Plots

April 25, 2019

In [0]:
```
from glob import glob
import os
import numpy as np
import matplotlib.pyplot as plt
import shutil
from torchvision import transforms
from torchvision import models
import torchvision
import torch
from torch.autograd import Variable
import torch.nn as nn
from torch.optim import lr_scheduler
from torch import optim
from torchvision.datasets import ImageFolder
from torchvision.utils import make_grid
import time
from torchvision import datasets,transforms
import torch.nn.functional as F
import torch.optim as optim


import os
from torchvision.utils import save_image

## Plotting library
from matplotlib.offsetbox import OffsetImage, AnnotationBbox
from matplotlib.backends.backend_agg import FigureCanvasAgg as FigureCanvas

from scipy.stats import norm
from sklearn import manifold

%matplotlib inline
import seaborn as sns
plt.style.use("seaborn")

print('Torch', torch.__version__, 'CUDA', torch.version.cuda)
print('Device:', torch.device('cuda:0'))
print(torch.cuda.is_available())
```

```
        is_cuda = torch.cuda.is_available()
        device = torch.device ( "cuda:0" if torch.cuda.is_available () else "cpu" )
```

```
Torch 1.0.1.post2 CUDA 9.0.176
Device: cuda:0
True
```

In [0]:
```
        ## Data loader
        def get_dataloaders(path, batch_size, pad = False):
            path = os.path.join(path,"MNIST/data")
            print(path)
            transform = transforms.Compose([transforms.ToTensor(),
                                            transforms.Normalize((0.1307,), (0.3081,))])
            train_dataset = datasets.MNIST(root = path,
                           train = True, download = False,
                           transform = transform)
            train_loader = torch.utils.data.DataLoader(dataset = train_dataset,
                            batch_size = batch_size,
                                   shuffle = True)

            test_dataset = datasets.MNIST(root=path,train=False,
                                          transform=transform,download=True)
            test_loader = torch.utils.data.DataLoader(test_dataset,
                                 batch_size=batch_size,shuffle=True)


            return (train_loader, test_loader)
```

In [0]:
```
        """
        Load model
        """
        def load_model(model, filepath):
            state = torch.load(filepath)
            model.load_state_dict(state['model'])
            model.cuda()


        def load_model_state(model, filepath):
            state = torch.load(filepath)
            model.load_state_dict(state)
            model.cuda()
```

In [0]:
```
        """
        Traverse Latents
        """
        def traverse_latents(model, datapoint, nb_latents, file):
```

```
    model.eval()
    datapoint = datapoint.to(device)
    if isinstance(model,ConvVAE):
      datapoint = datapoint.unsqueeze(0)
      mu, _ = model.encode(datapoint)
    else:
      datapoint = datapoint.unsqueeze(0)
      mu, _ = model.encoder(datapoint)

    recons = torch.zeros((7, nb_latents, 28, 28))

    for zi in range(nb_latents):
      muc = mu.squeeze().clone()
      for i, val in enumerate(np.linspace(-3, 3, 7)):
        muc[zi] = val
        recon = model.decode(muc).cpu()
          if isinstance(model,ConvVAE) else model.decoder(muc).cpu()
        recons[i, zi] = recon.view(28, 28)

    torchvision.utils.save_image(recons.view(-1, 1, 28, 28),
                                 file, nrow=nb_latents, pad_value=1)


import cv2
import numpy


def laplacian_variance(images):
    return [cv2.Laplacian(image.numpy(), cv2.CV_32F).var() for image in images]


def laplacian_variance_numpy(images):
    return [cv2.Laplacian(image, cv2.CV_32F).var() for image in images]
```

In [0]:
```
class ConvVAE(nn.Module):
    def __init__(self, nb_latents):
        super(ConvVAE, self).__init__()
        self.conv1 = nn.Sequential(
            nn.Conv2d(1, 32,
                      kernel_size=5, stride=1, padding=2),
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=2, stride=2))
        self.conv2 = nn.Sequential(
            nn.Conv2d(32, 64,
                      kernel_size=5, stride=1, padding=2),
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=2, stride=2))
```

```
        self.conv3 = nn.Sequential(
            nn.Conv2d(64, 128,
                      kernel_size=5, stride=1, padding=2),
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=2, stride=2))

        self.conv4 = nn.Sequential(
            nn.Conv2d(128, 256,
                      kernel_size=2, stride=1),
            nn.ReLU())

        self.fc1 = nn.Linear(1024, 256)

        self.fc_mean = nn.Linear(256, nb_latents)
        self.fc_std = nn.Linear(256, nb_latents)

        self.fc2 = nn.Linear(nb_latents, 256)
        self.fc3 = nn.Linear(256, 1024)



        self.fc4 = nn.Linear(1024,7*7*64)

        self.deconv1 = nn.ConvTranspose2d(64, 32,
                        kernel_size=2, stride=2)
        self.deconv2 = nn.ConvTranspose2d(32, 1,
                         kernel_size=2, stride=2)

        self.relu = nn.ReLU()
        self.sigmoid = nn.Sigmoid()

    def encode(self, x):
        x = (self.conv1(x))
        x =  (self.conv2(x))
        x =  (self.conv3(x))
        x =  (self.conv4(x))
        x = x.reshape(x.size(0), -1)
        x = self.relu(self.fc1(x))
        return self.fc_mean(x), self.fc_std(x)

    def reparameterize(self, mu, logvar):
        if self.training:
            std = logvar.mul(0.5).exp_()
            eps = Variable(std.data.new(std.size()).normal_())
            return eps.mul(std).add_(mu)
        else:
            return mu
```

```
            def decode(self, z):
                x = self.relu(self.fc2(z))
                x = self.relu(self.fc3(x))
                x = self.relu(self.fc4(x))
                x = self.relu(self.deconv1(x.view(-1, 64, 7, 7)))
                x = self.deconv2(x)
                return self.sigmoid(x)

            def forward(self, x):
                mu, logvar = self.encode(x)
                z = self.reparameterize(mu, logvar)
                return self.decode(z), mu, logvar
```

In [0]:
```
vae_model = ConvVAE(10)
if is_cuda:
    vae_model = vae_model.to(device)

## load model
checkpoint_dir = './vae-final/checkpoints'
filename = checkpoint_dir +"/model_state_ "+str(99)+ ".pth"
load_model(vae_model, filename)
```

In [0]:
```
class Params:
  nb_latents = 10
  batch_size = 128
  epochs = 100
  log_interval = 100
  save_interval = 1000
  data_dir =  "./vae-classifier/"
train_loader, test_loader = get_dataloaders(Params.data_dir, Params.batch_size)
```

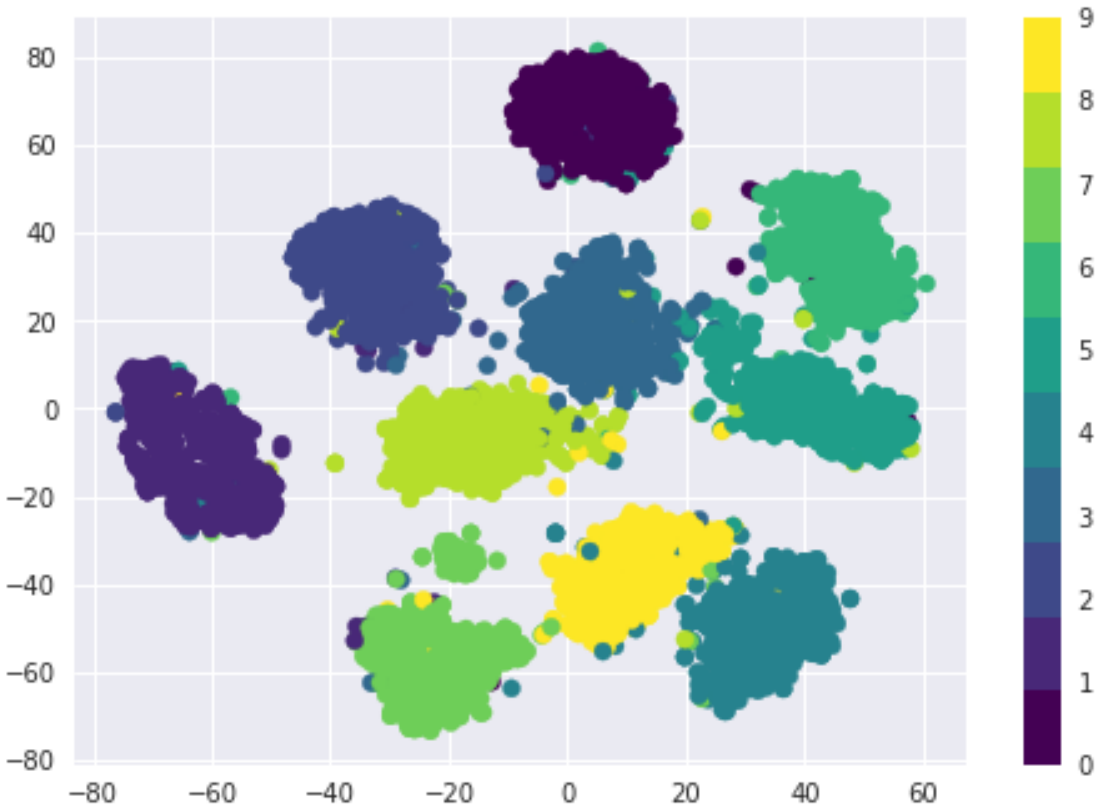
```
./vae-classifier/MNIST/data
```

In [0]:
```
## TSNE for VAE
## Test TSNE plot for reconstrunction on 1000 test samples

transformation = transforms.Compose([transforms.ToTensor(),
                 transforms.Normalize((0.1307,), (0.3081,))])
train_dataset = datasets.MNIST(os.path.join(Params.data_dir,"MNIST/data"),
              train=True,transform=transformation,download=False)
testing_tsne = torch.utils.data.DataLoader(train_dataset,
                 batch_size=len(train_dataset),shuffle=True)
test_data, test_labels = next(iter(testing_tsne))[:10000]
```

In [0]:
```
path = "./vae-final/samples/"+'/latent_space.png'
def visualize_tsne(X, labels, model, path):
    # Compute latent space representation
```

```
    print("Computing latent space projection...")

    #if isinstance(model,VAE_GAN_Generator):
     #   X_encoded, _ = model.encoder(X)
    #else:
    X_encoded, _ = model.encode(X)

    # Compute t-SNE embedding of latent space
    tsne = manifold.TSNE(n_components=2, init='pca', random_state=0)
    X_tsne = tsne.fit_transform(X_encoded.data.detach().cpu())

    # Plot images according to t-sne embedding
    fig, ax = plt.subplots()
    plt.scatter(X_tsne[:,0], X_tsne[:,1],
                c=labels, cmap=plt.cm.get_cmap("viridis", 10))
    plt.colorbar(ticks=range(10))
    fig.savefig(path, dpi=fig.dpi)

visualize_tsne(test_data[:5000].to(device),test_labels[:5000],vae_model,path)
```

```
Computing latent space projection...
```

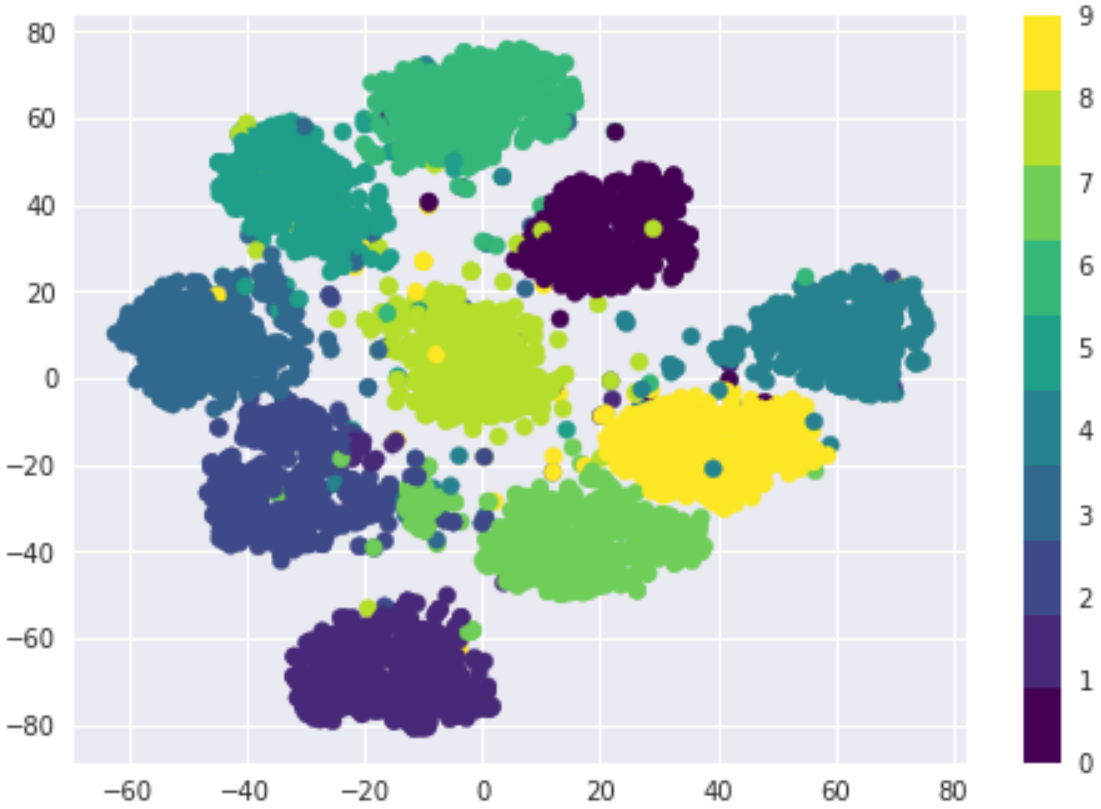


0.1 Beta VAE

```
In [0]: beta_vae = ConvVAE(Params.nb_latents)
        if is_cuda:
            beta_vae = beta_vae.to(device)


        ## load model
        #model_state_99.pth
        checkpoint_dir = 'beta-results'
        filename = checkpoint_dir +"/model_state_"+str(99)+ ".pth"
        load_model_state(beta_vae, filename)
```

```
In [0]: path = "beta-results/latent-space.png"
        visualize_tsne(test_data[:5000].to(device),
                       test_labels[:5000],beta_vae,path)
```

```
Computing latent space projection...
```




```
In [0]:
```

