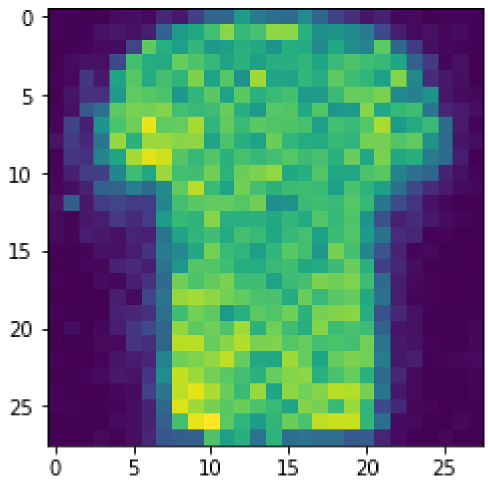
after 60 epochs



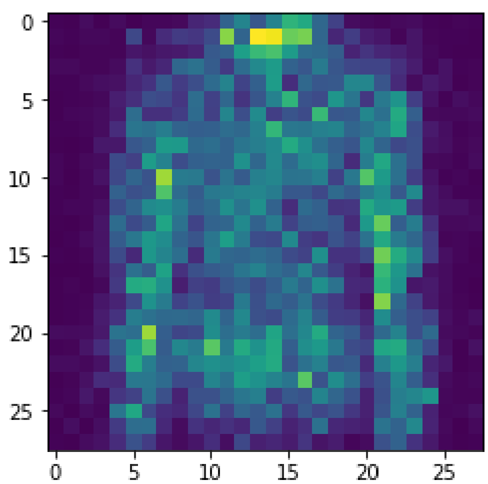
after 65 epochs



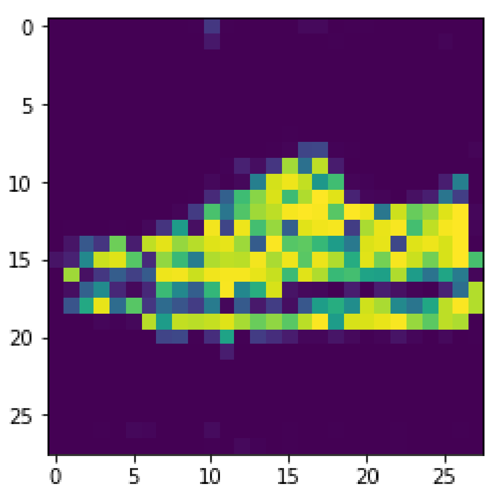
after 70 epochs



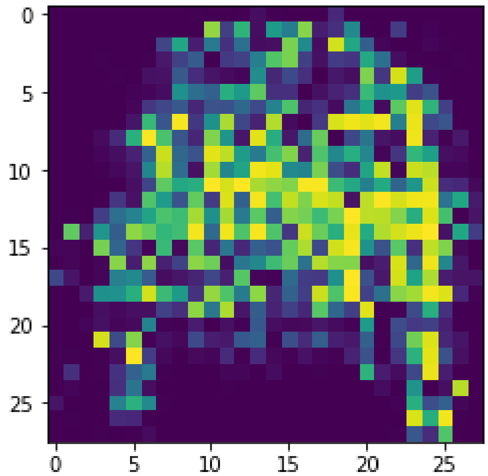
after 75 epochs



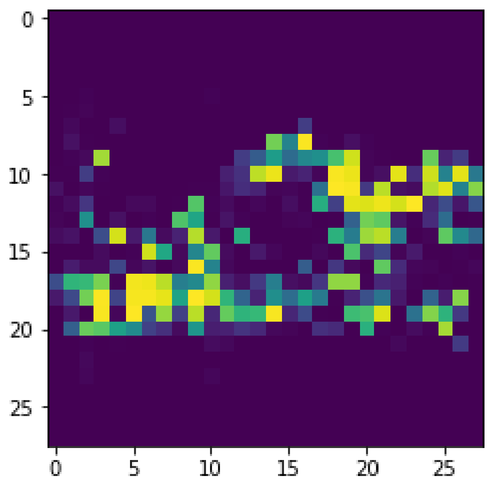
after 80 epochs



