# Autoencoder

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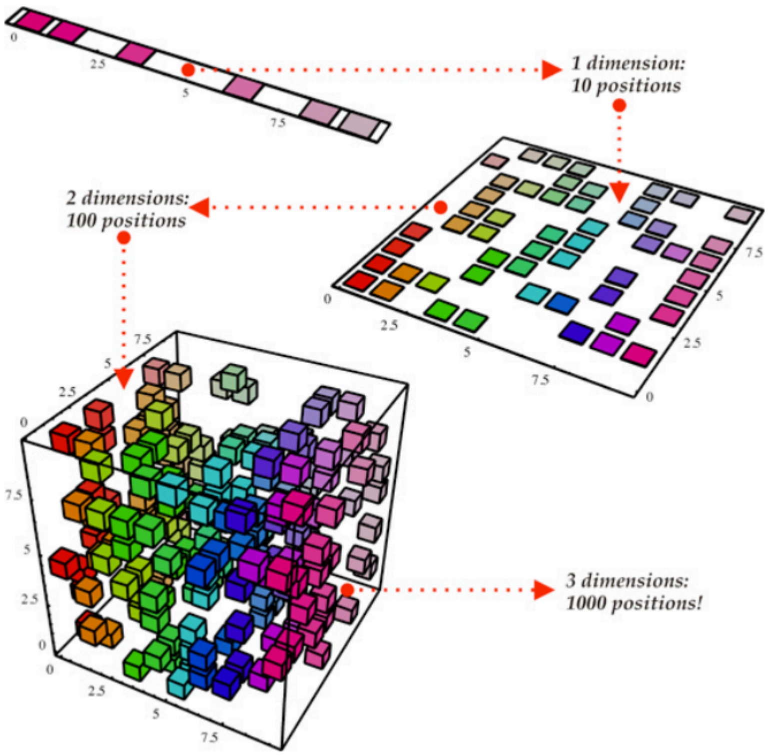
# 1. Unsupervised Learning

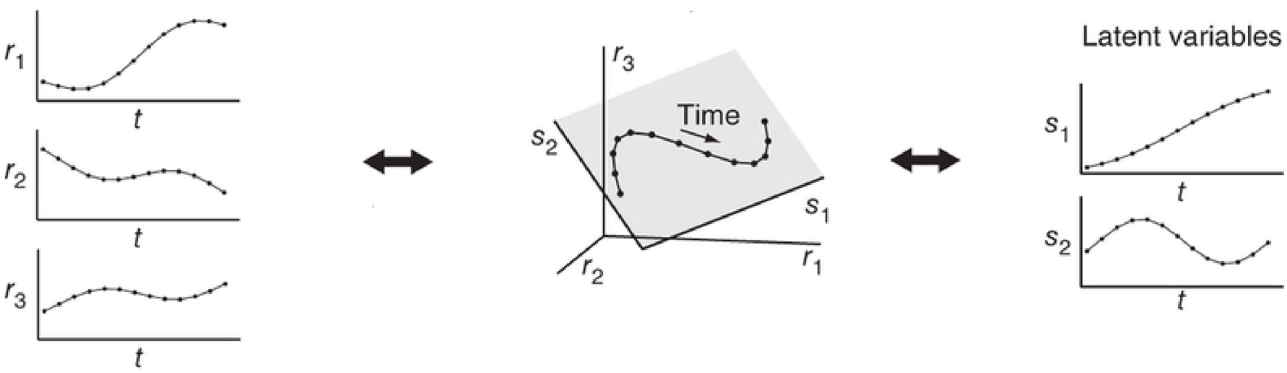
### Definition

- Unsupervised learning refers to most attempts to extract information from a distribution that do not require human labor to annotate example
- Main task is to find the 'best' representation of the data

### Dimension Reduction

- Attempt to compress as much information as possible in a smaller representation
- Preserve as much information as possible while obeying some constraint aimed at keeping the representation simpler