0.2 VAE+GAN

```
In [0]: ## Load GAN Model
        def load_Vae_gan(epoch, encoder, decoder, D):
            save_dir = "vae-gan"
            #  restore models
            decoder.load_state_dict(torch.load(save_dir+
                  '/VAE_GAN_decoder_%d.pth' % epoch))
            decoder.cuda()
            encoder.load_state_dict(torch.load(save_dir +
             '/VAE_GAN_encoder_%d.pth' % epoch))
            encoder.cuda()
            D.load_state_dict(torch.load(save_dir+
              '/VAE_GAN_D_%d.pth' % epoch))
            D.cuda()
```

```
In [0]: class Encoder(nn.Module):
            def __init__(self, input_channels, output_channels, representation_size = 32):
                super(Encoder, self).__init__()
                # input parameters
                self.input_channels = input_channels
                self.output_channels = output_channels #Params.nb_latents

                self.features = nn.Sequential(
                    # nc x 32 x 32
                    nn.Conv2d(self.input_channels,
                              representation_size, 5, stride=2, padding=2),
                    nn.BatchNorm2d(representation_size),
                    nn.ReLU(),
                    # hidden_size x 16 x 16
                    nn.Conv2d(representation_size,
                              representation_size*2, 5, stride=2, padding=2),
                    nn.BatchNorm2d(representation_size * 2),
                    nn.ReLU(),
                    # hidden_size*2 x 8 x 8
                    nn.Conv2d(representation_size*2,
                              representation_size*4, 5, stride=2, padding=2),
                    nn.BatchNorm2d(representation_size * 4),
                    nn.ReLU())
                    # hidden_size*4 x 4 x 4

                self.mean = nn.Sequential(
                    nn.Linear(representation_size*4*4*4, 1024),

                    nn.ReLU(),
                    nn.Linear(1024, output_channels))

                self.logvar = nn.Sequential(
                    nn.Linear(representation_size*4*4*4, 1024),
```

```
                nn.ReLU(),
                nn.Linear(1024, output_channels))

        def forward(self, x):
            batch_size = x.size()[0]

            hidden_representation = self.features(x)
            hidden_representation = hidden_representation
            .view(-1, self.num_flat_features(hidden_representation))

            mean = self.mean(hidden_representation)
            logvar = self.logvar(hidden_representation)

            return mean, logvar

        def hidden_layer(self, x):
            batch_size = x.size()[0]
            output = self.features(x)
            return output


        def num_flat_features(self,x):
          size = x.size()[1:] # all dimensions except the batch dimension
          num_features = 1
          for s in size:
            num_features *=s
          return num_features

In [0]: class Decoder(nn.Module):
        def __init__(self, input_size):
            super(Decoder, self).__init__()

            self.input_size = input_size ##

            self.fc1 = nn.Linear(self.input_size, 256)
            self.fc2 = nn.Linear(256, 1024)
            self.fc3 = nn.Linear(1024,7*7*64)

            self.deconv1 = nn.ConvTranspose2d(64, 32, kernel_size=2, stride=2)
            self.deconv2 = nn.ConvTranspose2d(32, 1, kernel_size=2, stride=2)

            # 1 x 28 x 28
            self.activation = nn.Sigmoid()
            self.relu = nn.Tanh()


        def forward(self, z):
```

```
        bs = z.size()[0]

        x = self.relu(self.fc1(z))
        x = self.relu(self.fc2(x))
        x = self.relu(self.fc3(x))
        x = self.relu(self.deconv1(x.view(-1, 64, 7, 7)))
        x = self.deconv2(x)

        return self.activation(x)
```

```
In [0]: class VAE_GAN_Generator(nn.Module):
    def __init__(self, input_channels, hidden_size):
        super(VAE_GAN_Generator, self).__init__()
        self.input_channels = input_channels
        self.hidden_size = hidden_size

        self.encoder = Encoder(input_channels, hidden_size)
        self.decoder = Decoder(hidden_size)

    def forward(self, x):
        batch_size = x.size()[0]
        mean, logvar = self.encoder(x)
        std = logvar.mul(0.5).exp_()

        reparametrized_noise = Variable(torch.randn(
            (batch_size, self.hidden_size))).cuda()

        reparametrized_noise = mean + std * reparametrized_noise

        rec_images = self.decoder(reparametrized_noise)

        return mean, logvar, rec_images
```

```
In [0]: class Discriminator(nn.Module):
    def __init__(self,input_channels, representation_size = 32):
        super(Discriminator, self).__init__()
        self.input_channels = input_channels
        dim = 128 * 4 * 4
        self.main = nn.Sequential(
            # nc x 32 x 32
            nn.Conv2d(self.input_channels,
               representation_size, 5, stride=2, padding=2),
            nn.BatchNorm2d(representation_size),
            nn.LeakyReLU(0.2),
            # hidden_size x 16 x 16
            nn.Conv2d(representation_size,
             representation_size*2, 5, stride=2, padding=2),
            nn.BatchNorm2d(representation_size * 2),
```

```
                nn.LeakyReLU(0.2),
                # hidden_size*2 x 8 x 8
                nn.Conv2d(representation_size*2,
                  representation_size*4, 5, stride=2, padding=2),
                nn.BatchNorm2d(representation_size * 4),
                nn.LeakyReLU(0.2))

            self.lth_features = nn.Sequential(
                nn.Linear(dim, 2048),
                nn.LeakyReLU(0.2))

            self.sigmoid_output =
            nn.Sequential(nn.Linear(2048,1),nn.Sigmoid())


        def forward(self, x):
            batch_size = x.size()[0]
            features = self.main(x)
            lth_rep = self.
            lth_features(features.view(batch_size, -1))
            output = self.sigmoid_output(lth_rep)
            return output

        def similarity(self, x):
            batch_size = x.size()[0]
            features = self.main(x)
            lth_rep = self.
            lth_features(features.view(batch_size, -1))
            return lth_rep
```

In [0]:
```
# define constant
input_channels = 1
hidden_size = 10
max_epochs = 250
lr = 3e-4

beta = 5
alpha = 0.1
gamma = 15
```

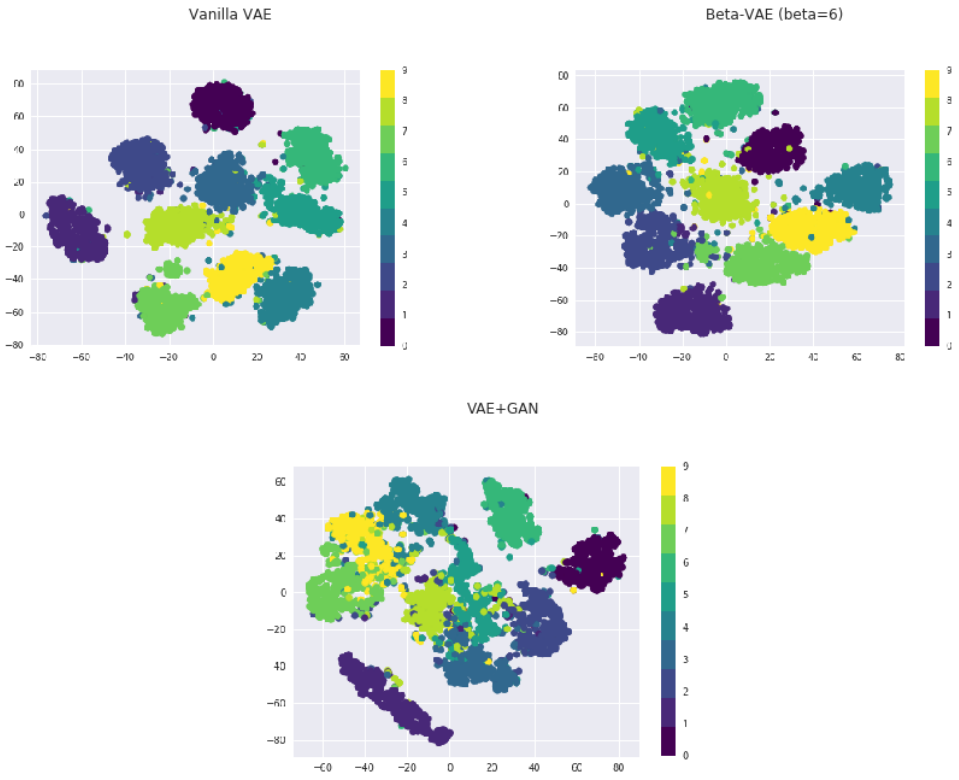
In [0]:
```
G = VAE_GAN_Generator(input_channels, hidden_size).cuda()
D = Discriminator(input_channels).cuda()

criterion = nn.BCELoss()
criterion.cuda()

opt_enc = optim.RMSprop(G.encoder.parameters(), lr=lr)
opt_dec = optim.RMSprop(G.decoder.parameters(), lr=lr)
opt_dis = optim.RMSprop(D.parameters(), lr=lr * alpha)
```

```
In [0]: load_Vae_gan(210, G.encoder, G.decoder, D)

In [ ]: path = "vae-gan/latent-space.png"
        visualize_tsne(test_data[:5000].to(device),test_labels[:5000],G,path)
```

0.3 PLOTS

```
In [0]: ## TSNE Plot of VAE, Beta VAE and VAE + GAN
        import matplotlib.pyplot as plt
        from IPython.display import Image
        import matplotlib.image as mpimg
        import matplotlib.gridspec as gridspec

        rows  = 2
        columns = 3

        fig_height = 5.
        length_x_axis = 100
        length_y_axis = 45
        height = length_y_axis * rows
        width = length_x_axis  * columns

        plot_aspect_ratio=2

        fig = plt.figure(figsize = (16,12))
        gs = gridspec.GridSpec(2,2)
        gs.update(wspace=0.025, hspace=0.05)

        ## Train
        ax1 = plt.subplot(gs[0, 0])
        vae_tsne = "vae-final/samples" + '/latent_space.png'
        img=mpimg.imread(vae_tsne)
        imgplot = plt.imshow(img)
        plt.axis("off")
        plt.title("Vanilla VAE")

        ax2 = plt.subplot(gs[0, 1])
        betavae_tsne = "beta-results/latent-space.png"
        img=mpimg.imread(betavae_tsne)
        imgplot = plt.imshow(img)
        plt.axis("off")
        plt.title("Beta-VAE (beta=6)")

        ax3 = plt.subplot(gs[1,0:])
        vae_gan_tsne = "./vae-gan/latent-space.png"
        img=mpimg.imread(vae_gan_tsne)
        imgplot = plt.imshow(img)
        plt.title("VAE+GAN")
```

```
plt.axis("off")
plt.savefig("vae-final/tsne-results.png")
```



0.4 Reconstructions

```
In [0]: def reconstruction(model, data,path):
            n = min(data.size(0), 10)
            recon_batch, mu, logvar = model(data)
            comparison = torch.cat([data[:n],recon_batch[:n]])
            save_image(comparison.cpu(),path, nrow=Params.nb_latents, pad_value=1)


        train_batch, train_label = next(iter(train_loader))
        test_batch, test_label = next(iter(test_loader))

In [0]: filename = os.path.join("vae-final/", 'vae_reconstruction.png')
        reconstruction(vae_model,train_batch.to(device),filename)

In [0]: filename = os.path.join("vae-final/", 'beta_vae_reconstruction.png')
        reconstruction(beta_vae,train_batch.to(device),filename)
```

```
In [0]: def reconstruction_vae_gan(model, data,path):
            n = min(data.size(0), 10)
            _, _, rec_imgs = model(data)
            comparison = torch.cat([data[:n],rec_imgs[:n]])
            save_image(comparison.cpu(),path,
                       nrow=Params.nb_latents, pad_value=1)

        filename = os.path.join("vae-final/",
                  'vae_gan_reconstruction.png')
        reconstruction_vae_gan(G,train_batch.to(device),filename)

In [0]: rows  = 2
        columns = 3

        fig_height = 5.
        length_x_axis = 100
        length_y_axis = 45
        height = length_y_axis * rows
        width = length_x_axis  * columns

        plot_aspect_ratio= float(width)/float(height)

        fig = plt.figure(figsize=(10,3))

        gs = gridspec.GridSpec(2,2)
        gs.update(wspace = 0.23, hspace = 0.05)
        ## Train
        ax1 = plt.subplot(gs[0, 0])
        vae_tsne = "vae-final/vae_reconstruction.png"
        img=mpimg.imread(vae_tsne)
        imgplot = plt.imshow(img)
        plt.title("Vanilla VAE")
        plt.axis("off")
        ax2 = plt.subplot(gs[0, 1])
        betavae_tsne = "vae-final/beta_vae_reconstruction.png"
        img=mpimg.imread(betavae_tsne)
        imgplot = plt.imshow(img)
        plt.title("Beta-VAE (beta=6)")
        plt.axis("off")
        ax3 = plt.subplot(gs[1,:])
        vae_gan_tsne = "vae-final/vae_gan_reconstruction.png"
        img=mpimg.imread(vae_gan_tsne)
        imgplot = plt.imshow(img)
        plt.title("VAE+GAN")
        plt.axis("off")
        plt.savefig("vae-final/reconstruction_results.png")
```

0.5 Samples

```
In [0]: sample = torch.randn(64, Params.nb_latents).to(device)
```

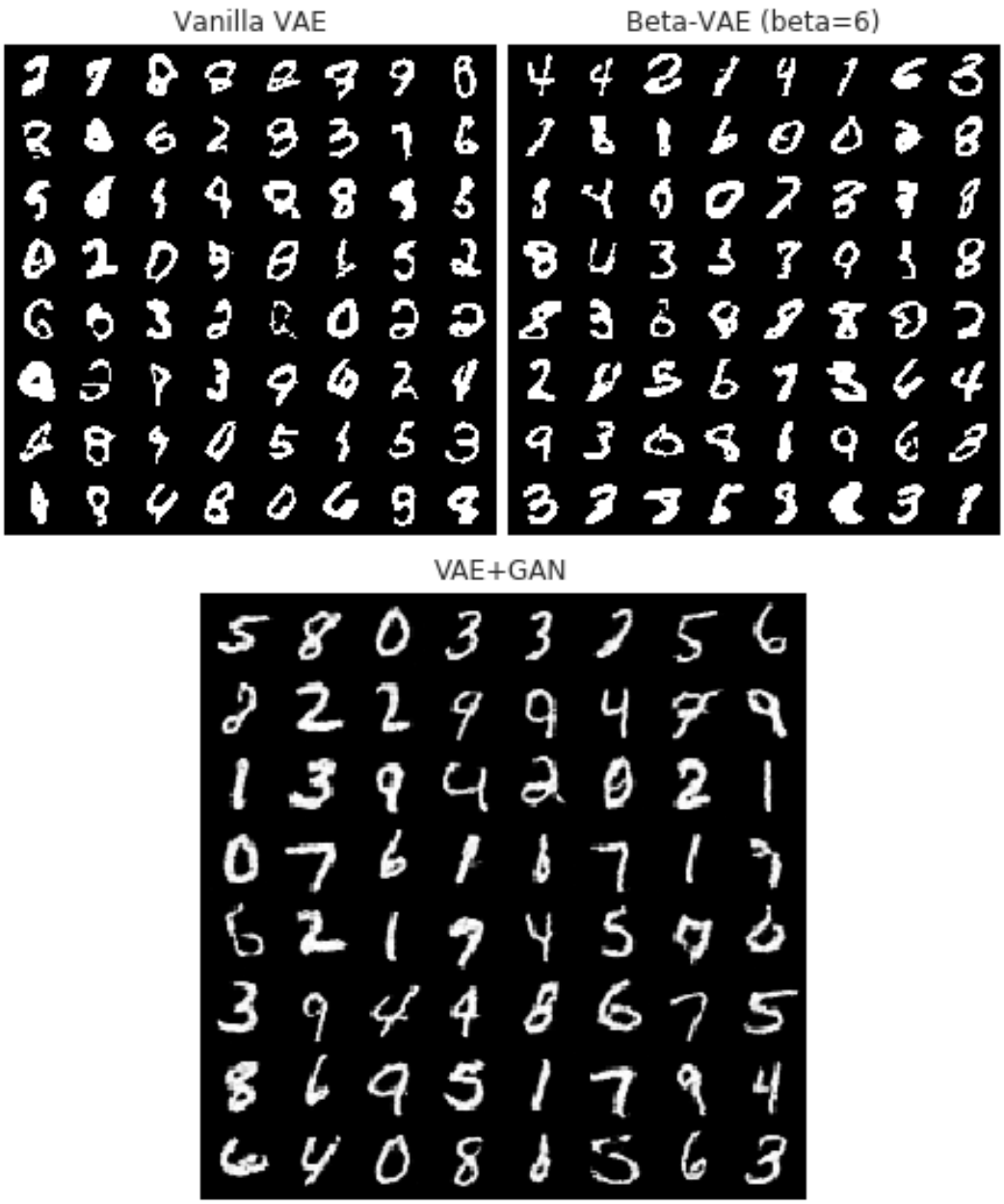
```
In [0]: # Generate samples of reconstruction
        vae_model.eval()
        with torch.no_grad():
            sample_vae = vae_model.decode(sample).cpu()
            save_image(sample_vae.view(64, 1, 28, 28),
                  'vae-final/vae_sample.png')
```

```
In [0]: # Generate samples of reconstruction
        beta_vae.eval()
        with torch.no_grad():
            sample_bvae = beta_vae.decode(sample).cpu()
            save_image(sample_bvae.view(64, 1, 28, 28),
                  'vae-final/bvae_sample.png')
```

```
In [0]: # Generate samples of reconstruction
        G.eval()
        with torch.no_grad():
            sample_vaeg = G.decoder(sample).cpu()
            save_image(sample_vaeg.view(64, 1, 28, 28),
                  'vae-final/vae_gan_sample.png')
```

```
In [0]: rows  = 2
        columns = 3

        fig_height = 5.
        length_x_axis = 100
        length_y_axis = 45
        height = length_y_axis * rows
        width = length_x_axis  * columns
```

```
plot_aspect_ratio= float(width)/float(height)

fig = plt.figure(figsize=(8,10))

gs = gridspec.GridSpec(2,2)
gs.update(wspace = 0.025, hspace = 0.0)
## Train
ax1 = plt.subplot(gs[0, 0])
vae_tsne = "vae-final/vae_sample.png"
img=mpimg.imread(vae_tsne)
imgplot = plt.imshow(img)
plt.title("Vanilla VAE")
plt.axis("off")
ax2 = plt.subplot(gs[0, 1])
betavae_tsne = "vae-final/bvae_sample.png"
img=mpimg.imread(betavae_tsne)
imgplot = plt.imshow(img)
plt.title("Beta-VAE (beta=6)")
plt.axis("off")
ax3 = plt.subplot(gs[1, :])
vae_gan_tsne = "vae-final/vae_gan_sample.png"
img=mpimg.imread(vae_gan_tsne)
imgplot = plt.imshow(img)
plt.title("VAE+GAN")
plt.axis("off")
plt.savefig("vae-final/sample_results.png")
```