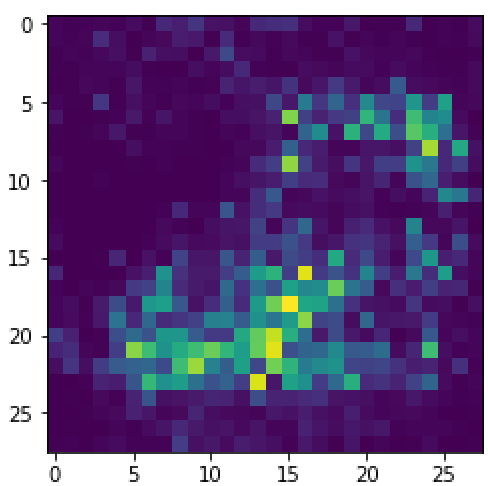
after 85 epochs



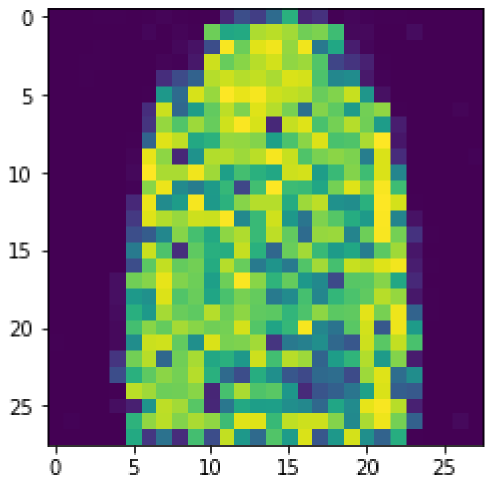
after 90 epochs



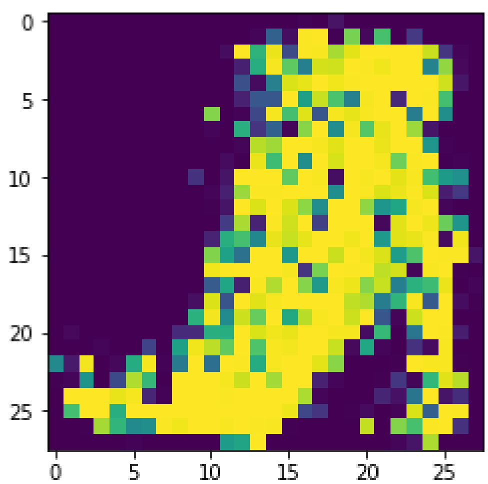
after 95 epochs



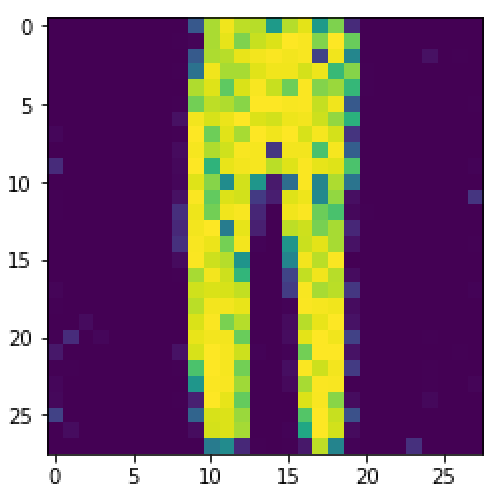
after 100 epochs



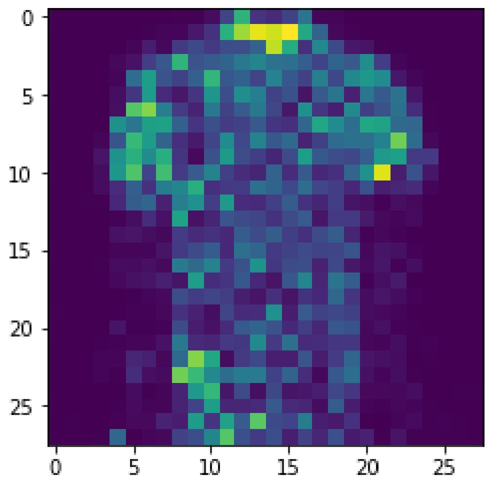
after 105 epochs



