

Here we visualize filters and outputs using the network architecture proposed by Krizhevsky et al. for ImageNet and implemented in caffe.

(This page follows DeCAF visualizations originally by Yangqing Jia.)

First, import required modules and set plotting parameters

```
In [1]: import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline

# Make sure that caffe is on the python path:
caffe_root = '../' # this file is expected to be in {caffe_root}/examples
import sys
sys.path.insert(0, caffe_root + 'python')

import caffe
import caffe.imagenet

plt.rcParams['figure.figsize'] = (10, 10)
plt.rcParams['image.interpolation'] = 'nearest'
plt.rcParams['image.cmap'] = 'gray'
```

Follow [instructions \(http://caffe.berkeleyvision.org/getting_pretrained_models.html\)](http://caffe.berkeleyvision.org/getting_pretrained_models.html) for getting the pretrained models, load the net and specify test phase and CPU mode.

```
In [2]: net = caffe.imagenet.ImageNetClassifier(caffe_root + 'examples/imagenet/imagenet_deploy.prototxt',
                                                caffe_root + 'examples/imagenet/caffe_reference_imagenet_model')
net.caffenet.set_phase_test()
net.caffenet.set_mode_cpu()
```

Run a classification pass

```
In [3]: scores = net.predict(caffe_root + 'examples/images/lena.png')
```

The layer features and their shapes (10 is the batch size, corresponding to the the ten subcrops used by Krizhevsky et al.)

```
In [4]: [(k, v.data.shape) for k, v in net.caffenet.blobs.items()]
```

```
Out[4]: [('data', (10, 3, 227, 227)),
          ('conv1', (10, 96, 55, 55)),
          ('pool1', (10, 96, 27, 27)),
          ('norm1', (10, 96, 27, 27)),
          ('conv2', (10, 256, 27, 27)),
          ('pool2', (10, 256, 13, 13)),
          ('norm2', (10, 256, 13, 13)),
```

```
( 'conv3', (10, 384, 13, 13)),
( 'conv4', (10, 384, 13, 13)),
( 'conv5', (10, 256, 13, 13)),
( 'pool5', (10, 256, 6, 6)),
( 'fc6', (10, 4096, 1, 1)),
( 'fc7', (10, 4096, 1, 1)),
( 'fc8', (10, 1000, 1, 1)),
( 'prob', (10, 1000, 1, 1))]
```

The parameters and their shapes (each of these layers also has biases which are omitted here)

```
In [5]: [(k, v[0].data.shape) for k, v in net.caffenet.params.items()]
```

```
Out[5]: [('conv1', (96, 3, 11, 11)),
('conv2', (256, 48, 5, 5)),
('conv3', (384, 256, 3, 3)),
('conv4', (384, 192, 3, 3)),
('conv5', (256, 192, 3, 3)),
('fc6', (1, 1, 4096, 9216)),
('fc7', (1, 1, 4096, 4096)),
('fc8', (1, 1, 1000, 4096))]
```

Helper functions for visualization

```
In [6]: # our network takes BGR images, so we need to switch color channels
def showimage(im):
    if im.ndim == 3:
        im = im[:, :, ::-1]
    plt.imshow(im)

# take an array of shape (n, height, width) or (n, height, width, channels)
# and visualize each (height, width) thing in a grid of size approx.
sqrt(n) by sqrt(n)
def vis_square(data, padsize=1, padval=0):
    data -= data.min()
    data /= data.max()

    # force the number of filters to be square
    n = int(np.ceil(np.sqrt(data.shape[0])))
    padding = ((0, n ** 2 - data.shape[0]), (0, padsize), (0, padsize)) + ((0, 0),) * (data.ndim - 3)
    data = np.pad(data, padding, mode='constant', constant_values=(padval, padval))

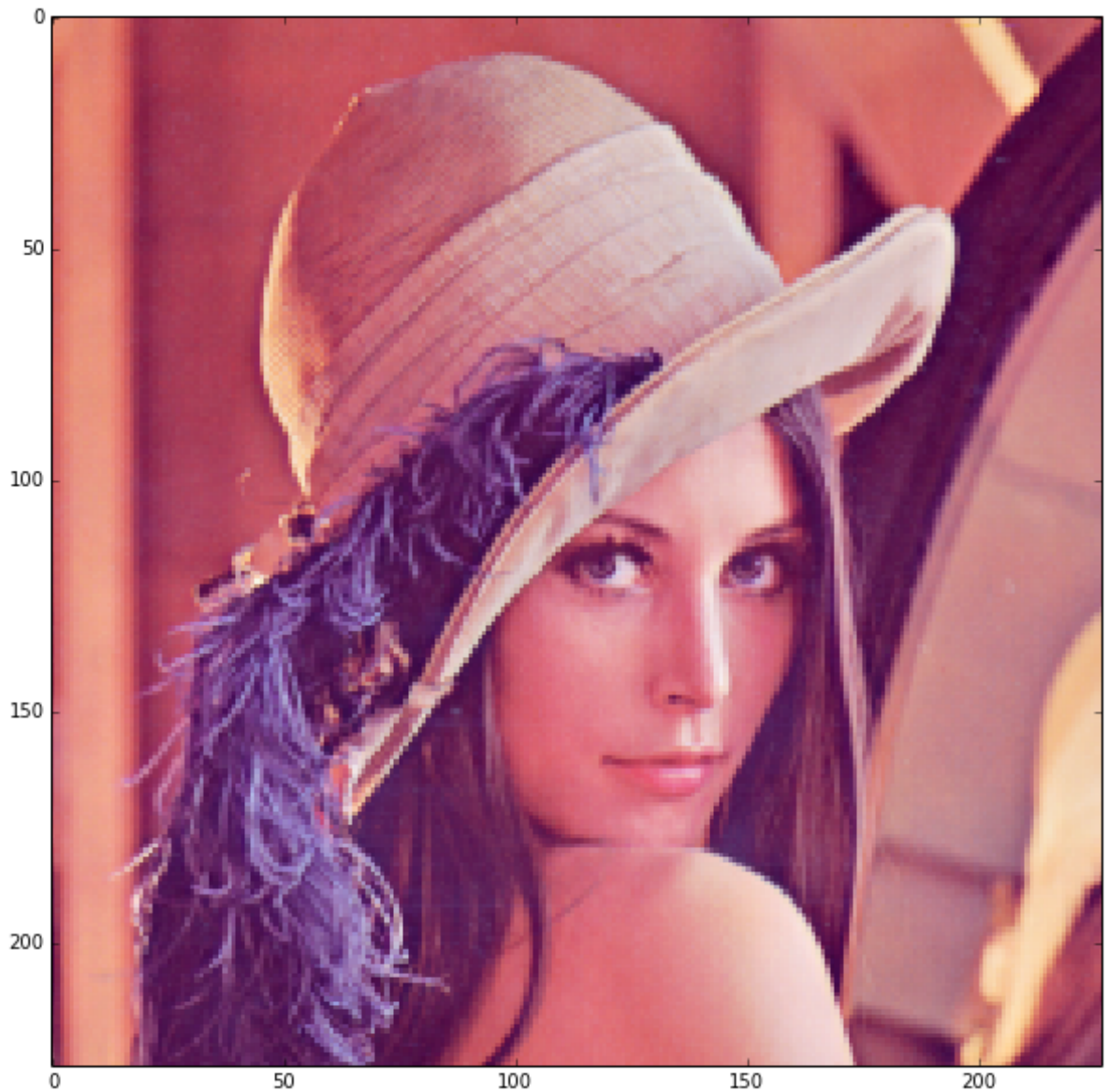
    # tile the filters into an image
    data = data.reshape((n, n) + data.shape[1:]).transpose((0, 2, 1, 3) + tuple(range(4, data.ndim + 1)))
    data = data.reshape((n * data.shape[1], n * data.shape[3]) + data.shape[4:])

    showimage(data)
```

The input image

```
In [7]: # index four is the center crop
```

```
image = net.caffenet.blobs['data'].data[4].copy()
image -= image.min()
image /= image.max()
showimage(image.transpose(1, 2, 0))
```

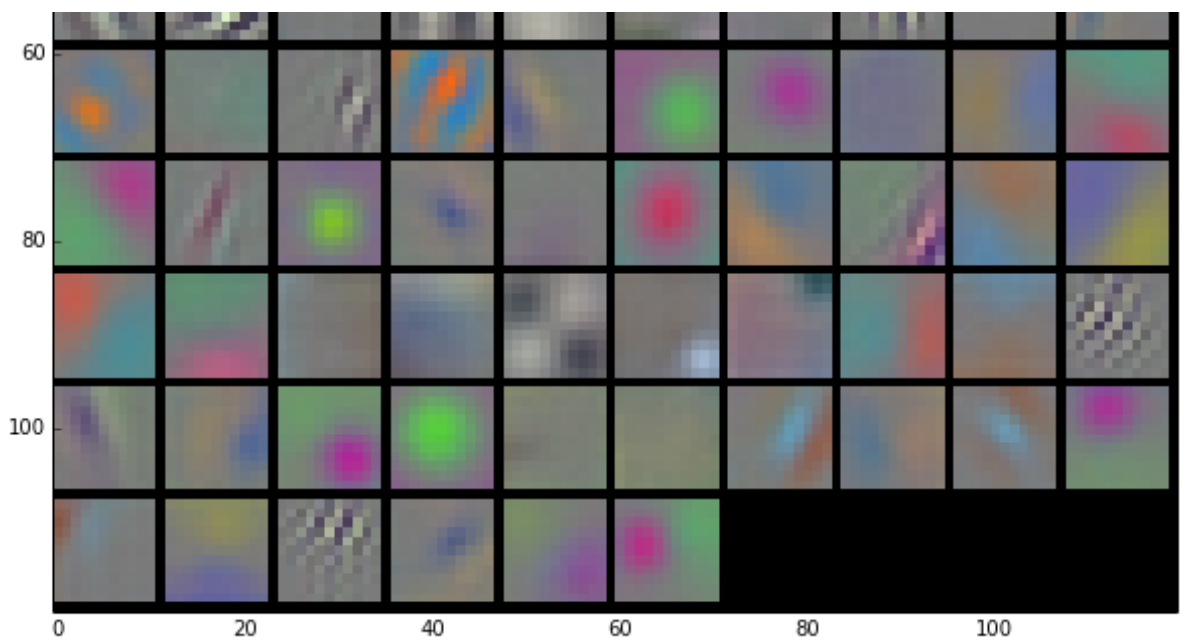


The first layer filters, conv1

In [8]:

```
# the parameters are a list of [weights, biases]
filters = net.caffenet.params['conv1'][0].data
vis_square(filters.transpose(0, 2, 3, 1))
```

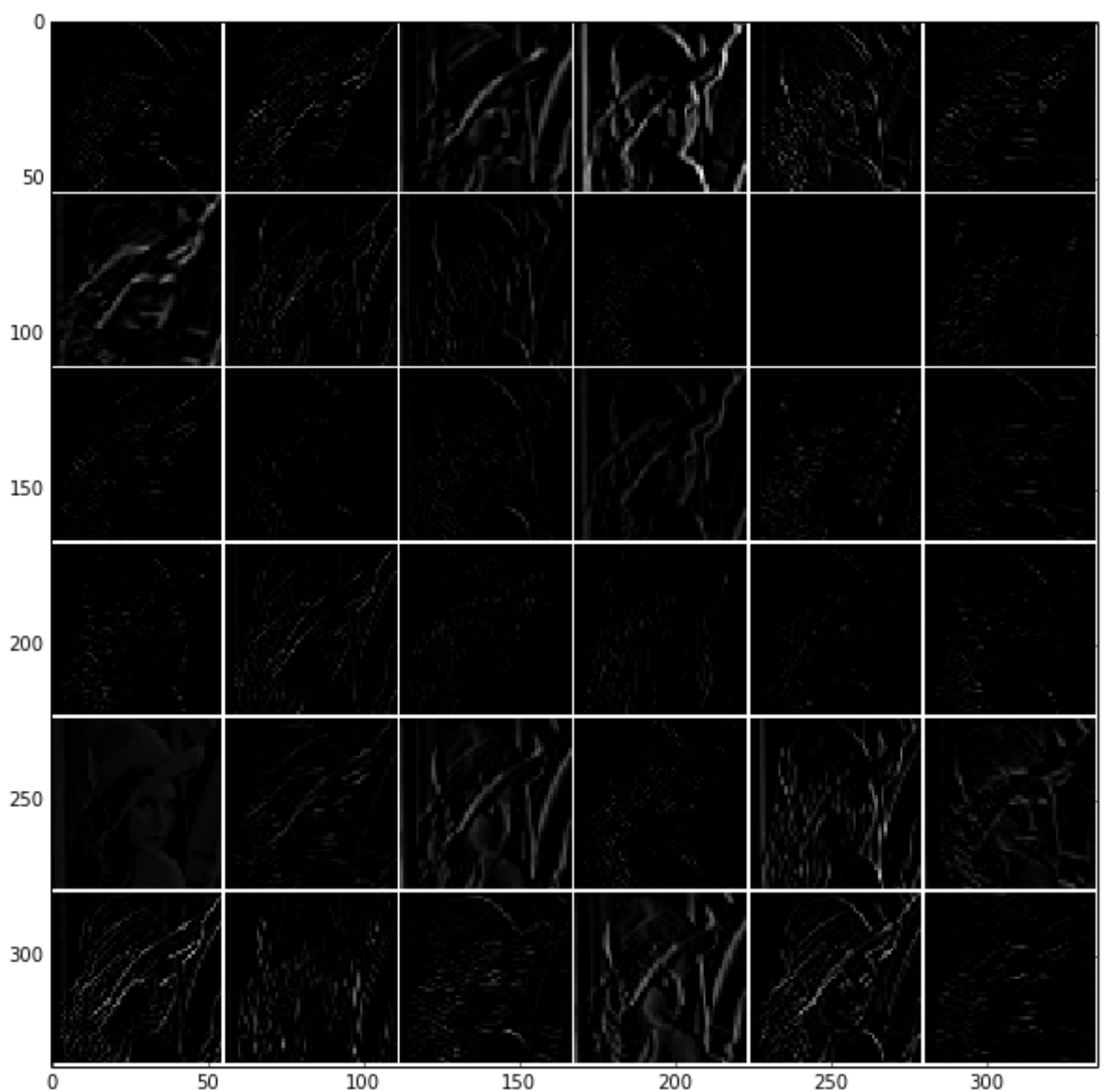




The first layer output, conv1 (rectified responses of the filters above, first 36 only)

In [9]:

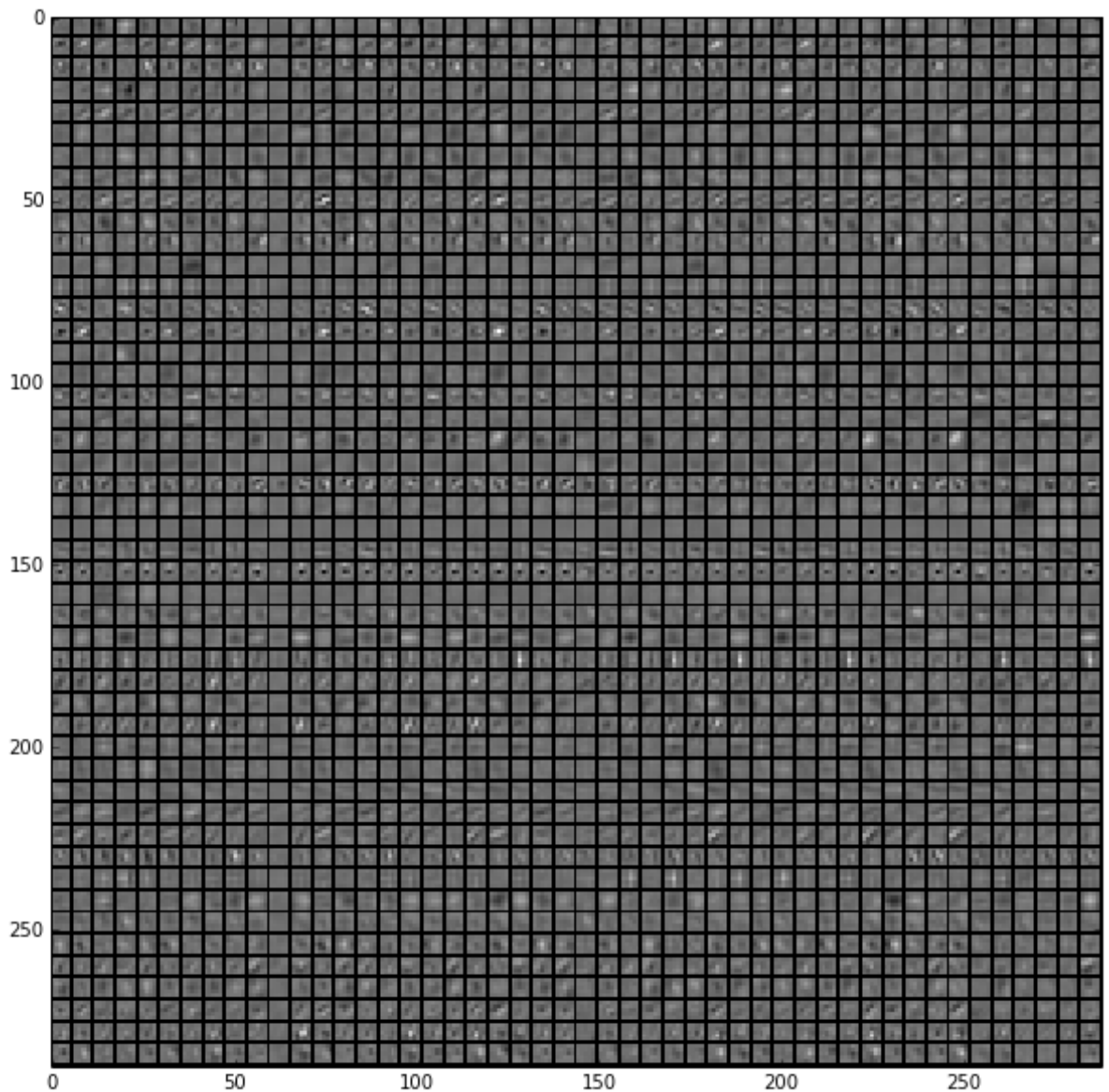
```
feat = net.caffenet.blobs['conv1'].data[4, :36]
vis_square(feat, padval=1)
```



The second layer filters, conv2

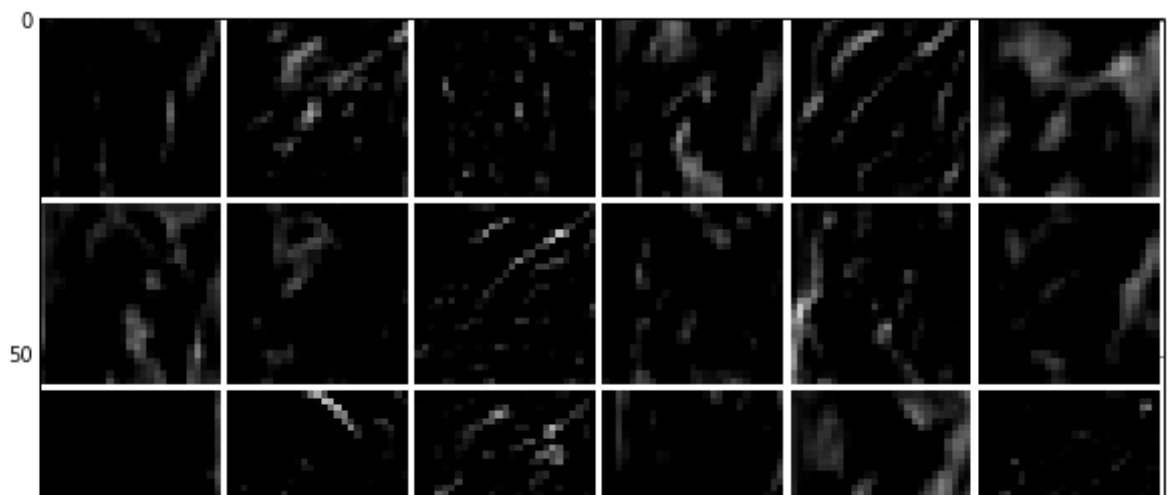
There are 128 filters, each of which has dimension 5 x 5 x 48. We show only the first 48 filters, with each channel shown separately, so that each filter is a row.

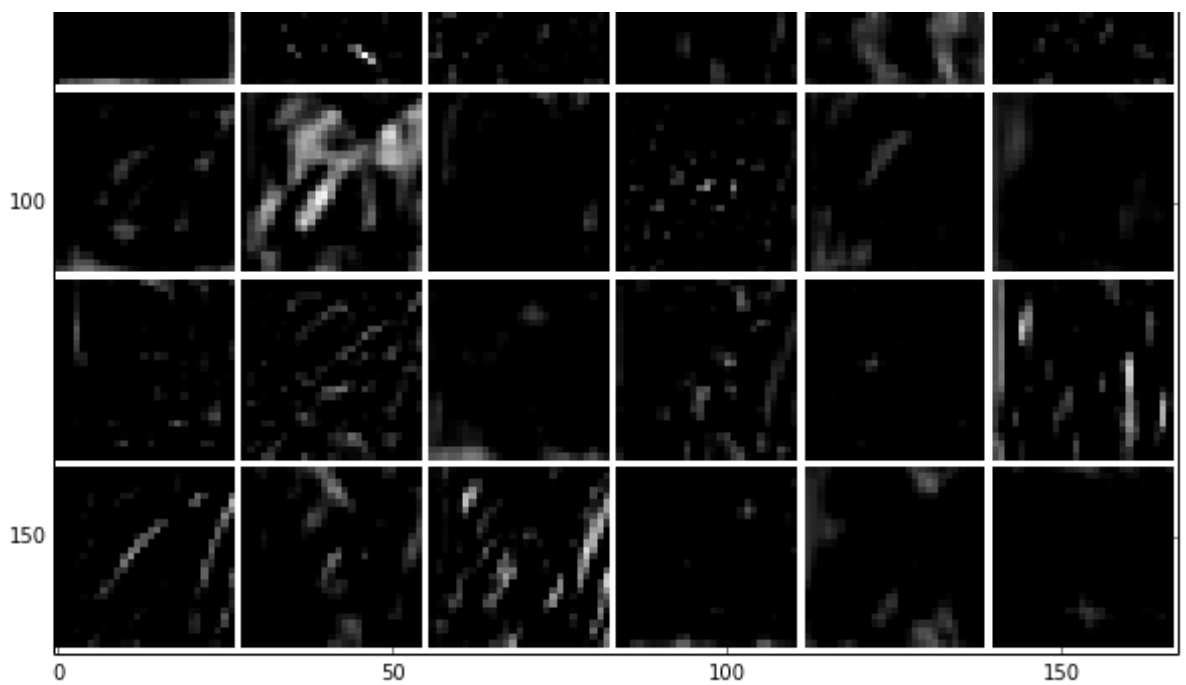
```
In [10]: filters = net.caffenet.params['conv2'][0].data  
vis_square(filters[:48].reshape(48**2, 5, 5))
```



The second layer output, conv2 (rectified, only the first 36 of 256 channels)

```
In [11]: feat = net.caffenet.blobs['conv2'].data[4, :36]  
vis_square(feat, padval=1)
```

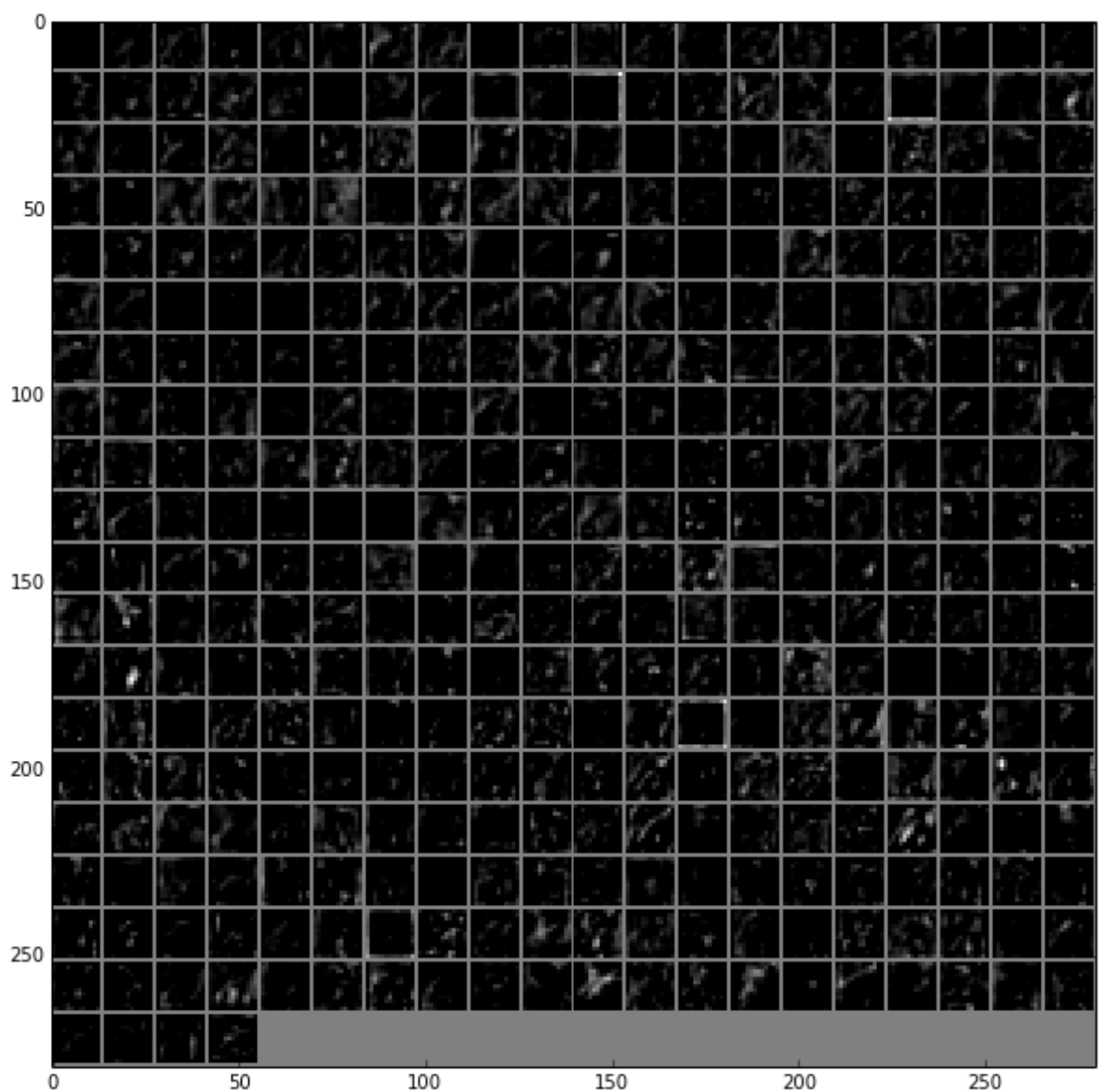




The third layer output, conv3 (rectified, all 384 channels)

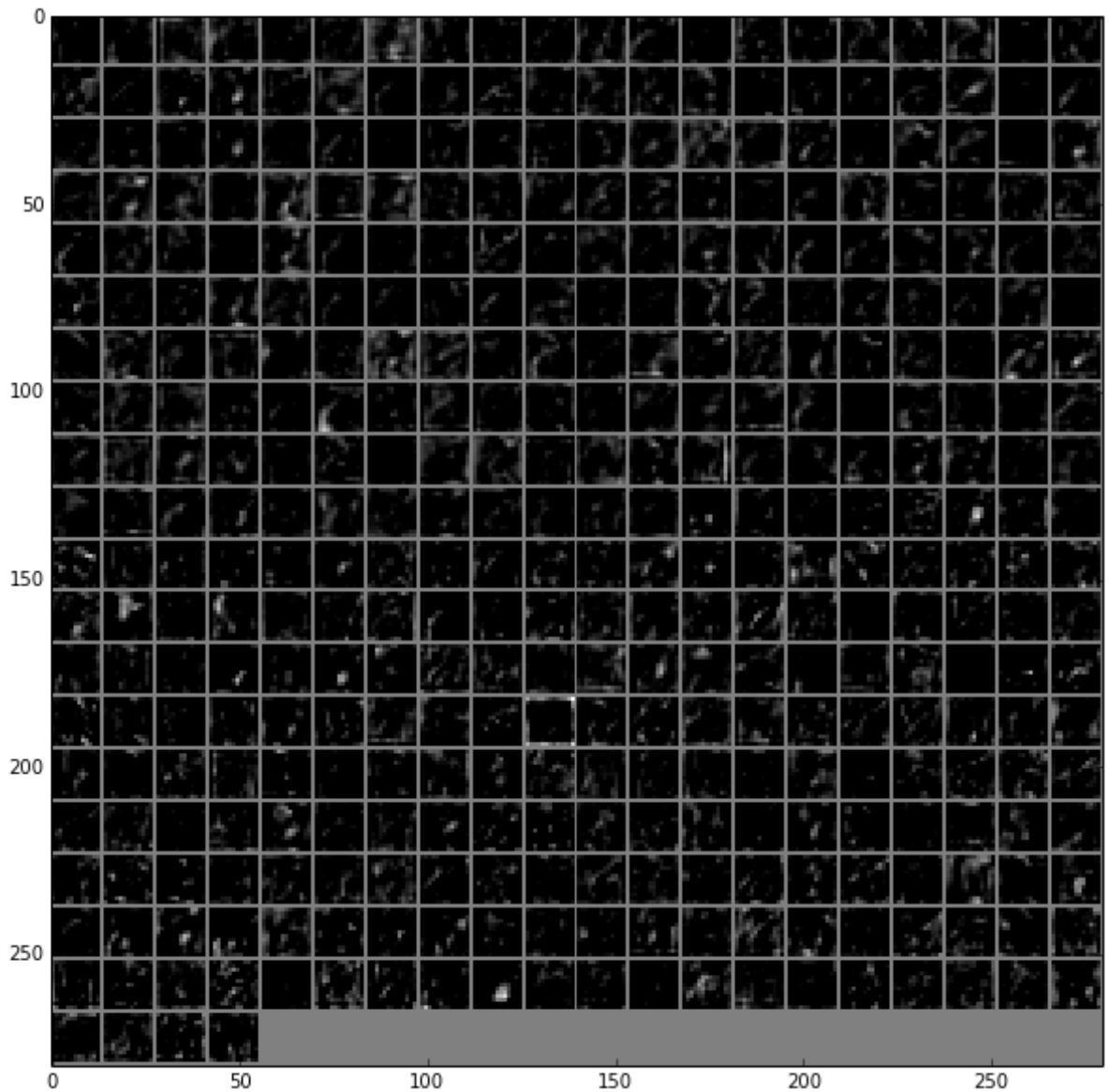
In [12]:

```
feat = net.caffenet.blobs['conv3'].data[4]
vis_square(feat, padval=0.5)
```



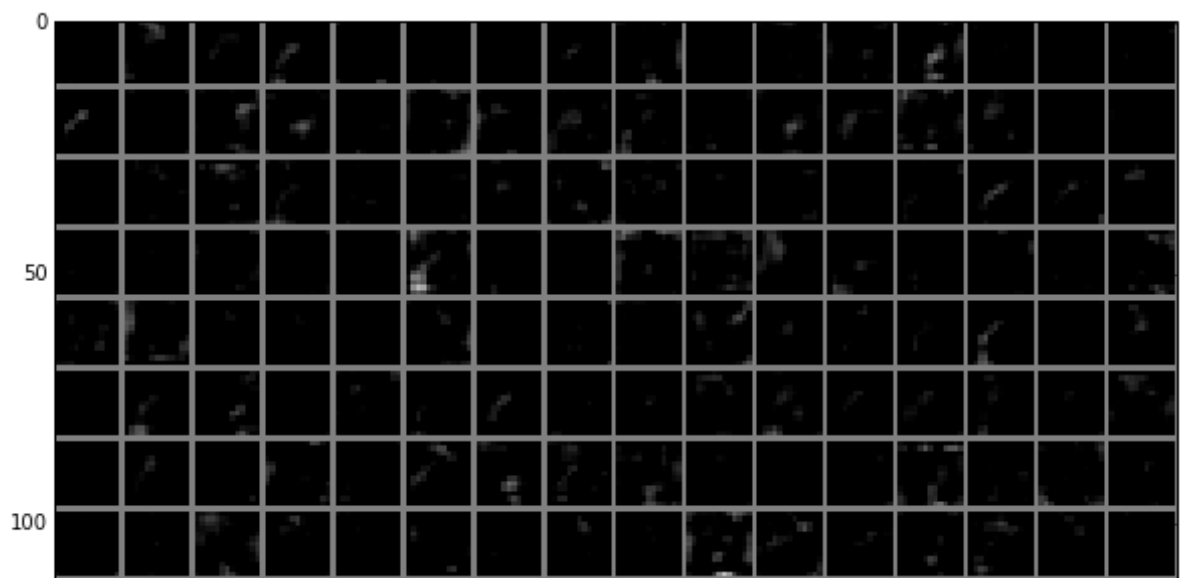
The fourth layer output, conv4 (rectified, all 384 channels)

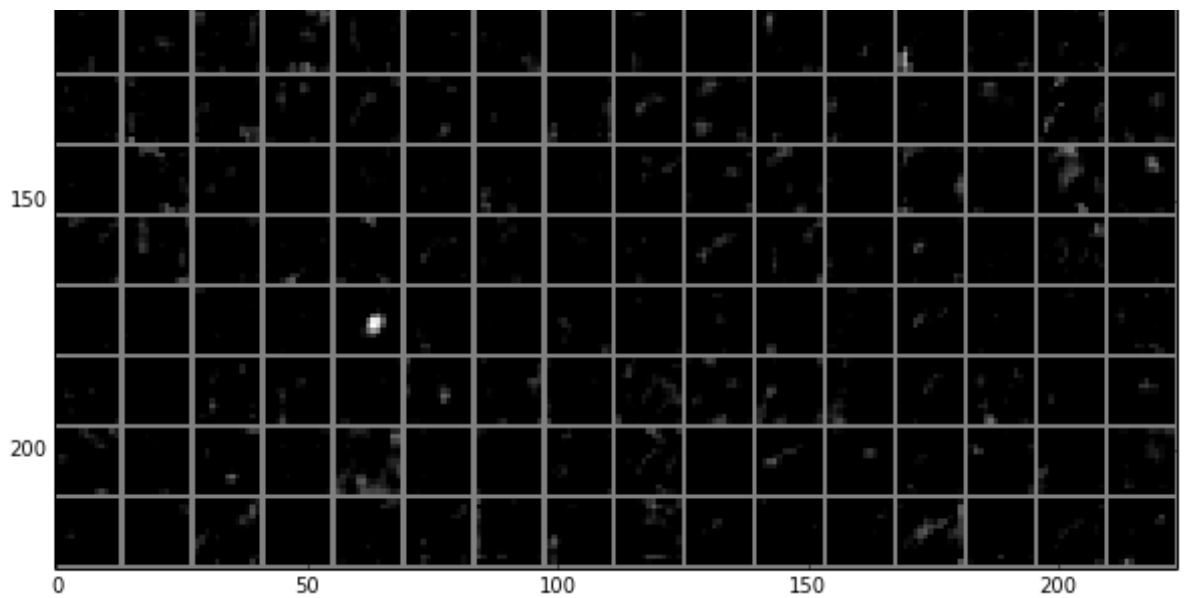
```
In [13]: feat = net.caffenet.blobs['conv4'].data[4]  
vis_square(feat, padval=0.5)
```



The fifth layer output, conv5 (rectified, all 256 channels)

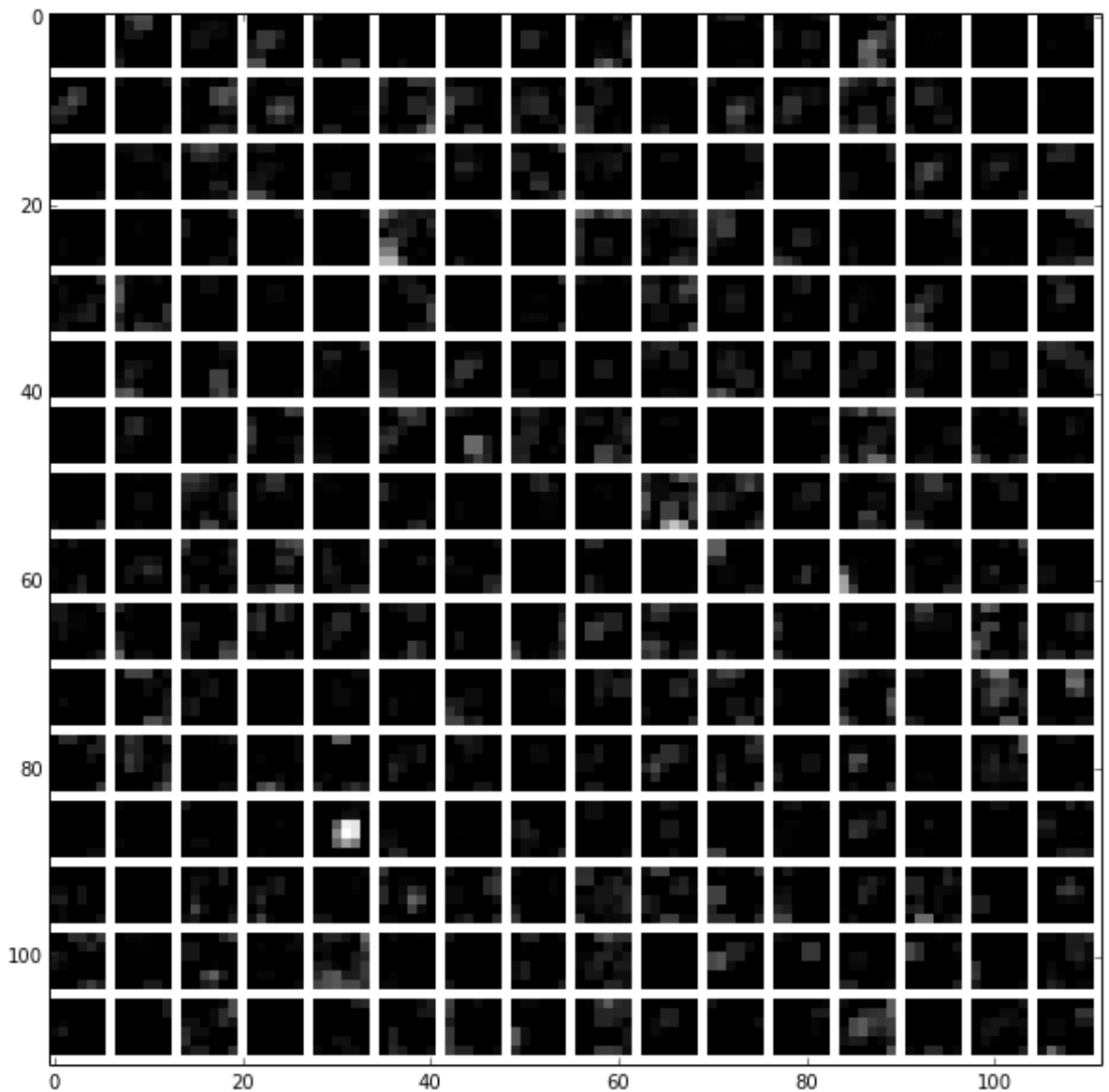
```
In [14]: feat = net.caffenet.blobs['conv5'].data[4]  
vis_square(feat, padval=0.5)
```





The fifth layer after pooling, pool5

```
In [15]: feat = net.caffenet.blobs['pool5'].data[4]
vis_square(feat, padval=1)
```

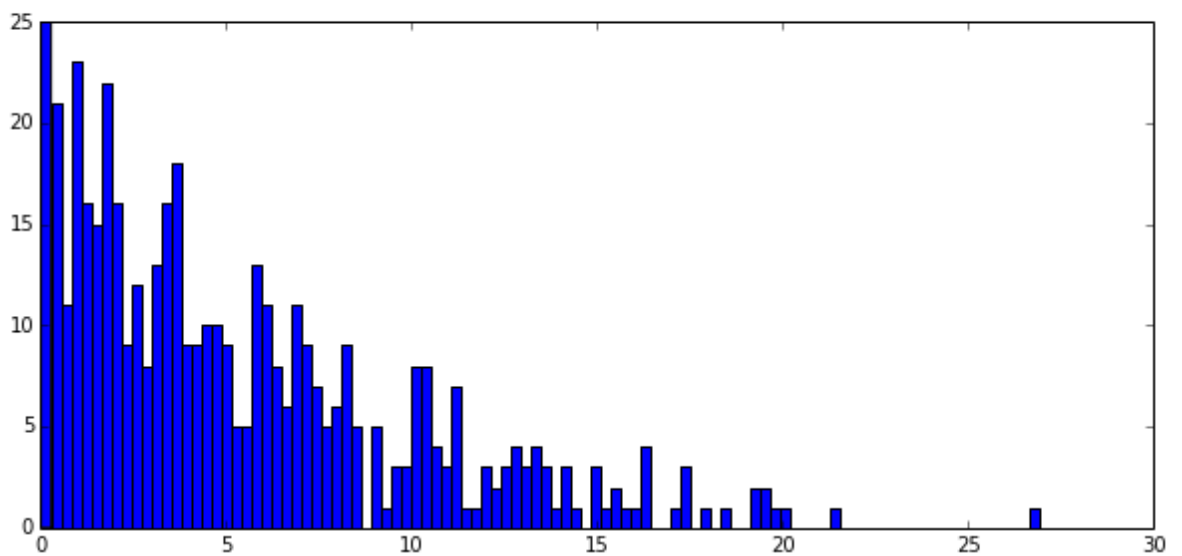
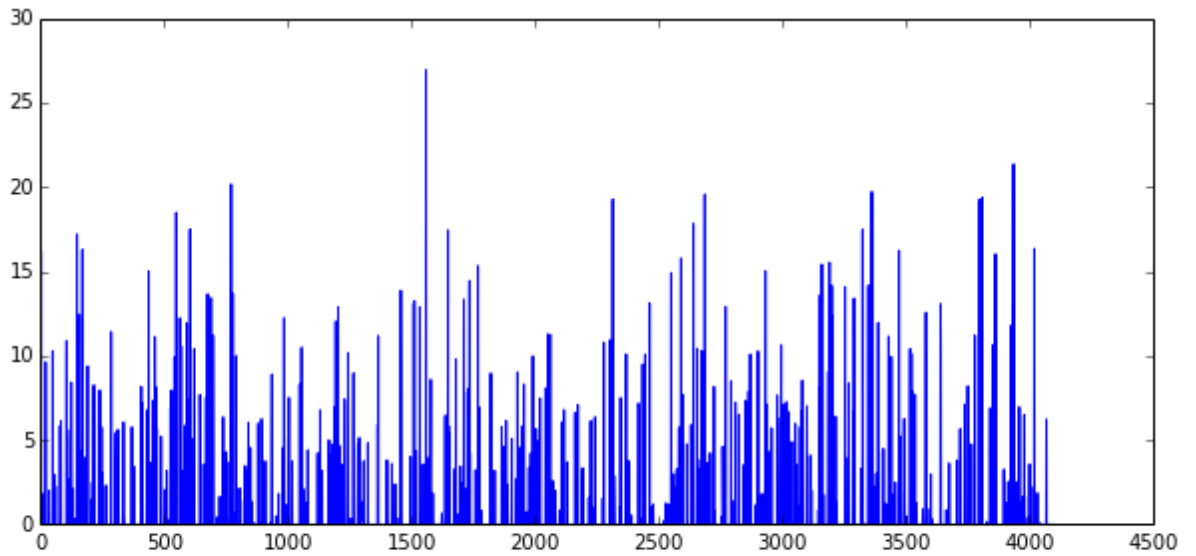


The first fully connected layer, fc6 (rectified)

We show the output values and the histogram of the positive values

In [16]:

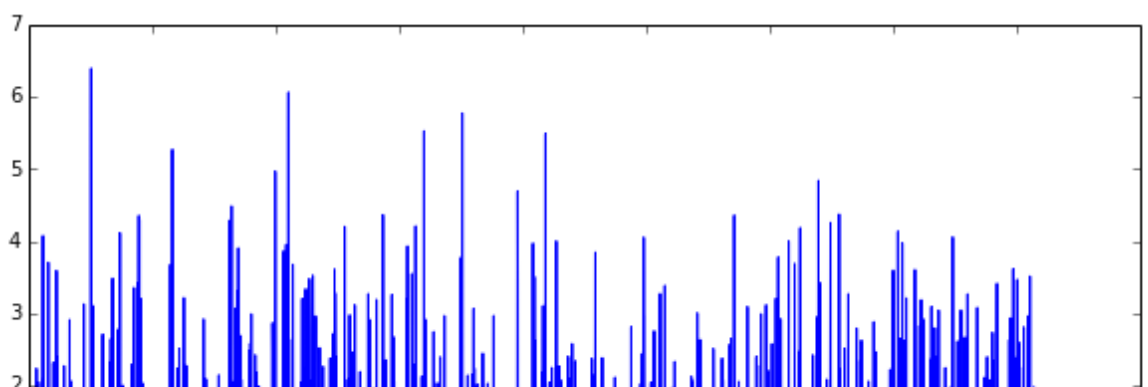
```
feat = net.caffenet.blobs['fc6'].data[4]
plt.subplot(2, 1, 1)
plt.plot(feat.flat)
plt.subplot(2, 1, 2)
_ = plt.hist(feat.flat[feat.flat > 0], bins=100)
```

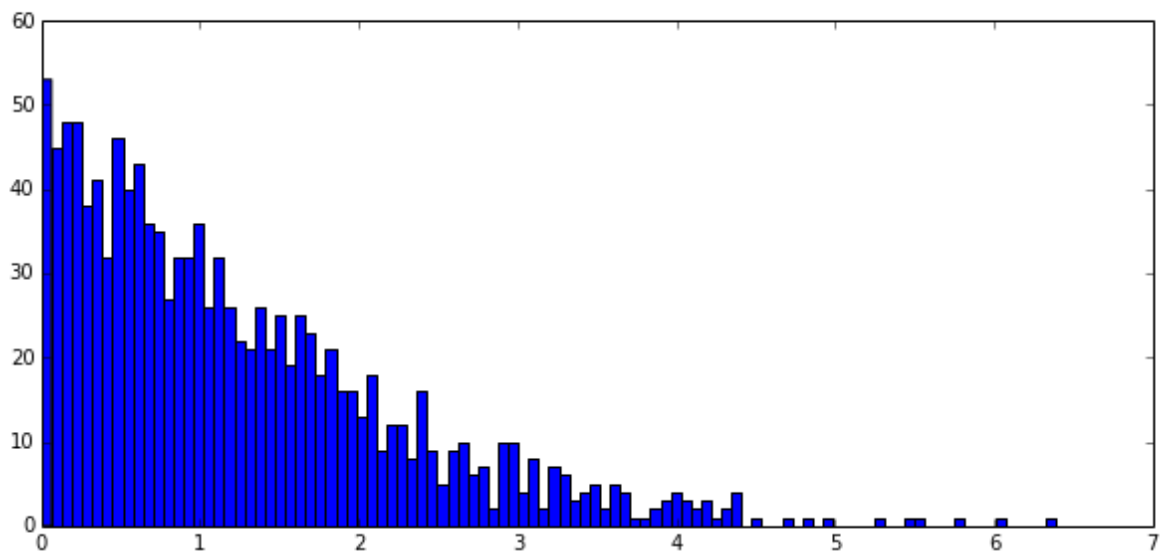
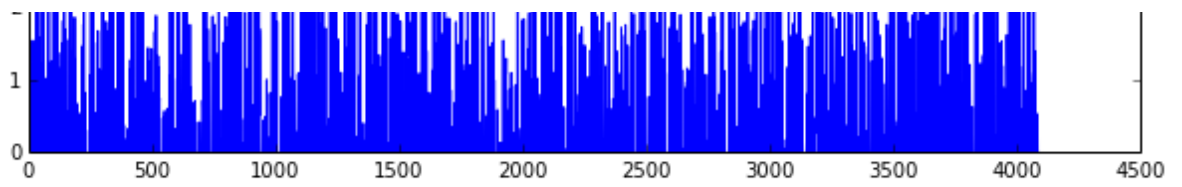


The second fully connected layer, fc7 (rectified)

In [17]:

```
feat = net.caffenet.blobs['fc7'].data[4]
plt.subplot(2, 1, 1)
plt.plot(feat.flat)
plt.subplot(2, 1, 2)
_ = plt.hist(feat.flat[feat.flat > 0], bins=100)
```

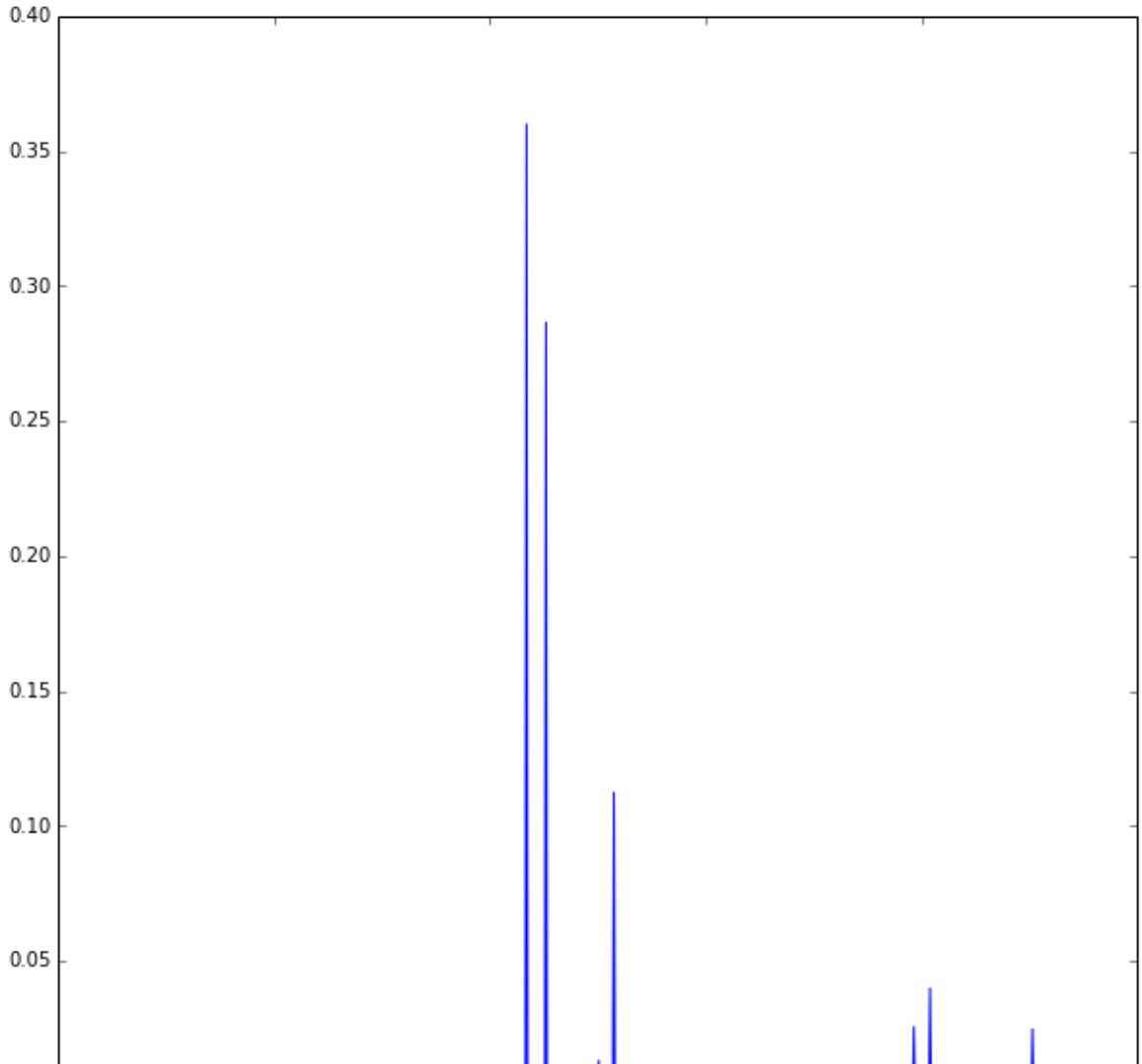


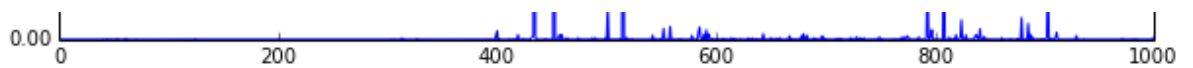


The final probability output, prob

```
In [18]: feat = net.caffenet.blobs['prob'].data[4]
plt.plot(feat.flat)
```

```
Out[18]: [<matplotlib.lines.Line2D at 0x13617f250>]
```





Let's see the top 5 predicted labels.

```
In [19]: imagenet_labels_filename = caffe_root + 'data/ilsvrc12/synset_words.txt'
try:
    labels = np.loadtxt(imagenet_labels_filename, str, delimiter='\t')
except:
    !../data/ilsvrc12/get_ilsvrc_aux.sh
    labels = np.loadtxt(imagenet_labels_filename, str, delimiter='\t')
)
```

```
In [20]: top_k = net.caffenet.blobs['prob'].data[4].flatten().argsort()[-1:-6:-1]
print labels[top_k]

['n02808304 bath towel' 'n02869837 bonnet, poke bonnet'
'n03124170 cowboy hat, ten-gallon hat' 'n04259630 sombrero'
'n04209133 shower cap']
```

Funnily enough, ImageNet does not include portraits as a category, so the classifier is quite bad at classifying images as containing people.