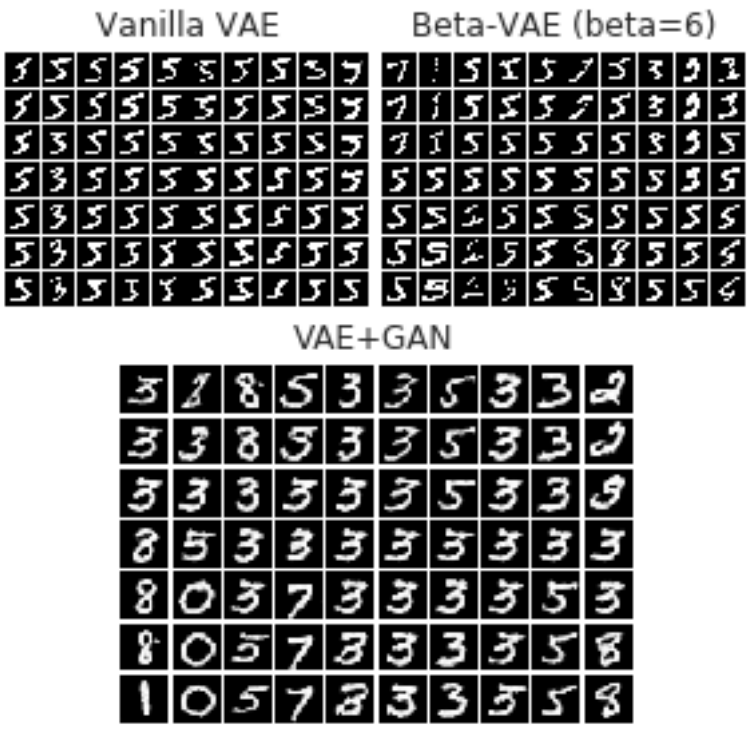


0.6 Latent Tranversal

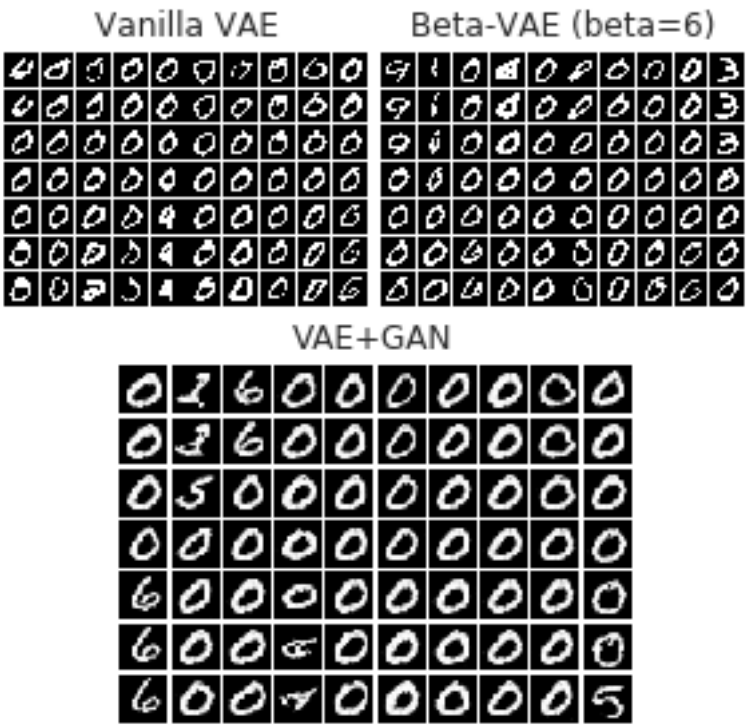
```
In [0]: testpoint1, testpointlabel1 = train_loader.dataset[0]
        testpoint2, testpoint2label2 = train_loader.dataset[1]
        testpoint3, testpoint3label3 = train_loader.dataset[2]

        print(testpointlabel1, testpoint2label2, testpoint3label3)
```

5 0 4

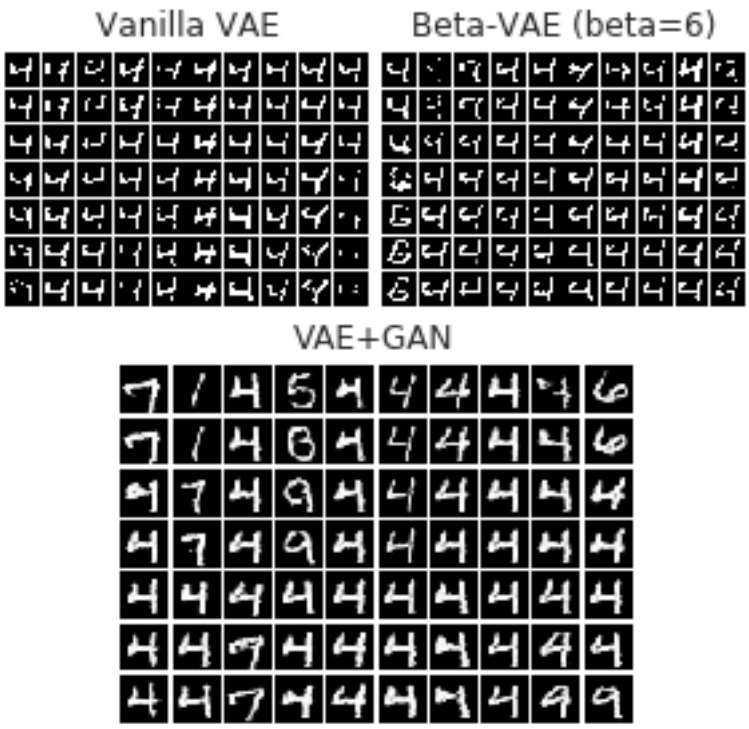
```
In [0]: filename = 'vae-final/vae_traversal_testpoint_5.png'
        traverse_latents(vae_model, testpoint1, Params.nb_latents, filename)
        filename = 'vae-final/beta_vae_traversal_testpoint_5.png'
        traverse_latents(beta_vae, testpoint1, Params.nb_latents, filename)

In [0]: filename = 'vae-final/vae_gan_traversal_testpoint_5.png'
        traverse_latents(G, testpoint1, Params.nb_latents, filename)

In [0]: def display_three_plots(filename1, filename2, filename3,save_name):



            fig = plt.figure(figsize=(5,5))
            gs = gridspec.GridSpec(2,2)
            gs.update(wspace = 0.025, hspace = 0.0)

            ## Train
            ax1 = plt.subplot(gs[0, 0])
            vae_tsne =  filename1
            img=mpimg.imread(vae_tsne)
            imgplot = plt.imshow(img)
            plt.title("Vanilla VAE")
            plt.axis("off")
            ax2 = plt.subplot(gs[0, 1])
            betavae_tsne = filename2
            img=mpimg.imread(betavae_tsne)
            imgplot = plt.imshow(img)
            plt.title("Beta-VAE (beta=6)")
            plt.axis("off")
            ax3 = plt.subplot(gs[1, :])
            vae_gan_tsne = filename3
            img=mpimg.imread(vae_gan_tsne)
            imgplot = plt.imshow(img)
            plt.title("VAE+GAN")
            plt.axis("off")
            plt.savefig("vae-final/"+save_name)

In [0]: filename1 = 'vae-final/vae_traversal_testpoint_5.png'
        filename2 = 'vae-final/beta_vae_traversal_testpoint_5.png'
        filename3 = 'vae-final/vae_gan_traversal_testpoint_5.png'


        display_three_plots(filename1,filename2,filename3,"traversal.png")
```




```
In [0]: filename1 = 'vae-final/vae_traversal_testpoint_0.png'
        traverse_latents(vae_model, testpoint2, Params.nb_latents, filename1)
        filename2 = 'vae-final/beta_vae_traversal_testpoint_0.png'
        #traverse_latents(beta_vae, testpoint2, Params.nb_latents, filename2)
        filename3 = 'vae-final/vae_gan_traversal_testpoint_0.png'
        traverse_latents(G, testpoint2, Params.nb_latents, filename3)
        display_three_plots(filename1, filename2,filename3,"traversal0.png")
```

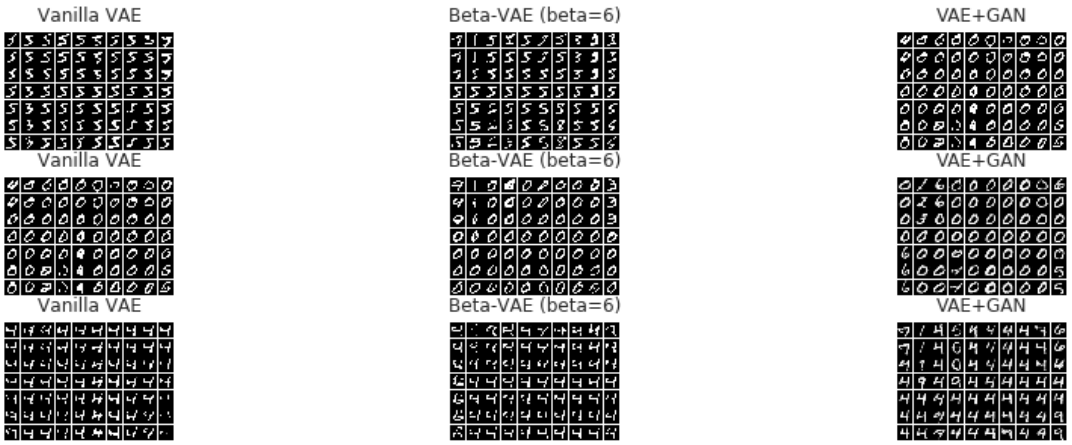



```
In [0]: filename1 = 'vae-final/vae_traversal_testpoint_4.png'
        traverse_latents(vae_model, testpoint3, Params.nb_latents, filename1)
        filename2 = 'vae-final/beta_vae_traversal_testpoint_4.png'
        #traverse_latents(beta_vae, testpoint3, Params.nb_latents, filename2)
        filename3 = 'vae-final/vae_gan_traversal_testpoint_4.png'
        traverse_latents(G, testpoint3, Params.nb_latents, filename3)
        display_three_plots(filename1, filename2,filename3,"traversal4.png")
```




```
In [0]: rows  = 3
        columns = 3

        fig_height = 5.
        length_x_axis = 100
        length_y_axis = 100
        height = length_y_axis * rows
        width = length_x_axis  * columns

        plot_aspect_ratio= 3

        fig = plt.figure(figsize=(fig_height  * plot_aspect_ratio, fig_height ))
        gs = gridspec.GridSpec(rows,columns)

        def add_subplot(row, col, filename,title):
            ## Train
            ax1 = plt.subplot(gs[row, col])
            vae_tsne = filename
            img=mpimg.imread(vae_tsne)
            imgplot = plt.imshow(img)
            plt.title(title)
            plt.axis("off")
```

```
filename1 = 'vae-final/vae_traversal_testpoint_5.png'
filename2 = 'vae-final/beta_vae_traversal_testpoint_5.png'
filename3 = 'vae-final/vae_gan_traversal_testpoint_5.png'

filename4 = 'vae-final/vae_traversal_testpoint_0.png'
filename5 = 'vae-final/beta_vae_traversal_testpoint_0.png'
filename6 = 'vae-final/vae_gan_traversal_testpoint_0.png'

filename7 = 'vae-final/vae_traversal_testpoint_4.png'
filename8 = 'vae-final/beta_vae_traversal_testpoint_4.png'
filename9 = 'vae-final/vae_gan_traversal_testpoint_4.png'

add_subplot(0,0,filename1, "Vanilla VAE")
add_subplot(0,1,filename2, "Beta-VAE (beta=6)")
add_subplot(0,2,filename3, "VAE+GAN")

add_subplot(1,0,filename4, "Vanilla VAE")
add_subplot(1,1,filename5, "Beta-VAE (beta=6)")
add_subplot(1,2,filename6, "VAE+GAN")

add_subplot(2,0,filename7, "Vanilla VAE")
add_subplot(2,1,filename8, "Beta-VAE (beta=6)")
add_subplot(2,2,filename9, "VAE+GAN")

plt.savefig("vae-final/all_traversal.png")
```



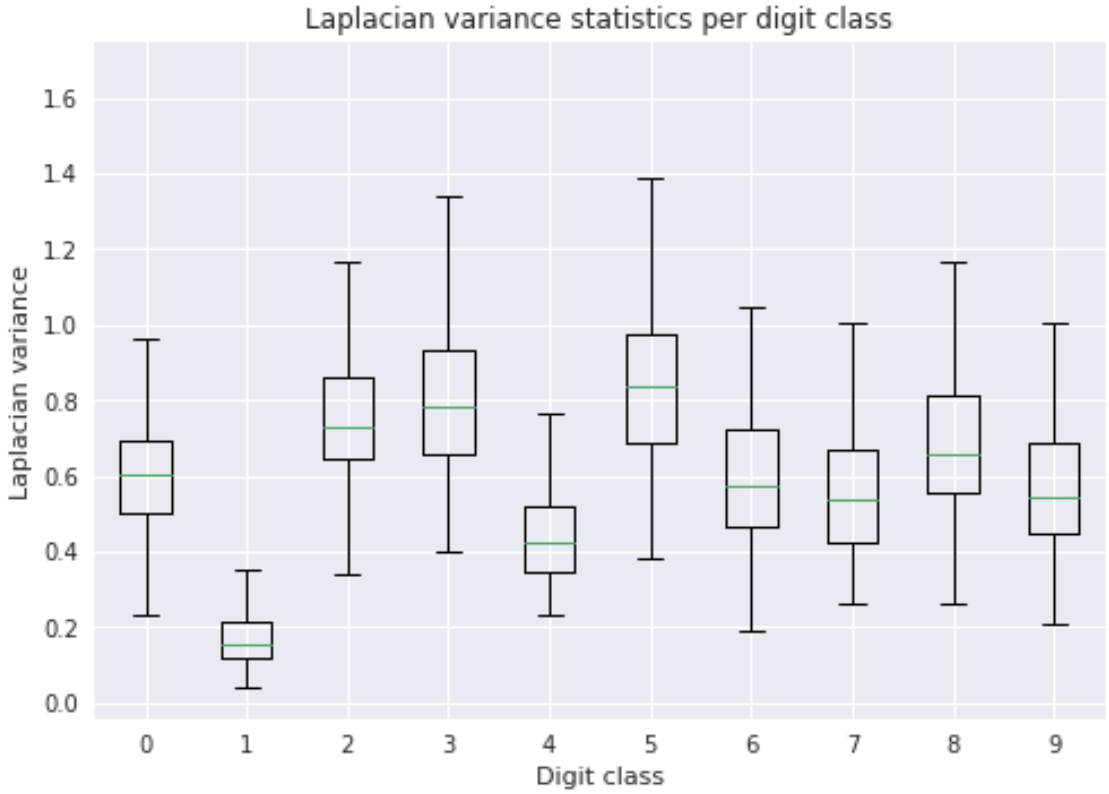
0.7 Laplacian Variance

In [0]:

```
In [0]: ## Import CV
        import cv2
        import numpy


        def laplacian_variance(images):
            return [cv2.Laplacian(image.numpy(), cv2.CV_32F).var() for image in images]


        def laplacian_variance_numpy(images):
            return [cv2.Laplacian(image, cv2.CV_32F).var() for image in images]
```

```
In [0]: x_test, y_test = test_data[:2000], test_labels[:2000]
        laplacian_variances = [laplacian_variance(x_test[y_test == i]) for i in range(10)]
```

