Convolutional Autoencoder

Sticking with the MNIST dataset, let's improve our autoencoder's performance using convolutional layers. Again, loading modules and the data.

In [1]:

```
%matplotlib inline

import numpy as np
import tensorflow as tf
import matplotlib.pyplot as plt
```

In [2]:

```
from tensorflow.examples.tutorials.mnist import input_data
mnist = input_data.read_data_sets('MNIST_data', validation_size=0)
```

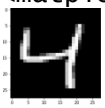
```
Extracting MNIST_data/train-images-idx3-ubyte.gz
Extracting MNIST_data/train-labels-idx1-ubyte.gz
Extracting MNIST_data/t10k-images-idx3-ubyte.gz
Extracting MNIST_data/t10k-labels-idx1-ubyte.gz
```

In [3]:

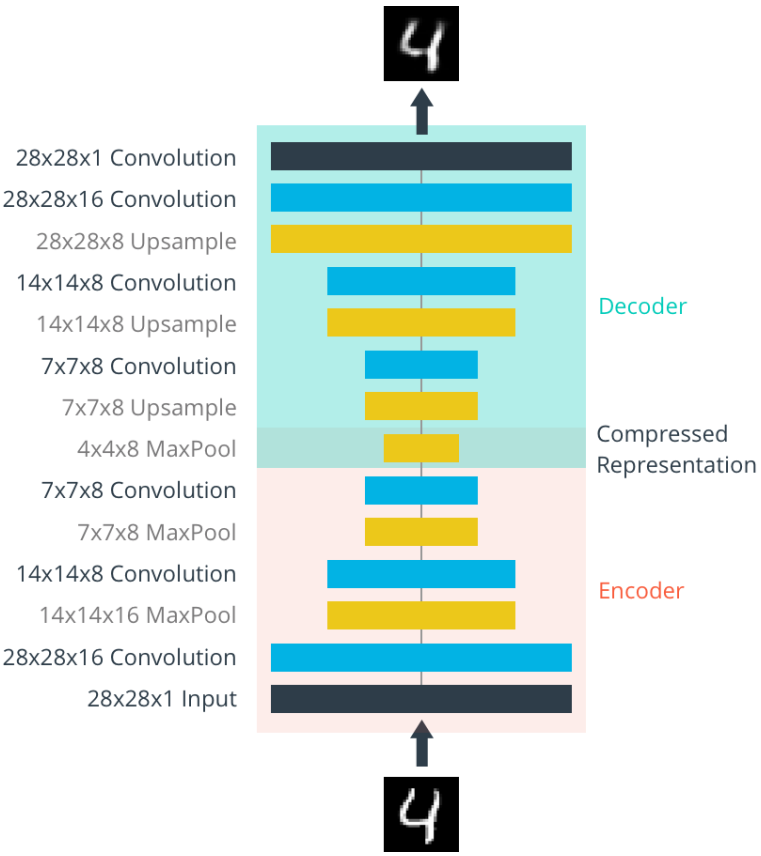
```
img = mnist.train.images[2]
plt.imshow(img.reshape((28, 28)), cmap='Greys_r')
```

Out[3]:

```
<matplotlib.image.AxesImage at 0x7f4631f1a4e0>
```



Network Architecture



The encoder part of the network will be a typical convolutional pyramid. Each convolutional layer will be followed by a max-pooling layer to reduce the dimensions of the layers. The decoder though might be something new to you. The decoder needs to convert from a narrow representation to a wide reconstructed image. For example, the representation could be a 4x4x8 max-pool layer. This is the output of the encoder, but also the input to the decoder. We want to get a 28x28x1 image out from the decoder so we need to work our way back up from the narrow decoder input layer. A schematic of the network is shown below.

Here our final encoder layer has size 4x4x8 = 128. The original images have size 28x28 = 784, so the encoded vector is roughlt 16% the size of the original image. These are just suggested sizes for each of the layers. Feel free to change the depths and sizes, but remember our goal here is to find a small representation of the input data.

What's going on with the decoder

Okay, so the decoder has these "Upsample" layers that you might not have seen before. First off, I'll discuss a bit what these layers *aren't*. Usually, you'll see **deconvolutional** layers used to increase the width and height of the layers. They work almost exactly the same as convolutional layers, but it reverse. A stride in the input layer results in a larger stride in the deconvolutional layer. For example, if you have a 3x3 kernel, a 3x3 patch in the input layer will be reduced to one unit in a convolutional layer. Comparatively, one unit in the input layer will be expanded to a 3x3 path in a deconvolutional layer. Deconvolution is often called "transpose convolution" which is what you'll find the TensorFlow API, with `tf.nn.conv2d_transpose`.

However, deconvolutional layers can lead to artifacts in the final images, such as checkerboard patterns. This is due to overlap in the kernels which can be avoided by setting the stride and kernel size equal. In this Distill article from Augustus Odena, *et al*, the authors show that these checkerboard artifacts can be avoided by resizing the layers using nearest neighbor or bilinear interpolation (upsampling) followed by a convolutional layer. In TensorFlow, this is easily done with `tf.image.resize_images`, followed by a convolution. Be sure to read the Distill article to get a better understanding of deconvolutional layers and why we're using upsampling.

> **Exercise:** Build the network shown above. Remember that a convolutional layer with strides of 1 and 'same' padding won't reduce the height and width. That is, if the input is 28x28 and the convolution layer has stride = 1 and 'same' padding, the convolutional layer will also be 28x28. The max-pool layers are used the reduce the width and height. A stride of 2 will reduce the size by 2. Odena *et al* claim that nearest neighbor interpolation works best for the upsampling, so make sure to include that as a parameter in `tf.image.resize_images` or use `tf.image.resize_nearest_neighbor`.

In [9]:

```
inputs_ = tf.placeholder(tf.float32, (None, 28, 28, 1), name='inputs')
targets_ = tf.placeholder(tf.float32, (None, 28, 28, 1), name='targets')

### Encoder
conv1 = tf.layers.conv2d(inputs_, 16, (3,3), padding='same',
activation=tf.nn.relu)
# Now 28x28x16

maxpool1 = tf.layers.max_pooling2d(conv1, (2,2), (2,2), padding='same')
# Now 14x14x16

conv2 = tf.layers.conv2d(maxpool1, 8, (3,3), padding='same',
activation=tf.nn.relu)
# Now 14x14x8

maxpool2 = tf.layers.max_pooling2d(conv2, (2,2), (2,2), padding='same')
# Now 7x7x8

conv3 = tf.layers.conv2d(maxpool2, 8, (3,3), padding='same',
activation=tf.nn.relu)
# Now 7x7x8

encoded = tf.layers.max_pooling2d(conv3, (2,2), (2,2), padding='same')
# Now 4x4x8
```

```
### Decoder
upsample1 = tf.image.resize_nearest_neighbor(encoded, (7,7))
# Now 7x7x8

conv4 = tf.layers.conv2d(upsample1, 8, (3,3), padding='same',
activation=tf.nn.relu)
# Now 7x7x8

upsample2 = tf.image.resize_nearest_neighbor(conv4, (14,14))
# Now 14x14x8

conv5 = tf.layers.conv2d(upsample2, 8, (3,3), padding='same',
activation=tf.nn.relu)
# Now 14x14x8

upsample3 = tf.image.resize_nearest_neighbor(conv5, (28,28))
# Now 28x28x8

conv6 = tf.layers.conv2d(upsample3, 16, (3,3), padding='same',
activation=tf.nn.relu)
# Now 28x28x16

logits = tf.layers.conv2d(conv6, 1, (3,3), padding='same', activation=None)
#Now 28x28x1

decoded = tf.nn.sigmoid(logits, name='decoded')

loss = tf.nn.sigmoid_cross_entropy_with_logits(labels=targets_, logits=logits)
cost = tf.reduce_mean(loss)
opt = tf.train.AdamOptimizer(0.001).minimize(cost)
```

Training

As before, here wi'll train the network. Instead of flattening the images though, we can pass them in as 28 x 28 x 1 arrays.

In [6]:

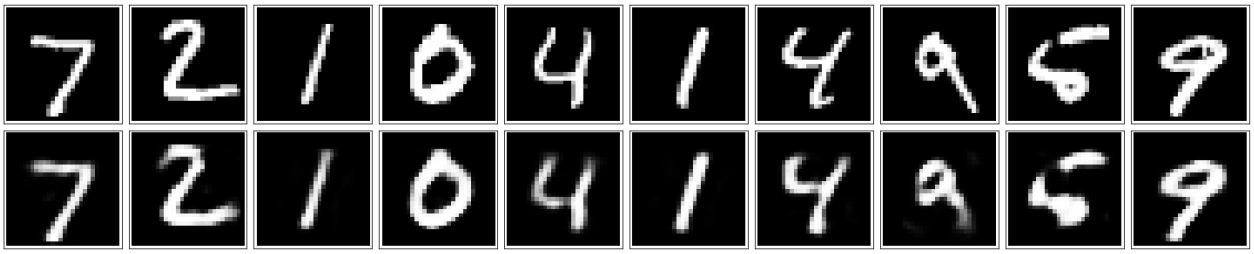
```
sess = tf.Session()
```

In [ ]:

```
epochs = 20
batch_size = 200
sess.run(tf.global_variables_initializer())
for e in range(epochs):
    for ii in range(mnist.train.num_examples//batch_size):
        batch = mnist.train.next_batch(batch_size)
        imgs = batch[0].reshape((-1, 28, 28, 1))
        batch_cost, _ = sess.run([cost, opt], feed_dict={inputs_: imgs,
                                                         targets_: imgs})

        print("Epoch: {}/{}...".format(e+1, epochs),
              "Training loss: {:.4f}".format(batch_cost))
```

In [13]:

```
fig, axes = plt.subplots(nrows=2, ncols=10, sharex=True, sharey=True,
figsize=(20,4))
in_imgs = mnist.test.images[:10]
reconstructed = sess.run(decoded, feed_dict={inputs_: in_imgs.reshape((10, 28,
28, 1))})

for images, row in zip([in_imgs, reconstructed], axes):
    for img, ax in zip(images, row):
        ax.imshow(img.reshape((28, 28)), cmap='Greys_r')
        ax.get_xaxis().set_visible(False)
        ax.get_yaxis().set_visible(False)

fig.tight_layout(pad=0.1)
```

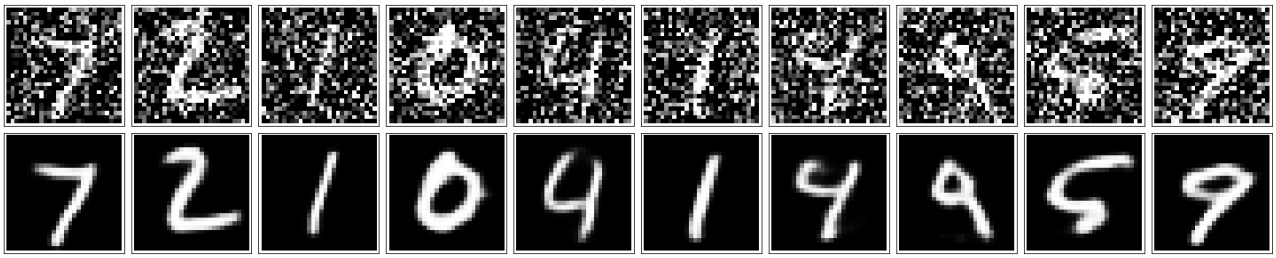


In [19]:

```
sess.close()
```

Denoising

As I've mentioned before, autoencoders like the ones you've built so far aren't too useful in practive. However, they can be used to denoise images quite successfully just by training the network on noisy images. We can create the noisy images ourselves by adding Gaussian noise to the training images, then clipping the values to be between 0 and 1. We'll use noisy images as input and the original, clean images as targets. Here's an example of the noisy images I generated and the denoised images.



Since this is a harder problem for the network, we'll want to use deeper convolutional layers here, more feature maps. I suggest something like 32-32-16 for the depths of the convolutional layers in the encoder, and the same depths going backward through the decoder. Otherwise the architecture is the same as before

.

> **Exercise:** Build the network for the denoising autoencoder. It's the same as before, but with deeper layers. I suggest 32-32-16 for the depths, but you can play with these numbers, or add more layers.

In [21]:

```
inputs_ = tf.placeholder(tf.float32, (None, 28, 28, 1), name='inputs')
targets_ = tf.placeholder(tf.float32, (None, 28, 28, 1), name='targets')

### Encoder
conv1 = tf.layers.conv2d(inputs_, 32, (3,3), padding='same',
activation=tf.nn.relu)
# Now 28x28x32
```

```
maxpool1 = tf.layers.max_pooling2d(conv1, (2,2), (2,2), padding='same')
# Now 14x14x32

conv2 = tf.layers.conv2d(maxpool1, 32, (3,3), padding='same',
activation=tf.nn.relu)
# Now 14x14x32

maxpool2 = tf.layers.max_pooling2d(conv2, (2,2), (2,2), padding='same')
# Now 7x7x32

conv3 = tf.layers.conv2d(maxpool2, 16, (3,3), padding='same',
activation=tf.nn.relu)
# Now 7x7x16

encoded = tf.layers.max_pooling2d(conv3, (2,2), (2,2), padding='same')
# Now 4x4x16

### Decoder
upsample1 = tf.image.resize_nearest_neighbor(encoded, (7,7))
# Now 7x7x16

conv4 = tf.layers.conv2d(upsample1, 16, (3,3), padding='same',
activation=tf.nn.relu)
# Now 7x7x16

upsample2 = tf.image.resize_nearest_neighbor(conv4, (14,14))
# Now 14x14x16

conv5 = tf.layers.conv2d(upsample2, 32, (3,3), padding='same',
activation=tf.nn.relu)
# Now 14x14x32

upsample3 = tf.image.resize_nearest_neighbor(conv5, (28,28))
# Now 28x28x32

conv6 = tf.layers.conv2d(upsample3, 32, (3,3), padding='same',
activation=tf.nn.relu)
# Now 28x28x32

logits = tf.layers.conv2d(conv6, 1, (3,3), padding='same', activation=None)
#Now 28x28x1

decoded = tf.nn.sigmoid(logits, name='decoded')

loss = tf.nn.sigmoid_cross_entropy_with_logits(labels=targets_, logits=logits)
cost = tf.reduce_mean(loss)
opt = tf.train.AdamOptimizer(0.001).minimize(cost)
```

In [22]:

```
sess = tf.Session()
```

In [ ]:

```
epochs = 100
batch_size = 200
```

```
# Set's how much noise we're adding to the MNIST images
noise_factor = 0.5
sess.run(tf.global_variables_initializer())
for e in range(epochs):
    for ii in range(mnist.train.num_examples//batch_size):
        batch = mnist.train.next_batch(batch_size)
        # Get images from the batch
        imgs = batch[0].reshape((-1, 28, 28, 1))

        # Add random noise to the input images
        noisy_imgs = imgs + noise_factor * np.random.randn(*imgs.shape)
        # Clip the images to be between 0 and 1
        noisy_imgs = np.clip(noisy_imgs, 0., 1.)

        # Noisy images as inputs, original images as targets
        batch_cost, _ = sess.run([cost, opt], feed_dict={inputs_: noisy_imgs,
                                                         targets_: imgs})

        print("Epoch: {}/{}...".format(e+1, epochs),
              "Training loss: {:.4f}".format(batch_cost))
```

Checking out the performance

Here I'm adding noise to the test images and passing them through the autoencoder. It does a suprising great job of removing the noise, even though it's sometimes difficult to tell what the original number is.

In [29]:

```
fig, axes = plt.subplots(nrows=2, ncols=10, sharex=True, sharey=True,
figsize=(20,4))
in_imgs = mnist.test.images[:10]
noisy_imgs = in_imgs + noise_factor * np.random.randn(*in_imgs.shape)
noisy_imgs = np.clip(noisy_imgs, 0., 1.)

reconstructed = sess.run(decoded, feed_dict={inputs_: noisy_imgs.reshape((10,
28, 28, 1))})

for images, row in zip([noisy_imgs, reconstructed], axes):
    for img, ax in zip(images, row):
        ax.imshow(img.reshape((28, 28)), cmap='Greys_r')
        ax.get_xaxis().set_visible(False)
        ax.get_yaxis().set_visible(False)

fig.tight_layout(pad=0.1)
```