# 2. Autoencoders

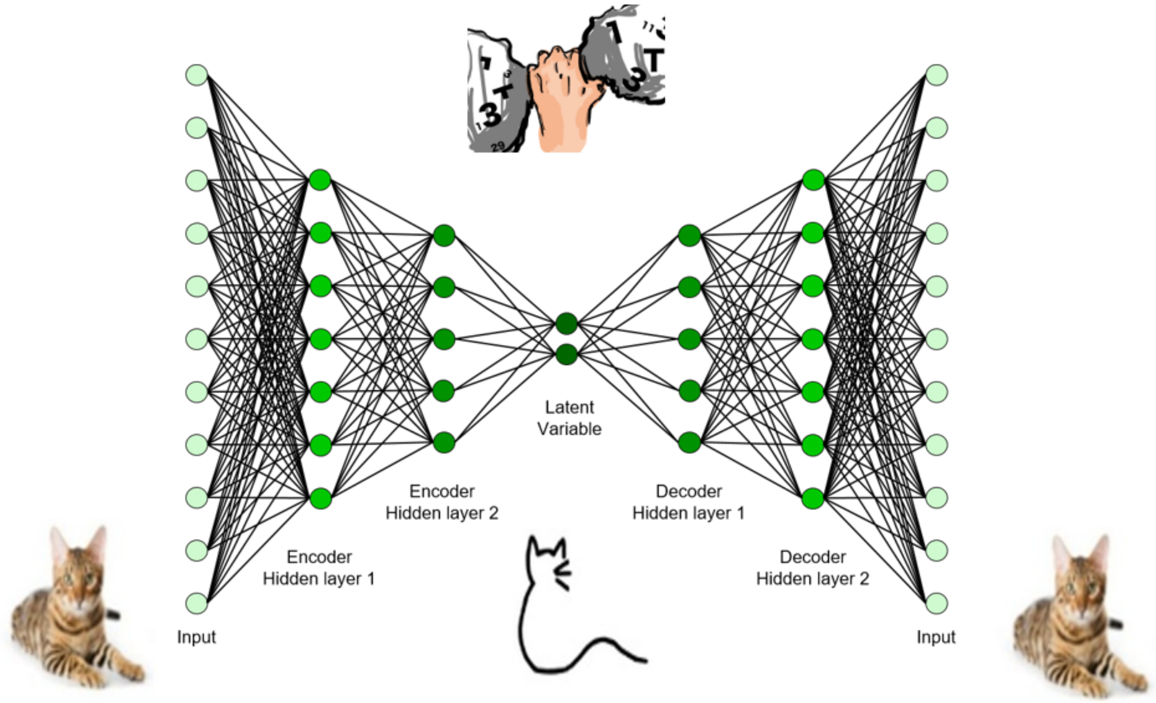
- It is like 'deep learning version' of unsupervised learning

**Definition**

- An autoencoder is a neural network that is trained to attempt to copy its input to its output
- The network consists of two parts: an **encoder** and a **decoder** that produce a reconstruction

**Encoder and Decoder**

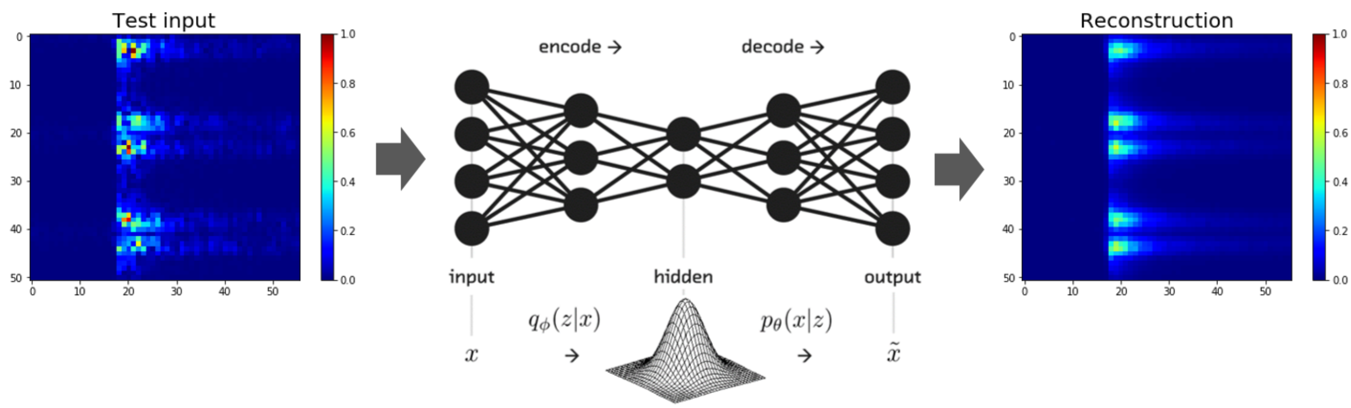
- Encoder function : $h = f(x)$
- Decoder function : $r = g(h)$
- We learn to set $g\left(f(x)\right) = x$