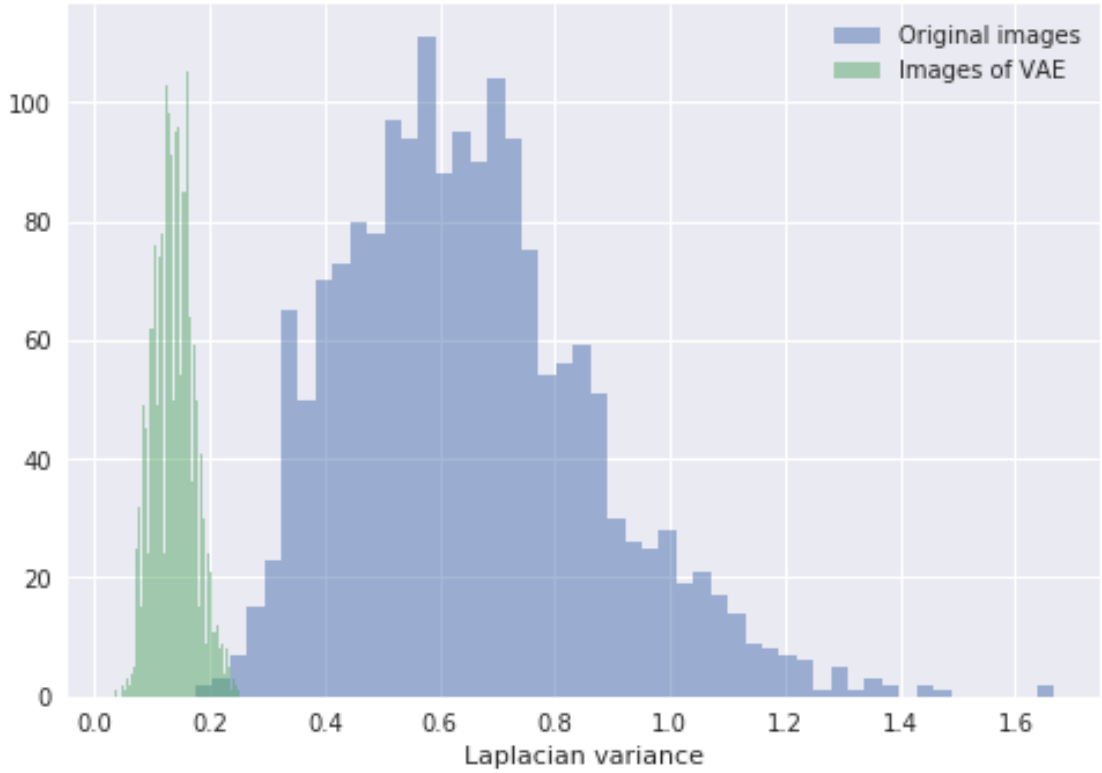
```
In [0]: plt.boxplot(laplacian_variances, labels=range(10));
        plt.xlabel('Digit class')
        plt.ylabel('Laplacian variance')
        plt.title('Laplacian variance statistics per digit class');
```



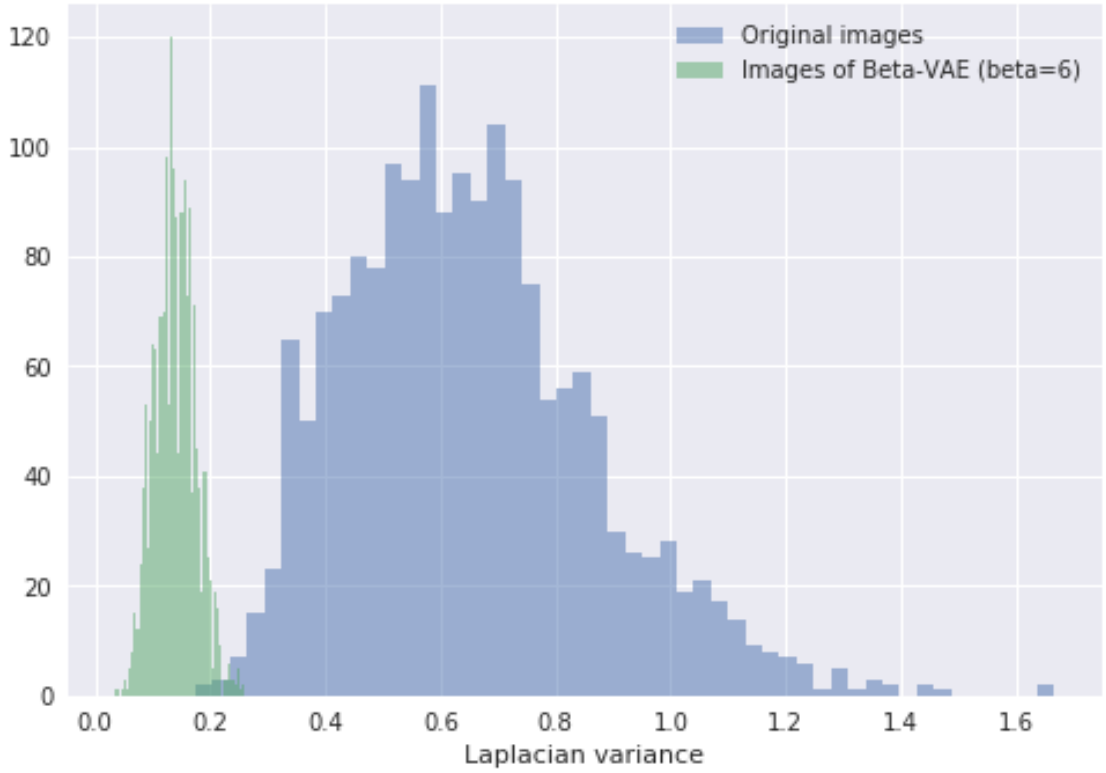

```
In [0]: ## Vanilla VAE
        def plot_laplacian_variances(lvs_1, lvs_2, label2, title,path):
```

```
        plt.hist(lvs_1, bins=50, alpha=0.5 , label='Original images');
        plt.hist(lvs_2, bins=50, alpha= 0.5 , label=label2);
        plt.xlabel('Laplacian variance')
        plt.title(title)
        plt.legend()
        plt.savefig(path)
```

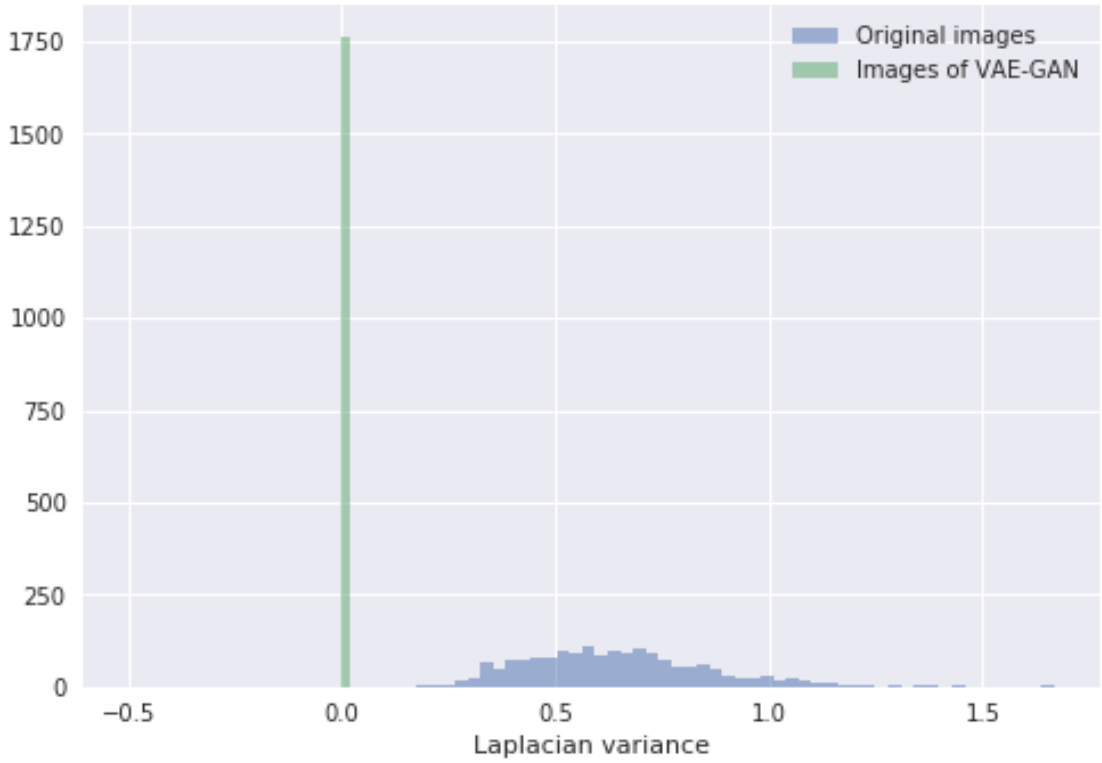
```
In [0]: not_ones = y_test != 1
        x_test_not_ones, y_test_not_ones = x_test[not_ones], y_test[not_ones]
        with torch.no_grad():
            vae_reconstructions = np.empty(shape=(len(x_test_not_ones),1,28,28))
            indx = 0
            for i, (x,y) in enumerate(zip(x_test_not_ones,y_test_not_ones)):
                if y != 1:
                    recon_batch, mu, logvar = vae_model(x.unsqueeze(1).to(device))
                    vae_reconstructions[indx]=(recon_batch.squeeze(0).detach().cpu())
                    indx+=1


        not_ones = y_test != 1
        lvs_1 = laplacian_variance(x_test[not_ones])
        lvs_2 = laplacian_variance_numpy(np.array(vae_reconstructions, dtype=np.uint8))
        filename1 = "vae-final/vae_laplacian_variance_reconstructed.png"
        plot_laplacian_variances(lvs_1, lvs_2, "Images of VAE", "", filename1)
```



```
In [0]: not_ones = y_test != 1
        x_test_not_ones, y_test_not_ones = x_test[not_ones], y_test[not_ones]
        with torch.no_grad():
            bvae_reconstructions = np.empty(shape=(len(x_test_not_ones),1,28,28))
            indx = 0
            for i, (x,y) in enumerate(zip(x_test_not_ones,y_test_not_ones)):
                if y != 1:
                    recon_batch, mu, logvar = beta_vae(x.unsqueeze(1).to(device))
                    bvae_reconstructions[indx]
                    =(recon_batch.squeeze(0).detach().cpu())
                    indx+=1


        not_ones = y_test != 1
        lvs_1 = laplacian_variance(x_test[not_ones])
        lvs_2 = laplacian_variance_numpy(
            np.array(bvae_reconstructions, dtype=np.uint8))
        filename2 = "vae-final/bvae_laplacian_variance_reconstructed.png"
        plot_laplacian_variances(lvs_1, lvs_2,
                "Images of Beta-VAE (beta=6)", "", filename2)
```

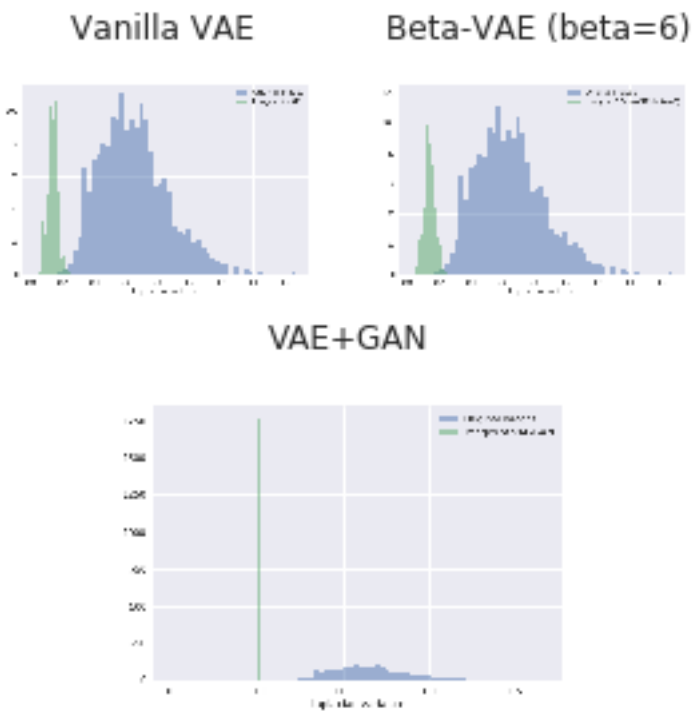


```
In [0]: not_ones = y_test != 1
        x_test_not_ones, y_test_not_ones = x_test[not_ones], y_test[not_ones]
        with torch.no_grad():
            vae_gan_reconstructions =
            np.empty(shape=(len(x_test_not_ones),1,28,28))
            indx = 0
            for i, (x,y) in enumerate(zip(x_test_not_ones,y_test_not_ones)):
                if y != 1:
                    _, _, recon_batch = G(x.unsqueeze(1).to(device))
                    vae_gan_reconstructions[indx]
                    =(recon_batch.squeeze(0).detach().cpu())
                    indx+=1


        not_ones = y_test != 1
        lvs_1 = laplacian_variance(x_test[not_ones])
        lvs_2 = laplacian_variance_numpy(np.array(vae_gan_reconstructions, dtype=np.uint8))
        filename3 = "vae-final/vae_gan_laplacian_variance_reconstructed.png"
        plot_laplacian_variances(lvs_1, lvs_2,
                "Images of VAE-GAN", "", filename3)
```




```
In [0]: filename1 = "vae-final/vae_laplacian_variance_reconstructed.png"
        filename2 = "vae-final/bvae_laplacian_variance_reconstructed.png"
```

```
filename3 = "vae-final/vae_gan_laplacian_variance_reconstructed.png"

display_three_plots(filename1, filename2,filename3,"laplacian_blur.png")
```