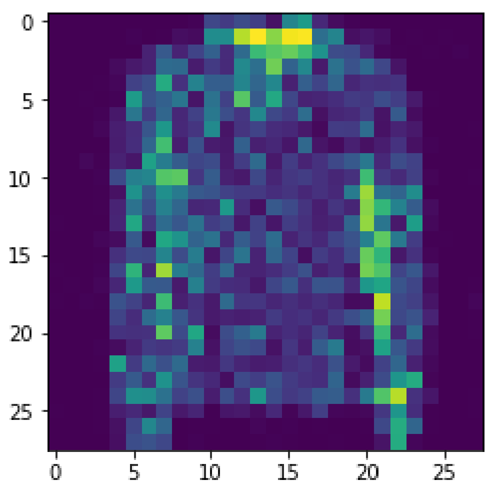
after 110 epochs



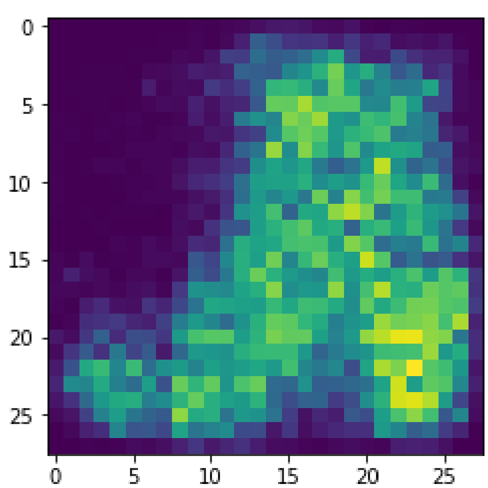
after 115 epochs



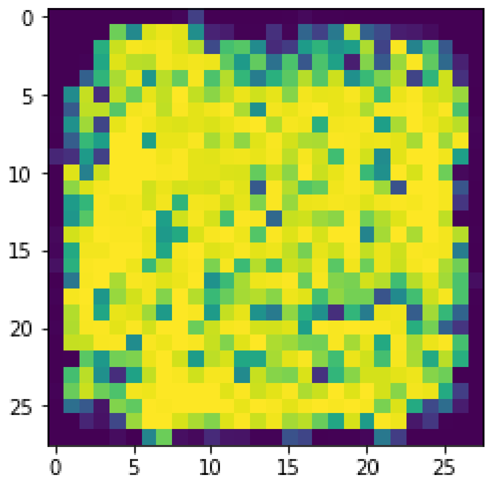
after 120 epochs



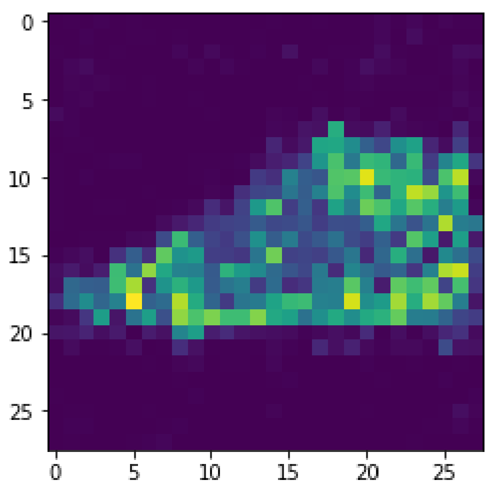
after 125 epochs



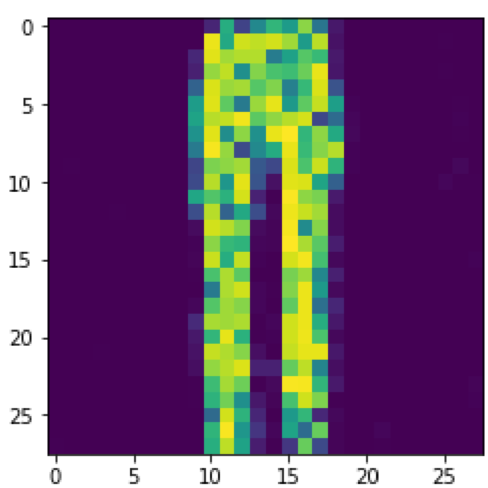
after 130 epochs



