CS4487 - Machine Learning

Lecture 10a - Deep Learning 2

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Outline

- Image Classification and Deep Architectures
- **Unsupervised Learning**

In [1]:
```
# setup
%matplotlib inline
import IPython.core.display         # setup output image forma
t (Chrome works best)
IPython.core.display.set_matplotlib_formats("svg")
import matplotlib.pyplot as plt
import matplotlib
from numpy import *
from sklearn import *
from scipy import stats

rbow = plt.get_cmap('rainbow')
```

In [2]:
```
# use TensorFlow backend
%env KERAS_BACKEND=tensorflow
from keras.models import Sequential, Model
from keras.layers import Dense, Activation, Dropout, Conv2D, F
latten, \
                    Input, MaxPooling2D, UpSampling2D, Lambda, Res
hape, BatchNormalization, \
                    GlobalAveragePooling2D
import keras
import tensorflow
import logging
logging.basicConfig()
import struct

# use channels first representation for images
from keras import backend as K
K.set_image_data_format('channels_first')

from keras.callbacks import TensorBoard
```

```
env: KERAS_BACKEND=tensorflow

Using TensorFlow backend.
```

In [3]:
```
def plot_history(history):
    fig, ax1 = plt.subplots()

    ax1.plot(history.history['loss'], 'r', label="training los
s ({:.6f})".format(history.history['loss'][-1]))
    ax1.plot(history.history['val_loss'], 'r--', label="valida
tion loss ({:.6f})".format(history.history['val_loss'][-1]))
    ax1.grid(True)
    ax1.set_xlabel('iteration')
    ax1.legend(loc="best", fontsize=9)
    ax1.set_ylabel('loss', color='r')
    ax1.tick_params('y', colors='r')

    if 'acc' in history.history:
        ax2 = ax1.twinx()

        ax2.plot(history.history['acc'], 'b', label="training
acc ({:.4f})".format(history.history['acc'][-1]))
        ax2.plot(history.history['val_acc'], 'b--', label="val
idation acc ({:.4f})".format(history.history['val_acc'][-1]))

        ax2.legend(loc="best", fontsize=9)
        ax2.set_ylabel('acc', color='b')
        ax2.tick_params('y', colors='b')
```

In [4]:

```
def show_imgs(W_list, nc=10, highlight_green=None, highlight_red=None, titles=None):
    nfilter = len(W_list)
    nr = (nfilter - 1) // nc + 1
    for i in range(nr):
        for j in range(nc):
            idx = i * nc + j
            if idx == nfilter:
                break
            plt.subplot(nr, nc, idx + 1)
            cur_W = W_list[idx]
            plt.imshow(cur_W,cmap='gray', interpolation='nearest')
            if titles is not None:
                plt.title(titles % idx)

            if ((highlight_green is not None) and highlight_green[idx]) or \
                ((highlight_red is not None) and highlight_red[idx]):
                ax = plt.gca()
                if highlight_green[idx]:
                    mycol = '#00FF00'
                else:
                    mycol = 'r'
                for S in ['bottom', 'top', 'right', 'left']:
                    ax.spines[S].set_color(mycol)
                    ax.spines[S].set_lw(2.0)
                ax.xaxis.set_ticks_position('none')
                ax.yaxis.set_ticks_position('none')
                ax.set_xticks([])
                ax.set_yticks([])
            else:
                plt.gca().set_axis_off()
```

In [5]:
```
def read_32int(f):
    return struct.unpack('>I', f.read(4))[0]
def read_img(img_path):
    with open(img_path, 'rb') as f:
        magic_num = read_32int(f)
        num_image = read_32int(f)
        n_row = read_32int(f)
        n_col = read_32int(f)
        #print 'num_image = {}; n_row = {}; n_col = {}'.format
(num_image, n_row, n_col)
        res = []
        npixel = n_row * n_col
        res_arr = fromfile(f, dtype='B')
        res_arr = res_arr.reshape((num_image, n_row, n_col), o
rder='C')
        #print 'image data shape = {}'.format(res_arr.shape)
        return num_image, n_row, n_col, res_arr
def read_label(label_path):
    with open(label_path, 'rb') as f:
        magic_num = read_32int(f)
        num_label = read_32int(f)
        #print 'num_label = {}'.format(num_label)
        res_arr = fromfile(f, dtype='B')
        #print res_arr.shape
        #res_arr = res_arr.reshape((num_label, 1))
        res_arr = res_arr.ravel()
        #print 'label data shape = {}'.format(res_arr.shape)
        return num_label, res_arr
```

In [6]:
```
n_train, nrow, ncol, trainimg = read_img('data/train-images.id
x3-ubyte')
_, trainY = read_label('data/train-labels.idx1-ubyte')
n_test, _, _, testimg = read_img('data/t10k-images.idx3-ubyte'
)
_, testY = read_label('data/t10k-labels.idx1-ubyte')

# for demonstration we only use 10% of the training data
sample_index = range(0, trainimg.shape[0], 10)
trainimg   = trainimg[sample_index]
trainY     = trainY[sample_index]
print(trainimg.shape)
print(trainY.shape)
print(testimg.shape)
print(testY.shape)
```

```
(6000, 28, 28)
(6000,)
(10000, 28, 28)
(10000,)
```

In [7]:
```
# Reshape the images to a vector
# and map the data to [0,1]
trainXraw = trainimg.reshape((len(trainimg), -1), order='C') /
255.0
testXraw = testimg.reshape((len(testimg), -1), order='C') / 25
5.0

# center the image data (but don't change variance)
scaler = preprocessing.StandardScaler(with_std=False)
trainX = scaler.fit_transform(trainXraw)
testX  = scaler.transform(testXraw)

# convert class labels to binary indicators
trainYb = keras.utils.np_utils.to_categorical(trainY)

print(trainX.shape)
print(trainYb.shape)
```

```
(6000, 784)
(6000, 10)
```

In [8]:
```
# generate a fixed validation set using 10% of the training se
t
vtrainX, validX, vtrainYb, validYb = \
  model_selection.train_test_split(trainX, trainYb,
  train_size=0.9, test_size=0.1, random_state=4487)

# validation data
validset  = (validX, validYb)
```

In [9]:
```
# scale to 0-1
trainI = (trainimg.reshape((6000,1,28,28)) / 255.0)
testI  = (testimg.reshape((10000,1,28,28)) / 255.0)
print(trainI.shape)
print(testI.shape)
```

```
(6000, 1, 28, 28)
(10000, 1, 28, 28)
```

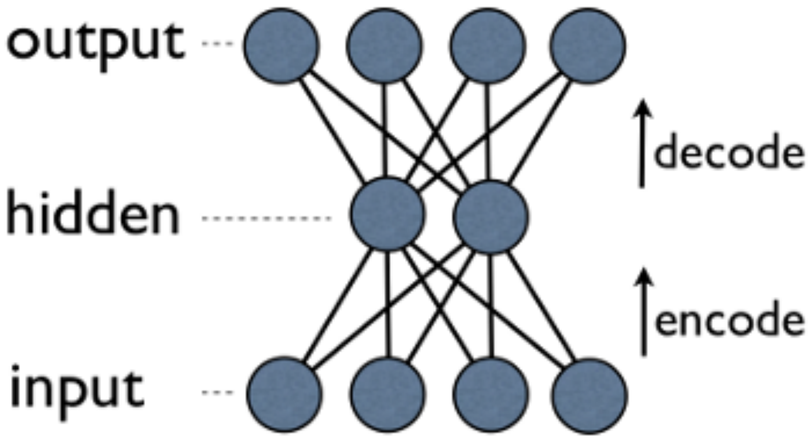
In [10]:
```
# generate fixed validation set of 10% of the training set
vtrainI, validI, vtrainYb, validYb = \
  model_selection.train_test_split(trainI, trainYb,
  train_size=0.9, test_size=0.1, random_state=4487)

validsetI = (validI, validYb)
```

Neural Networks and Unsupervised Learning

- How to use NN for dimensionality reduction or clustering?

Denoising Autoencoder

- Use the hidden layer as the lower-dimensional representation (code)
- Train the network to "encode" and "decode"
  - randomly corrupt the input (by setting values to 0)
  - run it through the encoding-decoding network
  - minimize the difference between the output and the original input



Example on MNIST

- Reshape the images into vectors, and scale to [0,1]

In [11]:
```
# Reshape the images and map the data to [0,1]
trainXraw = trainimg.reshape((len(trainimg), -1), order='C') / 255.0
testXraw = testimg.reshape((len(testimg), -1), order='C') / 255.0
```

In [12]:
```
# generate a fixed validation set using 10% of the training set
vtrainXraw, validXraw = \
  model_selection.train_test_split(trainXraw,
  train_size=0.9, test_size=0.1, random_state=4487)
```

- Train the autoencoder
  - specify the number of hidden nodes
  - corrupt the image using Dropout
    - corruption level = percentage of inputs that are zeroed out.

- Use `Model` class.
  - pass input and output layers.
  - The model consists of everything between input and output.

