

# assignment6

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## 1 Restricted Boltzman Machines and Unsupervised Data Reconstruction

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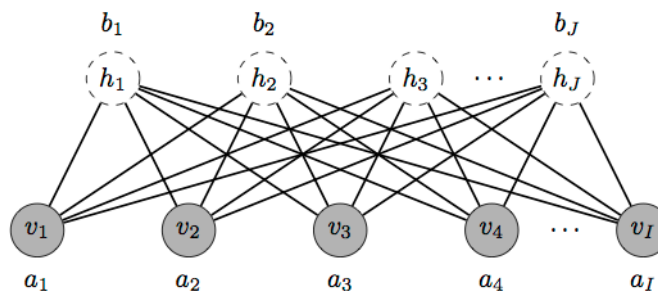
Boltzmann Machines (BM) are a particular form of energy-based models which typically contain hidden variables. A Boltzmann machine is fully connected within and between layers, whereas, Restricted Boltzmann Machines (RBM) have no intra-layer communication. RBM has an undirected graph model and a two layer neural net with visible units in one part of the graph (visible layer) and hidden units in the other part (hidden layer). No connection within layers results in that the random variables encoded by one layer are conditionally independent given the states of the other layer.

RBMs are able to learn to reconstruct the data by themselves in an unsupervised fashion, for example by making several forward and backward passes between the visible layer and the hidden layer, without involving a deeper network. In some cases (i.e, in the demo), RBM models can also be perceived as autoencoders with stochastic units which have particular probability distributions.

Figure below illustrates an example model of a Restricted Boltzmann Machine with  $I$  visible nodes and  $J$  hidden nodes. Weights on the undirected edges in the figure are omitted for clarity. Each visible node takes in a representation of low-level feature from an item in the dataset to be learned. For example, from a dataset of grayscale images, each visible node would receive one pixel-value for each pixel in one image.

```
In [1]: from IPython.display import Image as DImage
        DImage(filename='rbm_demo.png',height=150,width=500)
```

Out[1]:



Using the visible nodes  $v_i$  with biases  $a_i$ , hidden nodes  $h_j$  with biases  $b_j$  and connection weights  $w_{i,j}$ , we can define the **energy** function of a Bernoulli-Bernoulli (Binary) RBM network as:

$$E(\mathbf{v}, \mathbf{h}) = -\mathbf{v}^T \mathbf{W} \mathbf{h} - \mathbf{b}^T \mathbf{h} - \mathbf{a}^T \mathbf{v}$$

$$E(\mathbf{v}, \mathbf{h}) = - \sum_{j=1}^J \sum_{i=1}^I w_{i,j} h_j v_i - \sum_{j=1}^J b_j h_j - \sum_{i=1}^I a_i v_i$$

Then the probability distribution of the whole model (joint probability) is written as:

$$P(\mathbf{v}, \mathbf{h}) = \frac{e^{-E(\mathbf{v}, \mathbf{h})}}{Z},$$

where  $Z$  is a normalizing constant so that the sum of all events = 1. We can get the marginal distribution  $P(\mathbf{v})$  by summing over  $\mathbf{h}$ :

$$P(\mathbf{v}) = \sum_{\mathbf{h}} P(\mathbf{v}, \mathbf{h}) = \sum_{\mathbf{h}} \frac{e^{-E(\mathbf{v}, \mathbf{h})}}{Z}.$$

**The free energy of the visible units** can be calculated analytically without resorting to brute force summation:

$$F(\mathbf{v}) = -\ln \left( \sum_{\mathbf{h}} e^{-E(\mathbf{v}, \mathbf{h})} \right) = - \sum_i v_i a_i - \sum_j \log(1 + \exp(b_j + \sum_i w_{i,j} v_i))$$

The free energy derivation in the sample code (RBM.py) can be seen as an application of a general sum-product algorithm using conditional independence properties to do efficient inference in graphical models. [Belief propagation](#) is quite common for free energy approximation.

When we sample the hidden variables given the visible variables, we need conditional probability. An analogous expression can be derived for sampling visible units, too. If binary units are used for hidden and visible layers, we can define the conditional probabilities and the usual neuron activation function with a probabilistic model:

$$P(h_j = 1 | \mathbf{v}) = \text{sigm}(\mathbf{W}_{:,j}^T \mathbf{v} + b_j)$$

$$P(v_i = 1 | \mathbf{h}) = \text{sigm}(\mathbf{W}_{i,:} \mathbf{h} + a_i)$$

where the  $\mathbf{W}_{:,j}$  is the column vector and  $\mathbf{W}_{i,:}$  is the row vector of the weight matrix. Thus, RBM networks can be nicely related to neural network model running also backwards, and  $P(h_j = 1 | \mathbf{v})$  is considered as learned features.

For the RBM training, we typically can not tune network parameters (weights and biases) by maximizing the log likelihood:

$$\text{argmax}_{\mathbf{W}, \mathbf{a}, \mathbf{b}} \mathbb{E} \left[ \sum \log P(\mathbf{v}) \right],$$

because such is intractable.

RBM training can be based on a learning algorithm called **k step contrastive divergence (CD-k)** to generate samples that are needed to calculate an estimate of the gradient of the log-likelihood.

CD-k performs Gibbs sampling which is initialized with a training example  $\mathbf{v}_0$  on the training set and returns the sample  $\mathbf{v}_k$  after  $k$  sampling steps. Each step consists of sampling  $\mathbf{h}(t)$  from  $P(\mathbf{h}|\mathbf{v}(t))$  and sampling  $\mathbf{v}(t+1)$  from  $P(\mathbf{v}|\mathbf{h}(t))$  subsequently. In the demo, the back-and-forth sampling is done by the Theano [scan\(\)](#) function.

**Persistent contrastive divergence (PCD)** has been proposed to produce better approximations of log-likelihood gradient by replacing the sample  $\mathbf{v}_k$  with a sample from a Gibbs chain that is independent from the sample  $\mathbf{v}_0$  of the training distribution.

### 1.0.1 Demo:

This demo introduces a Theano implementation for RBMs using the MNIST dataset with a smaller version of the images. The code for constructing the RBM is taken from the [deep learning tutorial](#) and modified for you. Our RBM model has one binary visible and one hidden layer of nodes (similar to the figure above).

In this demo, we will use 'mnist-small.pkl.gz' with 14x14 images. The reason for dataset modification is due to the limited memory in CSC notebook. If you want, you can test the demo with the original dataset by using your own computer or in the computer classrooms.

We will experiment with both CD and PCD for RBM training. In the case of CD-k, we will use the reconstruction cost as the monitoring cost. In PCD-k, the pseudo likelihood cost will be used as the monitoring cost, which is basically computing the free energy on  $V$ , then on a randomly corrupted version of  $V$ , and returning the log of the logistic function of the difference.

Before beginning the assignment, if you need more help to understand RBMs or mathematical expressions behind it you can visit these pages:

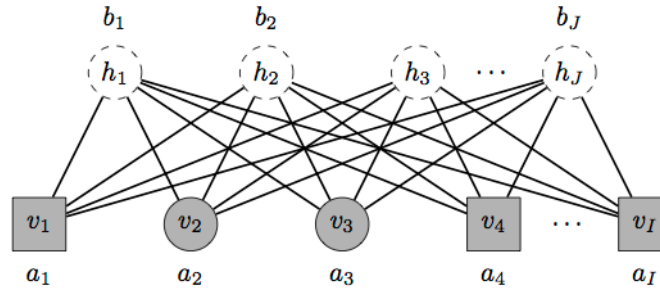
- [An Introduction to Restricted Boltzmann Machines](#)
- [Small Binary RBM on MNIST](#)
- [Coursera Course by Geoffrey Hinton on RBM](#)
- [A Practical Guide to Training Restricted Boltzmann Machines](#)
- [Boltzmann machines \(Scholarpedia article\)](#)
- [Product of experts \(Scholarpedia article\)](#)

### 1.0.2 Assignment:

In the assignment, you first train an RBM model as in the demo. Then you will do both (so-called) unconstrained and constrained synthesis from the model. Then, you will implement a masking function to fix (or *clamp*) some of the visible units to given values as visualized with the squared units in the figure below. With mask, you will fix a part of the Gibbs samples and the trained RBM model guesses the other pixels by also using the information on these fixed visible units. We can define this problem as reconstruction of an incomplete image by sampling from an RBM. The masking options will look like the grid figures below with five options: mask up, down, left, right and random pixels.

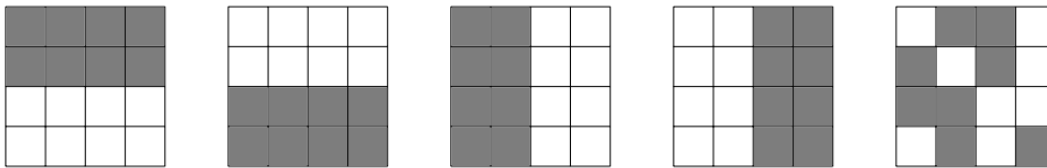
```
In [2]: DImage(filename='rbm_assignment.png',height=150,width=500)
```

```
Out [2]:
```



```
In [3]: DImage(filename='masks.png',height=200,width=600)
```

Out[3]:



You need to fill `vhv_clamping_mask()` function which is going to be used for testing the RBM model with a test dataset and sampling the dataset by Gibbs sampling. Remember that each MNIST image is represented as a vector, so they have the shape of  $(14 \times 14)$ . You also need to change the `gibbs_vhv_clamped()` function inside the `RBM.py` so that it gets the mask defined in the `vhv_clamping_mask()` and masks the inputs given as `v0_mean` and `v0_sample`. You do not need to return the whole `RBM.py` file for the assignment, just return the updated function by copy-pasting the code to a snippet at the end of this assignment in the Markdown mode.

You will also experiment with different initializing methods for the unmasked region of the clamped samples. In addition to keeping the masked region same, you will add noise to the unmasked part of the initial Gibbs samples. You will use Bernoulli distribution to generate the noisy data which takes the value  $\{0, 1\}$  for each pixel with probabilities  $\{p, (1 - p)\}$ . In the assignment, you will initialize this probability value with different methods and by using the pixelwise information of the training dataset.

```
In [4]: # IMPORTANT NOTE!
        # when run in CSC notebooks, one has to first create a terminal and run:
        # pip install Pillow

import time
import math
import timeit
```

```

import numpy
import theano
import theano.tensor as T
import os, sys
from theano.sandbox.rng_mrg import MRG_RandomStreams as RandomStreams
from PIL import Image
import matplotlib.pyplot as plt

rng = numpy.random.RandomState(123)
theano_rng = RandomStreams(rng.randint(2 ** 30))

from exercise_helper import tile_raster_images
from exercise_helper import load_data
from exercise_helper import plot_row
from exercise_helper import plot_mask
from exercise_helper import plot_image

import RBM
print('...Import completed...')

```

...Import completed...

First, we will create an RBM object and train it on our training set.

```

In [5]: def train_rbm(train_data, n_hidden,
                    learning_rate, batch_size,
                    initialize_chain, n_Gibbs_steps,
                    training_epochs=10, output_folder='rbm_plots'):

    # Inputs
    # train_data : dataset to be passed,
    #               in our case we will pass the training samples
    #               from the 'mnist.small.pkl.gz'
    # n_hidden : number of hidden units in the RBM
    # learning_rate : learning rate used for training the RBM
    # batch_size : size of a batch used to train the RBM
    # initialize_chain : string to define CD for contrastive divergence
    #                   or PCD for persistent contrastive divergence
    # n_Gibbs_steps : number of Gibbs steps to do in CD-k/PCD-k
    # training_epochs : number of epochs used for training

    # output_folder: folder to be filled with filters at each epoch
    #                   and sample mean fields

    # Outputs
    # rbm : trained RBM model
    # filters: filters (weights) after the RBM training

```

```

# compute the dimensions of input data
# D: dimension of one sample
# L: number of training samples
D = train_data.get_value(borrow=True).shape[1]
L = train_data.get_value(borrow=True).shape[0]
# get the dimension d from D with square root
# with smaller MNIST dataset ddim will be 14
ddim = int(math.sqrt(D))
assert ddim * ddim == D
print('dataset has a dimension of %d x %d' %(ddim, ddim))

# compute number of minibatches for training
n_train_batches = train_data.get_value(borrow=True).shape[0] // batch_size

# allocate symbolic variables for the data
index = T.lscalar() # index to a [mini]batch
x = T.matrix('x') # the data is presented as rasterized images

# construct the RBM class
rbm = RBM.RBM(input=x, n_visible=ddim * ddim,
              n_hidden=n_hidden, numpy_rng=rng, theano_rng=theano_rng)

# initialize storage for the persistent chain (state = hidden
# layer of chain)
if initialize_chain == 'PCD':
    print("the monitoring cost will show the pseudo likelihood cost")
    persistent_chain = theano.shared(numpy.zeros((batch_size, n_hidden),
                                                  dtype=theano.config.floatX),
                                     borrow=True)

    # get the cost and the gradient corresponding to one step of PCD-n_Gibbs_steps
    cost, updates = rbm.get_cost_updates(lr=learning_rate,
                                         persistent=persistent_chain,
                                         k=n_Gibbs_steps)

elif initialize_chain == 'CD':
    print("the monitoring cost will show the reconstruction cost")
    # get the cost and the gradient corresponding to one step of CD-n_Gibbs_steps
    cost, updates = rbm.get_cost_updates(lr=learning_rate,
                                         k=n_Gibbs_steps)

# create folder for output images
if not os.path.isdir(output_folder):
    os.makedirs(output_folder)
os.chdir(output_folder)

# create a Theano function to train the RBM
# the purpose of train_rbm is solely to update the RBM parameters

```

```

train_rbm = theano.function(
    [index],
    cost,
    updates=updates,
    givens={
        x: train_set_x[index * batch_size: (index + 1) * batch_size]
    },
    name='train_rbm'
)

plotting_time = 0.
start_time = timeit.default_timer()

# go through training epochs
for epoch in range(training_epochs):

    # go through the training set
    mean_cost = []
    for batch_index in range(n_train_batches):
        mean_cost += [train_rbm(batch_index)]

    print('Training epoch %d, cost is ' % epoch, numpy.mean(mean_cost))
    # Plot filters after each training epoch
    plotting_start = timeit.default_timer()
    # Construct image from the weight matrix
    weights = tile_raster_images(
        X=rbm.W.get_value(borrow=True).T,
        img_shape=(ddim, ddim),
        tile_shape=(10, 10),
        tile_spacing=(1, 1)
    )
    image = Image.fromarray(weights)
    image.save('filters_at_epoch_%i.png' % epoch)
    plotting_stop = timeit.default_timer()
    plotting_time += (plotting_stop - plotting_start)

end_time = timeit.default_timer()
pretraining_time = (end_time - start_time) - plotting_time
print ('Training took %f minutes' % (pretraining_time / 60.))
os.chdir('../')
return rbm, weights