0.8 Classifier

```
In [0]: ### Metrics - Base Class For all Metrics
        class Metric:
          def __init__(self):
            pass
          def __call__(self, outputs, target, loss):
            raise NotImplementedError

          def reset(self):
            raise NotImplementedError

          def value(self):
            raise NotImplementedError

          def name(self):
            raise NotImplementedError
```

```
## Accuracy Metric
class AccumulatedAccuracyMetric(Metric):
  def __init__(self):
      self.correct = 0
      self.total = 0

  def __call__(self, outputs, target):
      # Track the accuracy
      _, argmax = torch.max(outputs, 1)
      accuracy = (target == argmax.squeeze()).float().sum()
      self.correct += accuracy
      self.total += target.size(0)
      return self.value()

  def reset(self):
      self.correct = 0
      self.total = 0

  def value(self):
      return 100 * float(self.correct) / self.total

  def name(self):
      return 'Accuracy'


## Loss
class RunningAverage ():
    """A simple class that maintains the
    running average of a quantity
    Example:
    ```
    loss_avg = RunningAverage()
    loss_avg.update(2)
    loss_avg.update(4)
    loss_avg() = 3
    ```
    """

    def __init__( self ):
        self.steps = 0
        self.total = 0

    def update( self, val ):
        self.total += val
        self.steps += 1

    def __call__( self ):
        return self.total / float ( self.steps )
```

```
In [0]: class Classifier(nn.Module):
          def __init__(self):
            super(Classifier,self).__init__()

            ## Define NN
            self.fc1 = nn.Linear(10, 10)


          def forward(self,x):
            ## flat input features
            x = x.view(-1, self.num_flat_features(x))
            x = self.fc1(x)

            return F.log_softmax(x, dim=1)

          def num_flat_features(self,x):
            size = x.size()[1:] # all dimensions except the batch dimension
            num_features = 1
            for s in size:
              num_features *=s
            return num_features

In [0]: ## Training
        from tqdm import trange

        criterion = nn.CrossEntropyLoss()
        classifier = Classifier()
        if is_cuda:
          classifier = classifier.to(device)

        # Loss and optimizer
        learning_rate = 0.001
        momemtum = 0.9
        criterion = nn.CrossEntropyLoss()
        optimizer = torch.optim.Adam(classifier.parameters(), lr=learning_rate)
        scheduler = lr_scheduler.StepLR(optimizer,step_size = 7,gamma = 0.1)
        print(classifier)

Classifier(
  (fc1): Linear(in_features=10, out_features=10, bias=True)
)


In [0]: def train_classifier_epoch(model, epoch):
          model.train()
          metric = AccumulatedAccuracyMetric()

          for idx, (data, labels) in enumerate(train_loader):
```

```
    data= data.to(device)
    labels = labels.to(device)

    if isinstance(model,ConvVAE):
        recon_batch, mu, logvar = model(data)
    else:
        mu, logvar,recon_batch = model(data)

    ## classifier, pass latent vector
    outputs = classifier(mu)
    classifier_loss = criterion(outputs, labels)

    optimizer.zero_grad()
    classifier_loss.backward()
    optimizer.step()

    classifier_loss /= data.size(0)


    metric(outputs, labels)

  return 0.0, metric

## Test Epoch
"""
Test, classifier on learnt features
"""
def test_classifier_epoch(model,epoch):
  classifier.eval()
  metric = AccumulatedAccuracyMetric()

  for idx, (data, labels) in enumerate(test_loader):
    data= data.to(device)
    labels = labels.to(device)


    if isinstance(model,ConvVAE):
        recon_batch, mu, logvar = model(data)
    else:
        mu, logvar,recon_batch = model(data)

    ## classifier, pass latent vector
    outputs = classifier(mu)
    classifier_loss = criterion(outputs, labels)

    classifier_loss /= data.size(0)
```

```
            metric(outputs, labels)


          return 0.0, metric
```

In [0]:
```
## VAE - vanilla
vae_parameters  = list(vae_model.named_parameters())
for name, param in vae_parameters:
    param.requires_grad = False

beta_vae_parameters = list(beta_vae.named_parameters())
for name, param in vae_parameters:
    param.requires_grad = False

vae_gan_parameters = list(G.named_parameters())
for name, param in vae_gan_parameters:
    param.requires_grad = False
```

In [0]:
```
def train_and_test(model):

    train_accuracy = []

    test_accuracy = []
    n_epochs = 50
    for epoch in range(1, n_epochs):

      # Train stage
      train_loss, metric = train_classifier_epoch(model,epoch)

      train_accuracy.append(metric.value())

      message = 'Epoch: {}/{}. Train set: Average loss: {:.4f}'
            .format(epoch + 1, n_epochs,0.0)
      message += '\t Average Accuracy: \t{}: {}'
            .format(metric.name(), metric.value())
      print(message)

      val_loss, metrics = test_classifier_epoch(model,epoch)

      test_accuracy.append(metrics.value())

      message += '\nEpoch: {}/{}. Test set: Average loss: {:.4f}'
        .format(epoch + 1, n_epochs,   0.0)

      message += '\t Average Accuracy: \t{}: {}'
        .format(metrics.name(), metrics.value())
```

```
            print(message)

        return train_accuracy, test_accuracy
```

```
In [0]: vae_train_ac, vae_test_ac =  train_and_test(vae_model)
```

```
Epoch: 2/50. Train set: Average loss: 0.0058        Average Accuracy:        Accuracy: 88.363
Epoch: 2/50. Train set: Average loss: 0.0058        Average Accuracy:        Accuracy: 88.363
Epoch: 2/50. Test set: Average loss: 0.0049        Average Accuracy:        Accuracy: 92.15
Epoch: 3/50. Train set: Average loss: 0.0038        Average Accuracy:        Accuracy: 92.3
Epoch: 3/50. Train set: Average loss: 0.0038        Average Accuracy:        Accuracy: 92.3
Epoch: 3/50. Test set: Average loss: 0.0034        Average Accuracy:        Accuracy: 93.66
Epoch: 4/50. Train set: Average loss: 0.0029        Average Accuracy:        Accuracy: 93.563
Epoch: 4/50. Train set: Average loss: 0.0029        Average Accuracy:        Accuracy: 93.563
Epoch: 4/50. Test set: Average loss: 0.0028        Average Accuracy:        Accuracy: 94.37
Epoch: 5/50. Train set: Average loss: 0.0024        Average Accuracy:        Accuracy: 94.218
Epoch: 5/50. Train set: Average loss: 0.0024        Average Accuracy:        Accuracy: 94.218
Epoch: 5/50. Test set: Average loss: 0.0027        Average Accuracy:        Accuracy: 94.73
Epoch: 6/50. Train set: Average loss: 0.0021        Average Accuracy:        Accuracy: 94.64
Epoch: 6/50. Train set: Average loss: 0.0021        Average Accuracy:        Accuracy: 94.64
Epoch: 6/50. Test set: Average loss: 0.0022        Average Accuracy:        Accuracy: 95.02
Epoch: 7/50. Train set: Average loss: 0.0019        Average Accuracy:        Accuracy: 94.97
Epoch: 7/50. Train set: Average loss: 0.0019        Average Accuracy:        Accuracy: 94.97
Epoch: 7/50. Test set: Average loss: 0.0019        Average Accuracy:        Accuracy: 95.2
Epoch: 8/50. Train set: Average loss: 0.0018        Average Accuracy:        Accuracy: 95.111
Epoch: 8/50. Train set: Average loss: 0.0018        Average Accuracy:        Accuracy: 95.111
Epoch: 8/50. Test set: Average loss: 0.0020        Average Accuracy:        Accuracy: 95.34
Epoch: 9/50. Train set: Average loss: 0.0016        Average Accuracy:        Accuracy: 95.258
Epoch: 9/50. Train set: Average loss: 0.0016        Average Accuracy:        Accuracy: 95.258
Epoch: 9/50. Test set: Average loss: 0.0018        Average Accuracy:        Accuracy: 95.49
Epoch: 10/50. Train set: Average loss: 0.0016        Average Accuracy:        Accuracy: 95.38
Epoch: 10/50. Train set: Average loss: 0.0016        Average Accuracy:        Accuracy: 95.38
Epoch: 10/50. Test set: Average loss: 0.0015        Average Accuracy:        Accuracy: 95.64
Epoch: 11/50. Train set: Average loss: 0.0015        Average Accuracy:        Accuracy: 95.47
Epoch: 11/50. Train set: Average loss: 0.0015        Average Accuracy:        Accuracy: 95.47
Epoch: 11/50. Test set: Average loss: 0.0016        Average Accuracy:        Accuracy: 95.7
Epoch: 12/50. Train set: Average loss: 0.0014        Average Accuracy:        Accuracy: 95.57
Epoch: 12/50. Train set: Average loss: 0.0014        Average Accuracy:        Accuracy: 95.57
Epoch: 12/50. Test set: Average loss: 0.0014        Average Accuracy:        Accuracy: 95.76
Epoch: 13/50. Train set: Average loss: 0.0014        Average Accuracy:        Accuracy: 95.69
Epoch: 13/50. Train set: Average loss: 0.0014        Average Accuracy:        Accuracy: 95.69
Epoch: 13/50. Test set: Average loss: 0.0014        Average Accuracy:        Accuracy: 95.77
Epoch: 14/50. Train set: Average loss: 0.0014        Average Accuracy:        Accuracy: 95.74
Epoch: 14/50. Train set: Average loss: 0.0014        Average Accuracy:        Accuracy: 95.74
Epoch: 14/50. Test set: Average loss: 0.0013        Average Accuracy:        Accuracy: 95.84
Epoch: 15/50. Train set: Average loss: 0.0013        Average Accuracy:        Accuracy: 95.79
Epoch: 15/50. Train set: Average loss: 0.0013        Average Accuracy:        Accuracy: 95.79
Epoch: 15/50. Test set: Average loss: 0.0013        Average Accuracy:        Accuracy: 95.92
```

```
Epoch: 16/50. Train set: Average loss: 0.0013        Average Accuracy:        Accuracy: 95.84
Epoch: 16/50. Train set: Average loss: 0.0013        Average Accuracy:        Accuracy: 95.84
Epoch: 16/50. Test set: Average loss: 0.0013        Average Accuracy:        Accuracy: 95.95
Epoch: 17/50. Train set: Average loss: 0.0013        Average Accuracy:        Accuracy: 95.88
Epoch: 17/50. Train set: Average loss: 0.0013        Average Accuracy:        Accuracy: 95.88
Epoch: 17/50. Test set: Average loss: 0.0016        Average Accuracy:        Accuracy: 95.97
Epoch: 18/50. Train set: Average loss: 0.0013        Average Accuracy:        Accuracy: 95.91
Epoch: 18/50. Train set: Average loss: 0.0013        Average Accuracy:        Accuracy: 95.91
Epoch: 18/50. Test set: Average loss: 0.0014        Average Accuracy:        Accuracy: 95.95
Epoch: 19/50. Train set: Average loss: 0.0013        Average Accuracy:        Accuracy: 95.94
Epoch: 19/50. Train set: Average loss: 0.0013        Average Accuracy:        Accuracy: 95.94
Epoch: 19/50. Test set: Average loss: 0.0013        Average Accuracy:        Accuracy: 95.96
Epoch: 20/50. Train set: Average loss: 0.0013        Average Accuracy:        Accuracy: 95.96
Epoch: 20/50. Train set: Average loss: 0.0013        Average Accuracy:        Accuracy: 95.96
Epoch: 20/50. Test set: Average loss: 0.0015        Average Accuracy:        Accuracy: 95.94
Epoch: 21/50. Train set: Average loss: 0.0013        Average Accuracy:        Accuracy: 95.96
Epoch: 21/50. Train set: Average loss: 0.0013        Average Accuracy:        Accuracy: 95.96
Epoch: 21/50. Test set: Average loss: 0.0013        Average Accuracy:        Accuracy: 95.96
Epoch: 22/50. Train set: Average loss: 0.0012        Average Accuracy:        Accuracy: 95.95
Epoch: 22/50. Train set: Average loss: 0.0012        Average Accuracy:        Accuracy: 95.95
Epoch: 22/50. Test set: Average loss: 0.0012        Average Accuracy:        Accuracy: 95.99
Epoch: 23/50. Train set: Average loss: 0.0012        Average Accuracy:        Accuracy: 95.99
Epoch: 23/50. Train set: Average loss: 0.0012        Average Accuracy:        Accuracy: 95.99
Epoch: 23/50. Test set: Average loss: 0.0013        Average Accuracy:        Accuracy: 96.02
Epoch: 24/50. Train set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.00
Epoch: 24/50. Train set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.00
Epoch: 24/50. Test set: Average loss: 0.0016        Average Accuracy:        Accuracy: 96.0
Epoch: 25/50. Train set: Average loss: 0.0012        Average Accuracy:        Accuracy: 95.99
Epoch: 25/50. Train set: Average loss: 0.0012        Average Accuracy:        Accuracy: 95.99
Epoch: 25/50. Test set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.01
Epoch: 26/50. Train set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.02
Epoch: 26/50. Train set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.02
Epoch: 26/50. Test set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.01
Epoch: 27/50. Train set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.02
Epoch: 27/50. Train set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.02
Epoch: 27/50. Test set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.02
Epoch: 28/50. Train set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.02
Epoch: 28/50. Train set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.02
Epoch: 28/50. Test set: Average loss: 0.0015        Average Accuracy:        Accuracy: 96.02
Epoch: 29/50. Train set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.02
Epoch: 29/50. Train set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.02
Epoch: 29/50. Test set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.0
Epoch: 30/50. Train set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.04
Epoch: 30/50. Train set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.04
Epoch: 30/50. Test set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.02
Epoch: 31/50. Train set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.03
Epoch: 31/50. Train set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.03
Epoch: 31/50. Test set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.07
```