In [13]:
```
# initialize random seed
random.seed(4487); tensorflow.set_random_seed(4487)

# Build the Encoder model
input_img = Input(shape=(784,))
corrupted_img = Dropout(rate=0.3)(input_img)
encoded = Dense(10, activation='relu')(corrupted_img)
encoder = Model(input_img, encoded)

# Build the Decoder model
encoded_input = Input(shape=(10,))
decoded = Dense(784, activation='sigmoid')(encoded_input)
decoder = Model(encoded_input, decoded)

# build the full autoencoder model
autoencoder = Model(input_img, decoder(encoder(input_img)))
```

- Encoder and decoder subnetworks

In [14]:
```
encoder.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         (None, 784)               0
_________________________________________________________________
dropout_1 (Dropout)          (None, 784)               0
_________________________________________________________________
dense_1 (Dense)              (None, 10)                7850
=================================================================
Total params: 7,850
Trainable params: 7,850
Non-trainable params: 0
_________________________________________________________________
```

In [15]:
```
decoder.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_2 (InputLayer)         (None, 10)                0
_________________________________________________________________
dense_2 (Dense)              (None, 784)               8624
=================================================================
Total params: 8,624
Trainable params: 8,624
Non-trainable params: 0
_________________________________________________________________
```

- Full auto-encoder network
    - Composed of the encoder and decoder models

In [16]:
```
autoencoder.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         (None, 784)               0
_________________________________________________________________
model_1 (Model)              (None, 10)                7850
_________________________________________________________________
model_2 (Model)              (None, 784)               8624
=================================================================
Total params: 16,474
Trainable params: 16,474
Non-trainable params: 0
_________________________________________________________________
```

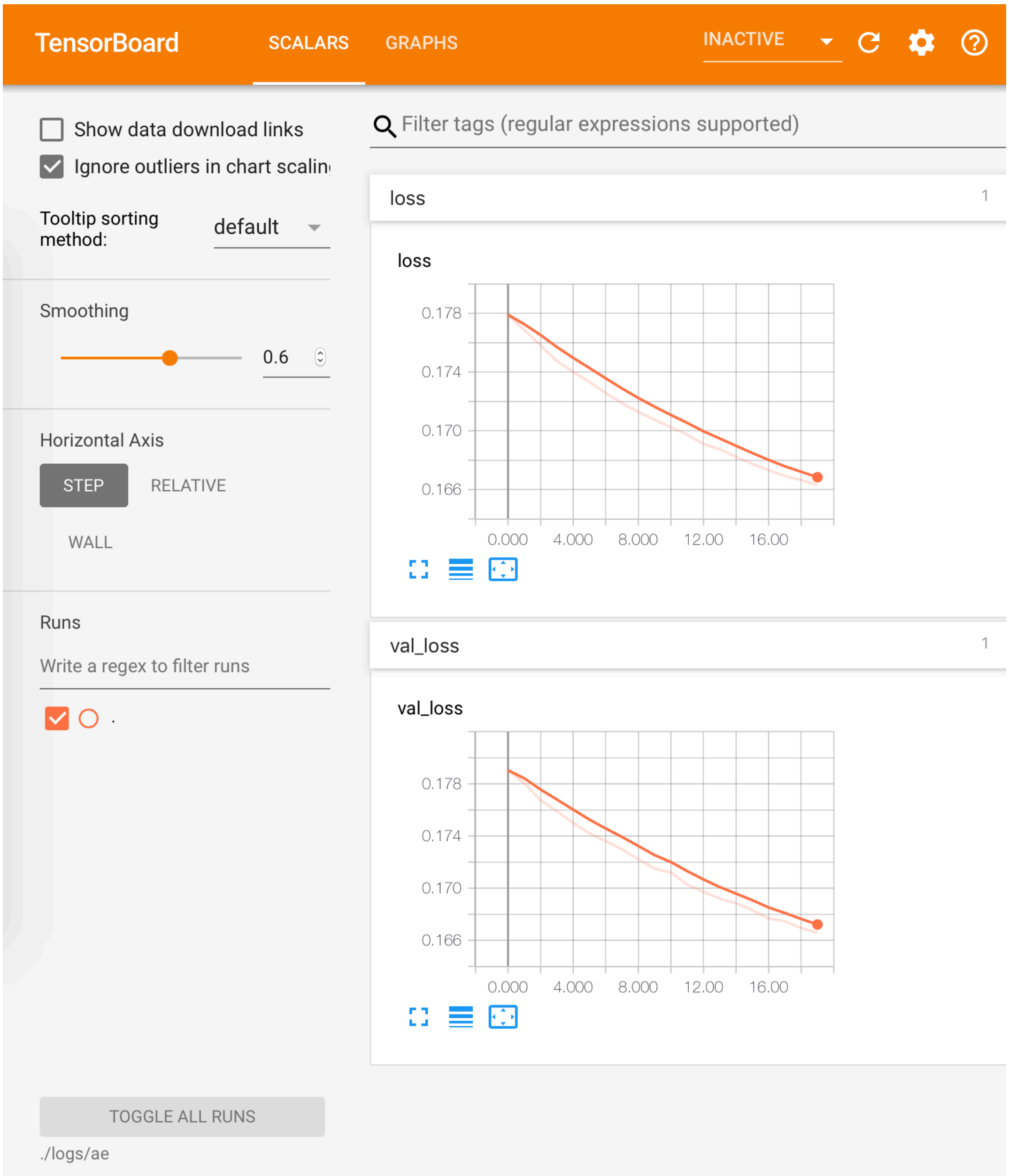
- Compile the model

In [17]:
```
# early stopping criteria
earlystop = keras.callbacks.EarlyStopping(monitor='val_loss',
                            min_delta=0.0001, patience=10,
                            verbose=1, mode='auto')

# compile and fit the network
autoencoder.compile(loss=keras.losses.binary_crossentropy,
           optimizer=keras.optimizers.SGD(lr=0.2, momentum=0.9
, nesterov=True))
```

- Fit the model

In [20]:
```
# fit the model: the input and output are the same
# write to a log directory to see training process
history = autoencoder.fit(vtrainXraw, vtrainXraw,
                 epochs=20, batch_size=50,
                 callbacks=[earlystop, TensorBoard(log_dir='./
logs/ae')],
                 validation_data=(validXraw, validXraw), verbo
se=False)
```

- Run tensorboard in console: `tensorboard --logdir=./logs.ae`
- View training procedure: [http://0.0.0.0:6006 (http://0.0.0.0:6006)](http://0.0.0.0:6006)



- Encode images into low-dim representation.

In [21]:
```
Z = encoder.predict(trainXraw)
Z.shape
```

Out[21]:
```
(6000, 10)
```

- Visualize the nearby neighbors in the low-dim representation.
  - each row represents one set of neighbors

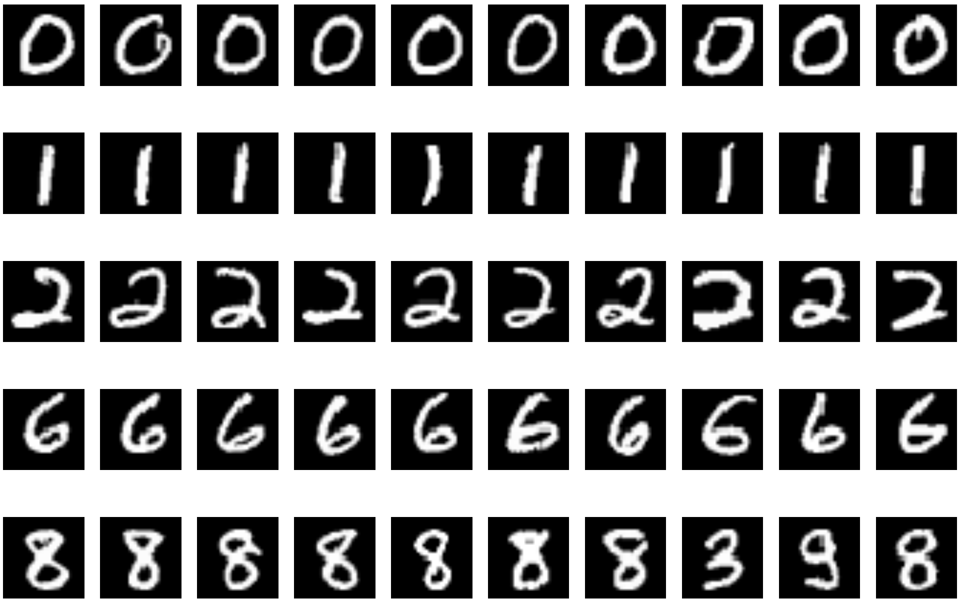
In [22]:

```
Wlist = []
for ii in [210,4,101,9,294]:
    d = metrics.pairwise.euclidean_distances(Z, [Z[ii]])
    inds = argsort(d.ravel())
    for x in inds[0:10]:
        Wlist.append(trainXraw[x].reshape((28,28)))

Zfig = plt.figure()
show_imgs(Wlist)
plt.close()
```

In [23]:

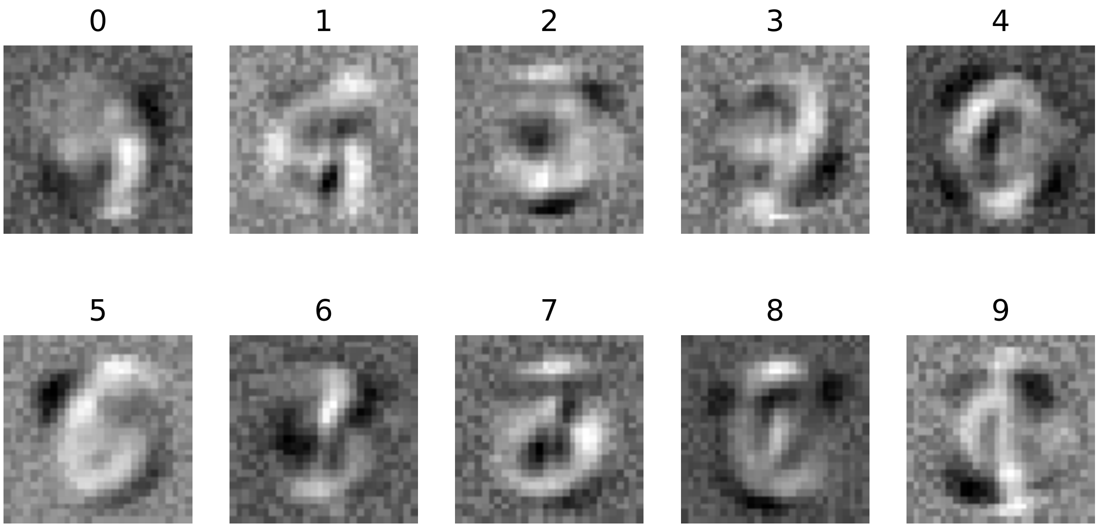
```
Zfig
```

Out[23]:



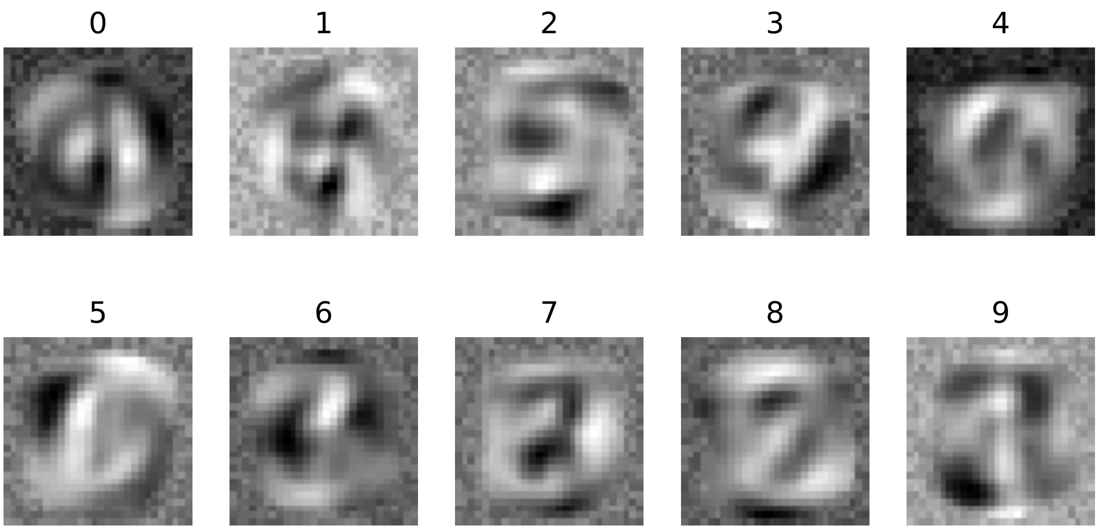
- Visualize the weights of the hidden layer that generate codes
  - each hidden node activates on a particular structure

In [24]:
```
W = encoder.get_layer(index=2).get_weights()[0]
filter_list = [W[:,i].reshape((28,28)) for i in range(W.shape[1])]
plt.figure(figsize=(8,4))
show_imgs(filter_list, nc=5, titles="%d")
```



- Visualize the weights that project the code into an image
    - the image structures match those of the encoder, but are smoother.

In [25]:
```
W = decoder.get_layer(index=1).get_weights()[0]
filter_list = [W[i,:].reshape((28,28)) for i in range(W.shape[0])]
plt.figure(figsize=(8,4))
show_imgs(filter_list, nc=5, titles="%d")
```



- Visualize the reconstruction of the input image

In [26]:
```
testXrecon = decoder.predict(encoder.predict(testXraw))
```

In [27]:
```
imglist = []
for j,i in enumerate(range(0,100,10)):
    tmp = hstack( (testXraw[i].reshape((28,28)), testXrecon[i]
.reshape((28,28))) )
    imglist.append(tmp)
rfig = plt.figure(figsize=(10,3))
show_imgs(imglist,nc=5)
plt.close()
rfig
```

Out[27]:

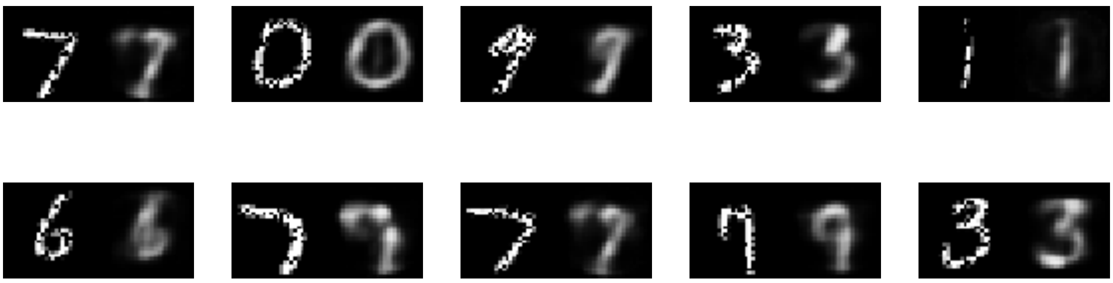
- Corrupt the input image and encode-decode
  - performs "denoising" of the input

In [28]:
```
noisytest = testXraw * random.binomial(n=1,p=1-0.3,size=testXr
aw.shape)
testXrecon = decoder.predict(encoder.predict(noisytest))
```

In [29]:
```
imglist = []
for j,i in enumerate(range(0,100,10)):
    tmp = hstack( (noisytest[i].reshape((28,28)), testXrecon[i
].reshape((28,28))) )
    imglist.append(tmp)
dfig = plt.figure(figsize=(10,3))
show_imgs(imglist,nc=5)
plt.close()
```

In [30]:
```
dfig
```

Out[30]:



Convolutional Auto-Encoder

- Encoder - a standard CNN (w/o classifier)
  - Extract a feature map

In [36]:
```
random.seed(4487); tensorflow.set_random_seed(4487)

# the Conv2D encoder
input_img2 = Input(shape=(1, 28, 28))
x = Conv2D(16, (3, 3), activation='relu', padding='same')(inpu
t_img2)
x = MaxPooling2D((2, 2), padding='same')(x)
x = Conv2D(8, (3, 3), activation='relu', padding='same')(x)
x = MaxPooling2D((2, 2), padding='same')(x)
x = Conv2D(8, (3, 3), activation='relu', padding='same')(x)
encoded2 = MaxPooling2D((2, 2), padding='same')(x)
encoder2 = Model(input_img2, encoded2)
# the representation is (8, 4, 4) i.e. 128-dimensional
```

- Decoder
  - the opposite architecture
  - Replace maxpooling with upsampling

In [37]:
```
# the Conv2D decoder
encoded_input2 = Input(shape=(8,4,4))
x = Conv2D(8, (3, 3), activation='relu', padding='same')(encod
ed_input2)
x = UpSampling2D((2, 2))(x)
x = Conv2D(8, (3, 3), activation='relu', padding='same')(x)
x = UpSampling2D((2, 2))(x)
x = Conv2D(16, (3, 3), activation='relu')(x)
x = UpSampling2D((2, 2))(x)
decoded2 = Conv2D(1, (3, 3), activation='sigmoid', padding='sa
me')(x)
decoder2 = Model(encoded_input2, decoded2)
```

- Connect the two to form the autoencoder

In [38]:
```
# connect the encoder to the decoder
autoencoder2 = Model(input_img2, decoder2(encoder2(input_img2)
))
autoencoder2.compile(optimizer='adadelta', loss='binary_crosse
ntropy')
```

- Encoder and Decoders

In [39]:
```
encoder2.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_5 (InputLayer)         (None, 1, 28, 28)         0
_________________________________________________________________
conv2d_8 (Conv2D)            (None, 16, 28, 28)        160
_________________________________________________________________
max_pooling2d_4 (MaxPooling2 (None, 16, 14, 14)        0
_________________________________________________________________
conv2d_9 (Conv2D)            (None, 8, 14, 14)         1160
_________________________________________________________________
max_pooling2d_5 (MaxPooling2 (None, 8, 7, 7)           0
_________________________________________________________________
conv2d_10 (Conv2D)           (None, 8, 7, 7)           584
_________________________________________________________________
max_pooling2d_6 (MaxPooling2 (None, 8, 4, 4)           0
=================================================================
Total params: 1,904
Trainable params: 1,904
Non-trainable params: 0
_________________________________________________________________
```

In [40]:
```
decoder2.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_6 (InputLayer)         (None, 8, 4, 4)           0
_________________________________________________________________
conv2d_11 (Conv2D)           (None, 8, 4, 4)           584
_________________________________________________________________
up_sampling2d_4 (UpSampling2 (None, 8, 8, 8)           0
_________________________________________________________________
conv2d_12 (Conv2D)           (None, 8, 8, 8)           584
_________________________________________________________________
up_sampling2d_5 (UpSampling2 (None, 8, 16, 16)         0
_________________________________________________________________
conv2d_13 (Conv2D)           (None, 16, 14, 14)        1168
_________________________________________________________________
up_sampling2d_6 (UpSampling2 (None, 16, 28, 28)        0
_________________________________________________________________
conv2d_14 (Conv2D)           (None, 1, 28, 28)         145
=================================================================
Total params: 2,481
Trainable params: 2,481
Non-trainable params: 0
_________________________________________________________________
```