```

```

In [6]: # load the MNIST dataset
dataset = 'mnist-small.pkl.gz'
datasets = load_data(dataset)

train_set_x, train_set_y = datasets[0]

```

```

test_set_x, test_set_y = datasets[2]
print('smaller MNIST dataset:')
print('%d samples for the training set' %train_set_x.get_value(borrow=True).shape[0])
print('%d samples for the test set' %test_set_x.get_value(borrow=True).shape[0])

... loading data
dataset is loaded
smaller MNIST dataset:
10000 samples for the training set
1000 samples for the test set

```

**Assignment part 1:** Fill the function below according to the task explained above. Remember, you also need to change `gibbs_vhv_clamped()` function inside the `RBM.py`.

```

In [7]: def vhv_clamping_mask(ddim, n_chains, n_clamps, place='bottom'):
    # Inputs:
    # ddim: dimension of the input
    # n_chains: number of parallel Gibbs chains to be used for sampling
    # n_clamps : number for pixels set to 1 in clamping
    # place: place for where the clamping is True (1)

    # Outputs:
    # mask: mask for clamping. It should have a size of (ddim*ddim,)
    # for MNIST images
    #####
    ##### INSERT YOUR CODE HERE #####
    #####
    mask = numpy.zeros((ddim*ddim,))
    if place == 'bottom':
        # the bottom placement is given to you as a hint for other
        # placement implementations
        dim_up = ddim-n_clamps
        dim_down = n_clamps
        mask = numpy.concatenate((
                                numpy.zeros((ddim*dim_up,)),
                                numpy.ones((ddim*dim_down,))), axis=0)
    elif place == 'top':
        # hint: use numpy concatenate() to create mask
        # dim_up should include ones, dim_down should include zeros
        dim_up = n_clamps
        dim_down = ddim-n_clamps
        mask = numpy.concatenate((
                                numpy.ones((ddim*dim_up,)),
                                numpy.zeros((ddim*dim_down,))), axis=0)
    elif place == 'left':
        # hint: first create one row with numpy concatenate()
        #         then use numpy tile() to construct the array by

```



```

#         repeating a the number of times given by ddim
# dim_left should include ones, dim_right should include zeros
dim_left = n_clamps
dim_right = ddim-n_clamps
row_mask = numpy.concatenate((
                                numpy.ones((dim_left,)),
                                numpy.zeros((dim_right,))),axis=0)
mask = numpy.tile(row_mask,ddim)
elif place == 'right':
    # hint: first create one row with numpy concatenate
    #         then use numpy tile to construct the array by
    #         repeating a the number of times given by ddim
    # dim_left should include zeros, dim_right should include ones
    dim_left = ddim-n_clamps
    dim_right = n_clamps
    row_mask = numpy.concatenate((
                                    numpy.zeros((dim_left,)),
                                    numpy.ones((dim_right,))),axis=0)
    mask = numpy.tile(row_mask,ddim)
elif place == 'random':
    # hint use numpy randint function for returning random integers
    mask = numpy.random.randint(2,size=ddim*ddim)
return mask
#####
##### END #####
#####

```

After the training, we will test our RBM model using test data with Gibbs sampling.

```

In [8]: def test_rbm(rbm, test_data, n_chains, n_samples,
                    n_Gibbs_steps, plot_every= 1000,
                    n_clamps= 0, place=None, noise_init=None, train_data=None):

    # Inputs:
    # rbm : trained rbm model
    # test_data : dataset to be passed for test,
    #             in our case we will pass the testing samples
    #             from the 'mnist.small.pkl.gz'
    # n_chains : number of parallel Gibbs chains to be used for sampling
    # n_samples : number of samples to plot for each chain
    # n_Gibbs_steps : number of Gibbs steps to do in CD-k/PCD-k
    # plot_every : it generates "plot_every" intermediate steps
    #               (every successible samples) that are discarded
    #               in Gibbs sampling
    # n_clamps : number for pixels used in clamping
    #             if zero, no clamping
    #             if bigger than zero, then RBM will be reconstructed
    #             with a pattern

```

```

# n_clamps : number for pixels used in clamping
# place: place for clamping starts

# Outputs:
# original_samples : samples starting the Gibbs chain
# image_data : Gibbs samples generated by the RBM after training
#             each row in the output represents a mini-batch
#             of negative particles
# clamping_mask : masking pattern for clamping

# sampling from the RBM
# find out the number of test samples
number_of_test_samples = test_data.get_value(borrow=True).shape[0]
# compute the dimensions of input data
# D: dimension of one sample
# L: number of training samples
D = test_data.get_value(borrow=True).shape[1]
L = test_data.get_value(borrow=True).shape[0]
# get the dimension d from D with square root
# with smaller MNIST dataset ddim will be 14
ddim = int(math.sqrt(D))
assert ddim * ddim == D

# pick random test examples, with which to initialize the persistent chain
test_idx = rng.randint(number_of_test_samples - n_chains)
persistent_vis_chain = theano.shared(
    numpy.asarray(
        test_set_x.get_value(borrow=True)[test_idx:test_idx + n_chains],
        dtype=theano.config.floatX
    )
)
#persistent_vis_chain_sample = numpy.asarray(
#    test_data.get_value(borrow=True)[test_idx:test_idx + n_chains],
#    dtype=theano.config.floatX)

# get the initialized test examples as an output, since
# the states of the visible units are initialized to test data

original_samples = tile_raster_images(
    X=persistent_vis_chain.get_value(borrow=True),
    img_shape=(ddim, ddim),
    tile_shape=(1, n_chains),
    tile_spacing=(1, 1)
)

#####
##### INSERT YOUR CODE HERE #####
#####

```

```

# initialize the first sample of Gibbs chain
# with a noise sampled from the Bernoulli distribution
# the noisy representations will only be used with clamping operations
# if noise_init is 'equal expectation', samples are drawn from a
# binomial distribution with p=0.5 (an equal probability of success)
# noisy_persistent_vis_chain is now consists of Bernoulli noise with a dimension of
# (ddim*ddim,)
if train_data == None:
    train_data = train_set_x

train_data_value = train_data.get_value(borrow=True)
# Hint: use numpy Binomial function with size=(ddim*ddim, ), n=1 trial
# and p=0.5 for equal expectation

if noise_init == 'equal_expectation':
    noise = numpy.random.binomial(n=1, p=0.5, size=(ddim*ddim, ))

# if noise_init is selected as "global_expectation", calculate the averaging
# pixel values as a one global value (global_mean) over examples and over
# pixels of the whole training dataset. Use this average value for p to
# construct a noise with dimensions of (ddim*ddim,) sampled from the Bernoulli
# distribution

elif noise_init == 'global_expectation':
    global_mean = T.mean(train_data_value).eval()
    noise = numpy.random.binomial(n=1, p=global_mean, size=(ddim*ddim, ))

# if the noise init is selected as "local_expectation", calculate the averaging
# pixel values as (ddim*ddim,) values (local_mean) over examples of the whole
# training dataset
# Use this average value per each pixel (ddim*ddim) for p to construct a noise with
# dimensions of (ddim*ddim,) sampled from the Bernoulli distribution

elif noise_init == 'local_expectation':
    local_mean = T.mean(train_data_value,axis=0).eval()
    noise = numpy.random.binomial(n=1, p=local_mean, size=(ddim*ddim, ))

#####
##### END #####
#####

# define one step of Gibbs sampling (mf = mean-field) define a
# function that does 'plot_every' steps before returning the
# sample for plotting
# if there is clapping, then change the initialization of both vis_mfs
# and vis_samples to persistent_vis_chain shared Theano variable. This
# trick will keep the masked part of the image same and try to guess the

```

```

# other part of the image from (noisy) the input
# otherwise, initialize only vis_samples to persistent_vis_chain variable
# use gibbs_vhv_clamped function, if the clamping is applied
if n_clamps > 0:
    clamping_mask = vhv_clamping_mask(ddim, n_chains, n_clamps, place)
    if noise_init is None:
        persistent_vis_chain_clamped = persistent_vis_chain
    else:
        persistent_vis_chain_clamped = (noise*(1-clamping_mask) +
                                         persistent_vis_chain*(clamping_mask))
    (
        [
            presig_hids,
            hid_mfs,
            hid_samples,
            presig_vis,
            vis_mfs,
            vis_samples
        ],
        updates
    ) = theano.scan(
        rbm.gibbs_vhv_clamped,
        non_sequences = clamping_mask,
        outputs_info=[None, None, None, None,
                      persistent_vis_chain_clamped, persistent_vis_chain_clamped],
        n_steps=plot_every,
        name="gibbs_vhv_clamped"
    )
else:
    clamping_mask = numpy.zeros((ddim,ddim), dtype=theano.config.floatX)
    (
        [
            presig_hids,
            hid_mfs,
            hid_samples,
            presig_vis,
            vis_mfs,
            vis_samples
        ],
        updates
    ) = theano.scan(
        rbm.gibbs_vhv,
        outputs_info=[None, None, None, None, None, persistent_vis_chain],
        n_steps=plot_every,
        name="gibbs_vhv"
    )

# add to updates the shared variable that takes

```

```

# care of our persistent chain
updates.update({persistent_vis_chain: vis_samples[-1]})
# construct the function that implements our persistent chain.
# we generate the "mean field" activations for plotting and the actual
# samples for reinitializing the state of our persistent chain
sample_fn = theano.function(
    [],
    [
        vis_samples[0],
        vis_mfs[-1],
        vis_samples[-1]
    ],
    updates=updates,
    name='sample_fn'
)

# create a space to store the image for plotting (we need to leave
# room for the tile_spacing as well)
image_data = numpy.zeros(
    ((ddim+1) * n_samples, (ddim+1) * n_chains),
    dtype='uint8'
)

for idx in range(n_samples):
    # generate 'plot_every' intermediate samples that we discard,
    # because successive samples in the chain are too correlated
    vis_mf0, vis_mf, vis_sample = sample_fn()
    # string for output
    s = ' ... plotting sample ' + str(idx)
    print (s, end="\r")
    # sleep for 200ms to rewrite the comment above
    time.sleep(0.2)
    image_data[(ddim+1) * idx:(ddim+1) * idx + ddim, :] = tile_raster_images(
        X=vis_mf,
        img_shape=(ddim, ddim),
        tile_shape=(1, n_chains),
        tile_spacing=(1, 1)
    )

# find the first clamped samples and rasterize
clamped_samples = tile_raster_images(
    X=vis_mf0,
    img_shape=(ddim, ddim),
    tile_shape=(1, n_chains),
    tile_spacing=(1, 1)
)

## construct image
image = Image.fromarray(image_data)

```

```
return original_samples, image_data, clamping_mask.reshape(ddim, ddim), clamped_samples
```

In the demo, we will first try out the CD-1 since it is relatively cheap. Then, we will experiment with CD-15, PCD-1 and PCD-15.

```
In [9]: # define hyperparameters
        n_hidden= 100
        learning_rate = 0.1
        batch_size = 20
        n_chains=20
        n_samples=10
        n_clamps = 0
        plot_every = 1000

        # CD-1 sampling, without clamping
        # select 'CD or PCD' to initialize the chain
        initialize_chain = 'CD'
        n_Gibbs_steps = 1
        print('CD-1 sampling, without clamping')
        rbmCD1, filters = train_rbm(train_set_x, n_hidden, learning_rate,
                                   batch_size, initialize_chain,
                                   n_Gibbs_steps, training_epochs=10,
                                   output_folder='rbm_plots_CD1_noclamp')
        plot_image(filters, 'The filters after the training (CD-1)')

        original_samples, sample_mean_fields, clamping_mask, clamped_samples = test_rbm(
                                                    rbmCD1, test_set_x,
                                                    n_chains, n_samples,
                                                    n_Gibbs_steps,
                                                    plot_every, n_clamps,
                                                    place=None)

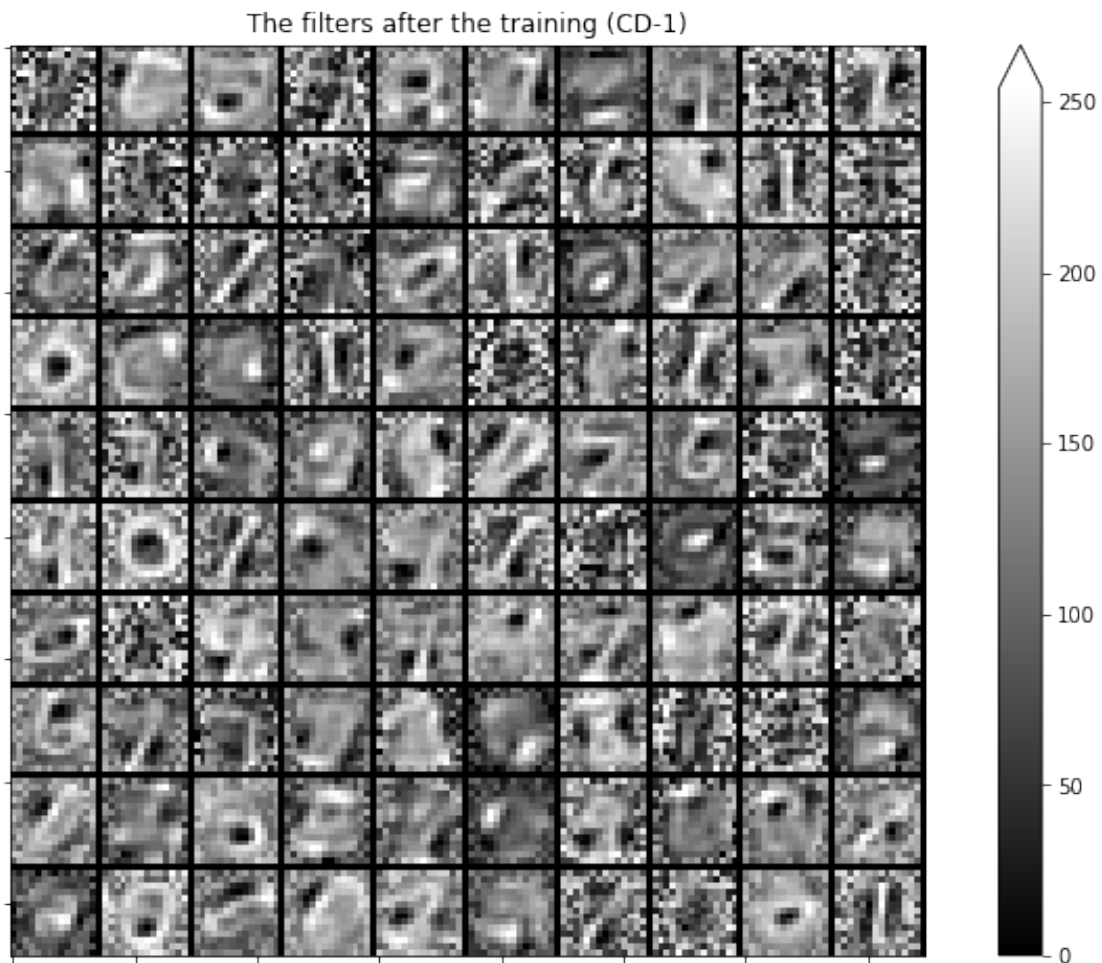
        plot_row(original_samples,
                  'Original samples initializing the Gibbs chain')
        plot_mask(clamping_mask, n_chains,
                  'Mask to be used to construct a pattern for samples')
        plot_row(clamped_samples, 'Initial samples (CD-1)')
        plot_image(sample_mean_fields,
                  'Gibbs sample mean fields generated by the RBM after training (CD-1)')
```

CD-1 sampling, without clamping  
dataset has a dimension of 14 x 14  
the monitoring cost will show the reconstruction cost

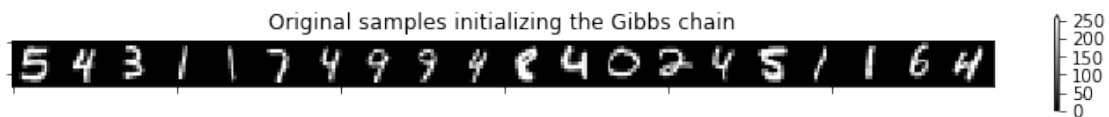
WARNING (theano.tensor.blas): We did not found a dynamic library into the library\_dir of the 1.