**Modern Autoencoders**

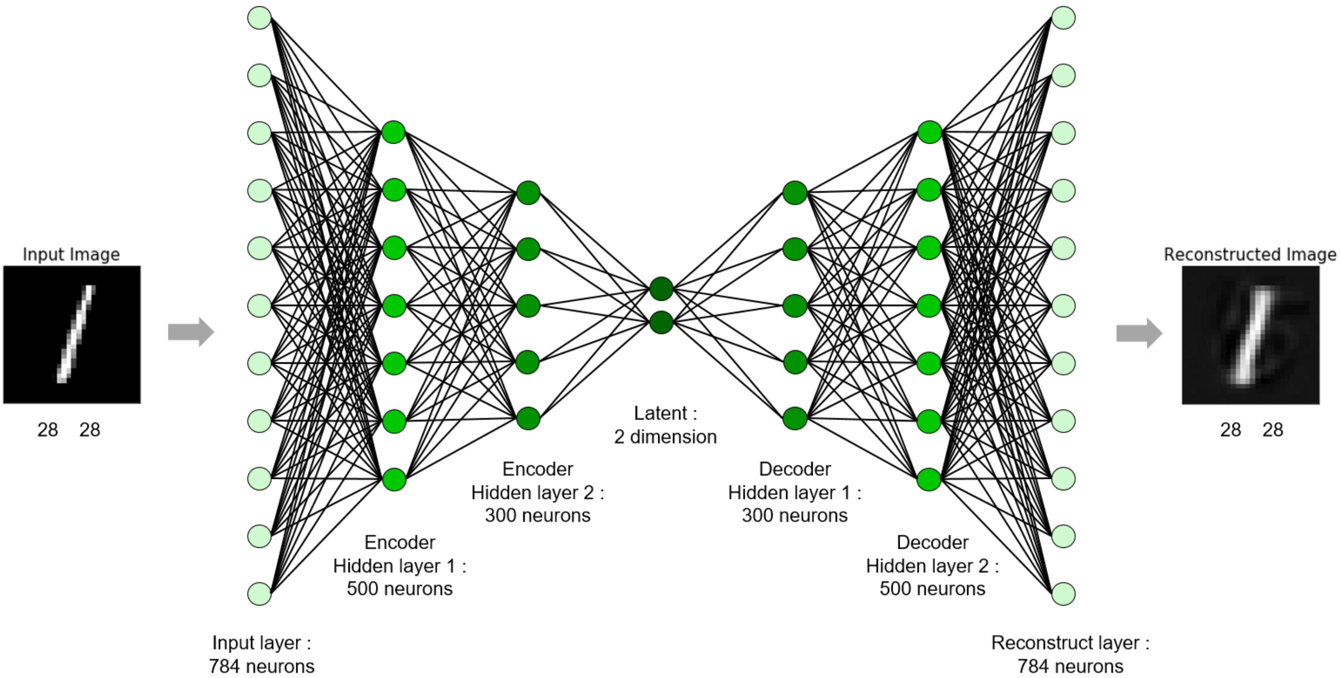
- Beyond deterministic functions to stochastic mapping: $p_{\text{encoder}}(h \mid x)$ and $p_{\text{decoder}}(x \mid h)$
  - Variabtional autoencoder (VAE)
  - Generative adversarial nerwork (GAN)

- Will not cover them in this tutorial




# 3. Autoencoder with TensorFlow

- MNIST example
- Use only (1, 5, 6) digits to visualize in 2-D




# 3.1. Import Library

In [1]:

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

# 3.2. Load MNIST Data

In [2]:

```
def batch_maker(batch_size, img, label):
    img_len = len(img)
    random_idx = np.random.randint(img_len, size = batch_size)
    return img[random_idx], label[random_idx]
```

In [3]:

```
from tensorflow.examples.tutorials.mnist import input_data
mnist = input_data.read_data_sets("MNIST_data/", one_hot=True)
```

```
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
```