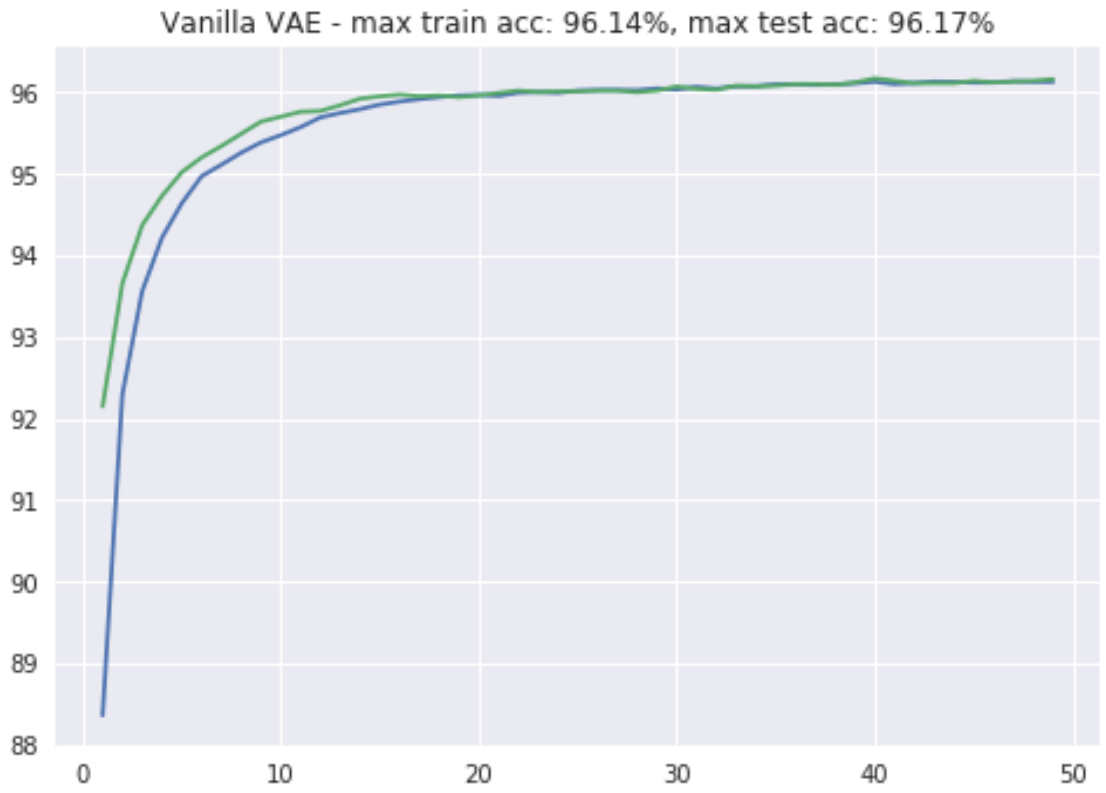
```
Epoch: 32/50. Train set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.06
Epoch: 32/50. Train set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.06
Epoch: 32/50. Test set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.04
Epoch: 33/50. Train set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.04
Epoch: 33/50. Train set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.04
Epoch: 33/50. Test set: Average loss: 0.0015        Average Accuracy:        Accuracy: 96.03
Epoch: 34/50. Train set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.07
Epoch: 34/50. Train set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.07
Epoch: 34/50. Test set: Average loss: 0.0014        Average Accuracy:        Accuracy: 96.08
Epoch: 35/50. Train set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.07
Epoch: 35/50. Train set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.07
Epoch: 35/50. Test set: Average loss: 0.0013        Average Accuracy:        Accuracy: 96.07
Epoch: 36/50. Train set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.09
Epoch: 36/50. Train set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.09
Epoch: 36/50. Test set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.08
Epoch: 37/50. Train set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.09
Epoch: 37/50. Train set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.09
Epoch: 37/50. Test set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.1
Epoch: 38/50. Train set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.09
Epoch: 38/50. Train set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.09
Epoch: 38/50. Test set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.1
Epoch: 39/50. Train set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.09
Epoch: 39/50. Train set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.09
Epoch: 39/50. Test set: Average loss: 0.0011        Average Accuracy:        Accuracy: 96.09
Epoch: 40/50. Train set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.10
Epoch: 40/50. Train set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.10
Epoch: 40/50. Test set: Average loss: 0.0016        Average Accuracy:        Accuracy: 96.12
Epoch: 41/50. Train set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.12
Epoch: 41/50. Train set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.12
Epoch: 41/50. Test set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.17
Epoch: 42/50. Train set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.1
Epoch: 42/50. Train set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.1
Epoch: 42/50. Test set: Average loss: 0.0016        Average Accuracy:        Accuracy: 96.14
Epoch: 43/50. Train set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.11
Epoch: 43/50. Train set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.11
Epoch: 43/50. Test set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.11
Epoch: 44/50. Train set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.13
Epoch: 44/50. Train set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.13
Epoch: 44/50. Test set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.11
Epoch: 45/50. Train set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.12
Epoch: 45/50. Train set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.12
Epoch: 45/50. Test set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.11
Epoch: 46/50. Train set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.11
Epoch: 46/50. Train set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.11
Epoch: 46/50. Test set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.14
Epoch: 47/50. Train set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.11
Epoch: 47/50. Train set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.11
Epoch: 47/50. Test set: Average loss: 0.0013        Average Accuracy:        Accuracy: 96.12
```

```
Epoch: 48/50. Train set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.13
Epoch: 48/50. Train set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.13
Epoch: 48/50. Test set: Average loss: 0.0013        Average Accuracy:        Accuracy: 96.13
Epoch: 49/50. Train set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.12
Epoch: 49/50. Train set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.12
Epoch: 49/50. Test set: Average loss: 0.0011        Average Accuracy:        Accuracy: 96.14
Epoch: 50/50. Train set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.12
Epoch: 50/50. Train set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.12
Epoch: 50/50. Test set: Average loss: 0.0012        Average Accuracy:        Accuracy: 96.16
```

```
In [0]: import pickle
        def save_lists(l, pickle_filename):
            with open(pickle_filename, 'wb') as f:
                pickle.dump(l, f)
        def load_lists(l, picklet_filename):
            with open(pickle_filename,'rb') as f:
                l = pickle.load(f)
```

```
In [0]: ## save lists
        save_lists(vae_train_ac,"vae-final/vae-train-classifier-acc.pkl")
        save_lists(vae_test_ac,"vae-final/vae-test-classifier-acc.pkl")
```

```
In [0]: n_epochs = 50
        plt.plot(range(1, n_epochs),vae_train_ac)
        plt.plot(range(1,n_epochs),vae_test_ac)
        plt.title("Vanilla VAE - max train acc: {}%, max test acc: {}%"
                  .format(round(max(vae_train_ac),2),max(vae_test_ac)))
        plt.savefig("vae-final/vae-train-test-acc-classifier.png")
```




```
In [0]: bvae_train_ac, bvae_test_ac =  train_and_test(beta_vae)
```

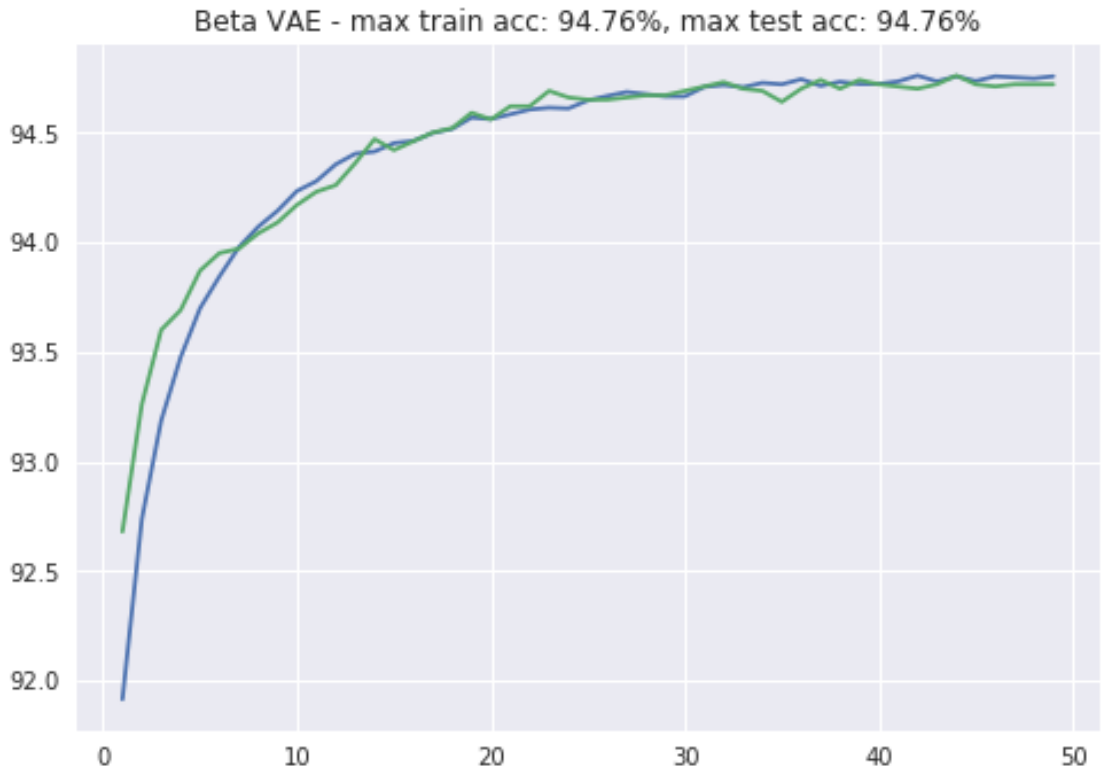
```
Epoch: 2/50. Train set: Average loss: 0.0000         Average Accuracy:         Accuracy: 91.915
Epoch: 2/50. Train set: Average loss: 0.0000         Average Accuracy:         Accuracy: 91.915
Epoch: 2/50. Test set: Average loss: 0.0000         Average Accuracy:         Accuracy: 92.68
Epoch: 3/50. Train set: Average loss: 0.0000         Average Accuracy:         Accuracy: 92.736
Epoch: 3/50. Train set: Average loss: 0.0000         Average Accuracy:         Accuracy: 92.736
Epoch: 3/50. Test set: Average loss: 0.0000         Average Accuracy:         Accuracy: 93.26
Epoch: 4/50. Train set: Average loss: 0.0000         Average Accuracy:         Accuracy: 93.186
Epoch: 4/50. Train set: Average loss: 0.0000         Average Accuracy:         Accuracy: 93.186
Epoch: 4/50. Test set: Average loss: 0.0000         Average Accuracy:         Accuracy: 93.6
Epoch: 5/50. Train set: Average loss: 0.0000         Average Accuracy:         Accuracy: 93.475
Epoch: 5/50. Train set: Average loss: 0.0000         Average Accuracy:         Accuracy: 93.475
Epoch: 5/50. Test set: Average loss: 0.0000         Average Accuracy:         Accuracy: 93.69
Epoch: 6/50. Train set: Average loss: 0.0000         Average Accuracy:         Accuracy: 93.698
Epoch: 6/50. Train set: Average loss: 0.0000         Average Accuracy:         Accuracy: 93.698
Epoch: 6/50. Test set: Average loss: 0.0000         Average Accuracy:         Accuracy: 93.87
Epoch: 7/50. Train set: Average loss: 0.0000         Average Accuracy:         Accuracy: 93.843
Epoch: 7/50. Train set: Average loss: 0.0000         Average Accuracy:         Accuracy: 93.843
Epoch: 7/50. Test set: Average loss: 0.0000         Average Accuracy:         Accuracy: 93.95
Epoch: 8/50. Train set: Average loss: 0.0000         Average Accuracy:         Accuracy: 93.976
Epoch: 8/50. Train set: Average loss: 0.0000         Average Accuracy:         Accuracy: 93.976
```

```
Epoch: 8/50. Test set: Average loss: 0.0000       Average Accuracy:       Accuracy: 93.97
Epoch: 9/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 94.07
Epoch: 9/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 94.07
Epoch: 9/50. Test set: Average loss: 0.0000       Average Accuracy:       Accuracy: 94.04
Epoch: 10/50. Train set: Average loss: 0.0000     Average Accuracy:       Accuracy: 94.14
Epoch: 10/50. Train set: Average loss: 0.0000     Average Accuracy:       Accuracy: 94.14
Epoch: 10/50. Test set: Average loss: 0.0000      Average Accuracy:       Accuracy: 94.09
Epoch: 11/50. Train set: Average loss: 0.0000     Average Accuracy:       Accuracy: 94.23
Epoch: 11/50. Train set: Average loss: 0.0000     Average Accuracy:       Accuracy: 94.23
Epoch: 11/50. Test set: Average loss: 0.0000      Average Accuracy:       Accuracy: 94.17
Epoch: 12/50. Train set: Average loss: 0.0000     Average Accuracy:       Accuracy: 94.27
Epoch: 12/50. Train set: Average loss: 0.0000     Average Accuracy:       Accuracy: 94.27
Epoch: 12/50. Test set: Average loss: 0.0000      Average Accuracy:       Accuracy: 94.23
Epoch: 13/50. Train set: Average loss: 0.0000     Average Accuracy:       Accuracy: 94.35
Epoch: 13/50. Train set: Average loss: 0.0000     Average Accuracy:       Accuracy: 94.35
Epoch: 13/50. Test set: Average loss: 0.0000      Average Accuracy:       Accuracy: 94.26
Epoch: 14/50. Train set: Average loss: 0.0000     Average Accuracy:       Accuracy: 94.40
Epoch: 14/50. Train set: Average loss: 0.0000     Average Accuracy:       Accuracy: 94.40
Epoch: 14/50. Test set: Average loss: 0.0000      Average Accuracy:       Accuracy: 94.36
Epoch: 15/50. Train set: Average loss: 0.0000     Average Accuracy:       Accuracy: 94.41
Epoch: 15/50. Train set: Average loss: 0.0000     Average Accuracy:       Accuracy: 94.41
Epoch: 15/50. Test set: Average loss: 0.0000      Average Accuracy:       Accuracy: 94.47
Epoch: 16/50. Train set: Average loss: 0.0000     Average Accuracy:       Accuracy: 94.45
Epoch: 16/50. Train set: Average loss: 0.0000     Average Accuracy:       Accuracy: 94.45
Epoch: 16/50. Test set: Average loss: 0.0000      Average Accuracy:       Accuracy: 94.42
Epoch: 17/50. Train set: Average loss: 0.0000     Average Accuracy:       Accuracy: 94.46
Epoch: 17/50. Train set: Average loss: 0.0000     Average Accuracy:       Accuracy: 94.46
Epoch: 17/50. Test set: Average loss: 0.0000      Average Accuracy:       Accuracy: 94.46
Epoch: 18/50. Train set: Average loss: 0.0000     Average Accuracy:       Accuracy: 94.49
Epoch: 18/50. Train set: Average loss: 0.0000     Average Accuracy:       Accuracy: 94.49
Epoch: 18/50. Test set: Average loss: 0.0000      Average Accuracy:       Accuracy: 94.5
Epoch: 19/50. Train set: Average loss: 0.0000     Average Accuracy:       Accuracy: 94.51
Epoch: 19/50. Train set: Average loss: 0.0000     Average Accuracy:       Accuracy: 94.51
Epoch: 19/50. Test set: Average loss: 0.0000      Average Accuracy:       Accuracy: 94.52
Epoch: 20/50. Train set: Average loss: 0.0000     Average Accuracy:       Accuracy: 94.56
Epoch: 20/50. Train set: Average loss: 0.0000     Average Accuracy:       Accuracy: 94.56
Epoch: 20/50. Test set: Average loss: 0.0000      Average Accuracy:       Accuracy: 94.59
Epoch: 21/50. Train set: Average loss: 0.0000     Average Accuracy:       Accuracy: 94.56
Epoch: 21/50. Train set: Average loss: 0.0000     Average Accuracy:       Accuracy: 94.56
Epoch: 21/50. Test set: Average loss: 0.0000      Average Accuracy:       Accuracy: 94.56
Epoch: 22/50. Train set: Average loss: 0.0000     Average Accuracy:       Accuracy: 94.58
Epoch: 22/50. Train set: Average loss: 0.0000     Average Accuracy:       Accuracy: 94.58
Epoch: 22/50. Test set: Average loss: 0.0000      Average Accuracy:       Accuracy: 94.62
Epoch: 23/50. Train set: Average loss: 0.0000     Average Accuracy:       Accuracy: 94.60
Epoch: 23/50. Train set: Average loss: 0.0000     Average Accuracy:       Accuracy: 94.60
Epoch: 23/50. Test set: Average loss: 0.0000      Average Accuracy:       Accuracy: 94.62
Epoch: 24/50. Train set: Average loss: 0.0000     Average Accuracy:       Accuracy: 94.61
Epoch: 24/50. Train set: Average loss: 0.0000     Average Accuracy:       Accuracy: 94.61
```

```
Epoch: 24/50. Test set: Average loss: 0.0000       Average Accuracy:       Accuracy: 94.69
Epoch: 25/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 94.6
Epoch: 25/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 94.6
Epoch: 25/50. Test set: Average loss: 0.0000       Average Accuracy:       Accuracy: 94.66
Epoch: 26/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 94.6
Epoch: 26/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 94.6
Epoch: 26/50. Test set: Average loss: 0.0000       Average Accuracy:       Accuracy: 94.65
Epoch: 27/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 94.6
Epoch: 27/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 94.6
Epoch: 27/50. Test set: Average loss: 0.0000       Average Accuracy:       Accuracy: 94.65
Epoch: 28/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 94.6
Epoch: 28/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 94.6
Epoch: 28/50. Test set: Average loss: 0.0000       Average Accuracy:       Accuracy: 94.66
Epoch: 29/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 94.6
Epoch: 29/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 94.6
Epoch: 29/50. Test set: Average loss: 0.0000       Average Accuracy:       Accuracy: 94.67
Epoch: 30/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 94.6
Epoch: 30/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 94.6
Epoch: 30/50. Test set: Average loss: 0.0000       Average Accuracy:       Accuracy: 94.67
Epoch: 31/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 94.6
Epoch: 31/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 94.6
Epoch: 31/50. Test set: Average loss: 0.0000       Average Accuracy:       Accuracy: 94.69
Epoch: 32/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 94.7
Epoch: 32/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 94.7
Epoch: 32/50. Test set: Average loss: 0.0000       Average Accuracy:       Accuracy: 94.71
Epoch: 33/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 94.7
Epoch: 33/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 94.7
Epoch: 33/50. Test set: Average loss: 0.0000       Average Accuracy:       Accuracy: 94.73
Epoch: 34/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 94.7
Epoch: 34/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 94.7
Epoch: 34/50. Test set: Average loss: 0.0000       Average Accuracy:       Accuracy: 94.7
Epoch: 35/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 94.7
Epoch: 35/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 94.7
Epoch: 35/50. Test set: Average loss: 0.0000       Average Accuracy:       Accuracy: 94.69
Epoch: 36/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 94.7
Epoch: 36/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 94.7
Epoch: 36/50. Test set: Average loss: 0.0000       Average Accuracy:       Accuracy: 94.64
Epoch: 37/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 94.7
Epoch: 37/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 94.7
Epoch: 37/50. Test set: Average loss: 0.0000       Average Accuracy:       Accuracy: 94.7
Epoch: 38/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 94.7
Epoch: 38/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 94.7
Epoch: 38/50. Test set: Average loss: 0.0000       Average Accuracy:       Accuracy: 94.74
Epoch: 39/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 94.7
Epoch: 39/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 94.7
Epoch: 39/50. Test set: Average loss: 0.0000       Average Accuracy:       Accuracy: 94.7
Epoch: 40/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 94.7
Epoch: 40/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 94.7
```

```
Epoch: 40/50. Test set: Average loss: 0.0000        Average Accuracy:        Accuracy: 94.74
Epoch: 41/50. Train set: Average loss: 0.0000        Average Accuracy:        Accuracy: 94.7
Epoch: 41/50. Train set: Average loss: 0.0000        Average Accuracy:        Accuracy: 94.7
Epoch: 41/50. Test set: Average loss: 0.0000        Average Accuracy:        Accuracy: 94.72
Epoch: 42/50. Train set: Average loss: 0.0000        Average Accuracy:        Accuracy: 94.7
Epoch: 42/50. Train set: Average loss: 0.0000        Average Accuracy:        Accuracy: 94.7
Epoch: 42/50. Test set: Average loss: 0.0000        Average Accuracy:        Accuracy: 94.71
Epoch: 43/50. Train set: Average loss: 0.0000        Average Accuracy:        Accuracy: 94.7
Epoch: 43/50. Train set: Average loss: 0.0000        Average Accuracy:        Accuracy: 94.7
Epoch: 43/50. Test set: Average loss: 0.0000        Average Accuracy:        Accuracy: 94.7
Epoch: 44/50. Train set: Average loss: 0.0000        Average Accuracy:        Accuracy: 94.7
Epoch: 44/50. Train set: Average loss: 0.0000        Average Accuracy:        Accuracy: 94.7
Epoch: 44/50. Test set: Average loss: 0.0000        Average Accuracy:        Accuracy: 94.72
Epoch: 45/50. Train set: Average loss: 0.0000        Average Accuracy:        Accuracy: 94.7
Epoch: 45/50. Train set: Average loss: 0.0000        Average Accuracy:        Accuracy: 94.7
Epoch: 45/50. Test set: Average loss: 0.0000        Average Accuracy:        Accuracy: 94.76
Epoch: 46/50. Train set: Average loss: 0.0000        Average Accuracy:        Accuracy: 94.7
Epoch: 46/50. Train set: Average loss: 0.0000        Average Accuracy:        Accuracy: 94.7
Epoch: 46/50. Test set: Average loss: 0.0000        Average Accuracy:        Accuracy: 94.72
Epoch: 47/50. Train set: Average loss: 0.0000        Average Accuracy:        Accuracy: 94.7
Epoch: 47/50. Train set: Average loss: 0.0000        Average Accuracy:        Accuracy: 94.7
Epoch: 47/50. Test set: Average loss: 0.0000        Average Accuracy:        Accuracy: 94.71
Epoch: 48/50. Train set: Average loss: 0.0000        Average Accuracy:        Accuracy: 94.7
Epoch: 48/50. Train set: Average loss: 0.0000        Average Accuracy:        Accuracy: 94.7
Epoch: 48/50. Test set: Average loss: 0.0000        Average Accuracy:        Accuracy: 94.72
Epoch: 49/50. Train set: Average loss: 0.0000        Average Accuracy:        Accuracy: 94.7
Epoch: 49/50. Train set: Average loss: 0.0000        Average Accuracy:        Accuracy: 94.7
Epoch: 49/50. Test set: Average loss: 0.0000        Average Accuracy:        Accuracy: 94.72
Epoch: 50/50. Train set: Average loss: 0.0000        Average Accuracy:        Accuracy: 94.7
Epoch: 50/50. Train set: Average loss: 0.0000        Average Accuracy:        Accuracy: 94.7
Epoch: 50/50. Test set: Average loss: 0.0000        Average Accuracy:        Accuracy: 94.72
```