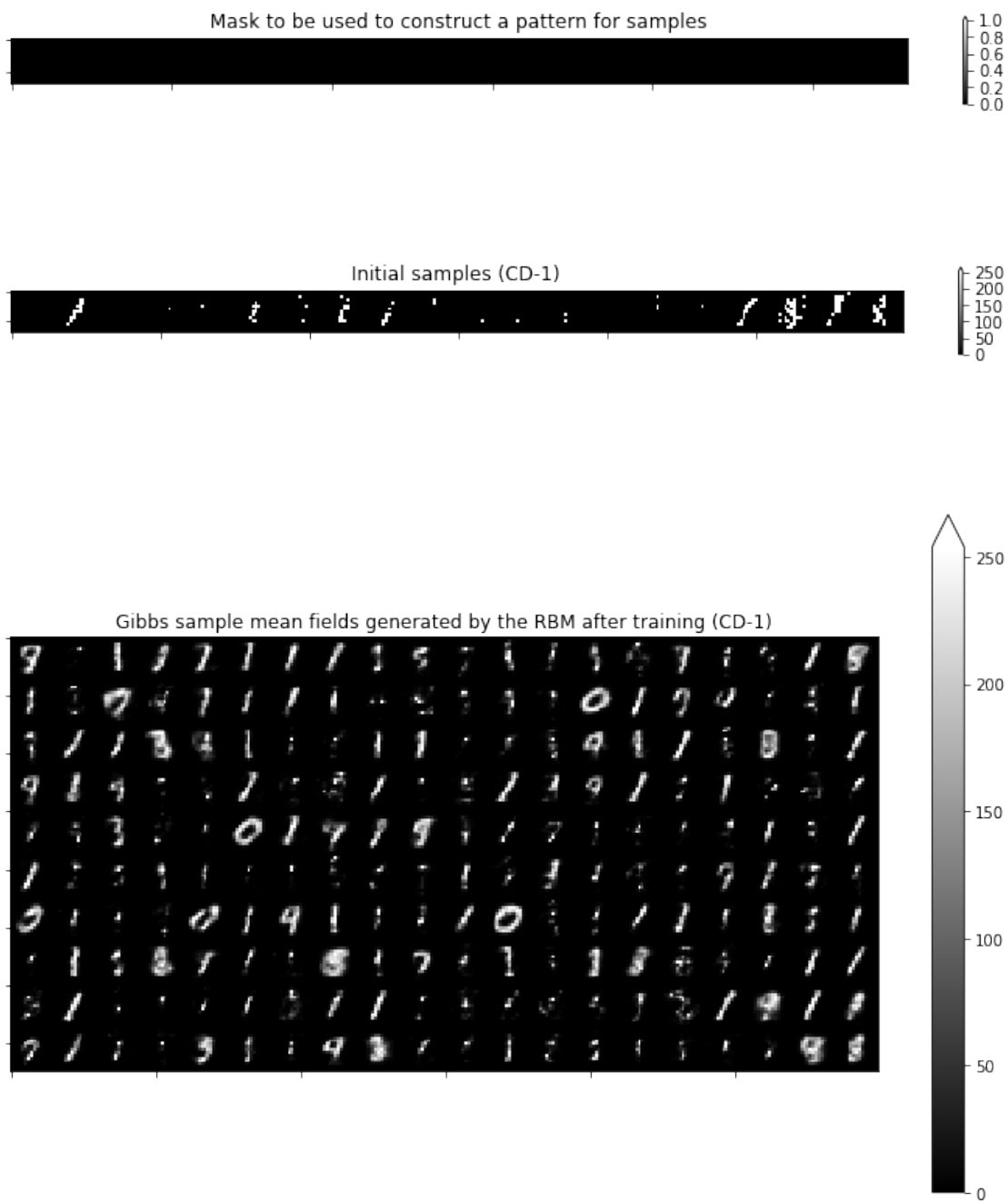
Training epoch 0, cost is -42.7901076268  
Training epoch 1, cost is -37.8378468198

Training epoch 2, cost is -36.8950274788  
 Training epoch 3, cost is -36.340249363  
 Training epoch 4, cost is -35.977715364  
 Training epoch 5, cost is -35.650949935  
 Training epoch 6, cost is -35.4658980016  
 Training epoch 7, cost is -35.227407462  
 Training epoch 8, cost is -35.076185063  
 Training epoch 9, cost is -34.9567619635  
 Training took 0.444896 minutes



... plotting sample 9





```
In [10]: # CD-15 sampling, without clamping
         # select 'CD or PCD' to initialize the chain
         initialize_chain = 'CD'
         n_Gibbs_steps = 15
```



```

print('CD-15 sampling, without clamping')
rbmCD15, filters = train_rbm(train_set_x, n_hidden, learning_rate,
                             batch_size, initialize_chain,
                             n_Gibbs_steps, training_epochs=10,
                             output_folder='rbm_plots_CD15_noclamp')
plot_image(filters, 'The filters after the training (CD-15)')

original_samples, sample_mean_fields, clamping_mask, clamped_samples = test_rbm(
    rbmCD15, test_set_x,
    n_chains, n_samples,
    n_Gibbs_steps,
    plot_every, n_clamps,
    place=None)

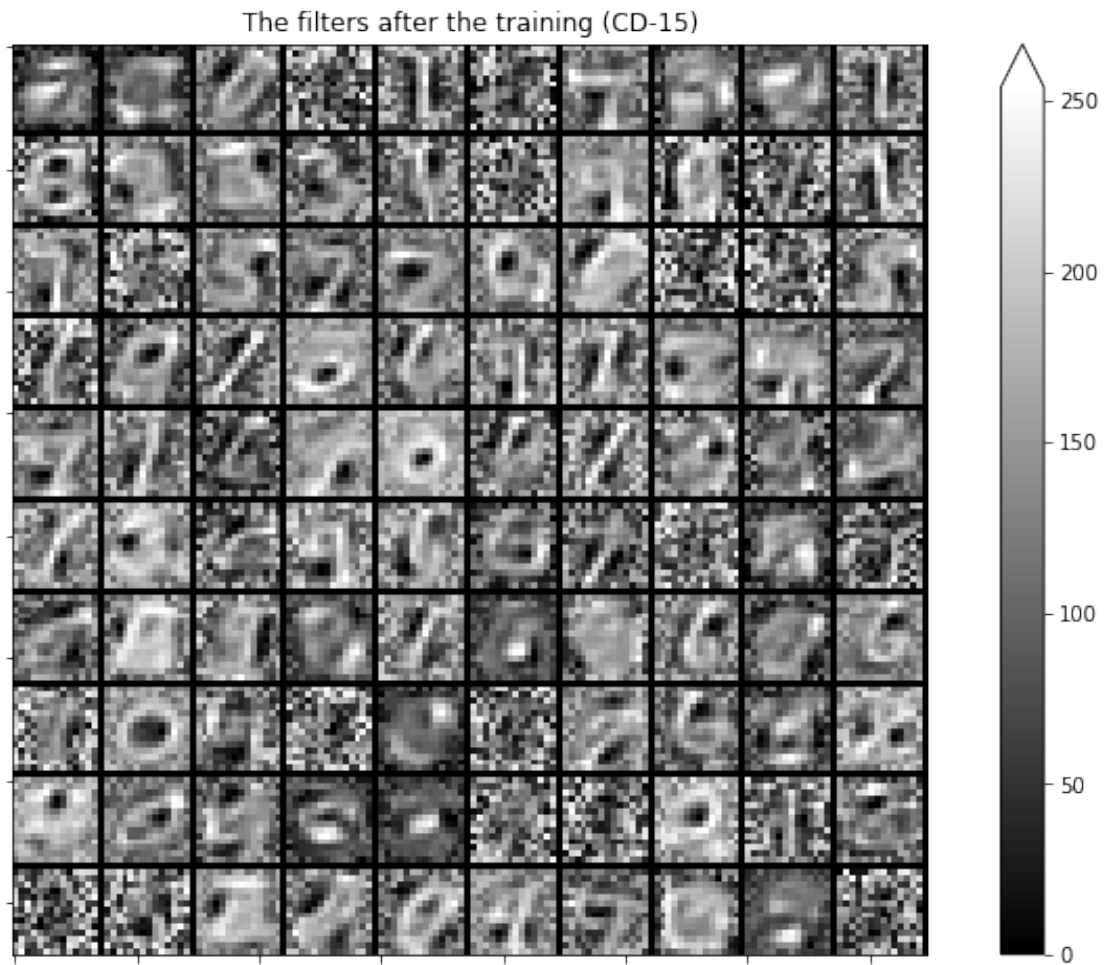
plot_row(original_samples, 'Original samples initializing the Gibbs chain')
plot_mask(clamping_mask, n_chains, 'Mask to be used to construct a pattern for samples')
plot_row(clamped_samples, 'Initial samples (CD-15)')
plot_image(sample_mean_fields,
            'Gibbs sample mean fields generated by the RBM after training (CD-15)')

```

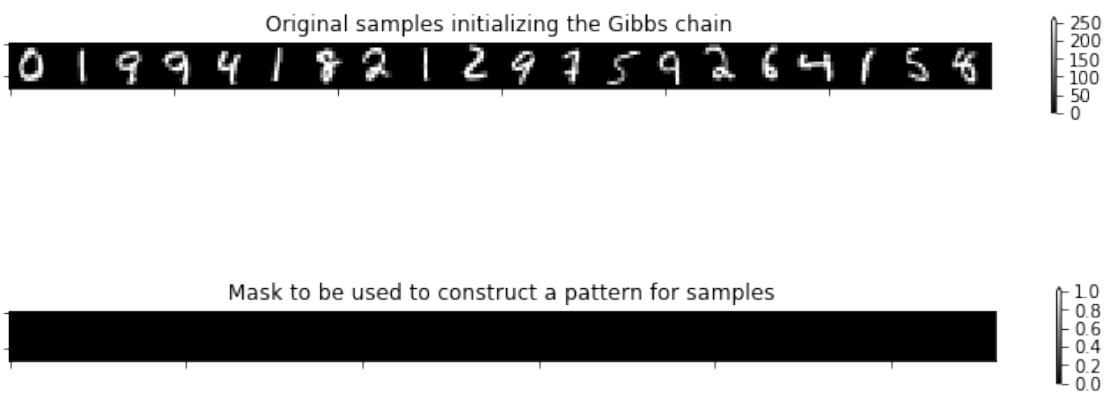
```

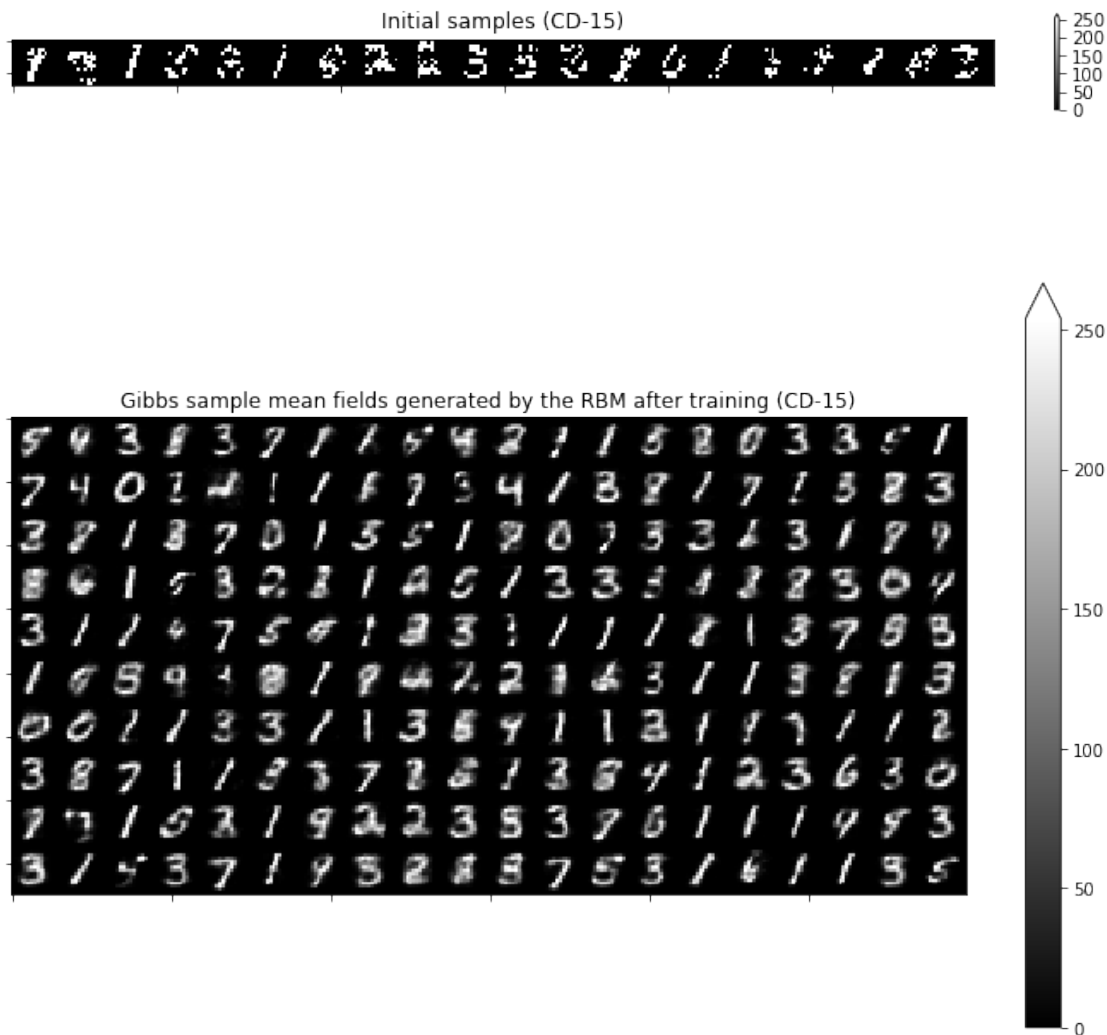
CD-15 sampling, without clamping
dataset has a dimension of 14 x 14
the monitoring cost will show the reconstruction cost
Training epoch 0, cost is -70.4910922266
Training epoch 1, cost is -67.5367860796
Training epoch 2, cost is -66.6952806723
Training epoch 3, cost is -66.8198384945
Training epoch 4, cost is -66.3664813389
Training epoch 5, cost is -66.1434003331
Training epoch 6, cost is -65.9286741542
Training epoch 7, cost is -65.8319482253
Training epoch 8, cost is -65.8775333402
Training epoch 9, cost is -65.5399303991
Training took 3.262494 minutes

```



... plotting sample 9





```
In [11]: # PCD-1 sampling, without clamping
# select 'CD or PCD' to initialize the chain
initialize_chain = 'PCD'
n_Gibbs_steps = 1

print('PCD-1 sampling, without clamping')
rbmPCD1, filters = train_rbm(train_set_x, n_hidden, learning_rate,
                             batch_size, initialize_chain,
                             n_Gibbs_steps, training_epochs=10,
                             output_folder='rbm_plots_PCD1_noclamp')
plot_image(filters, 'The filters after the training (PCD-1)')

original_samples, sample_mean_fields, clamping_mask, clamped_samples = test_rbm(
    rbmPCD1, test_set_x,
    n_chains, n_samples,
```

```

n_Gibbs_steps,
plot_every, n_clamps,
place=None)

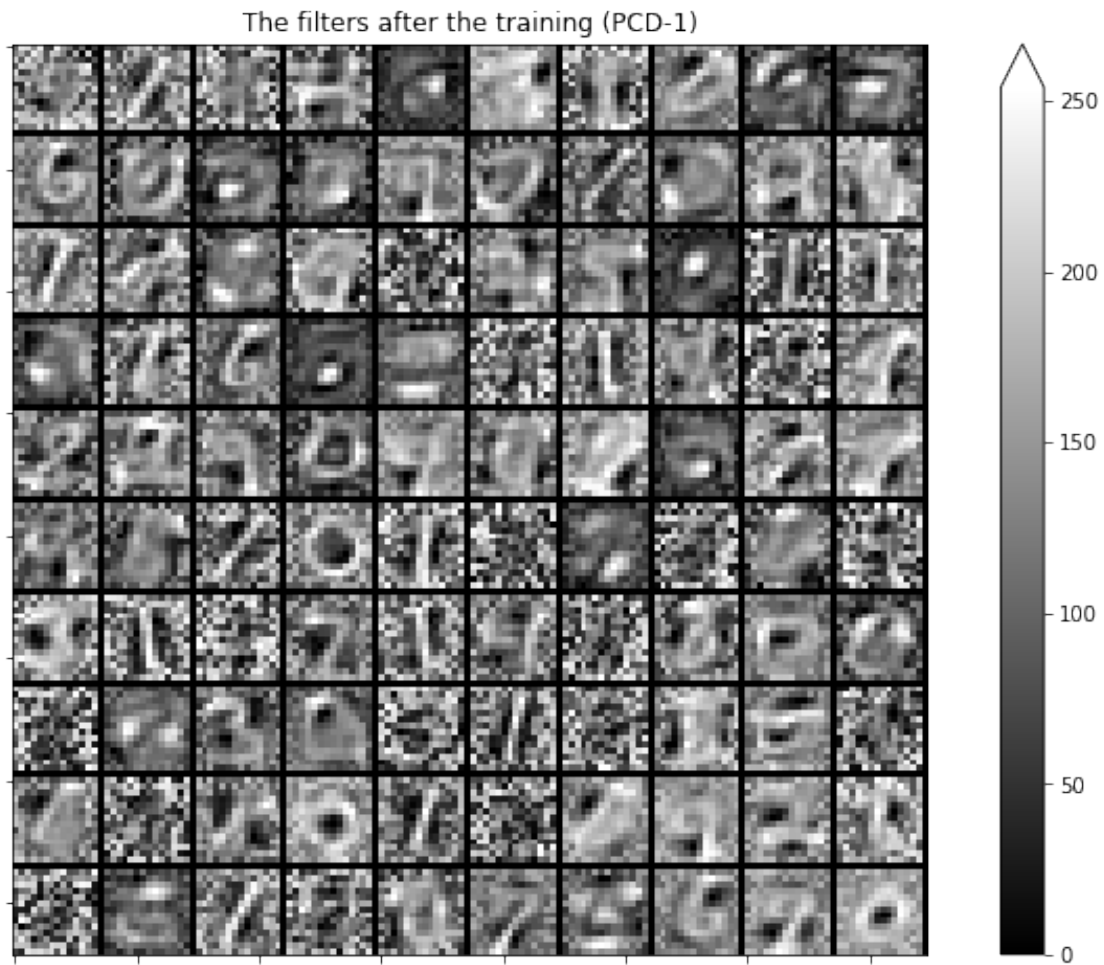
plot_row(original_samples,
          'Original samples initializing the Gibbs chain')
plot_mask(clamping_mask, n_chains,
          'Mask to be used to construct a pattern for samples')
plot_row(clamped_samples, 'Initial samples (PCD-1)')
plot_image(sample_mean_fields,
            'Gibbs sample mean fields generated by the RBM after training (PCD-1)')

```

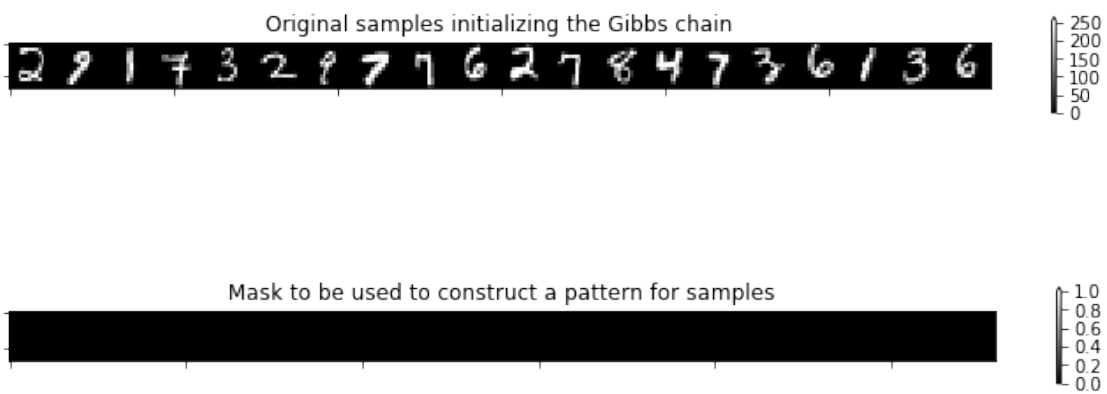
```

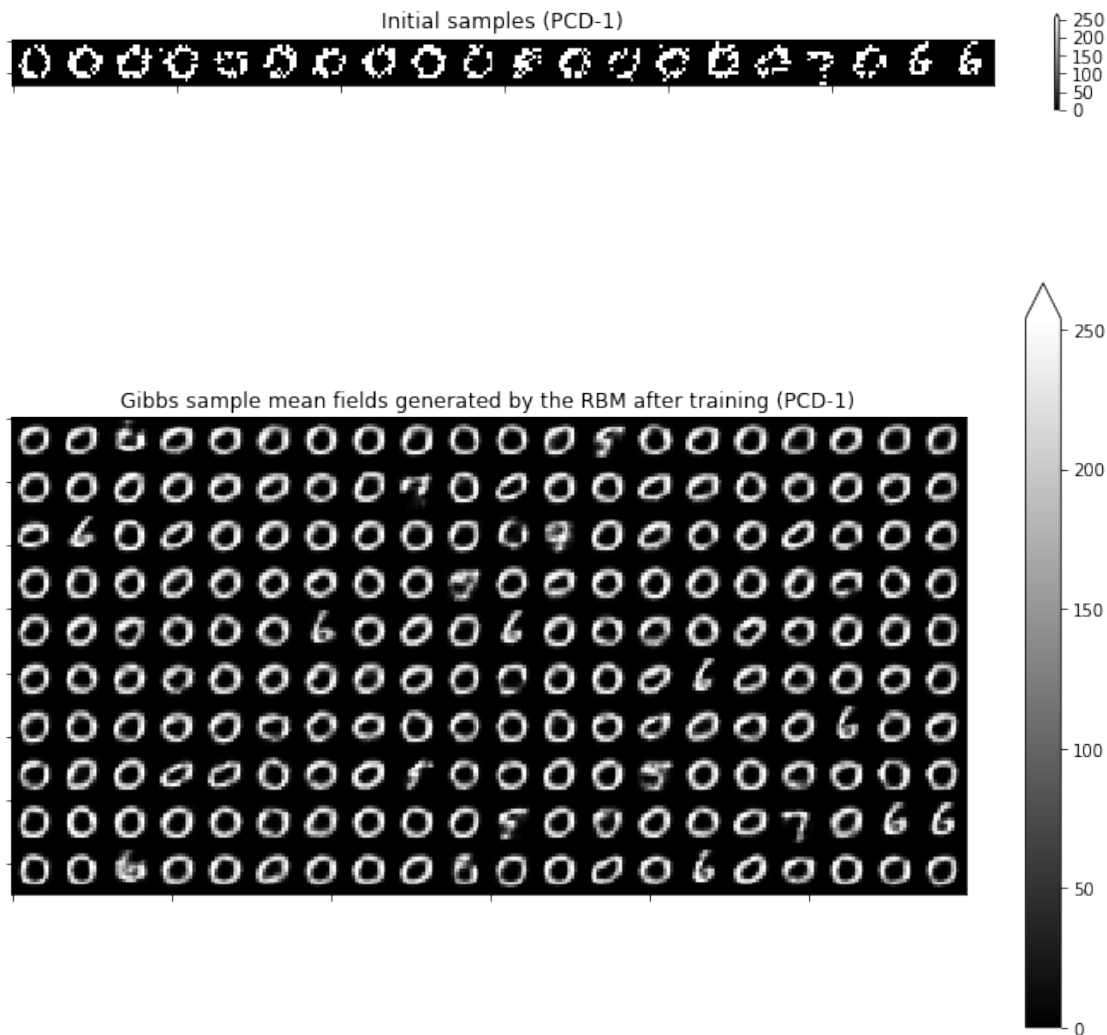
PCD-1 sampling, without clamping
dataset has a dimension of 14 x 14
the monitoring cost will show the pseudo likelihood cost
Training epoch 0, cost is -40.4868298911
Training epoch 1, cost is -34.0771783603
Training epoch 2, cost is -35.1455773997
Training epoch 3, cost is -30.1172945228
Training epoch 4, cost is -34.9944187596
Training epoch 5, cost is -27.6188737495
Training epoch 6, cost is -34.7349489958
Training epoch 7, cost is -28.9547258912
Training epoch 8, cost is -31.5873736846
Training epoch 9, cost is -30.0461914766
Training took 0.371891 minutes

```



... plotting sample 9





```
In [12]: # PCD-15 sampling, without clamping
# select 'CD or PCD' to initialize the chain
initialize_chain = 'PCD'
n_Gibbs_steps = 15

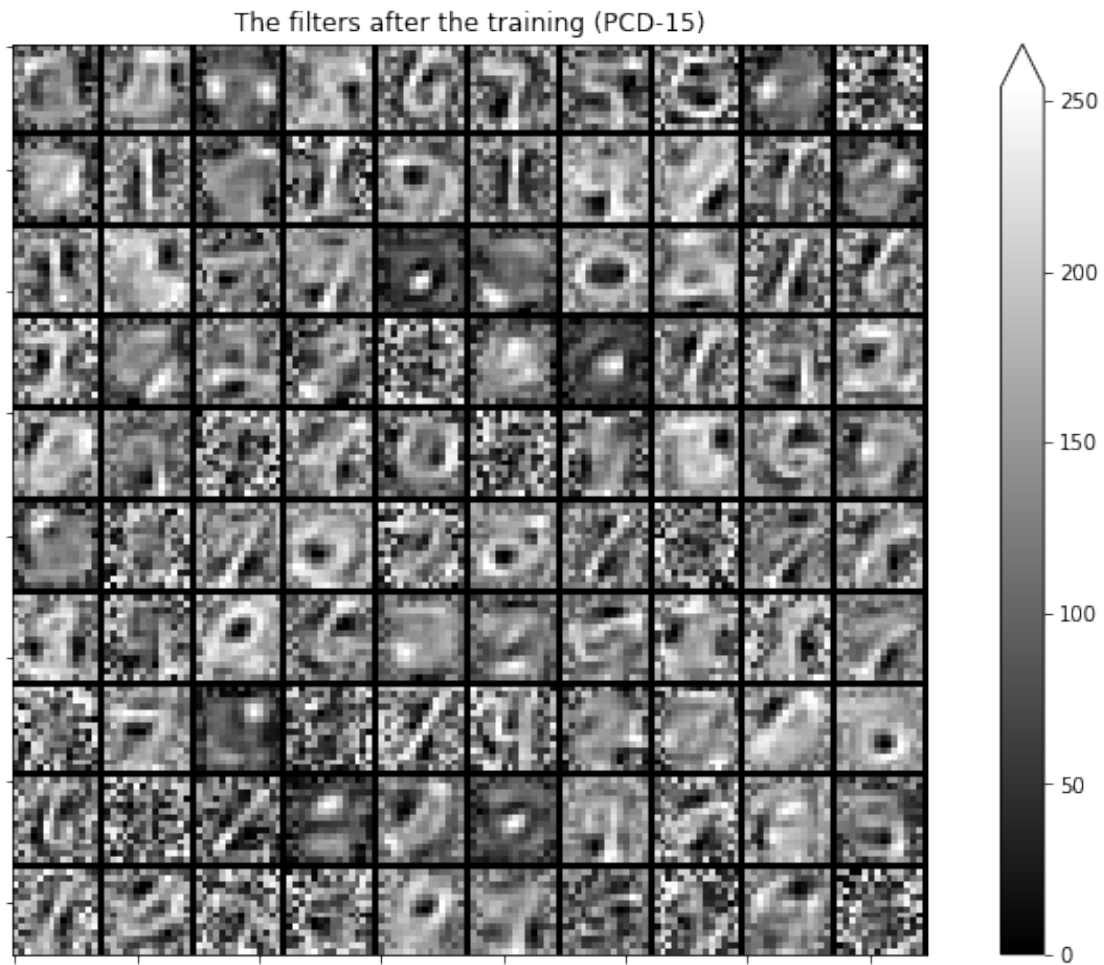
rbmPCD15, filters = train_rbm(train_set_x, n_hidden, learning_rate,
                              batch_size, initialize_chain,
                              n_Gibbs_steps, training_epochs=10,
                              output_folder='rbm_plots_PCD15_noclamp')
plot_image(filters, 'The filters after the training (PCD-15)')

print('PCD-15 sampling, without clamping')
original_samples, sample_mean_fields, clamping_mask, clamped_samples = test_rbm(
    rbmPCD15, test_set_x,
    n_chains, n_samples,
```

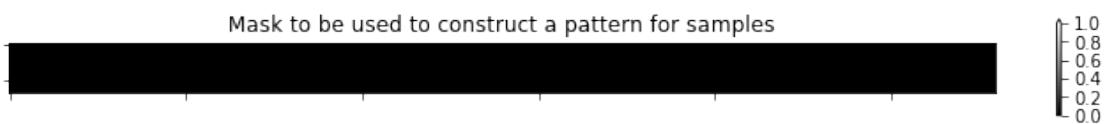
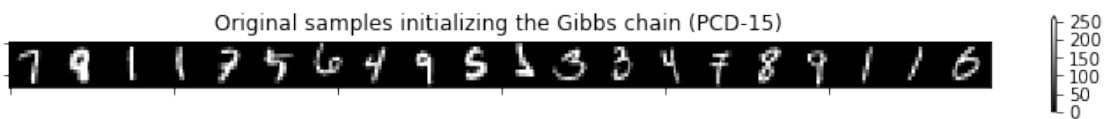
```
n_Gibbs_steps,  
plot_every, n_clamps,  
place=None)
```

```
plot_row(original_samples,  
          'Original samples initializing the Gibbs chain (PCD-15)')  
plot_mask(clamping_mask, n_chains,  
          'Mask to be used to construct a pattern for samples')  
plot_row(clamped_samples,  
          'Masked initial samples (PCD-15)')  
plot_image(sample_mean_fields,  
            'Gibbs sample mean fields generated by the RBM after training (PCD-15)')
```

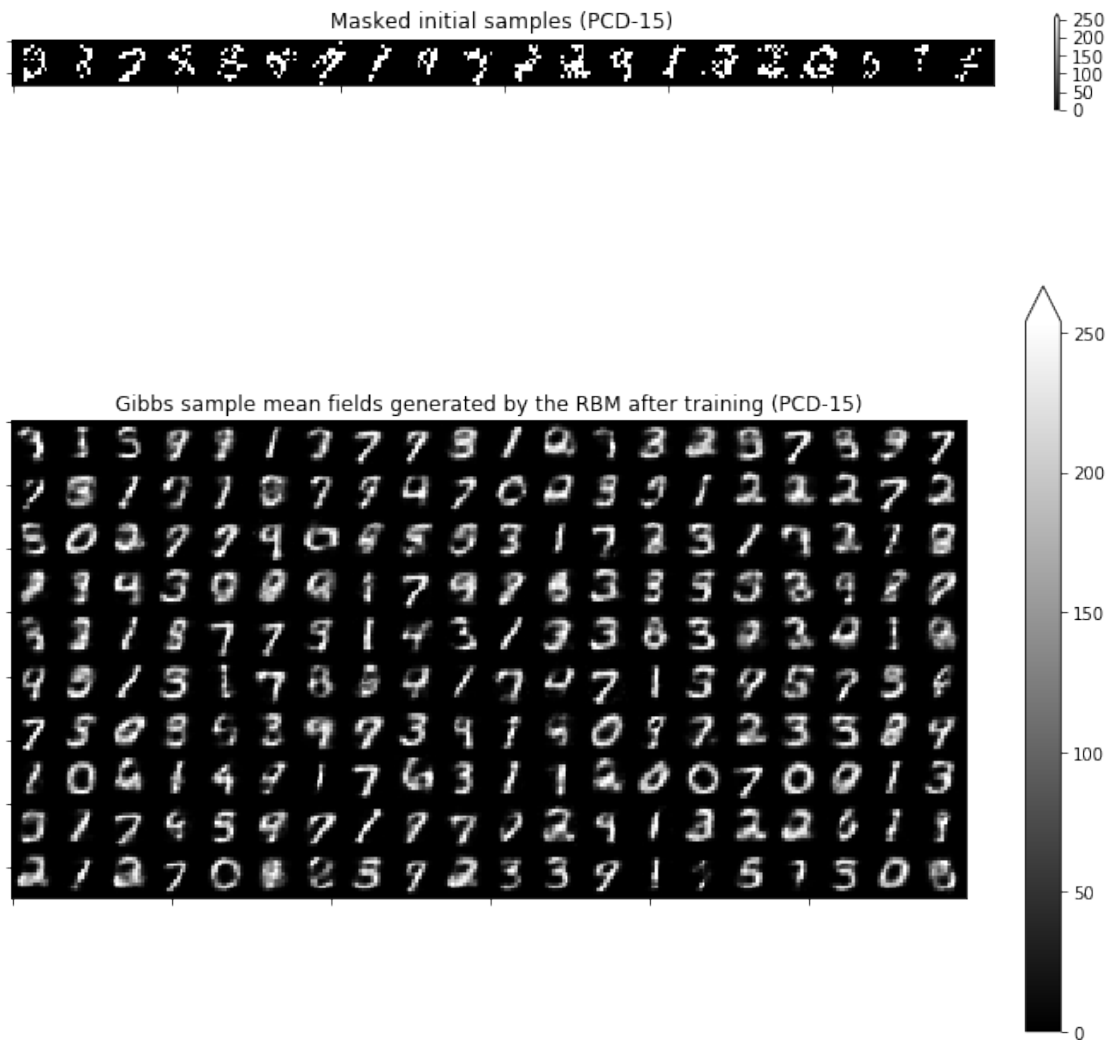
```
dataset has a dimension of 14 x 14  
the monitoring cost will show the pseudo likelihood cost  
Training epoch 0, cost is -39.9192850652  
Training epoch 1, cost is -33.6796261658  
Training epoch 2, cost is -34.9535253537  
Training epoch 3, cost is -29.6042486487  
Training epoch 4, cost is -34.3607584438  
Training epoch 5, cost is -27.2448703196  
Training epoch 6, cost is -34.2846068728  
Training epoch 7, cost is -28.4397296756  
Training epoch 8, cost is -30.8958598453  
Training epoch 9, cost is -29.541971128  
Training took 3.533522 minutes
```



PCD-15 sampling, without clamping  
... plotting sample 9







**Assignment Part 2:** Although the demo code with results are ready to run for you, first try to understand the RBM.py class and explain a little bit why the results with CD-15 look better than with CD-1. Also, explain why PCD seems to have more converging results. Write your observations in the discussion cell below.

The idea of  $k$ -step contrastive divergence learning (CD- $k$ ) is quite simple: instead of approximating the second term in the log-likelihood gradient by a sample from the RBM-distribution (which would require running a Markov chain until the stationary distribution is reached), a Gibbs chain is run for only  $k$  steps. Because usually the stationary distribution is not reached after  $k$  sampling steps. Thus, the single sample  $v(k)$  is not a sample from the model distribution and therefore the approximation is biased. Obviously, the bias vanishes as  $k \rightarrow \infty$ . So CD-15 look better than CD-1.

The PCD approximation is obtained from the CD approximation by replacing the sample  $v(k)$  by a sample from a Gibbs chain that is independent of the sample  $v(0)$  of the training distribution. The fundamental idea underlying PCD is that one could assume that the chains stay close to the stationary distribution if the learning rate is sufficiently small and thus the model changes only

slightly between parameter updates. The sample will be more close to the model distribution and therefore the approximation will be more unbiased. So PCD seems to have more converging results.

**Assignment Part 3:** Now try different clamping methods by changing the  $n\_clamps$  and the clamping *place* by using the best model found in the demo. Experiment with at least two of the clamping *place* (top, bottom, left, right, random) and with 2 different values for the  $n\_clamps$ . (In total, you need to show results for at least four experiments). Can you see the resemblance between the forced pixels from the original samples initializing the Gibbs chain and "mean fields" generated by the RBM? What effects do the different clamping mask placements and total clamped pixels have? What might be the reason for such behaviours? Write your observations in the discussion cell below.

```
In [13]: #####
##### INSERT YOUR CODE HERE #####
#####

# Hint: you can use test_rbm function the your best model
# found in the demo.
# use rbm model trained with the PCD-15 algorithm from the demo
rbm = rbmPCD15

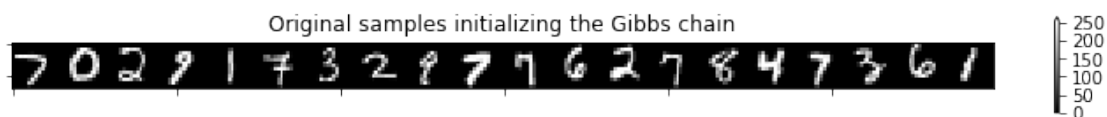
# then play with n_clamps and place for clamping
# perform and visualize the results with the functions given

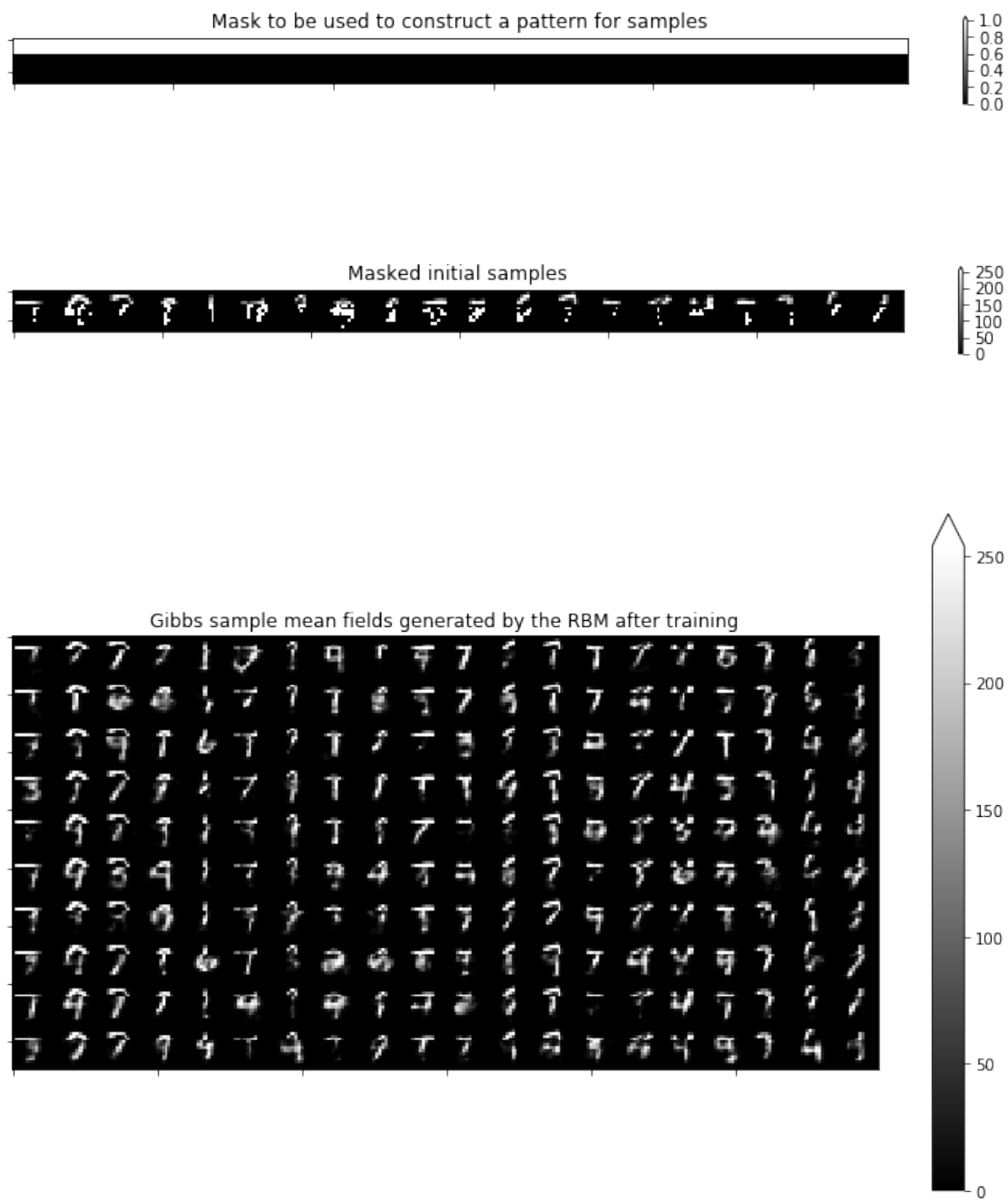
n_clamps = 5
place = 'top'
original_samples, sample_mean_fields, clamping_mask, clamped_samples = test_rbm(rbm, 10,
n_chains, n_samples,
n_Gibbs_steps,
plot_every, n_clamps,
place=place)

plot_row(original_samples, 'Original samples initializing the Gibbs chain')
plot_mask(clamping_mask, n_chains, 'Mask to be used to construct a pattern for samples')
plot_row(clamped_samples, 'Masked initial samples')
plot_image(sample_mean_fields,
            'Gibbs sample mean fields generated by the RBM after training')

#####
##### END #####
#####

... plotting sample 9
```





```
In [14]: #####
          ##### INSERT YOUR CODE HERE #####
          #####
```

```

# Hint: you can use test_rbm function the your best model
# found in the demo.
# use rbm model trained with the PCD-15 algorithm from the demo
rbm = rbmPCD15

# then play with n_clamps and place for clamping
# perform and visualize the results with the functions given

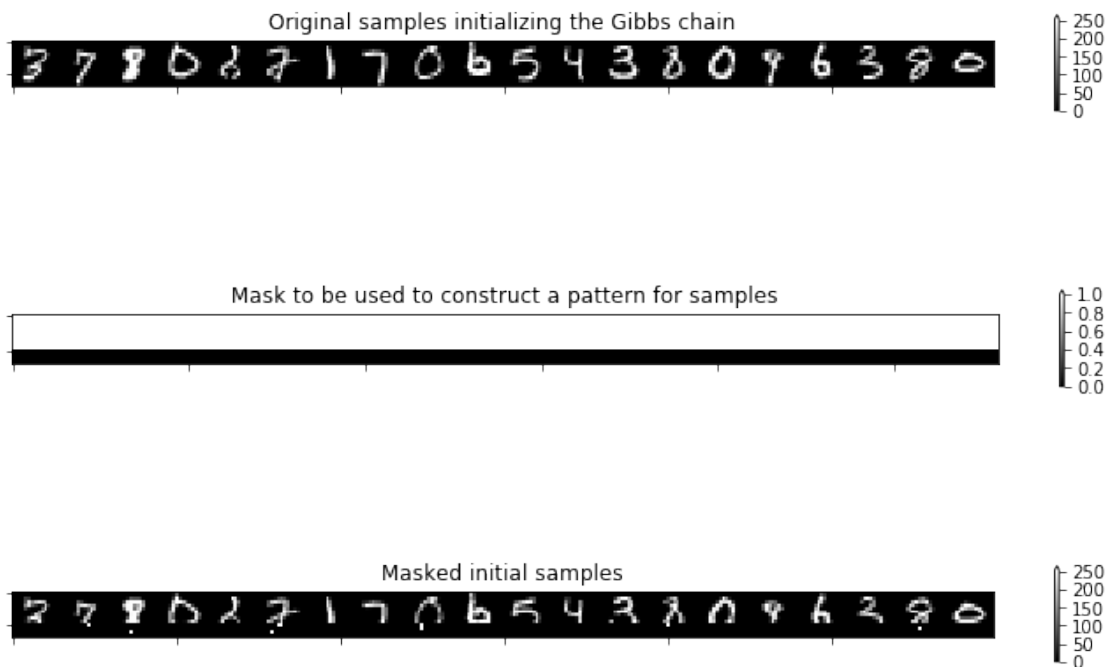
n_clamps = 10
place = 'top'
original_samples, sample_mean_fields, clamping_mask, clamped_samples = test_rbm(rbm, 1,
n_chains, n_samples,
n_Gibbs_steps,
plot_every, n_clamps,
place=place)

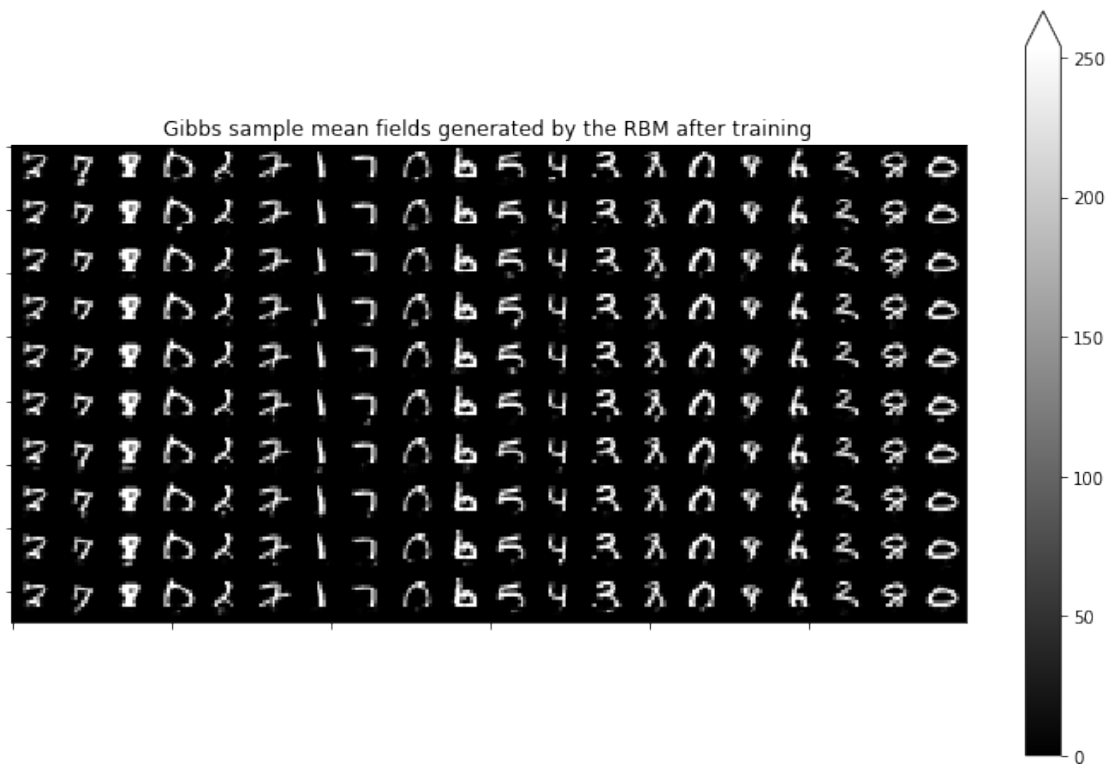
plot_row(original_samples, 'Original samples initializing the Gibbs chain')
plot_mask(clamping_mask, n_chains, 'Mask to be used to construct a pattern for samples')
plot_row(clamped_samples, 'Masked initial samples')
plot_image(sample_mean_fields,
            'Gibbs sample mean fields generated by the RBM after training')

#####
##### END #####
#####

```

... plotting sample 9





```
In [15]: #####
##### INSERT YOUR CODE HERE #####
#####
```

```
# Hint: you can use test_rbm function the your best model
# found in the demo.
# use rbm model trained with the PCD-15 algorithm from the demo
rbm = rbmPCD15
```

```
# then play with n_clamps and place for clamping
# perform and visualize the results with the functions given
```

```
n_clamps = 14
place = 'top'
```

```
original_samples, sample_mean_fields, clamping_mask, clamped_samples = test_rbm(rbm,
n_chains, n_samples,
n_Gibbs_steps,
plot_every, n_clamps,
place=place)
plot_row(original_samples, 'Original samples initializing the Gibbs chain')
```

```

plot_mask(clamping_mask, n_chains, 'Mask to be used to construct a pattern for samples')
plot_row(clamped_samples, 'Masked initial samples')
plot_image(sample_mean_fields,
            'Gibbs sample mean fields generated by the RBM after training')

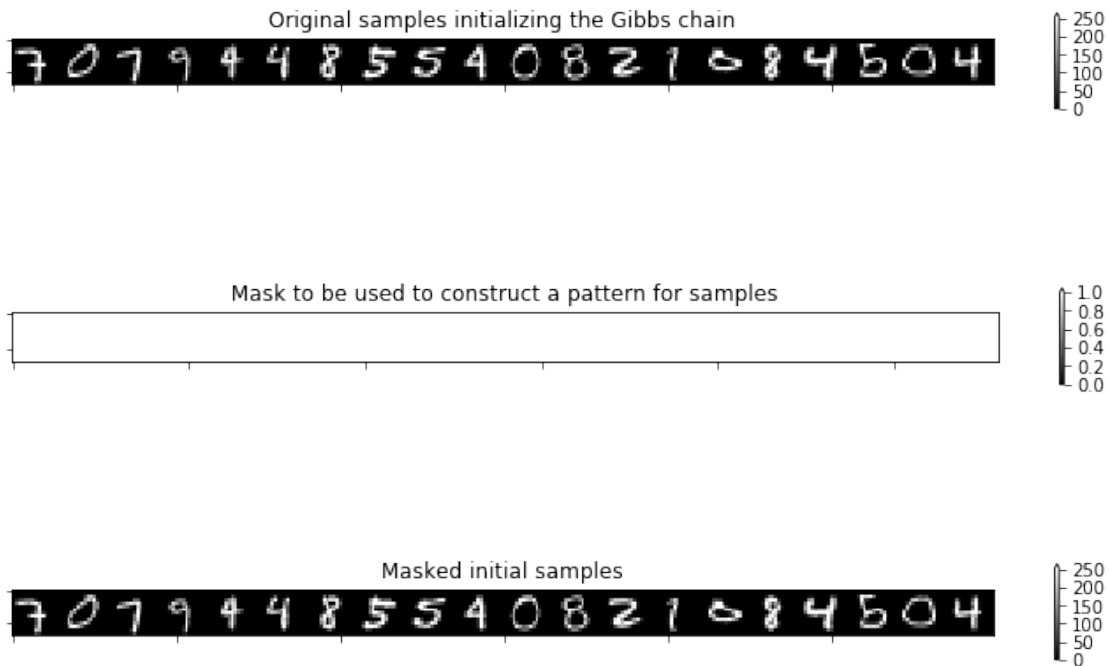
```

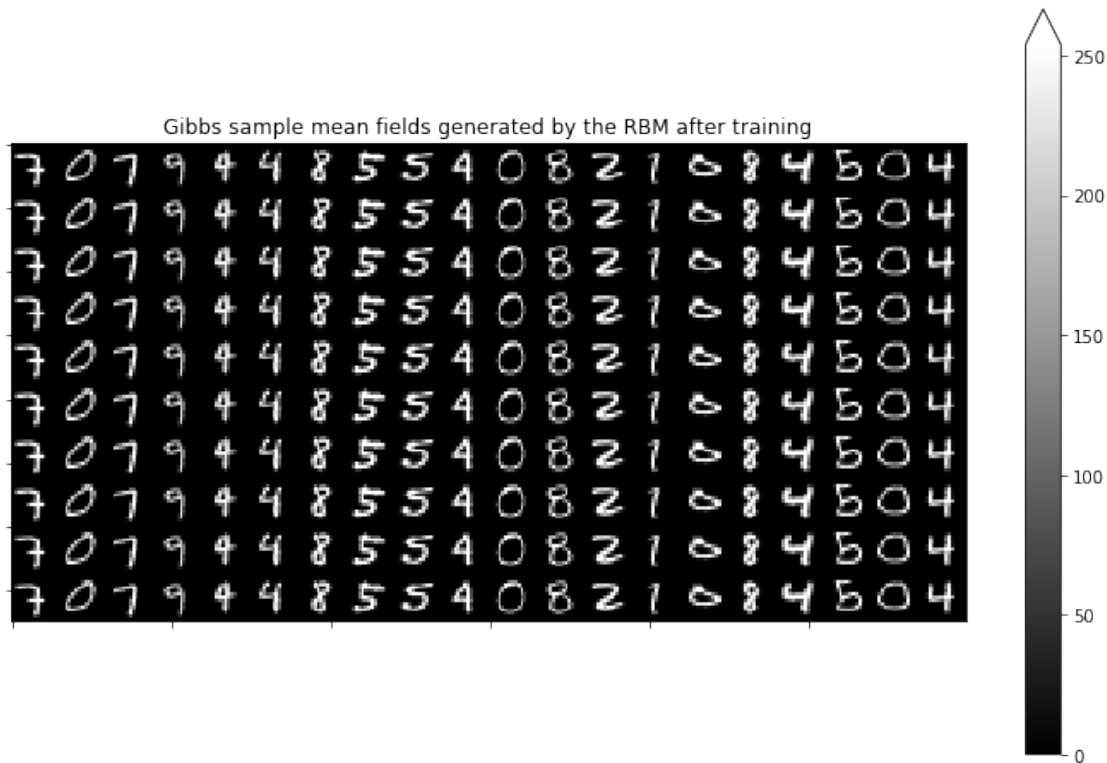
```

#####
##### END #####
#####

```

... plotting sample 9





```
In [16]: #####
##### INSERT YOUR CODE HERE #####
#####

# Hint: you can use test_rbm function the your best model
# found in the demo.
# use rbm model trained with the PCD-15 algorithm from the demo
rbm = rbmPCD15

# then play with n_clamps and place for clamping
# perform and visualize the results with the functions given

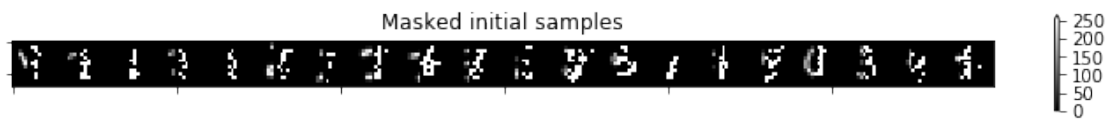
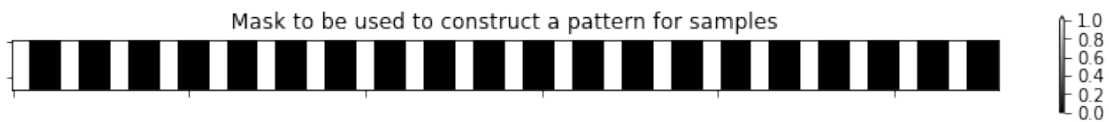
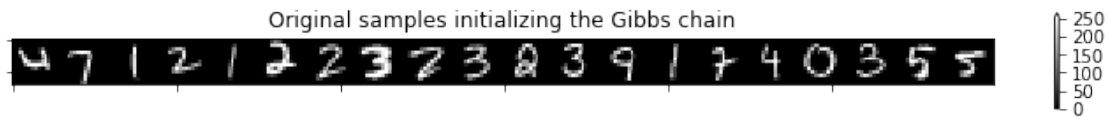
n_clamps = 5
place = 'left'
original_samples, sample_mean_fields, clamping_mask, clamped_samples = test_rbm(rbm,
n_chains, n_samples,
n_Gibbs_steps,
plot_every, n_clamps,
place=place)

plot_row(original_samples, 'Original samples initializing the Gibbs chain')
plot_mask(clamping_mask, n_chains, 'Mask to be used to construct a pattern for samples')
plot_row(clamped_samples, 'Masked initial samples')
```

```
plot_image(sample_mean_fields,
            'Gibbs sample mean fields generated by the RBM after training')
```

```
#####
##### END #####
#####
```

... plotting sample 9







```
In [17]: #####
##### INSERT YOUR CODE HERE #####
#####

# Hint: you can use test_rbm function the your best model
# found in the demo.
# use rbm model trained with the PCD-15 algorithm from the demo
rbm = rbmPCD15

# then play with n_clamps and place for clamping
# perform and visualize the results with the functions given

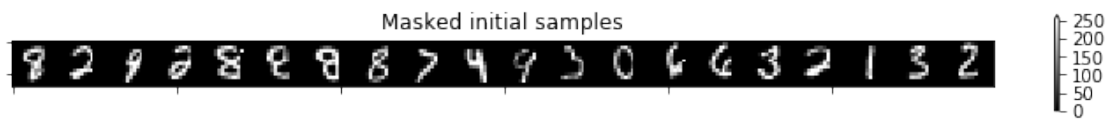
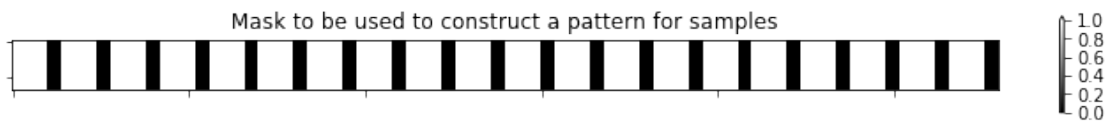
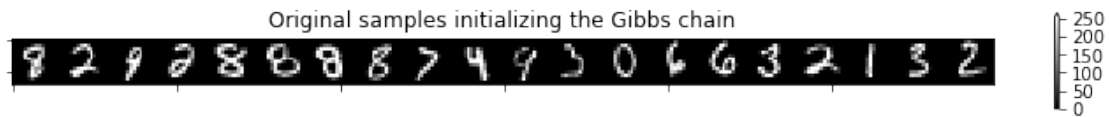
n_clamps = 10
place = 'left'
original_samples, sample_mean_fields, clamping_mask, clamped_samples = test_rbm(rbm,
n_chains, n_samples,
n_Gibbs_steps,
plot_every, n_clamps,
place=place)

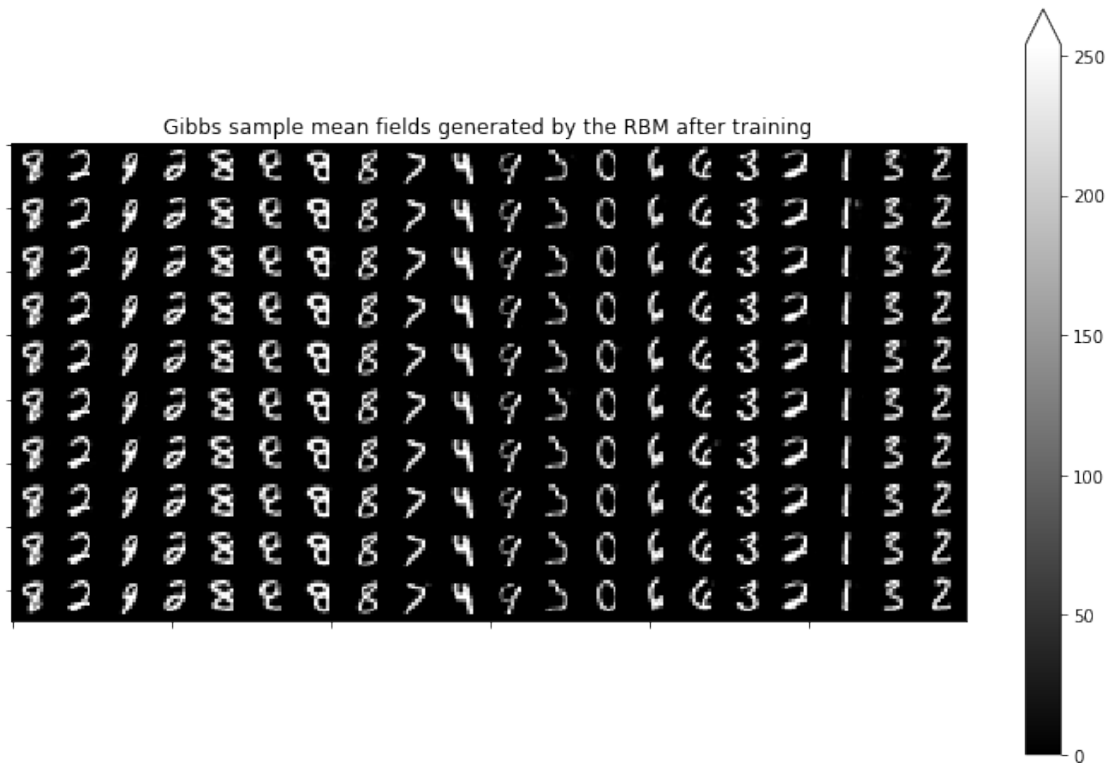
plot_row(original_samples, 'Original samples initializing the Gibbs chain')
plot_mask(clamping_mask, n_chains, 'Mask to be used to construct a pattern for samples')
plot_row(clamped_samples, 'Masked initial samples')
```

```
plot_image(sample_mean_fields,
           'Gibbs sample mean fields generated by the RBM after training')
```

```
#####
##### END #####
#####
```

... plotting sample 9





```
In [18]: #####
##### INSERT YOUR CODE HERE #####
#####

# Hint: you can use test_rbm function the your best model
# found in the demo.
# use rbm model trained with the PCD-15 algorithm from the demo
rbm = rbmPCD15

# then play with n_clamps and place for clamping
# perform and visualize the results with the functions given

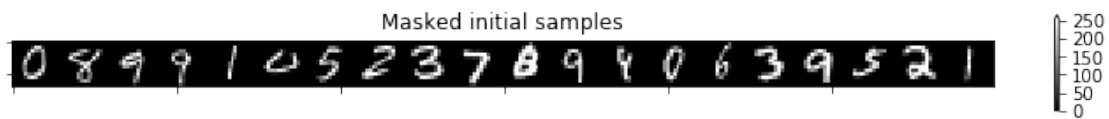
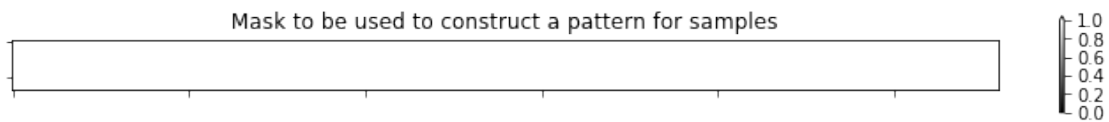
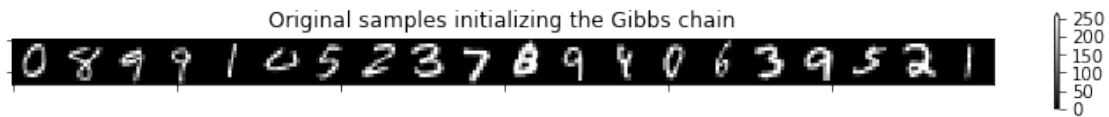
n_clamps = 14
place = 'left'
original_samples, sample_mean_fields, clamping_mask, clamped_samples = test_rbm(rbm,
n_chains, n_samples,
n_Gibbs_steps,
plot_every, n_clamps,
place=place)

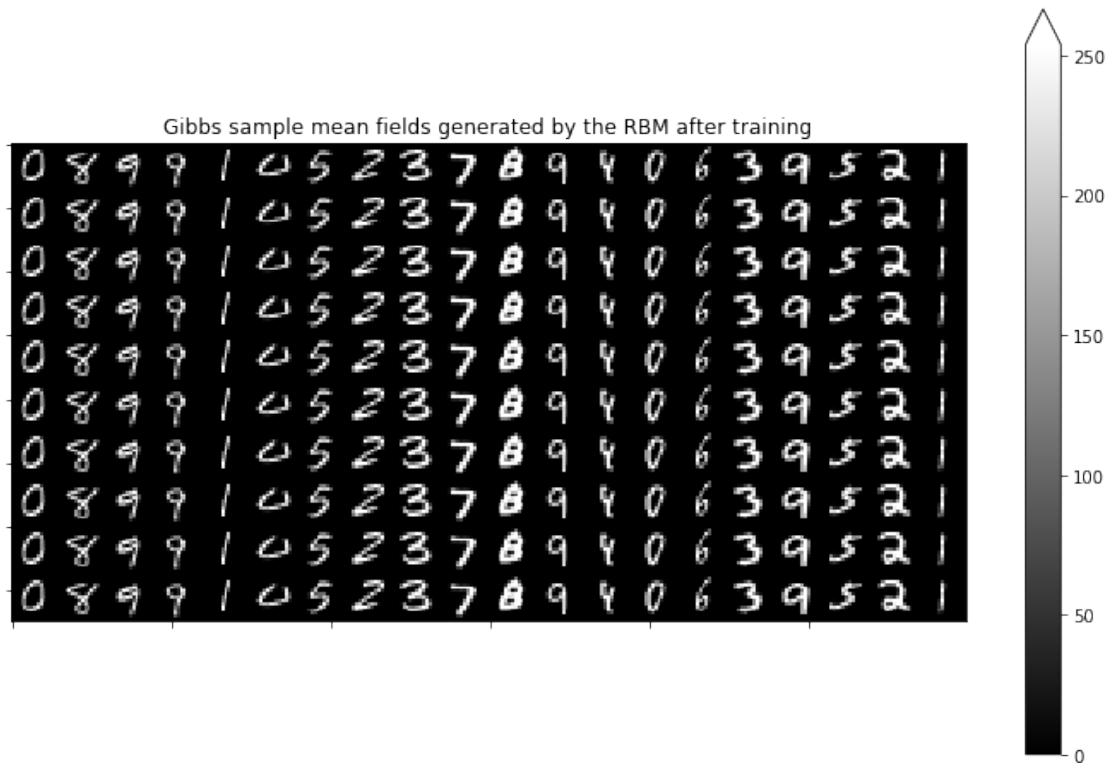
plot_row(original_samples, 'Original samples initializing the Gibbs chain')
plot_mask(clamping_mask, n_chains, 'Mask to be used to construct a pattern for samples')
plot_row(clamped_samples, 'Masked initial samples')
```

```
plot_image(sample_mean_fields,
           'Gibbs sample mean fields generated by the RBM after training')
```

```
#####
##### END #####
#####
```

... plotting sample 9





**Assignment Part 4:** Now, you will add noise to your masked (clamped) samples initializing the Gibbs chain. You need to fill the section in the `test_rbm( )` function to generate noise with a dimension of training data and sampled from the Bernoulli distribution. After completing the function, choose the clamping method with `n_clamps = 7` and `place = bottom` and experiment with all 3 noise generation methods. What effects did you see on the masked initial samples and the generated mean fields with different noise initialization methods? Comment on the results in the discussion part.

```
In [19]: #####
          ##### INSERT YOUR CODE HERE #####
          #####
          # choose 'bottom' for the masking (clamping) place and set n_clamps to 7 pixels
          n_clamps = 7
          place = 'bottom'

          # set train_data to train_set_x
          # and test_data to test_set_x
          train_data = train_set_x
          test_data = test_set_x

          # initialize noise_init with 'equal_expectation'/'global_expectation'/'local_expectat
          noise_init = 'equal_expectation'
```

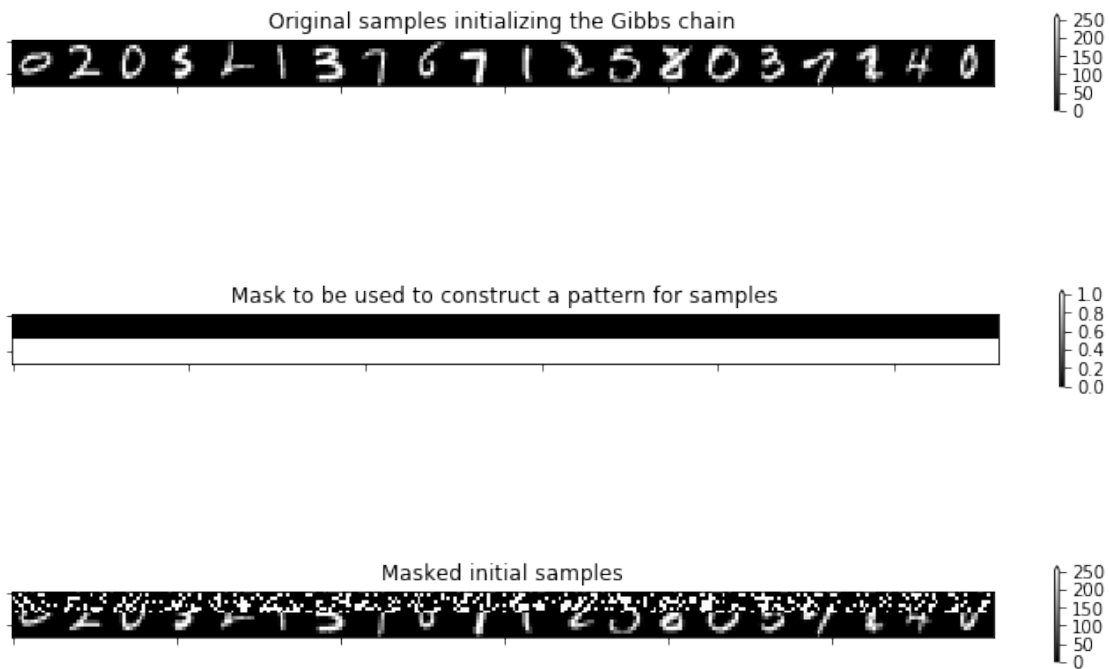
```

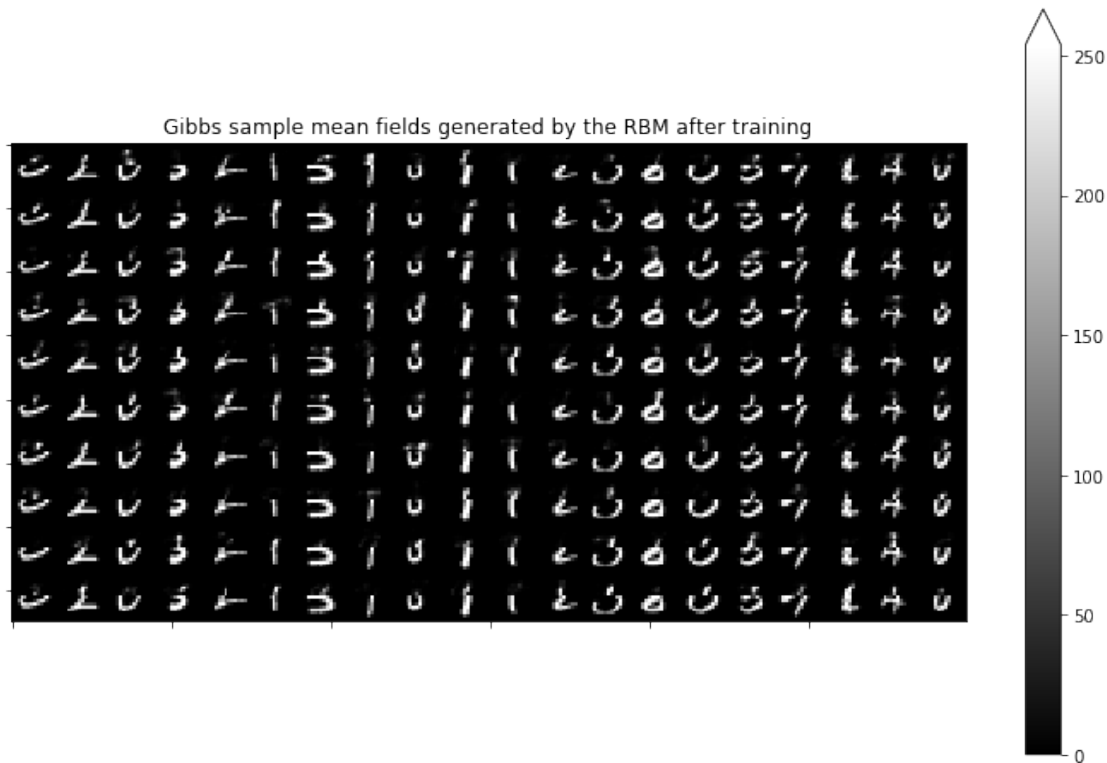
# perform and visualize experiments using test_rbm() function
original_samples, sample_mean_fields, clamping_mask, clamped_samples = test_rbm(rbm, 10000,
n_cha
n_Gibl
n_clar
noise
train

plot_row(original_samples, 'Original samples initializing the Gibbs chain')
plot_mask(clamping_mask, n_chains, 'Mask to be used to construct a pattern for samples')
plot_row(clamped_samples, 'Masked initial samples')
plot_image(sample_mean_fields,
            'Gibbs sample mean fields generated by the RBM after training')

... plotting sample 9

```





```
In [20]: #####
##### INSERT YOUR CODE HERE #####
#####
# choose 'bottom' for the masking (clamping) place and set n_clamps to 7 pixels
n_clamps = 7
place = 'bottom'

# set train_data to train_set_x
# and test_data to test_set_x
train_data = train_set_x
test_data = test_set_x

# initialize noise_init with 'equal_expectation'/'global_expectation'/'local_expectation'
noise_init = 'global_expectation'

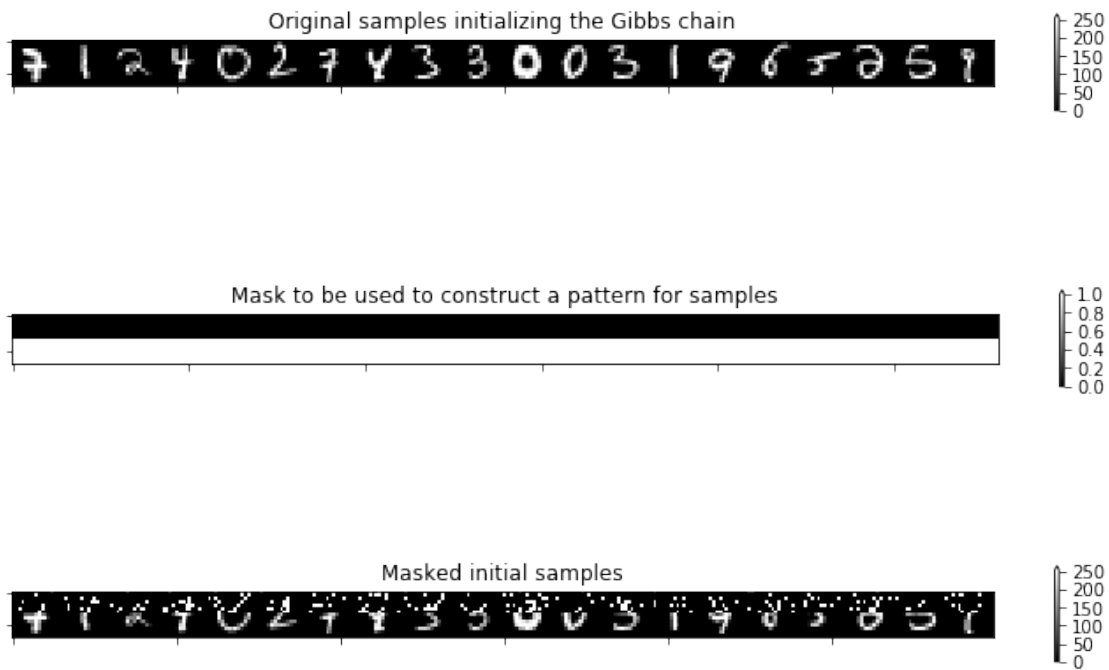
# perform and visualize experiments using test_rbm() function
original_samples, sample_mean_fields, clamping_mask, clamped_samples = test_rbm(rbm, train_data, test_data, n_clamps, noise_init, place)
```

```

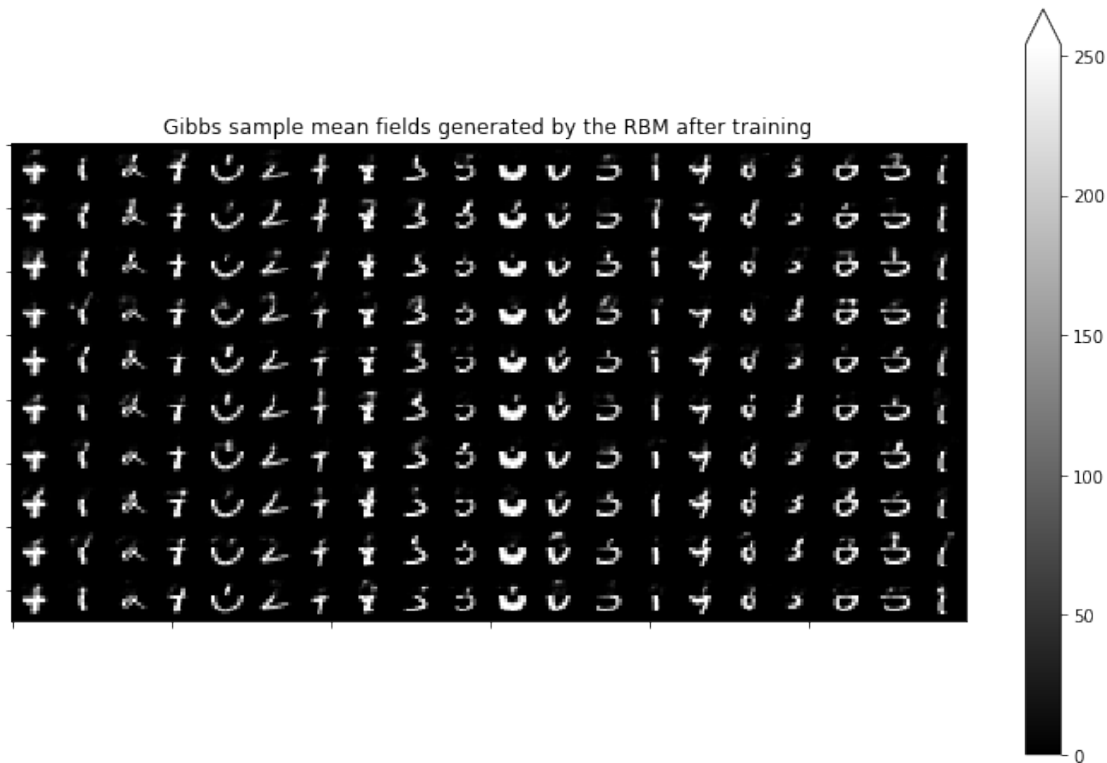
plot_row(original_samples, 'Original samples initializing the Gibbs chain')
plot_mask(clamping_mask, n_chains, 'Mask to be used to construct a pattern for samples')
plot_row(clamped_samples, 'Masked initial samples')
plot_image(sample_mean_fields,
            'Gibbs sample mean fields generated by the RBM after training')

```

... plotting sample 9







```
In [21]: #####
##### INSERT YOUR CODE HERE #####
#####
# choose 'bottom' for the masking (clamping) place and set n_clamps to 7 pixels
n_clamps = 7
place = 'bottom'

# set train_data to train_set_x
# and test_data to test_set_x
train_data = train_set_x
test_data = test_set_x

# initialize noise_init with 'equal_expectation'/'global_expectation'/'local_expectation'
noise_init = 'local_expectation'

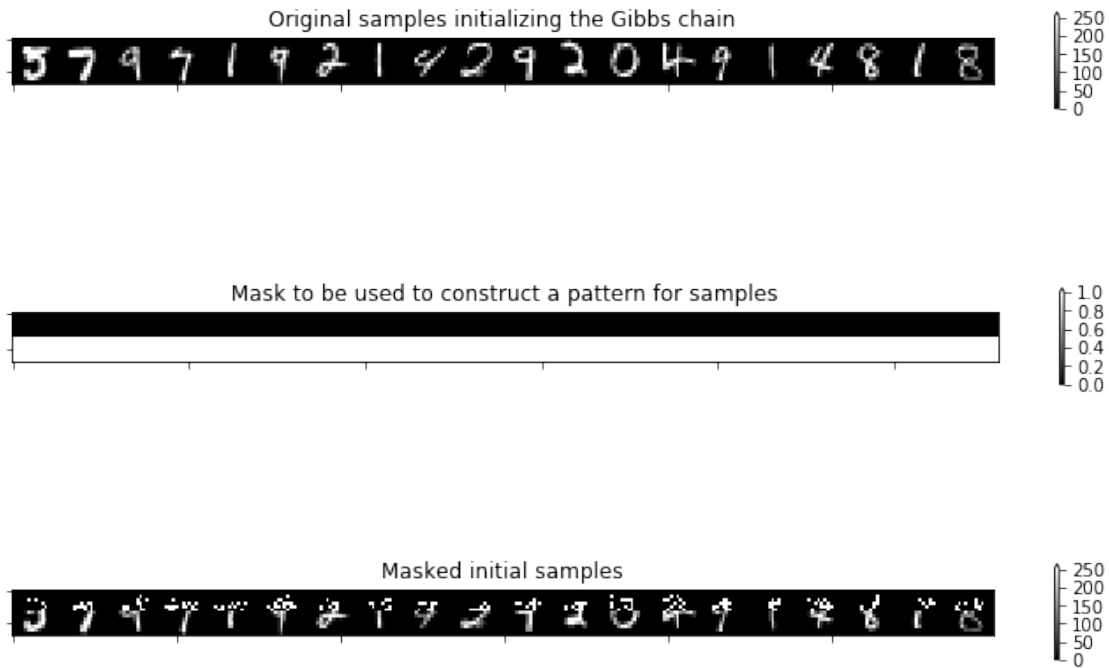
# perform and visualize experiments using test_rbm() function
original_samples, sample_mean_fields, clamping_mask, clamped_samples = test_rbm(rbm, train_data, test_data, n_clamps, noise_init, place)
```

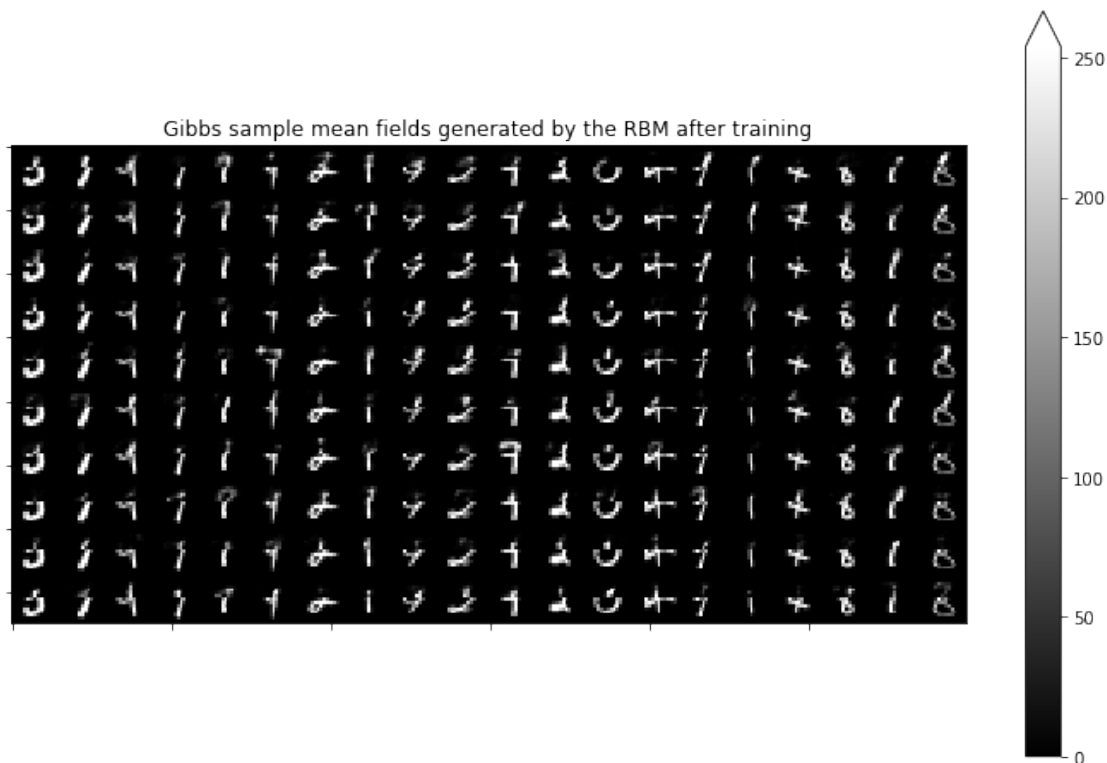
```

plot_row(original_samples, 'Original samples initializing the Gibbs chain')
plot_mask(clamping_mask, n_chains, 'Mask to be used to construct a pattern for samples')
plot_row(clamped_samples, 'Masked initial samples')
plot_image(sample_mean_fields,
            'Gibbs sample mean fields generated by the RBM after training')

```

... plotting sample 9





**Discussion** Replace this text with your discussion based on your experiments with different clamping methods and noise initializations.

The masked parts is the same as the initial parts after training.

Global\_expectation noise makes relatively small effect to the results, while Equal\_expectation makes relatively big effect to the results.

**COPY HERE THE DEFINITION OF *gibbs\_vhv\_clamped()* FROM RBM.py FILE** def gibbs\_vhv\_clamped(self, v0\_mean, v0\_sample, mask):

```
pre_sigmoid_h1, h1_mean, h1_sample = self.sample_h_given_v(v0_sample*(1-mask))

pre_sigmoid_v1, v1_mean, v1_sample = self.sample_v_given_h(h1_sample)

v1_sample_clamped = v1_sample*(1-mask) + v0_sample*mask

v1_mean_clamped = v1_mean*(1-mask) + v0_mean*mask

return [pre_sigmoid_h1, h1_mean, h1_sample,
        pre_sigmoid_v1, v1_mean_clamped, v1_sample_clamped]
```