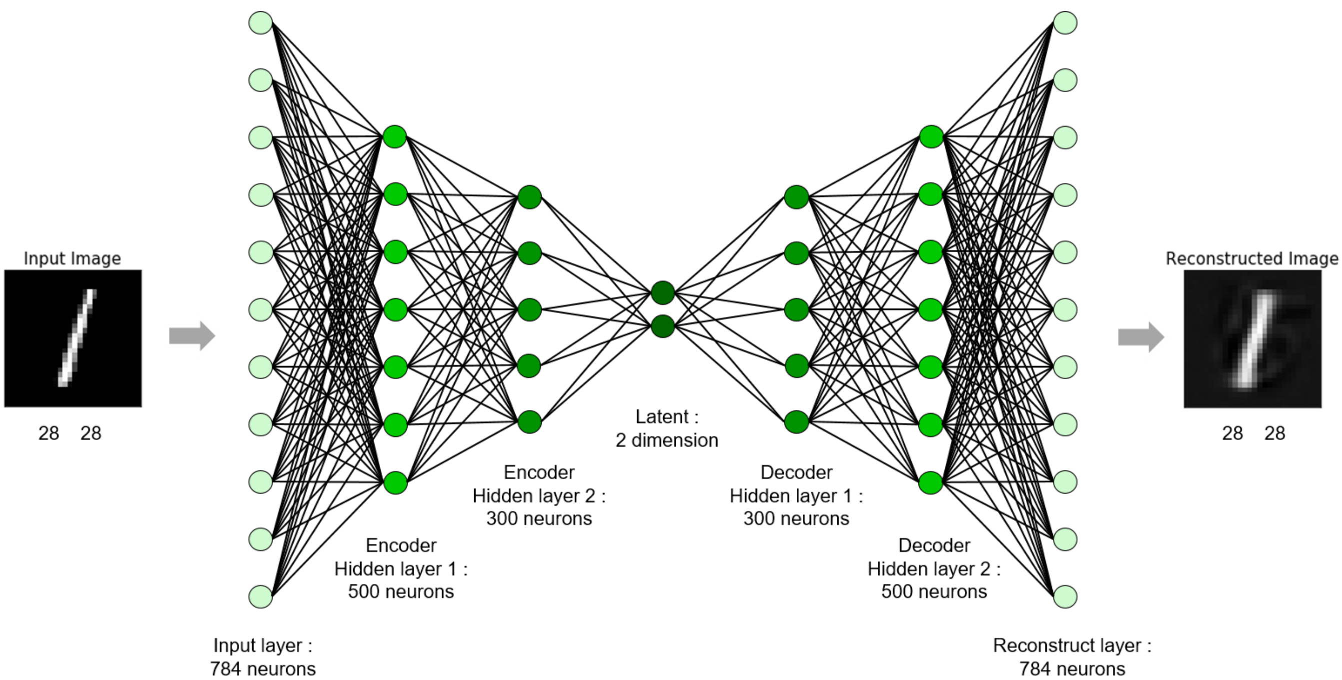
In [4]:

```
train_idx = ((np.argmax(mnist.train.labels, 1) == 1) | \
             (np.argmax(mnist.train.labels, 1) == 5) | \
             (np.argmax(mnist.train.labels, 1) == 6))
test_idx = ((np.argmax(mnist.test.labels, 1) == 1) | \
            (np.argmax(mnist.test.labels, 1) == 5) | \
            (np.argmax(mnist.test.labels, 1) == 6))

train_imgs   = mnist.train.images[train_idx]
train_labels = mnist.train.labels[train_idx]
test_imgs    = mnist.test.images[test_idx]
test_labels  = mnist.test.labels[test_idx]
n_train      = train_imgs.shape[0]
n_test       = test_imgs.shape[0]

print ("Packages loaded")
print ("The number of trainimgs : {}, shape : {}".format(n_train, train_imgs.shape))
print ("The number of testimgs : {}, shape : {}".format(n_test, test_imgs.shape))
```

```
Packages loaded
The number of trainimgs : 16583, shape : (16583, 784)
The number of testimgs : 2985, shape : (2985, 784)
```

## 3.3. Define an Autoencoder Shape

- Input shape and latent variable shape
- Encoder shape
- Decoder shape



In [5]:

```
# Shape of input and latent variable
n_input = 28*28

# Encoder shape
n_encoder1 = 500
n_encoder2 = 300

n_latent = 2

# Decoder shape
n_decoder1 = 300
n_decoder2 = 500
```

## 3.4. Define Weights and Biases

- Define weights and biases for encoder and decoder, separately
- Based on the predefied layer size
- Initialize with normal distribution with $\mu = 0$ and $\sigma = 0.01$

In [6]:

```
weights = {
    'encoder1' : tf.Variable(tf.random_normal([n_input, n_encoder1], stddev=0.1)),
    'encoder2' : tf.Variable(tf.random_normal([n_encoder1, n_encoder2], stddev=0.1)),
    'latent' : tf.Variable(tf.random_normal([n_encoder2, n_latent], stddev=0.1)),
    'decoder1' : tf.Variable(tf.random_normal([n_latent, n_decoder1], stddev=0.1)),
    'decoder2' : tf.Variable(tf.random_normal([n_decoder1, n_decoder2], stddev=0.1)),
    'reconst' : tf.Variable(tf.random_normal([n_decoder2, n_input], stddev=0.1))
}

biases = {
    'encoder1' : tf.Variable(tf.random_normal([n_encoder1], stddev=0.1)),
    'encoder2' : tf.Variable(tf.random_normal([n_encoder2], stddev=0.1)),
    'latent' : tf.Variable(tf.random_normal([n_latent], stddev=0.1)),
    'decoder1' : tf.Variable(tf.random_normal([n_decoder1], stddev=0.1)),
    'decoder2' : tf.Variable(tf.random_normal([n_decoder2], stddev=0.1)),
    'reconst' : tf.Variable(tf.random_normal([n_input], stddev=0.1))
}

x = tf.placeholder(tf.float32, [None, n_input])
```