In [0]:
```
## save lists
save_lists(bvae_train_ac,"vae-final/bvae-train-classifier-acc.pkl")
save_lists(bvae_test_ac,"vae-final/bvae-test-classifier-acc.pkl")

n_epochs = 50
plt.plot(range(1, n_epochs),bvae_train_ac)
plt.plot(range(1,n_epochs),bvae_test_ac)
plt.title("Beta VAE - max train acc: {}%, max test acc: {}%"
          .format(round(max(bvae_train_ac),2),max(bvae_test_ac)))
plt.savefig("vae-final/bvae-train-test-acc-classifier.png")
```



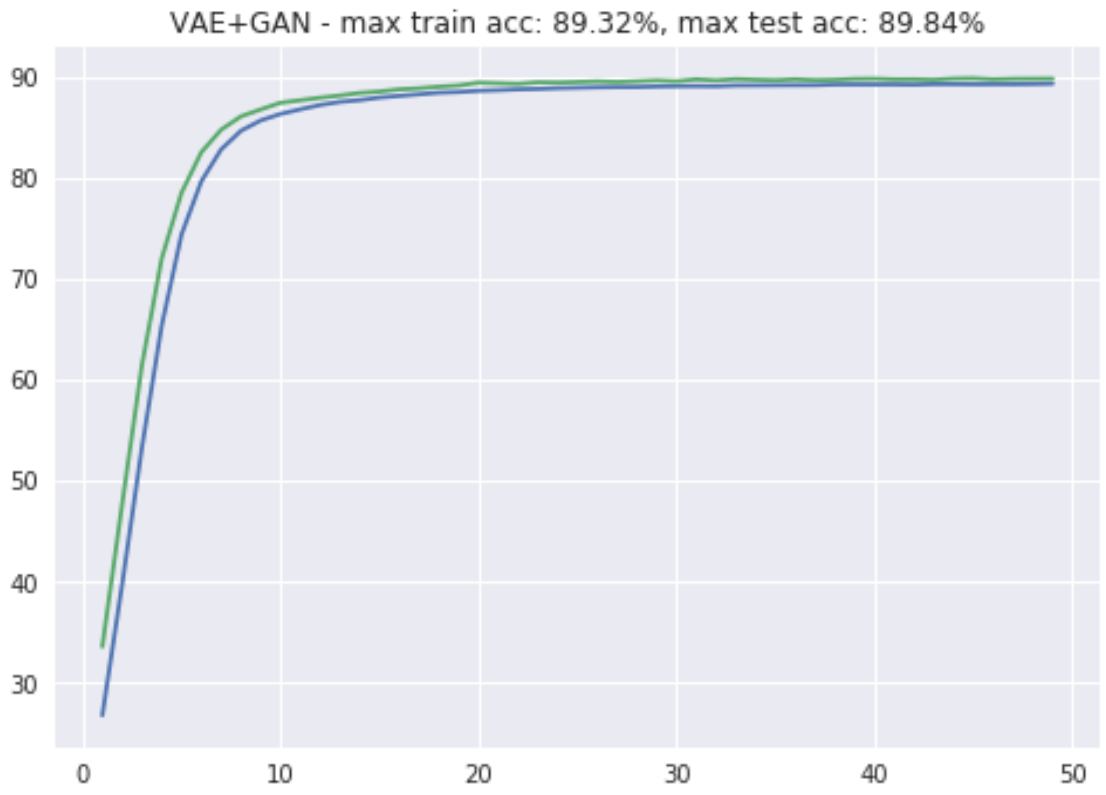

```
In [0]: vae_gan_train_ac, vae_gan_test_ac =  train_and_test(G)

Epoch: 2/50. Train set: Average loss: 0.0000         Average Accuracy:         Accuracy: 26.76
Epoch: 2/50. Train set: Average loss: 0.0000         Average Accuracy:         Accuracy: 26.76
Epoch: 2/50. Test set: Average loss: 0.0000         Average Accuracy:         Accuracy: 33.57
Epoch: 3/50. Train set: Average loss: 0.0000         Average Accuracy:         Accuracy: 39.71
Epoch: 3/50. Train set: Average loss: 0.0000         Average Accuracy:         Accuracy: 39.71
Epoch: 3/50. Test set: Average loss: 0.0000         Average Accuracy:         Accuracy: 47.65
Epoch: 4/50. Train set: Average loss: 0.0000         Average Accuracy:         Accuracy: 53.275
Epoch: 4/50. Train set: Average loss: 0.0000         Average Accuracy:         Accuracy: 53.275
Epoch: 4/50. Test set: Average loss: 0.0000         Average Accuracy:         Accuracy: 61.43
Epoch: 5/50. Train set: Average loss: 0.0000         Average Accuracy:         Accuracy: 65.358
Epoch: 5/50. Train set: Average loss: 0.0000         Average Accuracy:         Accuracy: 65.358
Epoch: 5/50. Test set: Average loss: 0.0000         Average Accuracy:         Accuracy: 72.0
Epoch: 6/50. Train set: Average loss: 0.0000         Average Accuracy:         Accuracy: 74.378
Epoch: 6/50. Train set: Average loss: 0.0000         Average Accuracy:         Accuracy: 74.378
Epoch: 6/50. Test set: Average loss: 0.0000         Average Accuracy:         Accuracy: 78.51
Epoch: 7/50. Train set: Average loss: 0.0000         Average Accuracy:         Accuracy: 79.643
Epoch: 7/50. Train set: Average loss: 0.0000         Average Accuracy:         Accuracy: 79.643
Epoch: 7/50. Test set: Average loss: 0.0000         Average Accuracy:         Accuracy: 82.52
Epoch: 8/50. Train set: Average loss: 0.0000         Average Accuracy:         Accuracy: 82.801
Epoch: 8/50. Train set: Average loss: 0.0000         Average Accuracy:         Accuracy: 82.801
```

```
Epoch: 8/50. Test set: Average loss: 0.0000       Average Accuracy:       Accuracy: 84.75
Epoch: 9/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 84.643
Epoch: 9/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 84.643
Epoch: 9/50. Test set: Average loss: 0.0000       Average Accuracy:       Accuracy: 86.07
Epoch: 10/50. Train set: Average loss: 0.0000     Average Accuracy:       Accuracy: 85.67
Epoch: 10/50. Train set: Average loss: 0.0000     Average Accuracy:       Accuracy: 85.67
Epoch: 10/50. Test set: Average loss: 0.0000      Average Accuracy:       Accuracy: 86.76
Epoch: 11/50. Train set: Average loss: 0.0000     Average Accuracy:       Accuracy: 86.31
Epoch: 11/50. Train set: Average loss: 0.0000     Average Accuracy:       Accuracy: 86.31
Epoch: 11/50. Test set: Average loss: 0.0000      Average Accuracy:       Accuracy: 87.42
Epoch: 12/50. Train set: Average loss: 0.0000     Average Accuracy:       Accuracy: 86.77
Epoch: 12/50. Train set: Average loss: 0.0000     Average Accuracy:       Accuracy: 86.77
Epoch: 12/50. Test set: Average loss: 0.0000      Average Accuracy:       Accuracy: 87.67
Epoch: 13/50. Train set: Average loss: 0.0000     Average Accuracy:       Accuracy: 87.19
Epoch: 13/50. Train set: Average loss: 0.0000     Average Accuracy:       Accuracy: 87.19
Epoch: 13/50. Test set: Average loss: 0.0000      Average Accuracy:       Accuracy: 87.92
Epoch: 14/50. Train set: Average loss: 0.0000     Average Accuracy:       Accuracy: 87.50
Epoch: 14/50. Train set: Average loss: 0.0000     Average Accuracy:       Accuracy: 87.50
Epoch: 14/50. Test set: Average loss: 0.0000      Average Accuracy:       Accuracy: 88.14
Epoch: 15/50. Train set: Average loss: 0.0000     Average Accuracy:       Accuracy: 87.68
Epoch: 15/50. Train set: Average loss: 0.0000     Average Accuracy:       Accuracy: 87.68
Epoch: 15/50. Test set: Average loss: 0.0000      Average Accuracy:       Accuracy: 88.39
Epoch: 16/50. Train set: Average loss: 0.0000     Average Accuracy:       Accuracy: 87.93
Epoch: 16/50. Train set: Average loss: 0.0000     Average Accuracy:       Accuracy: 87.93
Epoch: 16/50. Test set: Average loss: 0.0000      Average Accuracy:       Accuracy: 88.53
Epoch: 17/50. Train set: Average loss: 0.0000     Average Accuracy:       Accuracy: 88.10
Epoch: 17/50. Train set: Average loss: 0.0000     Average Accuracy:       Accuracy: 88.10
Epoch: 17/50. Test set: Average loss: 0.0000      Average Accuracy:       Accuracy: 88.75
Epoch: 18/50. Train set: Average loss: 0.0000     Average Accuracy:       Accuracy: 88.26
Epoch: 18/50. Train set: Average loss: 0.0000     Average Accuracy:       Accuracy: 88.26
Epoch: 18/50. Test set: Average loss: 0.0000      Average Accuracy:       Accuracy: 88.85
Epoch: 19/50. Train set: Average loss: 0.0000     Average Accuracy:       Accuracy: 88.41
Epoch: 19/50. Train set: Average loss: 0.0000     Average Accuracy:       Accuracy: 88.41
Epoch: 19/50. Test set: Average loss: 0.0000      Average Accuracy:       Accuracy: 89.01
Epoch: 20/50. Train set: Average loss: 0.0000     Average Accuracy:       Accuracy: 88.48
Epoch: 20/50. Train set: Average loss: 0.0000     Average Accuracy:       Accuracy: 88.48
Epoch: 20/50. Test set: Average loss: 0.0000      Average Accuracy:       Accuracy: 89.13
Epoch: 21/50. Train set: Average loss: 0.0000     Average Accuracy:       Accuracy: 88.60
Epoch: 21/50. Train set: Average loss: 0.0000     Average Accuracy:       Accuracy: 88.60
Epoch: 21/50. Test set: Average loss: 0.0000      Average Accuracy:       Accuracy: 89.41
Epoch: 22/50. Train set: Average loss: 0.0000     Average Accuracy:       Accuracy: 88.67
Epoch: 22/50. Train set: Average loss: 0.0000     Average Accuracy:       Accuracy: 88.67
Epoch: 22/50. Test set: Average loss: 0.0000      Average Accuracy:       Accuracy: 89.35
Epoch: 23/50. Train set: Average loss: 0.0000     Average Accuracy:       Accuracy: 88.75
Epoch: 23/50. Train set: Average loss: 0.0000     Average Accuracy:       Accuracy: 88.75
Epoch: 23/50. Test set: Average loss: 0.0000      Average Accuracy:       Accuracy: 89.29
Epoch: 24/50. Train set: Average loss: 0.0000     Average Accuracy:       Accuracy: 88.79
Epoch: 24/50. Train set: Average loss: 0.0000     Average Accuracy:       Accuracy: 88.79
```