- The whole autoencoder

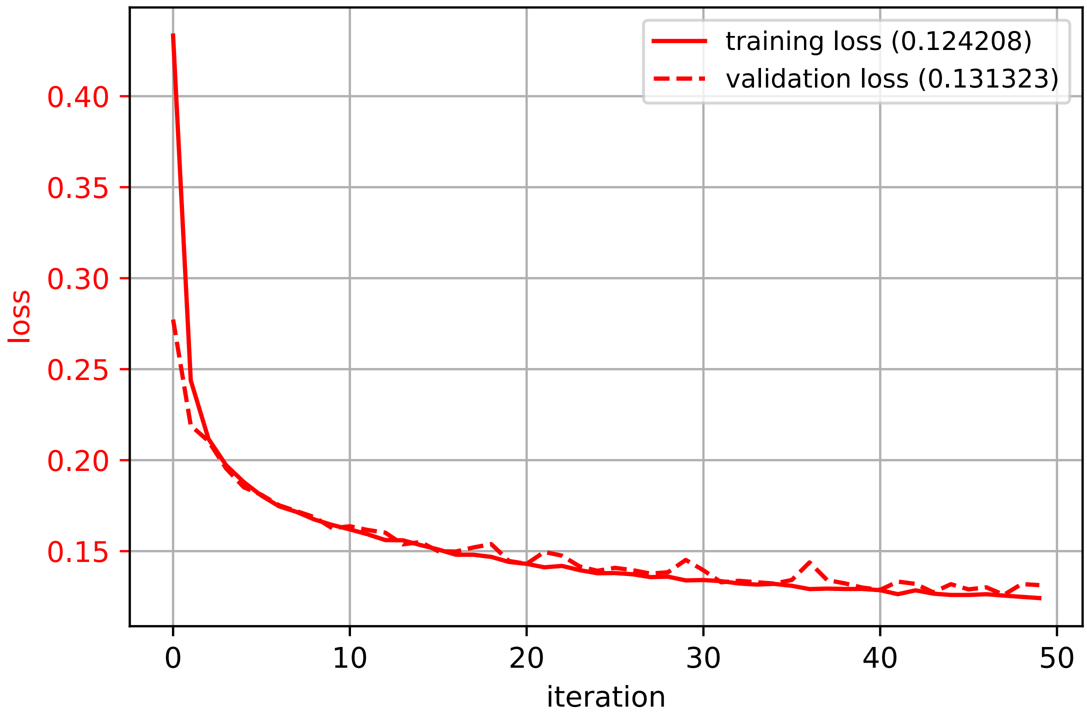
In [41]:
```
autoencoder2.summary()
```

```
____________________________________________________________
_____
Layer (type)                 Output Shape              Param
#
============================================================
====
input_5 (InputLayer)         (None, 1, 28, 28)         0
____________________________________________________________
_____
model_7 (Model)              (None, 8, 4, 4)           1904
____________________________________________________________
_____
model_8 (Model)              (None, 1, 28, 28)         2481
============================================================
====
Total params: 4,385
Trainable params: 4,385
Non-trainable params: 0
____________________________________________________________
_____
```

- Now fit the model

In [42]:
```
# training with images
history = autoencoder2.fit(vtrainI, vtrainI,
                            epochs=50,
                            batch_size=128,
                            shuffle=True,
                            callbacks=[earlystop, TensorBoard(
log_dir='./logs/ae2')],
                            validation_data=(validI, validI),
verbose=False)
```

In [43]:
```
plot_history(history)
```



- Encode and reconstruct an image

In [44]:
```
testIrecon = decoder2.predict(encoder2.predict(testI))
```

- Better visualization

In [45]:
```
imglist = []
for j,i in enumerate(range(0,100,10)):
    tmp = hstack( (testI[i].reshape((28,28)), testIrecon[i].re
shape((28,28))) )
    imglist.append(tmp)
rfig = plt.figure(figsize=(10,3))
show_imgs(imglist,nc=5)
plt.close()
rfig
```

Out[45]:

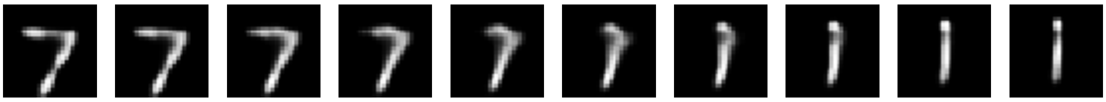
- Traverse the latent space
- Change a 7 into a 1

In [46]:
```
def Xinterp(X,sp=10):
    alpha = linspace(0,1,sp).reshape((sp,)+(ndim(X)-1)*(1,))
    Xint = X[0,:]*(1-alpha) + X[1,:]*alpha
    return Xint
```

In [47]:
```
inds = [0,40]
X = encoder2.predict(testI[inds,:])
Xd = decoder2.predict(Xinterp(X))
```

In [48]:
```
rfig = plt.figure(figsize=(10,3))
show_imgs(Xd.reshape((10,28,28)),nc=10)
plt.close()
rfig
```

Out[48]:



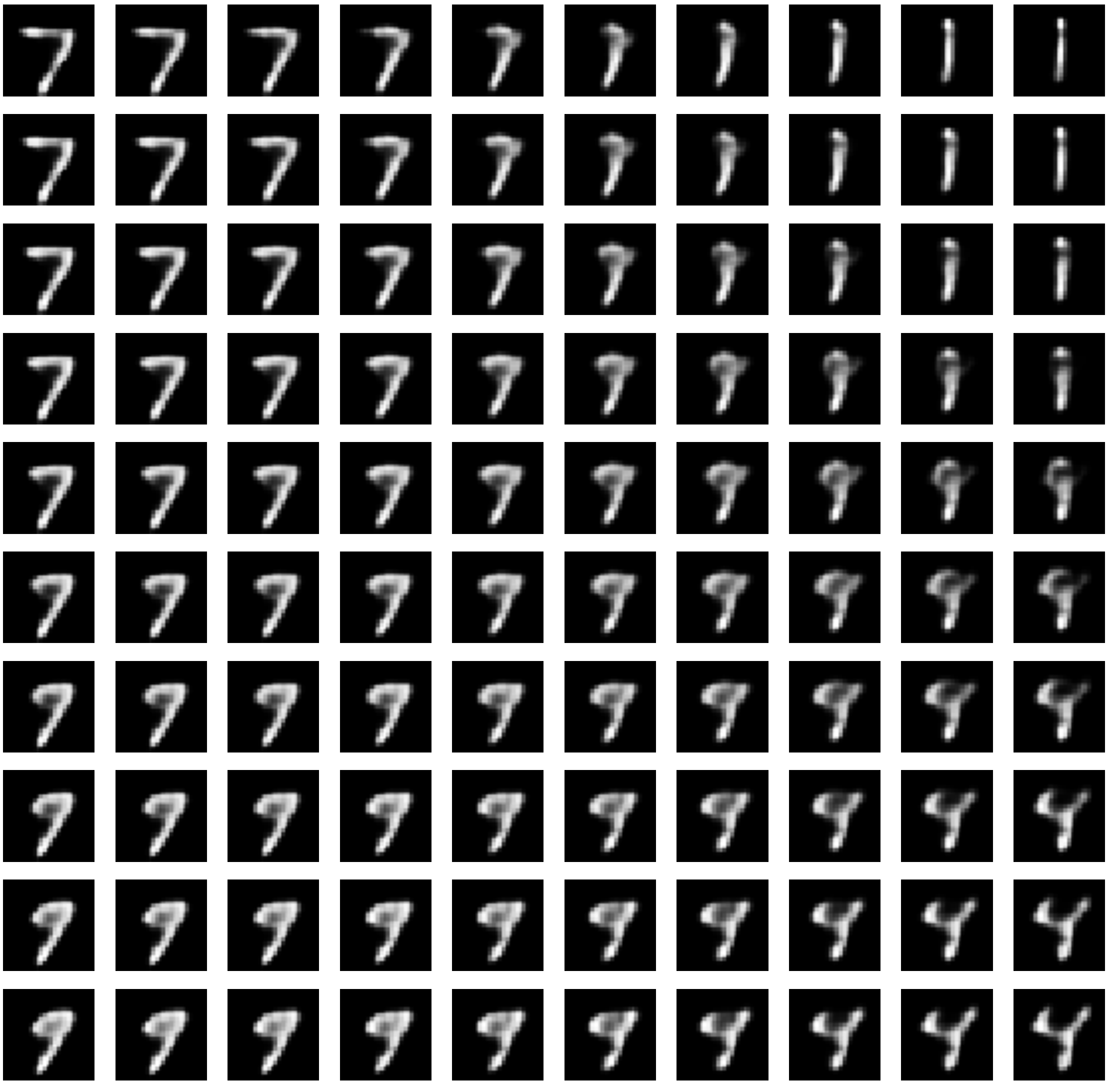
- Traverse the latent space between a 7, 1, 9, and 4
  - captures shapes in between

In [49]:
```
def Xinterp2(X, sp=10):
    # [TL, TR, BL, BR]

    Xtbl = Xinterp(X[[0,2],:])
    Xtbr = Xinterp(X[[1,3],:])

    # interpolate inbetween
    Xall = zeros((sp*sp,) + Xtbl.shape[1:])

    tmps = array(Xtbl.shape)
    tmps[0] = 1
    for i in range(10):
        tmpX = concatenate((Xtbl[i,:].reshape(tmps), Xtbr[i,:]
.reshape(tmps)), axis=0)
        Xall[10*i:10*(i+1),:] = Xinterp(tmpX)
    return Xall
```

In [50]:

```
inds = [0, 40, 20, 6]
X = encoder2.predict(testI[inds,:])
Xd = decoder2.predict(Xinterp2(X))
rfig = plt.figure(figsize=(10,10))
show_imgs(Xd.reshape((100,28,28)),nc=10)
plt.close()
rfig
```

Out[50]:

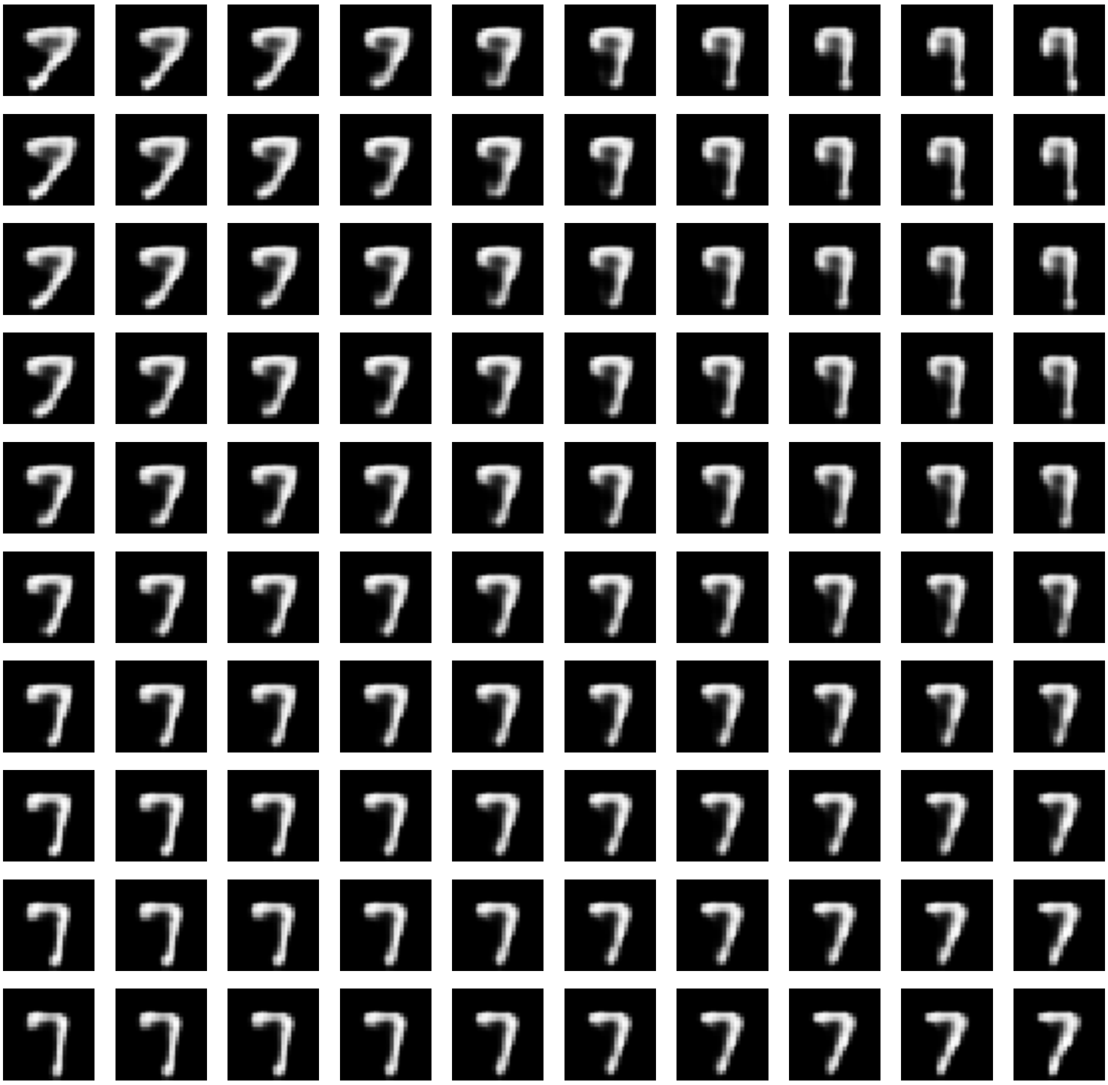


- Traverse the latent space between different 7s
  - captures different shapes of 7

In [51]:

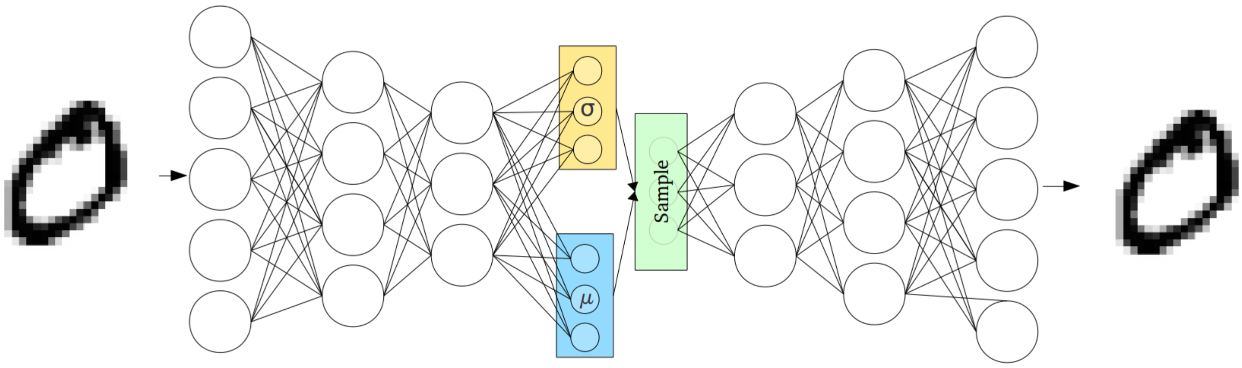
```
mydigits = where(testY==7)[0]
inds = mydigits[10:14]
X = encoder2.predict(testI[inds,:])
Xd = decoder2.predict(Xinterp2(X))
rfig = plt.figure(figsize=(10,10))
show_imgs(Xd.reshape((100,28,28)),nc=10)
plt.close()
rfig
```

Out[51]:



Variational AutoEncoder (VAE)

- The standard autoencoder can have difficulty encoding/decoding new images
  - the decoder never sees (encoded) latent vectors outside of the training set
- VAE fixes this by introducing noise in the latent vectors
  - the noise lets the decoder network see slightly different latent vectors for each training image.
  - improves the ability to interpolate between training samples



In [52]:
```
# some settings
random.seed(4487); tensorflow.set_random_seed(4487)
original_dim = 784
input_shape = (original_dim, )
intermediate_dim = 512
batch_size = 128
latent_dim = 2
epochs = 50
```

- Build the encoder
- Map the input into the mean and log(sigma) of the Gaussian distribution
  - the mean is the encoded vector

In [53]:
```
# encoder mapping to distribution (mean and log_sigma)
x = Input(shape=(original_dim,))
h = Dense(intermediate_dim, activation='relu')(x)

# the man and log-sigma
z_mean = Dense(latent_dim)(h)
z_log_sigma = Dense(latent_dim)(h)

# encoder, from inputs to latent space
encoder = Model(x, z_mean)
```

- Use the mean and log(sigma) to sample a latent variable z

In [54]:

```
# sampling function - draw Gaussian random noise
epsilon_std = 0.001
def sampling(args):
    z_mean, z_log_sigma = args
    epsilon = K.random_normal(shape=K.shape(z_mean), mean=0.,
stddev=epsilon_std)
    return z_mean + K.exp(z_log_sigma) * epsilon

# layer that samples according to mean and sigma
z = Lambda(sampling)([z_mean, z_log_sigma])
```

- Decode the latent variable z
- Construct the whole VAE

In [55]:

```
# create the layers and assign to a variable, since we need
# to use it later
decoder_h = Dense(intermediate_dim, activation='relu')
decoder_mean = Dense(original_dim, activation='sigmoid')

# connect the latent variable and hidden states
h_decoded = decoder_h(z)
x_decoded_mean = decoder_mean(h_decoded)

# end-to-end variational autoencoder
vae = Model(x, x_decoded_mean)
```

- Construxct the generator (decoder)
  - attach another input to the saved layers, and connect them

In [56]:

```
# generator, from latent space to reconstructed inputs
decoder_input = Input(shape=(latent_dim,))  # make an input an
d attach it to the hidden state layer
_h_decoded = decoder_h(decoder_input)       # and other layers
_x_decoded_mean = decoder_mean(_h_decoded)

# the generator model
generator = Model(decoder_input, _x_decoded_mean)
```

- VAE uses a special loss function
  - minimize the KL divergence between the distributions

In [57]:
```
# define the VAE loss
def vae_loss(x, x_decoded_mean):
    # cross-entropy loss
    xent_loss = keras.losses.binary_crossentropy(x, x_decoded_
mean)
    # KL divergence loss
    kl_loss = - 0.5 * K.mean(1 + z_log_sigma - K.square(z_mean
) - K.exp(z_log_sigma), axis=-1)
    return xent_loss + kl_loss

# compile the model for optimization
vae.compile(optimizer='rmsprop', loss=vae_loss)
```

- The final VAE model
    - note that there are two layers going into lambda_1

In [58]:
```
vae.summary()
```

```
______________________________________________________________
_____________________________________
Layer (type)                     Output Shape         Param #
Connected to
==============================================================
=====================================
input_7 (InputLayer)             (None, 784)          0

______________________________________________________________
_____________________________________
dense_3 (Dense)                  (None, 512)          401920
input_7[0][0]

______________________________________________________________
_____________________________________
dense_4 (Dense)                  (None, 2)            1026
dense_3[0][0]

______________________________________________________________
_____________________________________
dense_5 (Dense)                  (None, 2)            1026
dense_3[0][0]

______________________________________________________________
_____________________________________
lambda_1 (Lambda)                (None, 2)            0
dense_4[0][0]

dense_5[0][0]

______________________________________________________________
_____________________________________
dense_6 (Dense)                  (None, 512)          1536
lambda_1[0][0]

______________________________________________________________
_____________________________________
dense_7 (Dense)                  (None, 784)          402192
dense_6[0][0]
==============================================================
=====================================
Total params: 807,700
Trainable params: 807,700
Non-trainable params: 0

______________________________________________________________
_____________________________________
```

- The encoder and decoder

In [59]:
```
encoder.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_7 (InputLayer)         (None, 784)               0
_________________________________________________________________
dense_3 (Dense)              (None, 512)               401920
_________________________________________________________________
dense_4 (Dense)              (None, 2)                 1026
=================================================================
Total params: 402,946
Trainable params: 402,946
Non-trainable params: 0
_________________________________________________________________
```

