```
    hidden1 = fully_connected(X, n_hidden1)
    hidden2 = fully_connected(hidden1, n_hidden2)
    hidden3_mean = fully_connected(hidden2, n_hidden3, activation_fn=None)
    hidden3_gamma = fully_connected(hidden2, n_hidden3, activation_fn=None)
    hidden3_sigma = tf.exp(0.5 * hidden3_gamma)
    noise = tf.random_normal(tf.shape(hidden3_sigma), dtype=tf.float32)
    hidden3 = hidden3_mean + hidden3_sigma * noise
    hidden4 = fully_connected(hidden3, n_hidden4)
    hidden5 = fully_connected(hidden4, n_hidden5)
    logits = fully_connected(hidden5, n_outputs, activation_fn=None)
    outputs = tf.sigmoid(logits)

reconstruction_loss = tf.reduce_sum(
    tf.nn.sigmoid_cross_entropy_with_logits(labels=X, logits=logits))
latent_loss = 0.5 * tf.reduce_sum(
    tf.exp(hidden3_gamma) + tf.square(hidden3_mean) - 1 - hidden3_gamma)
cost = reconstruction_loss + latent_loss

optimizer = tf.train.AdamOptimizer(learning_rate=learning_rate)
training_op = optimizer.minimize(cost)

init = tf.global_variables_initializer()
```

Generating Digits

Now let's use this variational autoencoder to generate images that look like handwritten digits. All we need to do is train the model, then sample random codings from a Gaussian distribution and decode them.

```
import numpy as np

n_digits = 60
n_epochs = 50
batch_size = 150

with tf.Session() as sess:
    init.run()
    for epoch in range(n_epochs):
        n_batches = mnist.train.num_examples // batch_size
        for iteration in range(n_batches):
            X_batch, y_batch = mnist.train.next_batch(batch_size)
            sess.run(training_op, feed_dict={X: X_batch})

    codings_rnd = np.random.normal(size=[n_digits, n_hidden3])
    outputs_val = outputs.eval(feed_dict={hidden3: codings_rnd})
```

That's it. Now we can see what the "handwritten" digits produced by the autoencoder look like (see Figure 15-12):

```
for iteration in range(n_digits):
    plt.subplot(n_digits, 10, iteration + 1)
    plot_image(outputs_val[iteration])
```

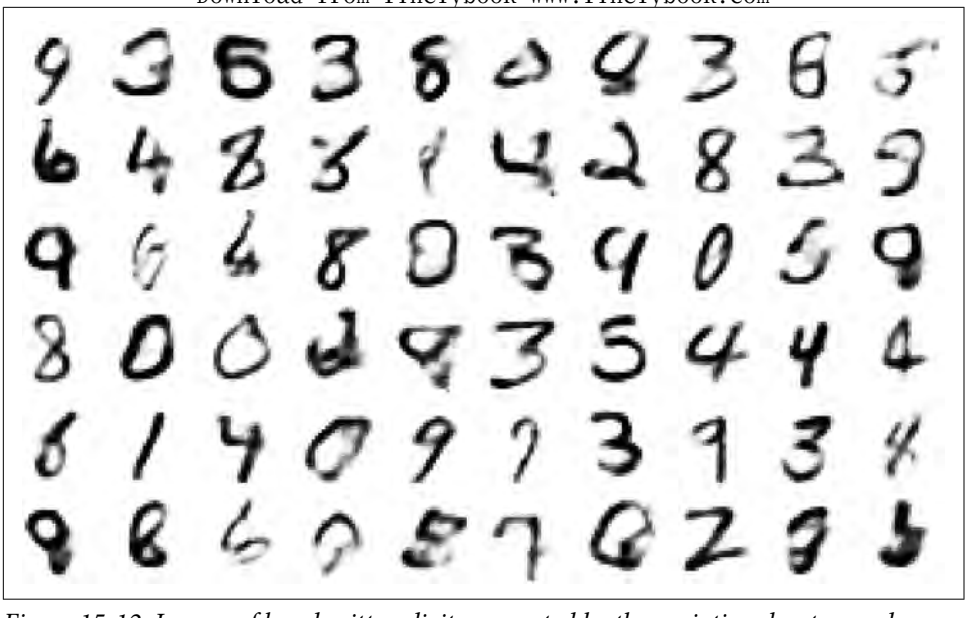

Figure 15-12. Images of handwritten digits generated by the variational autoencoder

A majority of these digits look pretty convincing, while a few are rather "creative." But don't be too harsh on the autoencoder—it only started learning less than an hour ago. Give it a bit more training time, and those digits will look better and better.

Other Autoencoders

The amazing successes of supervised learning in image recognition, speech recognition, text translation, and more have somewhat overshadowed unsupervised learning, but it is actually booming. New architectures for autoencoders and other unsupervised learning algorithms are invented regularly, so much so that we cannot cover them all in this book. Here is a brief (by no means exhaustive) overview of a few more types of autoencoders that you may want to check out:

Contractive autoencoder (CAE)[8]
: The autoencoder is constrained during training so that the derivatives of the codings with regards to the inputs are small. In other words, two similar inputs must have similar codings.

8 "Contractive Auto-Encoders: Explicit Invariance During Feature Extraction," S. Rifai et al. (2011).