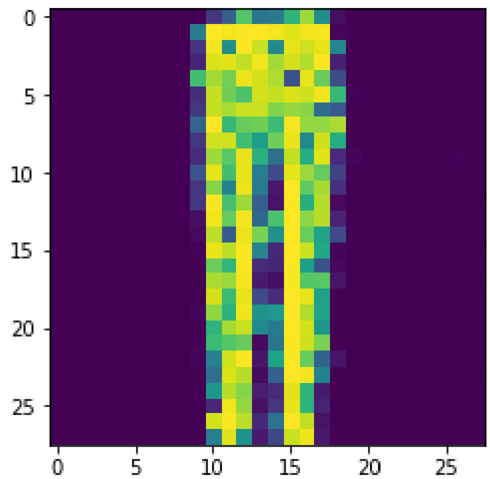
after 135 epochs



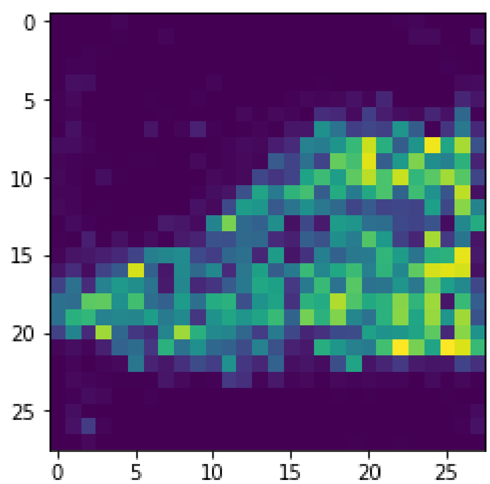
after 140 epochs



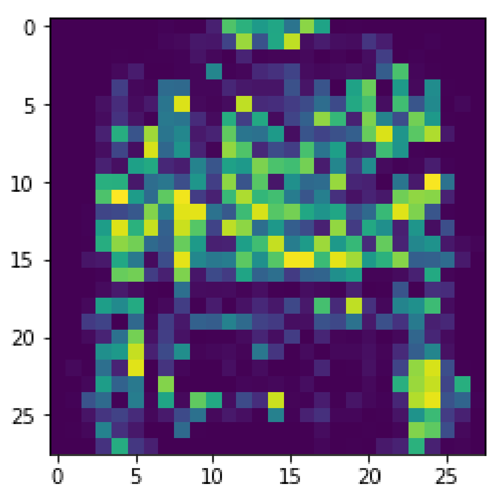
after 145 epochs



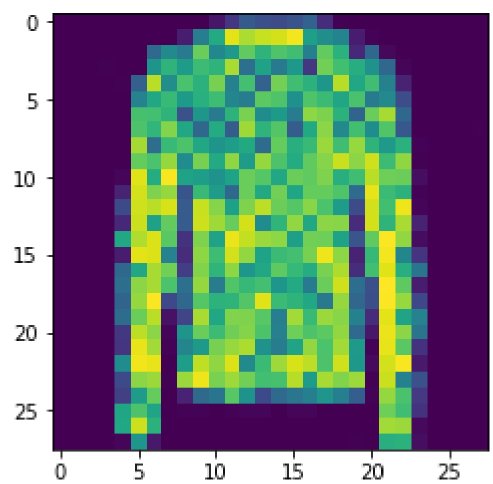
after 150 epochs



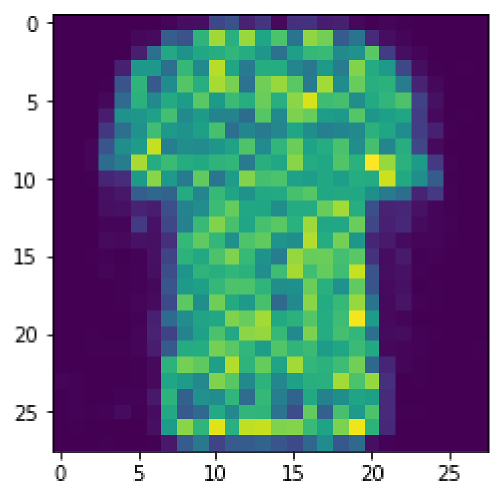
after 155 epochs