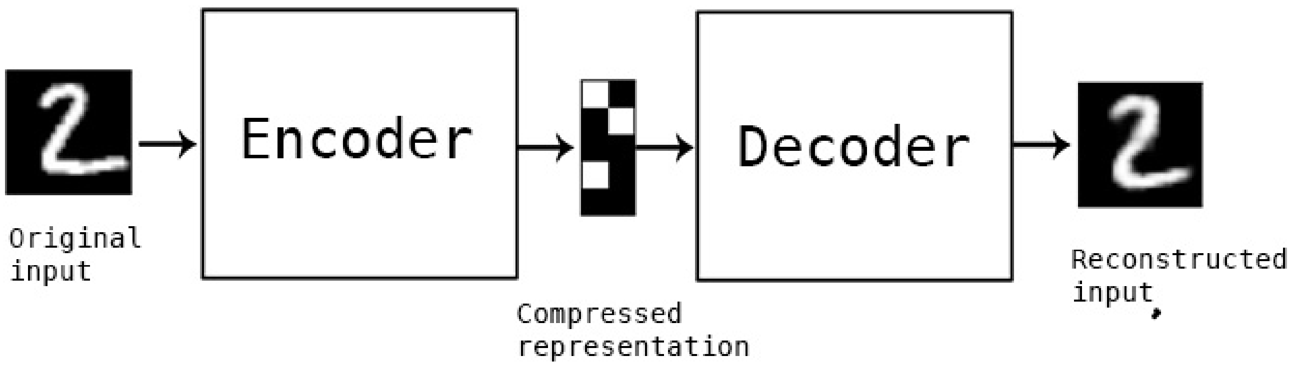
# 3.5. Build a Model

**Encoder**

- Simple ANN (MLP) model
- Use `tanh` for a nonlinear activation function
- `latent` is not applied with a nonlinear activation function

**Decoder**

- Simple ANN (MLP) model
- Use `tanh` for a nonlinear activation function
- `reconst` is not applied with a nonlinear activation function




In [7]:

```
def encoder(x, weights, biases):
    encoder1 = tf.add(tf.matmul(x, weights['encoder1']), biases['encoder1'])
    encoder1 = tf.nn.tanh(encoder1)

    encoder2 = tf.add(tf.matmul(encoder1, weights['encoder2']), biases['encoder2'])
    encoder2 = tf.nn.tanh(encoder2)

    latent = tf.add(tf.matmul(encoder2, weights['latent']), biases['latent'])

    return latent
```

In [8]:

```
def decoder(latent, weights, biases):
    decoder1 = tf.add(tf.matmul(latent, weights['decoder1']), biases['decoder1'])
    decoder1 = tf.nn.tanh(decoder1)

    decoder2 = tf.add(tf.matmul(decoder1, weights['decoder2']), biases['decoder2'])
    decoder2 = tf.nn.tanh(decoder2)

    reconst = tf.add(tf.matmul(decoder2, weights['reconst']), biases['reconst'])

    return reconst
```

# 3.6. Define Loss, Initializer and Optimizer

**Loss**

- Squared loss

$$\frac{1}{N}\sum_{i=1}^{N}(t_i - y_i)^2$$

**Optimizer**

- AdamOptimizer: the most popular optimizer

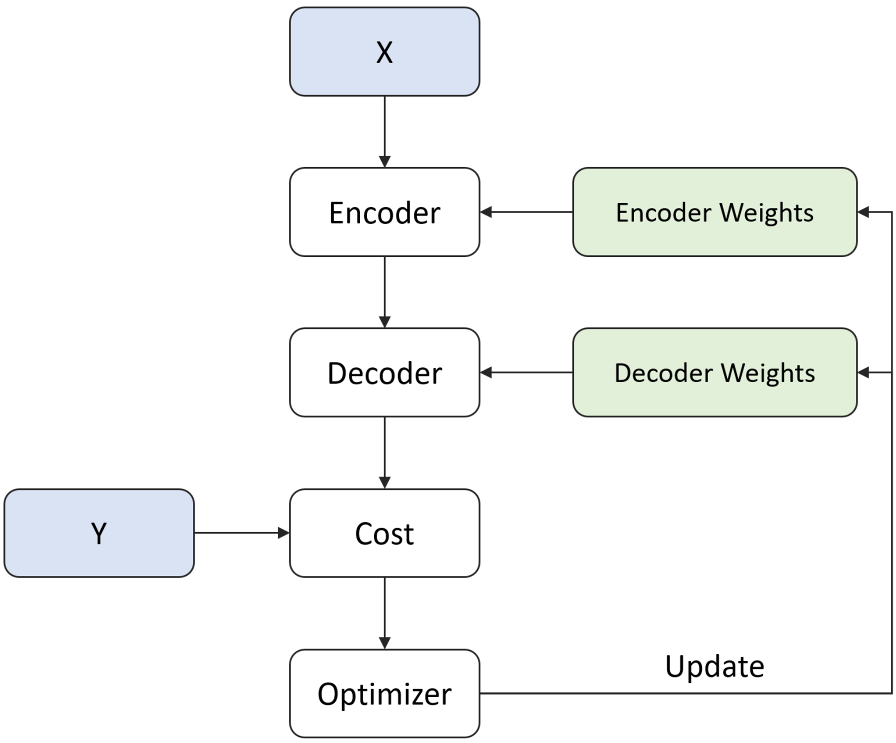
**Initializer**

- Initialize all the empty variables

In [9]:

```
LR = 0.0001

latent = encoder(x, weights, biases)
reconst = decoder(latent, weights, biases)
loss = tf.square(tf.subtract(x, reconst))
loss = tf.reduce_mean(loss)

optm = tf.train.AdamOptimizer(LR).minimize(loss)

init = tf.global_variables_initializer()
```