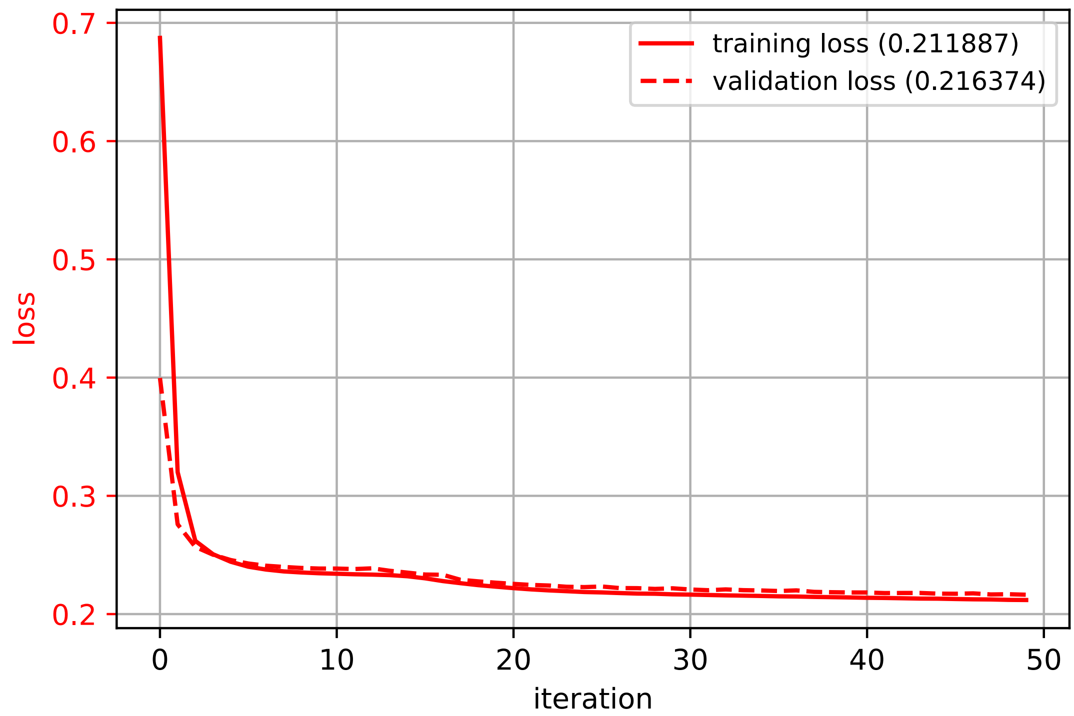
In [60]:
```
generator.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_8 (InputLayer)         (None, 2)                 0
_________________________________________________________________
dense_6 (Dense)              (None, 512)               1536
_________________________________________________________________
dense_7 (Dense)              (None, 784)               402192
=================================================================
Total params: 403,728
Trainable params: 403,728
Non-trainable params: 0
_________________________________________________________________
```

- Fit the model

In [61]:
```
history = vae.fit(vtrainXraw, vtrainXraw,
            shuffle=True,
            epochs=epochs,
            batch_size=batch_size,
            validation_data=(validXraw, validXraw),
            callbacks=[TensorBoard(log_dir='./logs/vae')],
            verbose=False
           )
```

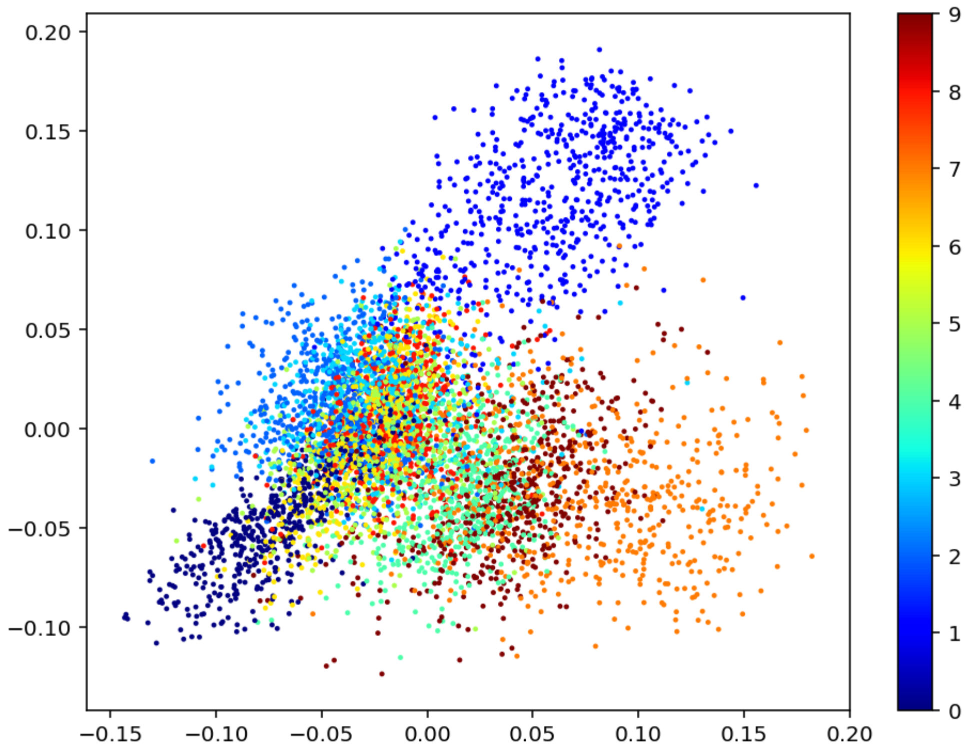
In [62]:
```
plot_history(history)
```



- View a scatter plot of the encoded data
  - some digits are located inthe same area

In [67]:
```
IPython.core.display.set_matplotlib_formats("retina") # switch
to png since the next figure is complex
```

In [68]:
```
x_test_encoded = encoder.predict(trainXraw)
plt.figure(figsize=(8, 6))
plt.scatter(x_test_encoded[:, 0], x_test_encoded[:, 1], c=trai
nY, s=2, cmap=plt.get_cmap('jet'))
plt.colorbar()
plt.show()
```



In [69]:
```
IPython.core.display.set_matplotlib_formats("svg") # switch to
svg
```

- View some reconstruction results

In [70]:
```
testXrecon = generator.predict(encoder.predict(testXraw))
imglist = []
for j,i in enumerate(range(0,100,10)):
    tmp = hstack( (testXraw[i].reshape((28,28)), testXrecon[i]
.reshape((28,28))) )
    imglist.append(tmp)
rfig = plt.figure(figsize=(10,3))
show_imgs(imglist,nc=5)
plt.close()
rfig
```

Out[70]:

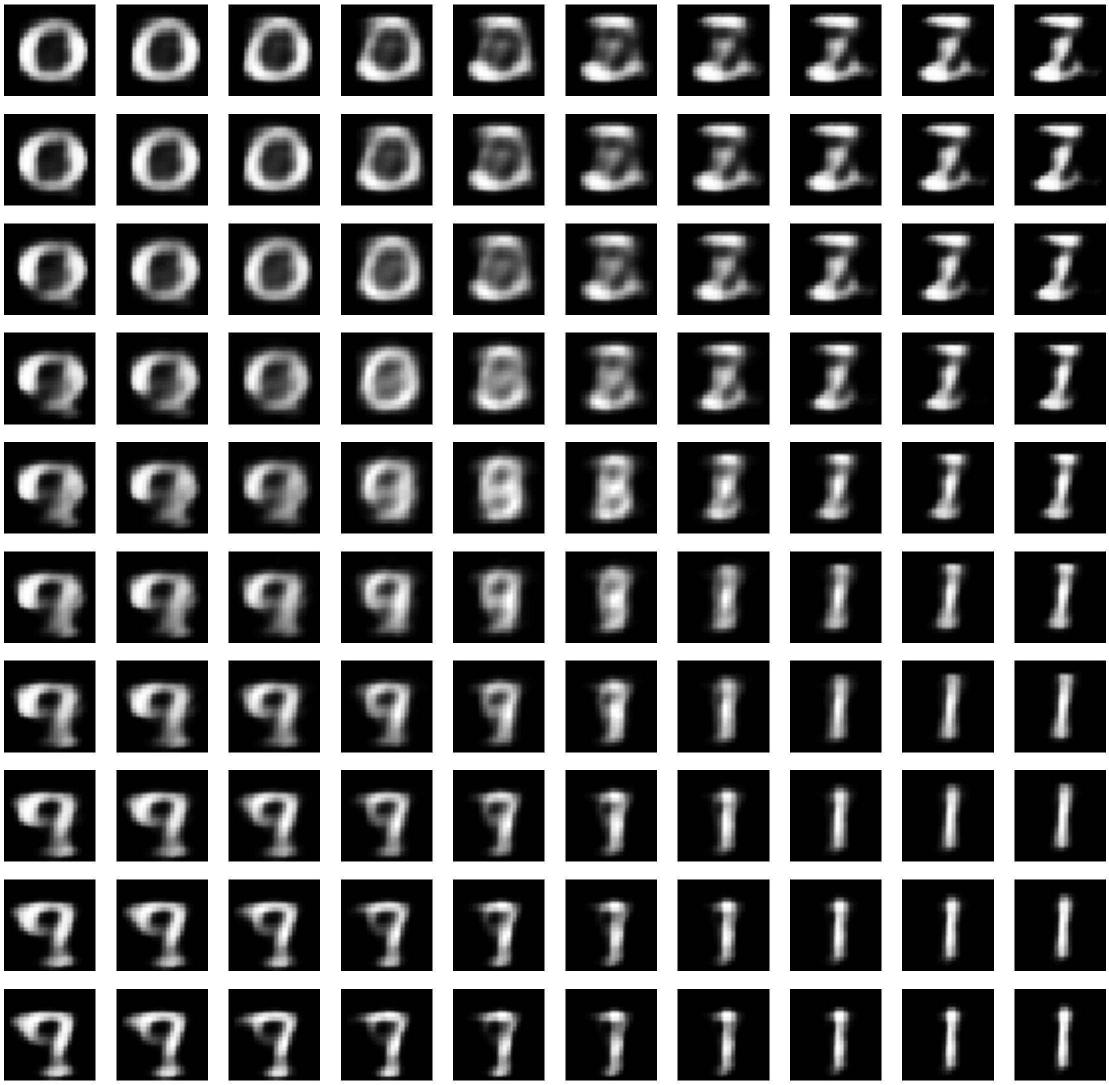
- visualize the 2D latent space

In [74]:
```
# select points on a grid from 3 standard deviations around th
e mean
mn = mean(x_test_encoded, axis=0)
sd = std(x_test_encoded, axis=0)
X = array(
    [ [mn[0]-3*sd[0], mn[1]-3*sd[1]],
      [mn[0]-3*sd[0], mn[1]+3*sd[1]],
      [mn[0]+3*sd[0], mn[1]-3*sd[1]],
      [mn[0]+3*sd[0], mn[1]+3*sd[1]]
    ] )
X.shape
```

Out[74]: (4, 2)

In [73]:
```
Xd = generator.predict(Xinterp2(X))
rfig = plt.figure(figsize=(10,10))
show_imgs(Xd.reshape((100,28,28)),nc=10)
plt.close()
rfig
```

Out[73]:



Convolutional VAE

- The previous VAE is using fully-connected layers
- Since the inputs are images, then replace the Dense layers with Conv2D and Pooling
    - The encoder has 3 outputs: the latent mean, log-sigma, and the sampled z
    - Latent dimension is 10

In [75]:
```
# the Conv2D encoder
latent_dim = 10
input_img2 = Input(shape=(1, 28, 28))
x = Conv2D(16, (3, 3), activation='relu', padding='same')(inpu
t_img2)
x = MaxPooling2D((2, 2), padding='same')(x)
x = Conv2D(8, (3, 3), activation='relu', padding='same')(x)
x = MaxPooling2D((2, 2), padding='same')(x)
x = Conv2D(8, (3, 3), activation='relu', padding='same')(x)
x = MaxPooling2D((2, 2), padding='same')(x)
x = Flatten()(x)

# the mean and log-sigma
z_mean      = Dense(latent_dim)(x)
z_log_sigma = Dense(latent_dim)(x)

# sampling step
epsilon_std = 0.01
def sampling(args):
    z_mean, z_log_sigma = args
    #epsilon = K.random_normal(shape=(batch_size, latent_dim))
    epsilon = K.random_normal(shape=K.shape(z_mean), stddev=ep
silon_std)
    return z_mean + K.exp(z_log_sigma) * epsilon

z = Lambda(sampling)([z_mean, z_log_sigma])

# build the encoder
encoder = Model(input_img2, [z_mean, z_log_sigma, z])
```

- Encoder summary

In [76]:
```
encoder.summary()
```

```
______________________________________________________________
______________________________________
Layer (type)                    Output Shape         Param #
Connected to
==============================================================
======================================
input_9 (InputLayer)            (None, 1, 28, 28)    0

______________________________________________________________
______________________________________
conv2d_15 (Conv2D)              (None, 16, 28, 28)   160
input_9[0][0]
______________________________________________________________
______________________________________
max_pooling2d_7 (MaxPooling2D)  (None, 16, 14, 14)   0
conv2d_15[0][0]
______________________________________________________________
______________________________________
conv2d_16 (Conv2D)              (None, 8, 14, 14)    1160
max_pooling2d_7[0][0]
______________________________________________________________
```

```
_____________________________________
max_pooling2d_8 (MaxPooling2D)  (None, 8, 7, 7)      0
conv2d_16[0][0]

_____________________________________________________________
_____________________________________
conv2d_17 (Conv2D)              (None, 8, 7, 7)      584
max_pooling2d_8[0][0]

_____________________________________________________________
_____________________________________
max_pooling2d_9 (MaxPooling2D)  (None, 8, 4, 4)      0
conv2d_17[0][0]

_____________________________________________________________
_____________________________________
flatten_1 (Flatten)             (None, 128)          0
max_pooling2d_9[0][0]

_____________________________________________________________
_____________________________________
dense_8 (Dense)                 (None, 10)           1290
flatten_1[0][0]

_____________________________________________________________
_____________________________________
dense_9 (Dense)                 (None, 10)           1290
flatten_1[0][0]

_____________________________________________________________
_____________________________________
lambda_2 (Lambda)               (None, 10)           0
dense_8[0][0]

dense_9[0][0]
=============================================================
=====================================
Total params: 4,484
Trainable params: 4,484
Non-trainable params: 0

_____________________________________________________________
_____________________________________
```

- Same for the decoder

In [77]:

```python
# the Conv2D decoder
encoded_input2 = Input(shape=(latent_dim,))
x = Dense(128, activation='relu')(encoded_input2)
x = Reshape((8,4,4))(x)
x = Conv2D(8, (3, 3), activation='relu', padding='same')(x)
x = UpSampling2D((2, 2))(x)
x = Conv2D(8, (3, 3), activation='relu', padding='same')(x)
x = UpSampling2D((2, 2))(x)
x = Conv2D(16, (3, 3), activation='relu')(x)
x = UpSampling2D((2, 2))(x)
x = Conv2D(1, (3, 3), activation='sigmoid', padding='same')(x)

decoder = Model(encoded_input2, x)
```

In [89]:
```
decoder.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_10 (InputLayer)        (None, 10)                0
_________________________________________________________________
dense_10 (Dense)             (None, 128)               1408
_________________________________________________________________
reshape_1 (Reshape)          (None, 8, 4, 4)           0
_________________________________________________________________
conv2d_18 (Conv2D)           (None, 8, 4, 4)           584
_________________________________________________________________
up_sampling2d_7 (UpSampling2 (None, 8, 8, 8)           0
_________________________________________________________________
conv2d_19 (Conv2D)           (None, 8, 8, 8)           584
_________________________________________________________________
up_sampling2d_8 (UpSampling2 (None, 8, 16, 16)         0
_________________________________________________________________
conv2d_20 (Conv2D)           (None, 16, 14, 14)        1168
_________________________________________________________________
up_sampling2d_9 (UpSampling2 (None, 16, 28, 28)        0
_________________________________________________________________
conv2d_21 (Conv2D)           (None, 1, 28, 28)         145
=================================================================
Total params: 3,889
Trainable params: 3,889
Non-trainable params: 0
_________________________________________________________________
```

- Connect the encoder and decoder
  - select the sampled z of the encoder output

In [78]:
```
vae = Model(input_img2, decoder(encoder(input_img2)[2]))
```

In [79]:
```
vae.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_9 (InputLayer)         (None, 1, 28, 28)         0
_________________________________________________________________
model_13 (Model)             [(None, 10), (None, 10),  4484
_________________________________________________________________
model_14 (Model)             (None, 1, 28, 28)         3889
=================================================================
Total params: 8,373
Trainable params: 8,373
Non-trainable params: 0
_________________________________________________________________
```

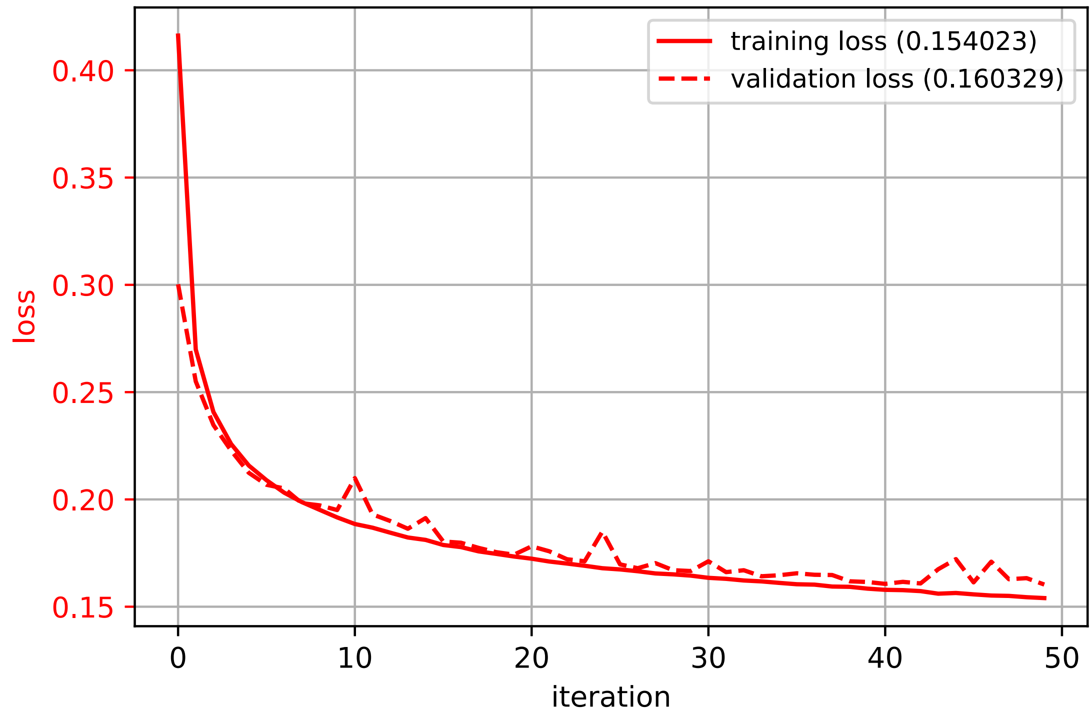
- The VAE loss as before

In [80]:
```
def vae_loss(x, x_decoded_mean):
    xent_loss = keras.losses.binary_crossentropy(x, x_decoded_mean)
    kl_loss = - 0.5 * K.mean(K.mean(1 + z_log_sigma - K.square(z_mean) - K.exp(z_log_sigma), axis=-1), axis=-1)
    return xent_loss + kl_loss

vae.compile(optimizer='rmsprop', loss=vae_loss)
```

- Train the model

In [81]:
```
history = vae.fit(vtrainI, vtrainI,
            shuffle=True,
            epochs=epochs,
            batch_size=batch_size,
            validation_data=(validI, validI),
            callbacks=[earlystop, TensorBoard(log_dir='./logs/vae')],
            verbose=False
           )
```

In [82]:
```
plot_history(history)
```



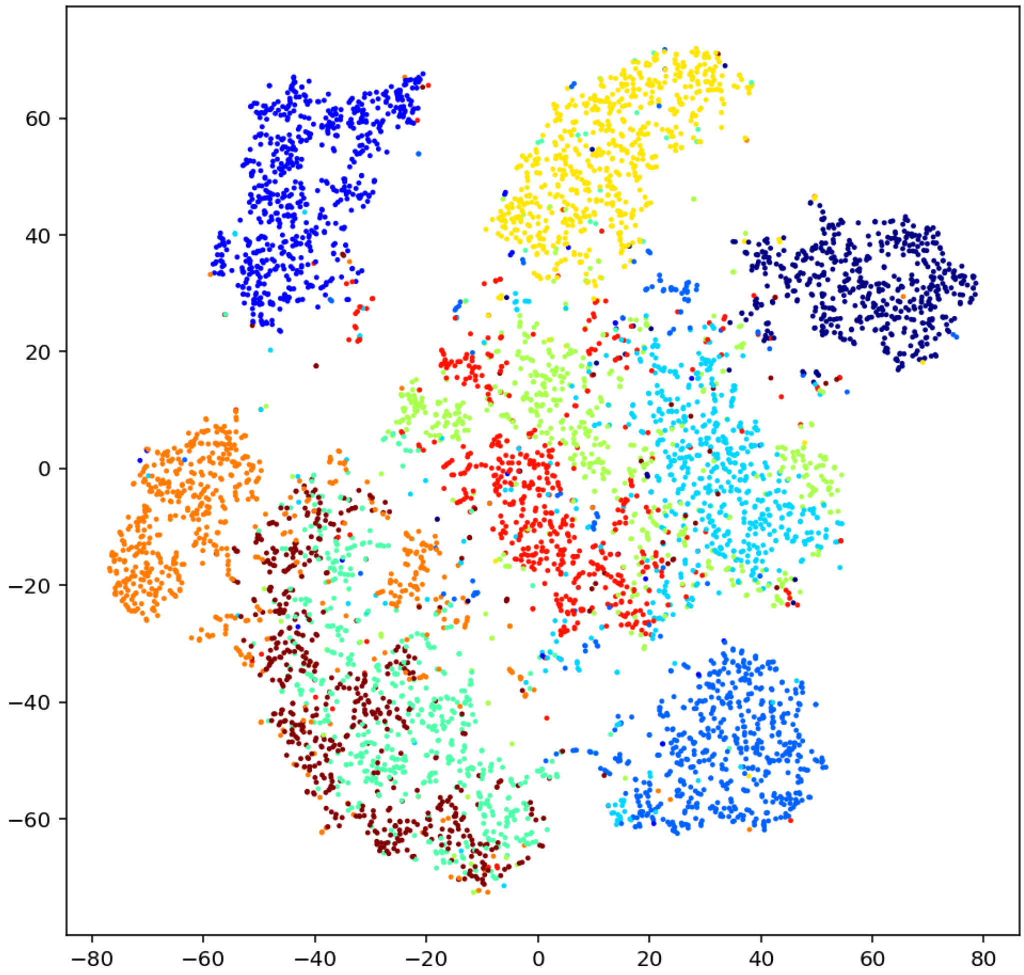
- Visualize the 10-dim latent space using t-SNE

In [114]:
```
IPython.core.display.set_matplotlib_formats("retina") # switch to png since the next figure is complex
```

In [110]:
```
x_test_encoded = encoder.predict(trainI)[0]
tsne = manifold.TSNE(n_components=2, perplexity=30.0, random_state=11)
x_test_encoded_2 = tsne.fit_transform(x_test_encoded)
```

In [115]:
```
plt.figure(figsize=(8,8))
plt.scatter(x_test_encoded_2[:, 0], x_test_encoded_2[:, 1], c=
trainY, s=2, cmap=plt.get_cmap('jet'))
```

Out[115]: <matplotlib.collections.PathCollection at 0x1d1e813438>



In [116]:
```
IPython.core.display.set_matplotlib_formats("svg")
```

- Visualize the reconstruction

In [84]:

```
testIrecon = decoder.predict(encoder.predict(testI)[0])
imglist = []
for j,i in enumerate(range(0,100,10)):
    tmp = hstack( (testI[i].reshape((28,28)), testIrecon[i].reshape((28,28))) )
    imglist.append(tmp)
rfig = plt.figure(figsize=(10,3))
show_imgs(imglist,nc=5)
plt.close()
rfig
```

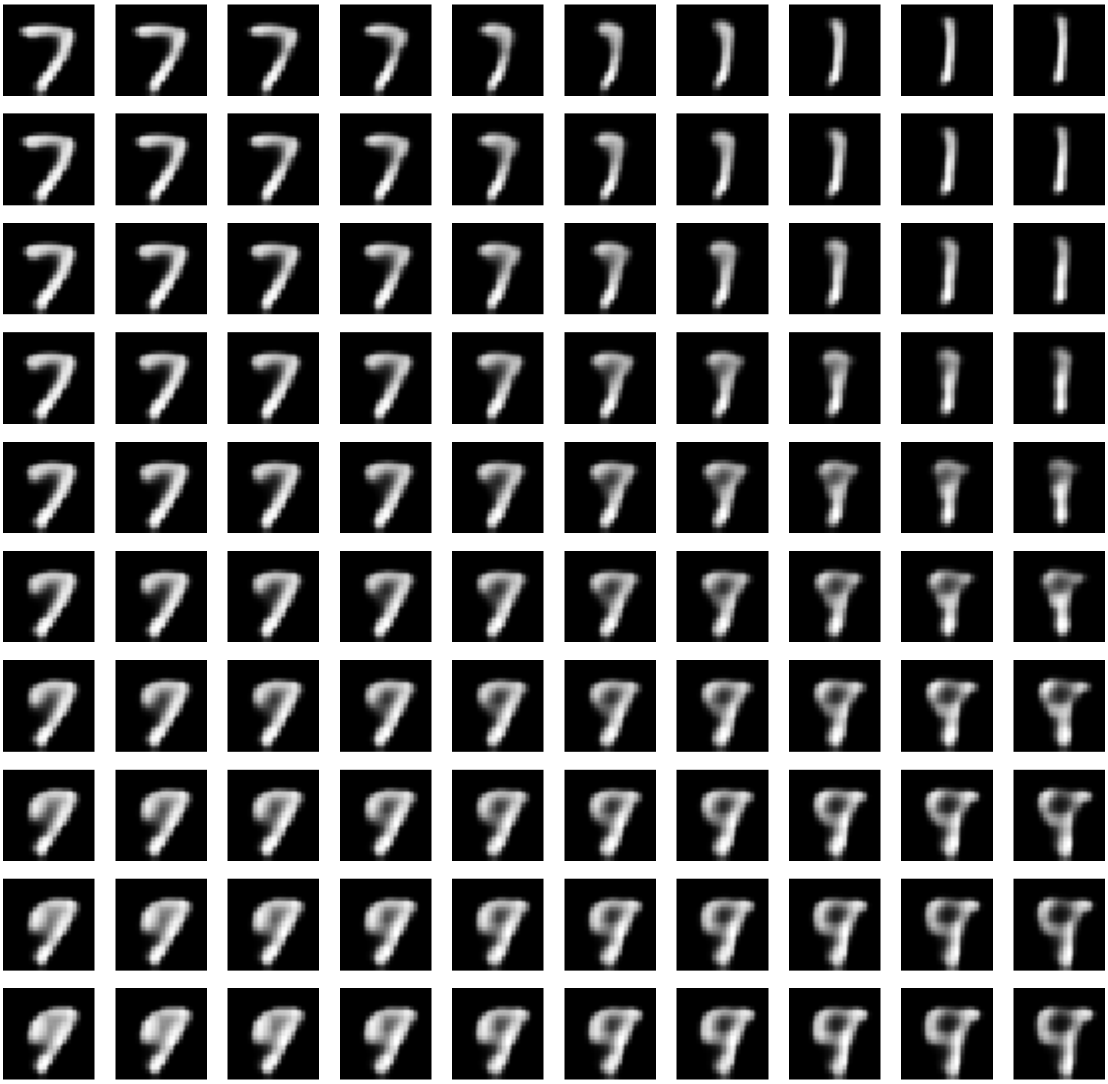
Out[84]:

- Visualize the latent space between a 7, 1, 9, and 4

In [85]:

```
inds = [0, 40, 20, 6]
X = encoder.predict(testI[inds,:])[0]
Xd = decoder.predict(Xinterp2(X))
rfig = plt.figure(figsize=(10,10))
show_imgs(Xd.reshape((100,28,28)),nc=10)
plt.close()
rfig
```

Out[85]:



Summary

- **Deep architectures**
  - advances of deep learning has been driven by the ImageNet competiton.
  - error rate decreases as the depth increases.
  - as depth increases, need to have a smart architecture design to make training more effective.
- **Unsupervised Learning**
  - Autoencoder - unsupervised dimensionality reduction and clustering.
  - Convolutional autoencoder - AE for images.
  - Variational autoencoder - improve interpolation ability.