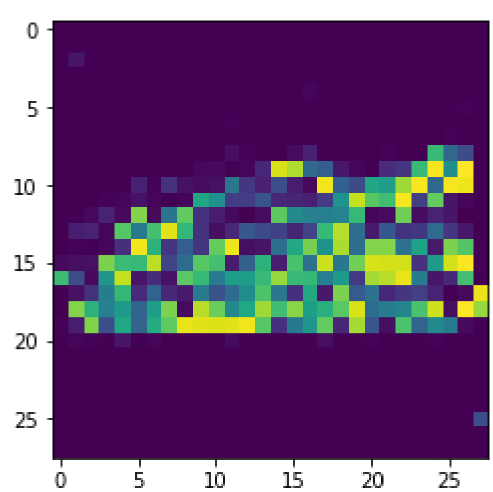
after 160 epochs



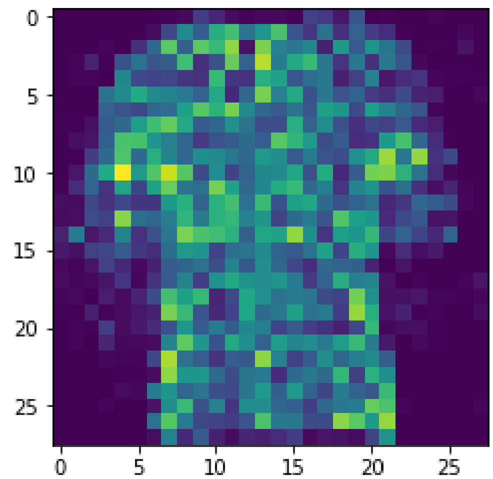
after 165 epochs



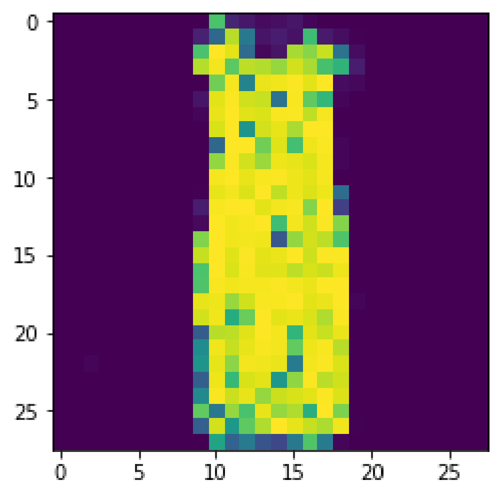
after 170 epochs



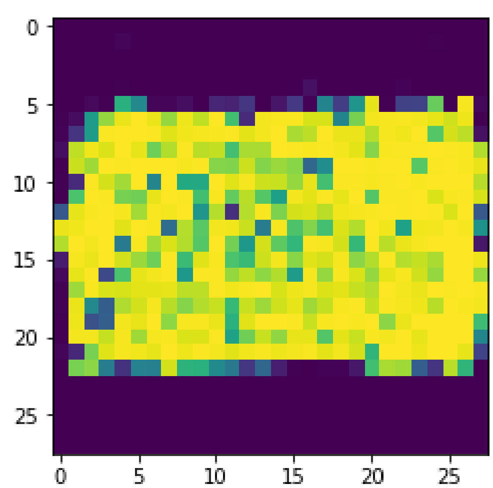
after 175 epochs



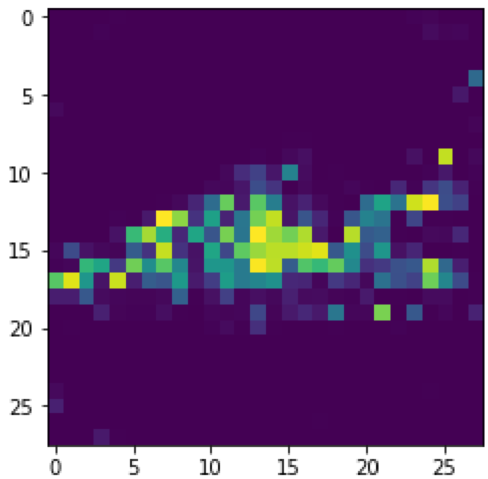
after 180 epochs



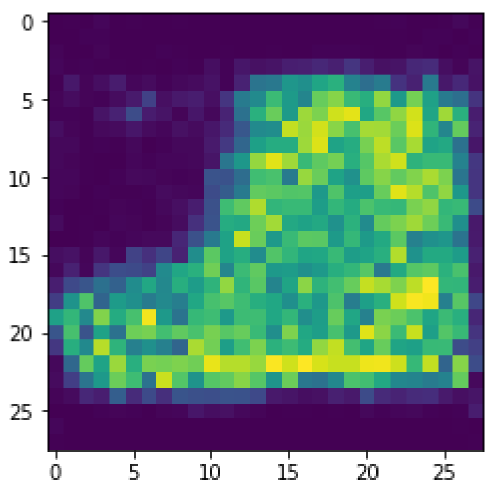
after 185 epochs



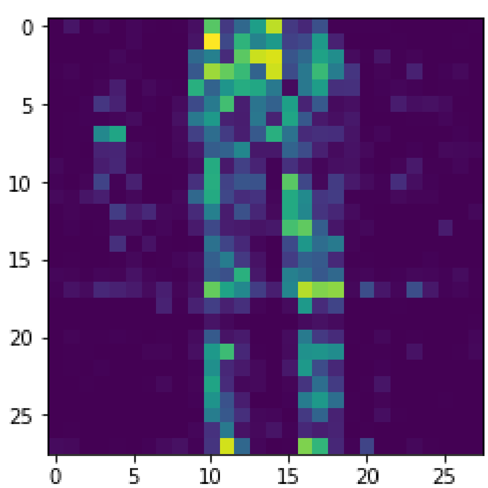
after 190 epochs



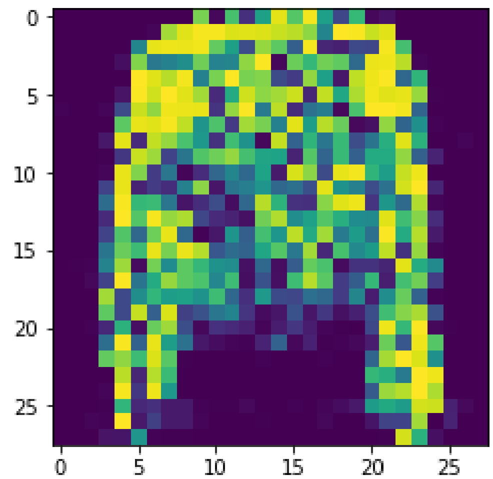
after 195 epochs



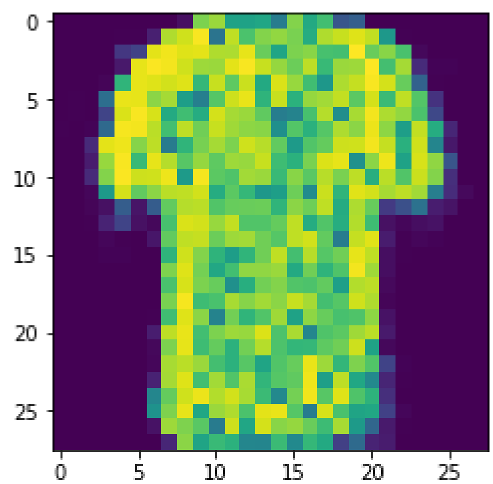
after 200 epochs



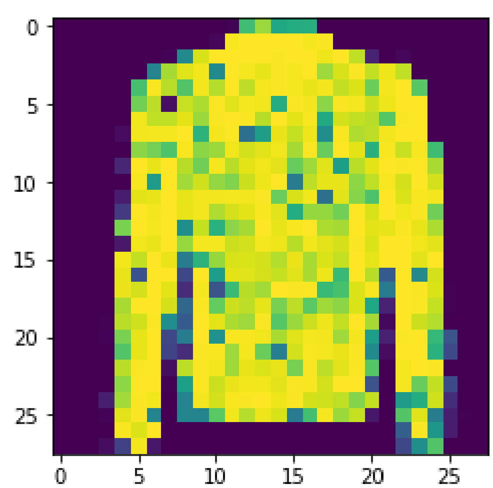
after 205 epochs



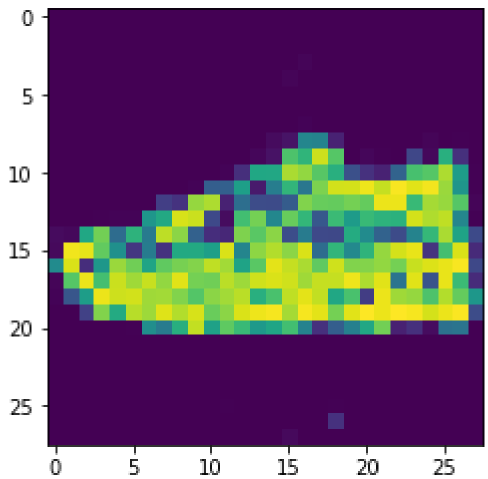
after 210 epochs



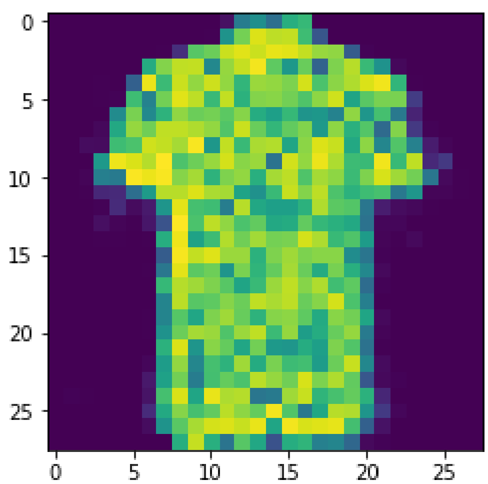
after 215 epochs



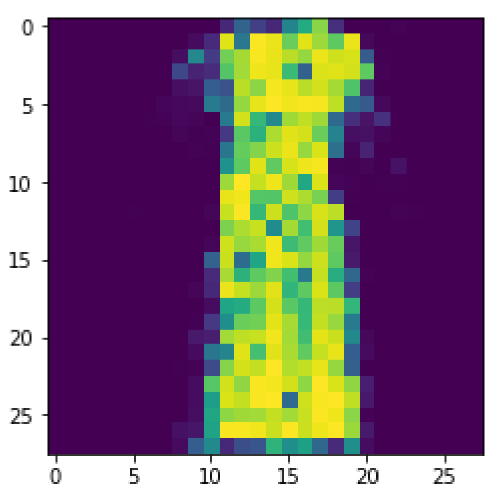
after 220 epochs



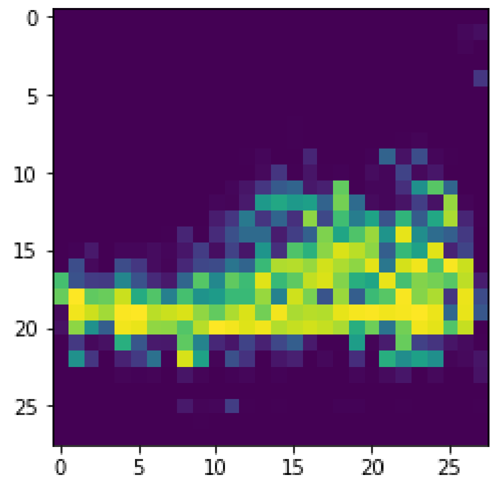
after 225 epochs



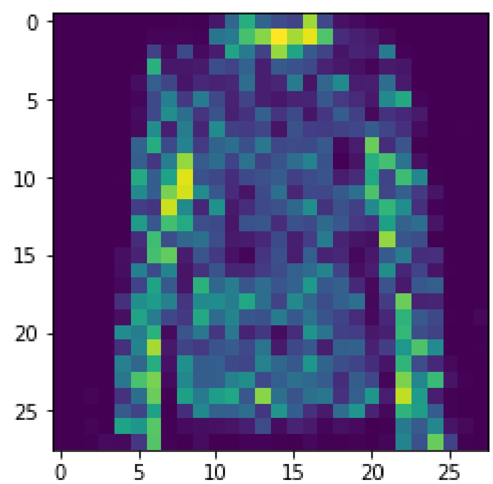
after 230 epochs



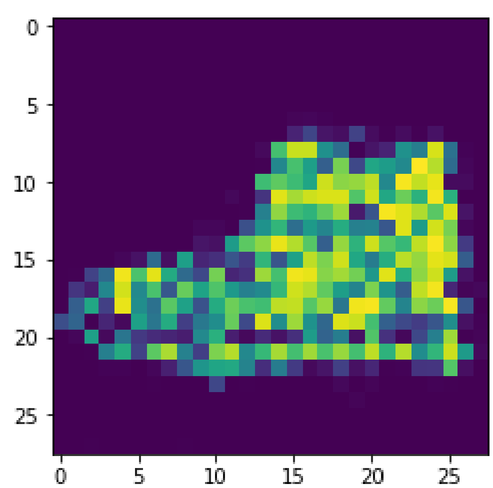
after 235 epochs



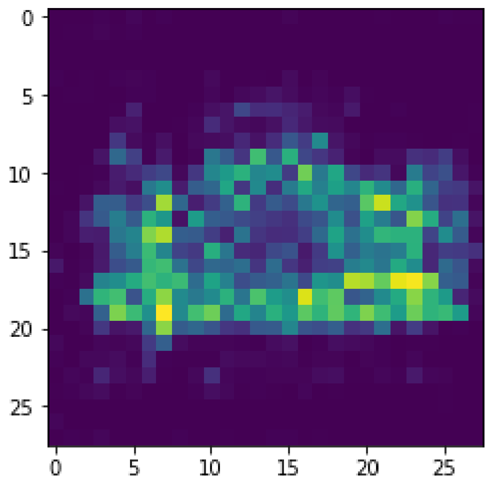
after 240 epochs



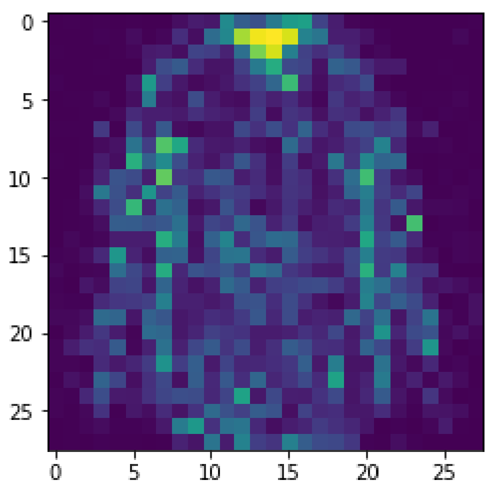
after 245 epochs



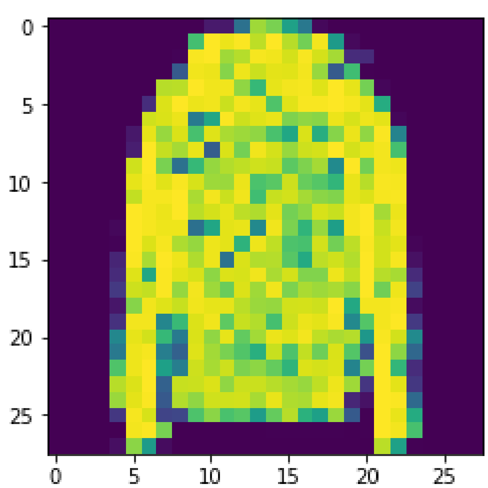
after 249 epochs



after 250 epochs



after 255 epochs



In [15]:
```
len(samples)
```

Out[15]: 256