# 3.7. Summary of Model



## 2.8. Define Configuration

- Define parameters for training autoencoder
    - `n_batch` : batch size for stochastic gradient descent
    - `n_iter` : the number of training steps
    - `n_prt` : check loss for every `n_prt` iteration

In [10]:

```
n_batch = 50
n_iter = 2500
n_prt = 250
```

## 2.9. Optimization

In [11]:

```
# Run initialize
# config = tf.ConfigProto(allow_soft_placement=True)  # GPU Allocating policy
# sess = tf.Session(config=config)
sess = tf.Session()
sess.run(init)

# Training cycle
for epoch in range(n_iter):
    train_x, train_y = batch_maker(n_batch, train_imgs, train_labels)
    sess.run(optm, feed_dict={x : train_x})

    if epoch % n_prt == 0:
        c = sess.run(loss, feed_dict={x: train_x})
        print ("Iter : {}".format(epoch))
        print ("Cost : {}".format(c))
```

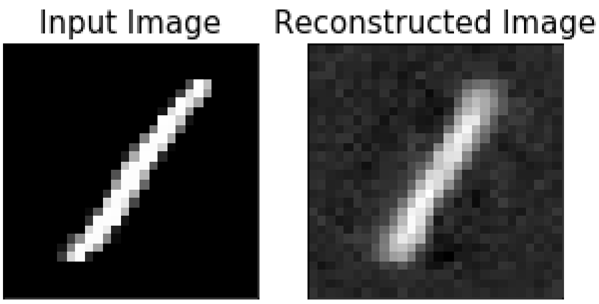
```
Iter : 0
Cost : 0.457559883594512940
Iter : 250
Cost : 0.05336207896471023 6
Iter : 500
Cost : 0.04479807987809181
Iter : 750
Cost : 0.04472903534770012
Iter : 1000
Cost : 0.0445869155228138
Iter : 1250
Cost : 0.04172228276729584
Iter : 1500
Cost : 0.037908948957920074
Iter : 1750
Cost : 0.03930409997701645
Iter : 2000
Cost : 0.03531509265303612
Iter : 2250
Cost : 0.03825182095170021
```

## 2.10. Test

- Test reconstruction performance of the autoencoder

In [12]:

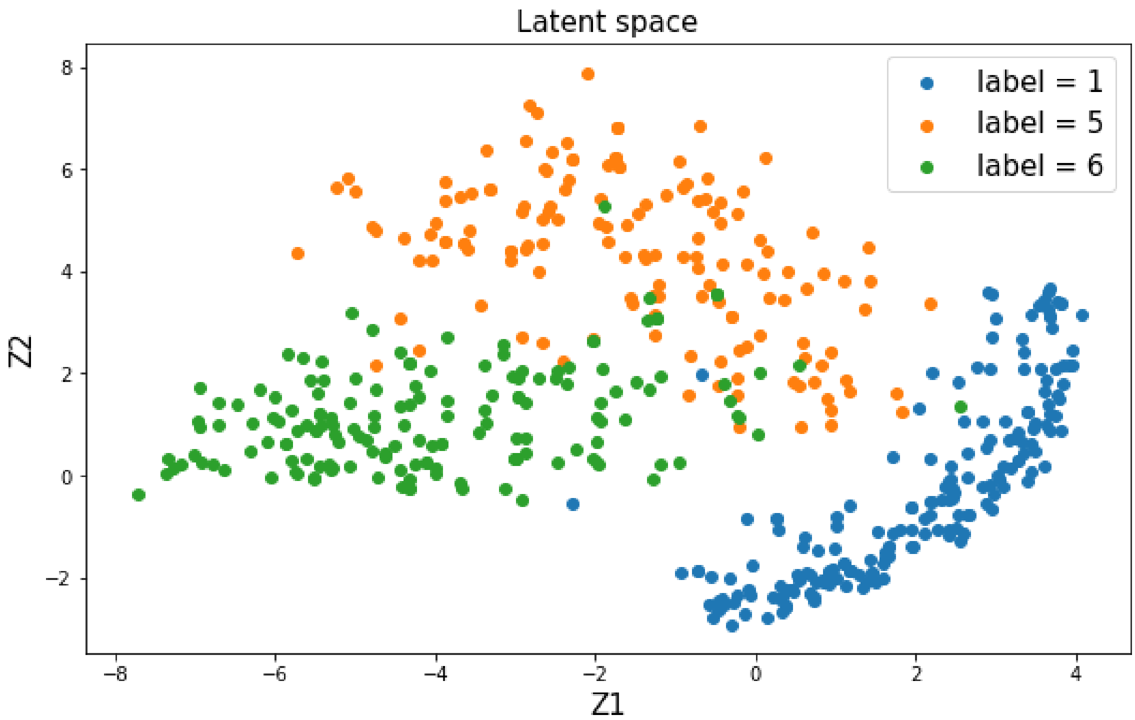
```
test_x, test_y = batch_maker(1, test_imgs, test_labels)
x_reconst = sess.run(reconst, feed_dict={x : test_x})

fig = plt.figure(figsize=(5, 3))
ax1 = fig.add_subplot(1, 2, 1)
ax1.imshow(test_x.reshape(28, 28), 'gray')
ax1.set_title('Input Image', fontsize=15)
ax1.set_xticks([])
ax1.set_yticks([])

ax2 = fig.add_subplot(1, 2, 2)
ax2.imshow(x_reconst.reshape(28, 28), 'gray')
ax2.set_title('Reconstructed Image', fontsize=15)
ax2.set_xticks([])
ax2.set_yticks([])
plt.show()
```




- To see the distribution of latent variables, we make a projection of 784-dimensional image space onto 2-dimensional latent space

In [13]:

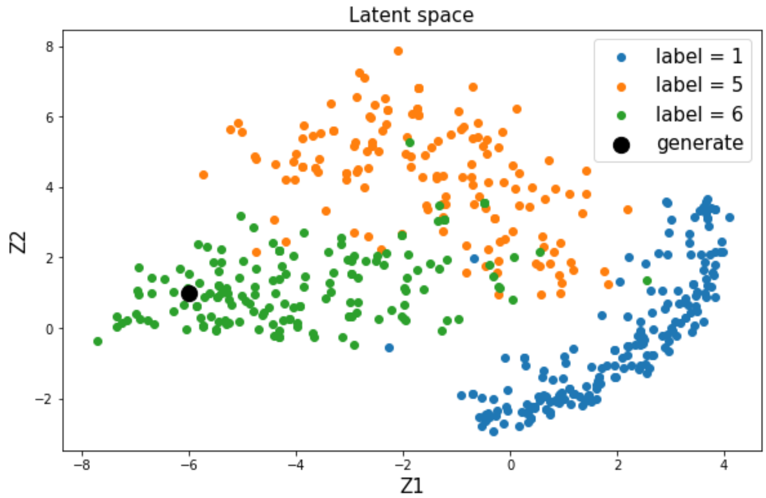
```
test_x, test_y = batch_maker(500, test_imgs, test_labels)
test_y = np.argmax(test_y, axis=1)
test_latent = sess.run(latent, feed_dict={x : test_x})

plt.figure(figsize=(10,6))
plt.scatter(test_latent[test_y == 1,0], test_latent[test_y == 1,1], label = 'label = 
1')
plt.scatter(test_latent[test_y == 5,0], test_latent[test_y == 5,1], label = 'label = 
5')
plt.scatter(test_latent[test_y == 6,0], test_latent[test_y == 6,1], label = 'label = 
6')
plt.title('Latent space', fontsize=15)
plt.xlabel('Z1', fontsize=15)
plt.ylabel('Z2', fontsize=15)
plt.legend(fontsize = 15)
plt.show()
```

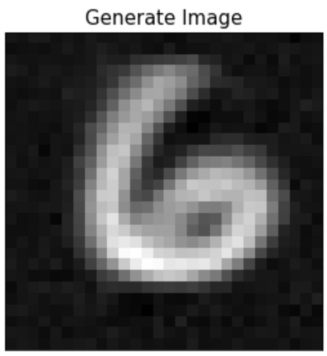



**Data Generation**

In [14]:

```
generate_data = np.array([[-6, 1]])

fig = plt.figure(figsize=(15,6))
ax = plt.subplot2grid((1,3), (0,0), colspan=2)
ax.scatter(test_latent[test_y == 1,0], test_latent[test_y == 1,1], label = 'label = 1')
ax.scatter(test_latent[test_y == 5,0], test_latent[test_y == 5,1], label = 'label = 5')
ax.scatter(test_latent[test_y == 6,0], test_latent[test_y == 6,1], label = 'label = 6')
ax.scatter(generate_data[:,0], generate_data[:,1], label = 'generate', s = 150, c =
'k', marker = 'o')
ax.set_title('Latent space', fontsize=15)
ax.set_xlabel('Z1', fontsize=15)
ax.set_ylabel('Z2', fontsize=15)
ax.legend(fontsize = 15)

latent_input = tf.placeholder(tf.float32, [None, n_latent])
reconst = decoder(latent_input, weights, biases)
generate_x = sess.run(reconst, feed_dict={latent_input : generate_data})


ax = plt.subplot2grid((1, 3), (0, 2), colspan=1)
ax.imshow(generate_x.reshape(28, 28), 'gray')
ax.set_title('Generate Image', fontsize=15)
ax.set_xticks([])
ax.set_yticks([])
plt.show()
```




# 3. Visualization

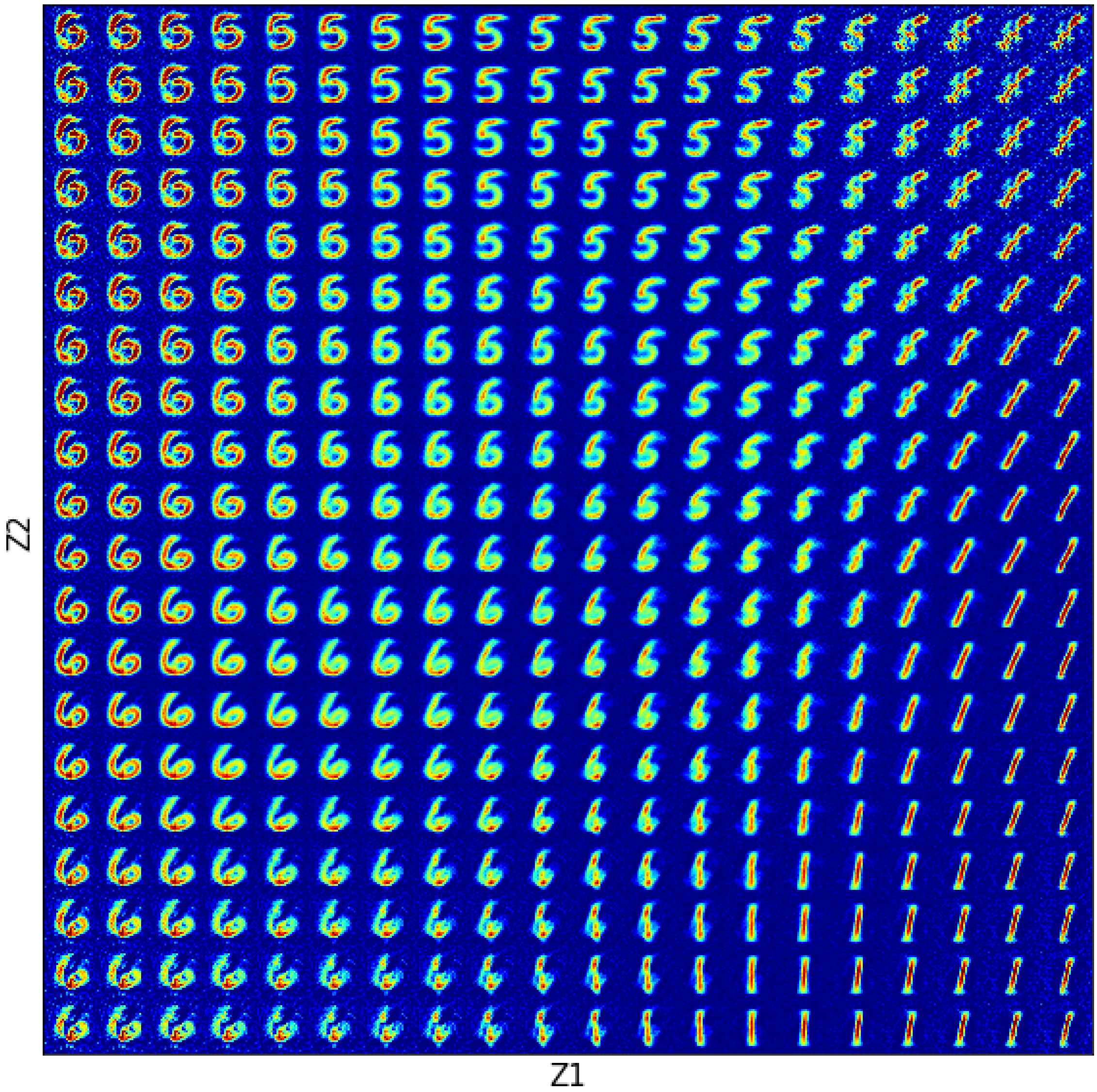
### Image Generation

- Select an arbitrary latent varibale $z$
- Generate images using the learned decoder

In [15]:

```
# Initialize canvas
nx = ny = 20
x_values = np.linspace(-8, 4, nx)
y_values = np.linspace(-2, 6, ny)
canvas = np.empty((28*ny, 28*nx))

# Define placeholder
latent_input = tf.placeholder(tf.float32, [None, n_latent])
reconst = decoder(latent_input, weights, biases)

for i, yi in enumerate(y_values):
        for j, xi in enumerate(x_values):
            latent_ = np.array([[xi, yi]])
            reconst_ = sess.run(reconst, feed_dict={latent_input : latent_})
            canvas[(nx-i-1)*28:(nx-i)*28,j*28:(j+1)*28] = reconst_.reshape(28, 28)

plt.figure(figsize=(10, 10))
plt.imshow(canvas, clim=(0, 1), cmap=plt.cm.jet)
plt.title('Manifold', fontsize=15)
plt.xticks([])
plt.xlabel('Z1', fontsize=15)
plt.yticks([])
plt.ylabel('Z2', fontsize=15)
plt.show()
```

Manifold




In [16]:

```
%%javascript
$.getScript('https://kmahelona.github.io/ipython_notebook_goodies/ipython_notebook_toc.js')
```