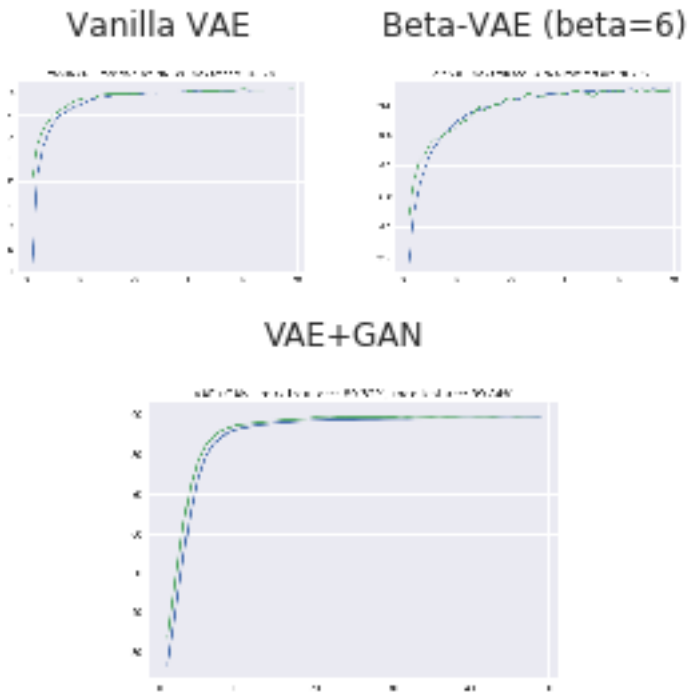
```
Epoch: 24/50. Test set: Average loss: 0.0000       Average Accuracy:       Accuracy: 89.45
Epoch: 25/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 88.86
Epoch: 25/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 88.86
Epoch: 25/50. Test set: Average loss: 0.0000       Average Accuracy:       Accuracy: 89.42
Epoch: 26/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 88.90
Epoch: 26/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 88.90
Epoch: 26/50. Test set: Average loss: 0.0000       Average Accuracy:       Accuracy: 89.48
Epoch: 27/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 88.95
Epoch: 27/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 88.95
Epoch: 27/50. Test set: Average loss: 0.0000       Average Accuracy:       Accuracy: 89.54
Epoch: 28/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 88.97
Epoch: 28/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 88.97
Epoch: 28/50. Test set: Average loss: 0.0000       Average Accuracy:       Accuracy: 89.48
Epoch: 29/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 88.97
Epoch: 29/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 88.97
Epoch: 29/50. Test set: Average loss: 0.0000       Average Accuracy:       Accuracy: 89.55
Epoch: 30/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 89.03
Epoch: 30/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 89.03
Epoch: 30/50. Test set: Average loss: 0.0000       Average Accuracy:       Accuracy: 89.63
Epoch: 31/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 89.06
Epoch: 31/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 89.06
Epoch: 31/50. Test set: Average loss: 0.0000       Average Accuracy:       Accuracy: 89.55
Epoch: 32/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 89.07
Epoch: 32/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 89.07
Epoch: 32/50. Test set: Average loss: 0.0000       Average Accuracy:       Accuracy: 89.74
Epoch: 33/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 89.05
Epoch: 33/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 89.05
Epoch: 33/50. Test set: Average loss: 0.0000       Average Accuracy:       Accuracy: 89.63
Epoch: 34/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 89.13
Epoch: 34/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 89.13
Epoch: 34/50. Test set: Average loss: 0.0000       Average Accuracy:       Accuracy: 89.76
Epoch: 35/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 89.14
Epoch: 35/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 89.14
Epoch: 35/50. Test set: Average loss: 0.0000       Average Accuracy:       Accuracy: 89.7
Epoch: 36/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 89.15
Epoch: 36/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 89.15
Epoch: 36/50. Test set: Average loss: 0.0000       Average Accuracy:       Accuracy: 89.65
Epoch: 37/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 89.16
Epoch: 37/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 89.16
Epoch: 37/50. Test set: Average loss: 0.0000       Average Accuracy:       Accuracy: 89.74
Epoch: 38/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 89.17
Epoch: 38/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 89.17
Epoch: 38/50. Test set: Average loss: 0.0000       Average Accuracy:       Accuracy: 89.66
Epoch: 39/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 89.23
Epoch: 39/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 89.23
Epoch: 39/50. Test set: Average loss: 0.0000       Average Accuracy:       Accuracy: 89.69
Epoch: 40/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 89.23
Epoch: 40/50. Train set: Average loss: 0.0000      Average Accuracy:       Accuracy: 89.23
```

```
Epoch: 40/50. Test set: Average loss: 0.0000        Average Accuracy:        Accuracy: 89.78
Epoch: 41/50. Train set: Average loss: 0.0000        Average Accuracy:        Accuracy: 89.23
Epoch: 41/50. Train set: Average loss: 0.0000        Average Accuracy:        Accuracy: 89.23
Epoch: 41/50. Test set: Average loss: 0.0000        Average Accuracy:        Accuracy: 89.8
Epoch: 42/50. Train set: Average loss: 0.0000        Average Accuracy:        Accuracy: 89.23
Epoch: 42/50. Train set: Average loss: 0.0000        Average Accuracy:        Accuracy: 89.23
Epoch: 42/50. Test set: Average loss: 0.0000        Average Accuracy:        Accuracy: 89.73
Epoch: 43/50. Train set: Average loss: 0.0000        Average Accuracy:        Accuracy: 89.21
Epoch: 43/50. Train set: Average loss: 0.0000        Average Accuracy:        Accuracy: 89.21
Epoch: 43/50. Test set: Average loss: 0.0000        Average Accuracy:        Accuracy: 89.74
Epoch: 44/50. Train set: Average loss: 0.0000        Average Accuracy:        Accuracy: 89.26
Epoch: 44/50. Train set: Average loss: 0.0000        Average Accuracy:        Accuracy: 89.26
Epoch: 44/50. Test set: Average loss: 0.0000        Average Accuracy:        Accuracy: 89.69
Epoch: 45/50. Train set: Average loss: 0.0000        Average Accuracy:        Accuracy: 89.26
Epoch: 45/50. Train set: Average loss: 0.0000        Average Accuracy:        Accuracy: 89.26
Epoch: 45/50. Test set: Average loss: 0.0000        Average Accuracy:        Accuracy: 89.81
Epoch: 46/50. Train set: Average loss: 0.0000        Average Accuracy:        Accuracy: 89.25
Epoch: 46/50. Train set: Average loss: 0.0000        Average Accuracy:        Accuracy: 89.25
Epoch: 46/50. Test set: Average loss: 0.0000        Average Accuracy:        Accuracy: 89.84
Epoch: 47/50. Train set: Average loss: 0.0000        Average Accuracy:        Accuracy: 89.26
Epoch: 47/50. Train set: Average loss: 0.0000        Average Accuracy:        Accuracy: 89.26
Epoch: 47/50. Test set: Average loss: 0.0000        Average Accuracy:        Accuracy: 89.73
Epoch: 48/50. Train set: Average loss: 0.0000        Average Accuracy:        Accuracy: 89.26
Epoch: 48/50. Train set: Average loss: 0.0000        Average Accuracy:        Accuracy: 89.26
Epoch: 48/50. Test set: Average loss: 0.0000        Average Accuracy:        Accuracy: 89.79
Epoch: 49/50. Train set: Average loss: 0.0000        Average Accuracy:        Accuracy: 89.28
Epoch: 49/50. Train set: Average loss: 0.0000        Average Accuracy:        Accuracy: 89.28
Epoch: 49/50. Test set: Average loss: 0.0000        Average Accuracy:        Accuracy: 89.8
Epoch: 50/50. Train set: Average loss: 0.0000        Average Accuracy:        Accuracy: 89.31
Epoch: 50/50. Train set: Average loss: 0.0000        Average Accuracy:        Accuracy: 89.31
Epoch: 50/50. Test set: Average loss: 0.0000        Average Accuracy:        Accuracy: 89.81
```

In [0]:
```
## save lists
save_lists(vae_gan_train_ac,"vae-final/vaeg-train-classifier-acc.pkl")
save_lists(vae_gan_test_ac,"vae-final/vaeg-test-classifier-acc.pkl")

n_epochs = 50
plt.plot(range(1, n_epochs),vae_gan_train_ac)
plt.plot(range(1,n_epochs),vae_gan_test_ac)
plt.title("VAE+GAN - max train acc: {}%, max test acc: {}%"
          .format(round(max(vae_gan_train_ac),2),max(vae_gan_test_ac)))
plt.savefig("vae-final/vae_gan-train-test-acc-classifier.png")
```

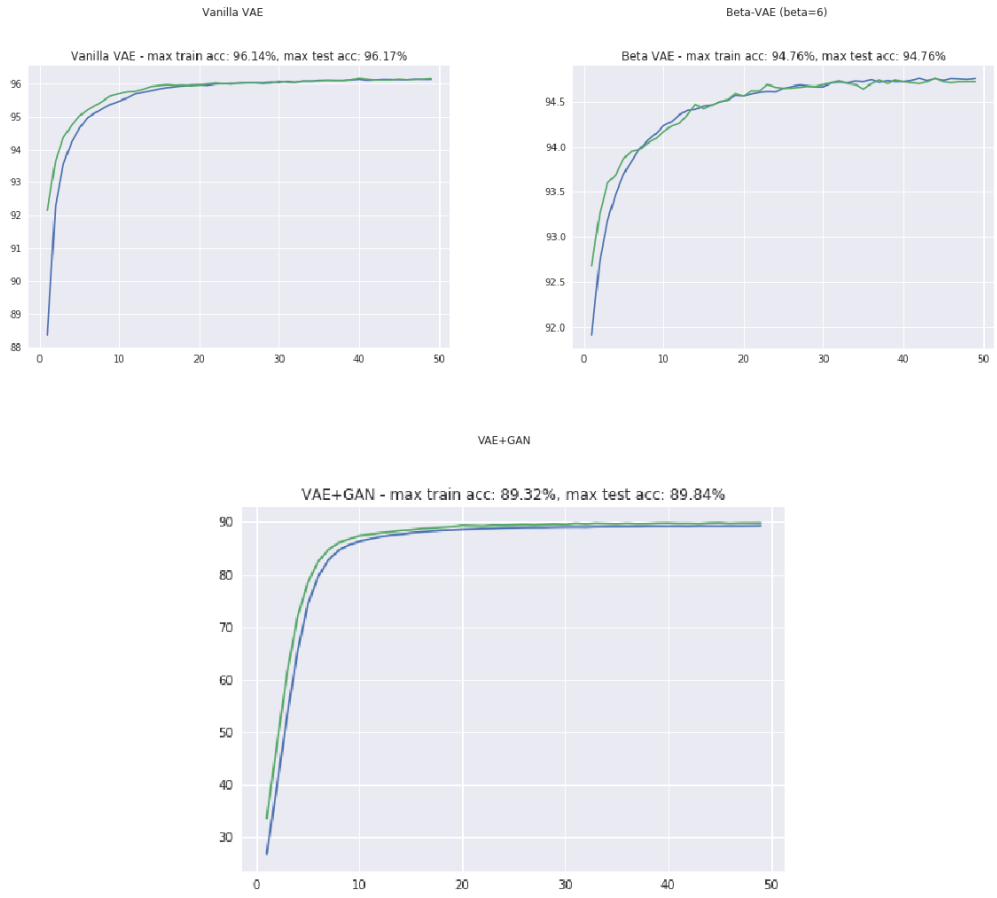



```
In [0]: import matplotlib.pyplot as plt
        from IPython.display import Image
        import matplotlib.image as mpimg
        import matplotlib.gridspec as gridspec
        filename1 = "vae-final/vae-train-test-acc-classifier.png"
        filename2 = "vae-final/bvae-train-test-acc-classifier.png"
        filename3 = "vae-final/vae_gan-train-test-acc-classifier.png"

        display_three_plots(filename1, filename2,filename3,"classifier.png")
```



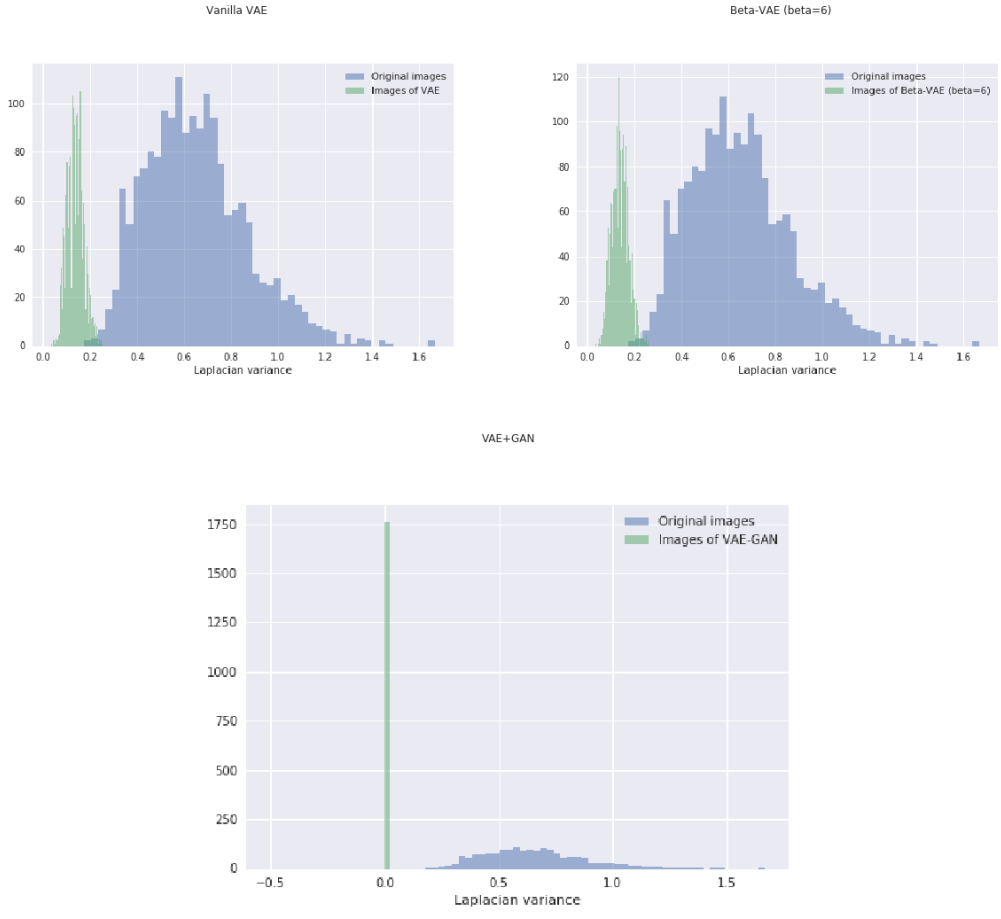

```
In [0]: fig = plt.figure(figsize = (22,20))
        gs = gridspec.GridSpec(2,2)
        gs.update(wspace=0.0, hspace=0.0)
        plt.grid(b=None)
        ## Train
        ax1 = plt.subplot(gs[0, 0])
        vae_tsne = filename1
        img=mpimg.imread(vae_tsne)
        imgplot = plt.imshow(img)
        plt.title("Vanilla VAE")
        plt.axis("off")
        ax1.set_aspect('equal')
        ax2 = plt.subplot(gs[0, 1])
        betavae_tsne = filename2
        img=mpimg.imread(betavae_tsne)
        imgplot = plt.imshow(img)
        plt.title("Beta-VAE (beta=6)")
        plt.axis("off")
        ax2.set_aspect('equal')
        ax3 = plt.subplot(gs[1,:])
        vae_gan_tsne =filename3
        img=mpimg.imread(vae_gan_tsne)
```

```
imgplot = plt.imshow(img)
ax3.set_aspect('equal')
plt.title("VAE+GAN")
plt.axis("off")
plt.savefig("vae-final/classifier.png")
```




```
In [0]: fig = plt.figure(figsize = (22,20))
        gs = gridspec.GridSpec(2,2)
        gs.update(wspace=0.0, hspace=0.0)
        plt.grid(b=None)
        ## Train
        ax1 = plt.subplot(gs[0, 0])
        vae_tsne = filename1
        img=mpimg.imread(vae_tsne)
        imgplot = plt.imshow(img)
        plt.title("Vanilla VAE")
        plt.axis("off")
        ax1.set_aspect('equal')
```

```
ax2 = plt.subplot(gs[0, 1])
betavae_tsne = filename2
img=mpimg.imread(betavae_tsne)
imgplot = plt.imshow(img)
plt.title("Beta-VAE (beta=6)")
plt.axis("off")
ax2.set_aspect('equal')
ax3 = plt.subplot(gs[1,:])
vae_gan_tsne =filename3
img=mpimg.imread(vae_gan_tsne)
imgplot = plt.imshow(img)
ax3.set_aspect('equal')
plt.title("VAE+GAN")
plt.axis("off")
plt.savefig("vae-final/laplacian_blur.png")
```



In [0]: