Convolutional Networks

We have talked about convolutional neural networks. We will implement convolutional operations and max-pooling operation in this task to get a deeper understanding of the network.

In [7]:
```
# As usual, a bit of setup
import numpy as np
import tensorflow as tf
import matplotlib.pyplot as plt
from implementations.layers import *
from data_utils import get_CIFAR10_data

%matplotlib inline
plt.rcParams['figure.figsize'] = (10.0, 8.0) # set default size of plots
plt.rcParams['image.interpolation'] = 'nearest'
plt.rcParams['image.cmap'] = 'gray'

# for auto-reloading external modules
# see http://stackoverflow.com/questions/1907993/autoreload-of-modules-in-i
%load_ext autoreload
%autoreload 2

def rel_error(x, y):
  """ returns relative error """
  return np.max(np.abs(x - y) / (np.maximum(1e-8, np.abs(x) + np.abs(y))))
```

```
The autoreload extension is already loaded. To reload it, use:
  %reload_ext autoreload
```

In [8]:
```
# Load the (preprocessed) CIFAR10 data.

data = get_CIFAR10_data()
for k, v in data.items():
  print('%s: ' % k, v.shape)
```

```
X_train:  (49000, 3, 32, 32)
y_train:  (49000,)
X_val:  (1000, 3, 32, 32)
y_val:  (1000,)
X_test:  (1000, 3, 32, 32)
y_test:  (1000,)
```

Convolution Operation

We will implement a convolutional operation with numpy and compare it against an existing convolutional operation.

In [2]:
```
# shape is NCHW
x_shape = (2, 3, 4, 4)

# shape is FCHW
w_shape = (3, 3, 4, 4)

x = np.linspace(-0.1, 0.5, num=np.prod(x_shape)).reshape(x_shape)
w = np.linspace(-0.2, 0.3, num=np.prod(w_shape)).reshape(w_shape)
b = np.linspace(-0.1, 0.2, num=3)
print(x.shape)
print(w.shape)
print(b.shape)
# permute dimensions to NHWC
x = np.transpose(x, [0, 2, 3, 1])
# permute dimensions to HWCF
w = np.transpose(w, [2, 3, 1, 0])

conv_param = {'stride': 2, 'pad': 1}

correct_out = np.array([[[[-0.08759809, -0.10987781],
                           [-0.18387192, -0.2109216 ]],
                          [[ 0.21027089,  0.21661097],
                           [ 0.22847626,  0.23004637]],
                          [[ 0.50813986,  0.54309974],
                           [ 0.64082444,  0.67101435]]],
                         [[[-0.98053589, -1.03143541],
                           [-1.19128892, -1.24695841]],
                          [[ 0.69108355,  0.66880383],
                           [ 0.59480972,  0.56776003]],
                          [[ 2.36270298,  2.36904306],
                           [ 2.38090835,  2.38247847]]]])
correct_out = np.transpose(correct_out, [0, 2, 3, 1])


tf_out = tf.nn.conv2d(
    tf.constant(x, dtype=tf.float32),
    tf.constant(w, dtype=tf.float32),
    strides=[1, 2, 2, 1],
    padding='SAME',
    use_cudnn_on_gpu=False,
    data_format='NHWC' # NHWC is the default setting of tensorflow
)

tf_conv = tf.nn.bias_add(
    tf_out,
    tf.constant(b, dtype=tf.float32),
    data_format='NHWC')


print('Difference between correct output and tf calculation:', \
                                       rel_error(tf.Session().run(tf_conv),

# Compare your output to ours; difference should be around e-8
out = conv_forward_naive(x, w, b, conv_param)
print('Difference between my implementation and correct output:', rel_error
```

```
print('Difference between my implementation and tf calculation:', rel_error
```

```
(2, 3, 4, 4)
(3, 3, 4, 4)
(3,)
Difference between correct output and tf calculation: 4.427582433439594e-08
Difference between my implementation and correct output: 2.212147649671884e-08
Difference between my implementation and tf calculation: 4.5275181161989593e-08
```

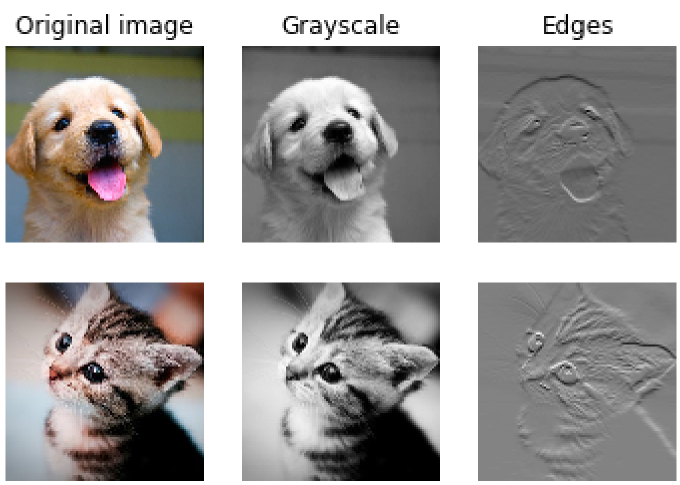
Aside: Image processing via convolutions

As fun way to both check your implementation and gain a better understanding of the type of operation that convolutional layers can perform, we will set up an input containing two images and manually set up filters that perform common image processing operations (grayscale conversion and edge detection). The convolution forward pass will apply these operations to each of the input images. We can then visualize the results as a sanity check.

In [5]:
```
from scipy.misc import imread, imresize

kitten, puppy = imread('kitten.jpg'), imread('puppy.jpg')
# kitten is wide, and puppy is already square
d = kitten.shape[1] - kitten.shape[0]
kitten_cropped = kitten[:, d//2:-d//2, :]

img_size = 200   # Make this smaller if it runs too slow
x = np.zeros((2, img_size, img_size, 3))
x[0, :, :, :] = imresize(puppy, (img_size, img_size))
x[1, :, :, :] = imresize(kitten_cropped, (img_size, img_size))

# Set up a convolutional weights holding 2 filters, each 3x3
w = np.zeros((2, 3, 3, 3))

# The first filter converts the image to grayscale.
# Set up the red, green, and blue channels of the filter.
w[0, 0, :, :] = [[0, 0, 0], [0, 0.3, 0], [0, 0, 0]]
w[0, 1, :, :] = [[0, 0, 0], [0, 0.6, 0], [0, 0, 0]]
w[0, 2, :, :] = [[0, 0, 0], [0, 0.1, 0], [0, 0, 0]]

# Second filter detects horizontal edges in the blue channel.
w[1, 2, :, :] = [[1, 2, 1], [0, 0, 0], [-1, -2, -1]]

w = np.transpose(w, [2, 3, 1, 0])

# Vector of biases. We don't need any bias for the grayscale
# filter, but for the edge detection filter we want to add 128
# to each output so that nothing is negative.
b = np.array([0, 128])

# Compute the result of convolving each input in x with each filter in w,
# offsetting by b, and storing the results in out.
out = conv_forward_naive(x, w, b, {'stride': 1, 'pad': 1})

def imshow_noax(img, normalize=True):
    """ Tiny helper to show images as uint8 and remove axis labels """
    if normalize:
        img_max, img_min = np.max(img), np.min(img)
        img = 255.0 * (img - img_min) / (img_max - img_min)
    plt.imshow(img.astype('uint8'))
    plt.gca().axis('off')

# Show the original images and the results of the conv operation
plt.subplot(2, 3, 1)
imshow_noax(puppy, normalize=False)
plt.title('Original image')
plt.subplot(2, 3, 2)
imshow_noax(out[0, :, :, 0])
plt.title('Grayscale')
plt.subplot(2, 3, 3)
imshow_noax(out[0, :, :, 1])
plt.title('Edges')
plt.subplot(2, 3, 4)
imshow_noax(kitten_cropped, normalize=False)
plt.subplot(2, 3, 5)
```

```
imshow_noax(out[1, :, :, 0])
plt.subplot(2, 3, 6)
imshow_noax(out[1, :, :, 1])
plt.show()
```

```
/Users/thomasklimek/anaconda3/lib/python3.7/site-packages/ipykernel_launc
her.py:3: DeprecationWarning: `imread` is deprecated!
`imread` is deprecated in SciPy 1.0.0, and will be removed in 1.2.0.
Use ``imageio.imread`` instead.
  This is separate from the ipykernel package so we can avoid doing impor
ts until
/Users/thomasklimek/anaconda3/lib/python3.7/site-packages/ipykernel_launc
her.py:10: DeprecationWarning: `imresize` is deprecated!
`imresize` is deprecated in SciPy 1.0.0, and will be removed in 1.2.0.
Use ``skimage.transform.resize`` instead.
  # Remove the CWD from sys.path while we load stuff.
/Users/thomasklimek/anaconda3/lib/python3.7/site-packages/ipykernel_launc
her.py:11: DeprecationWarning: `imresize` is deprecated!
`imresize` is deprecated in SciPy 1.0.0, and will be removed in 1.2.0.
Use ``skimage.transform.resize`` instead.
  # This is added back by InteractiveShellApp.init_path()
```



Max-Pooling: Naive forward

Implement the forward pass for the max-pooling operation in the function `max_pool_forward_naive` in the file `implementations/layers.py` . Again, don't worry too much about computational efficiency.

Check your implementation by running the following:

In [3]:
```
# shape is NCHW
x_shape = (2, 3, 4, 4)
x = np.linspace(-0.3, 0.4, num=np.prod(x_shape)).reshape(x_shape)
x = np.transpose(x, [0, 2, 3, 1])

pool_param = {'pool_width': 2, 'pool_height': 2, 'stride': 2}

out = max_pool_forward_naive(x, pool_param)

correct_out = np.array([[[[-0.26315789, -0.24842105],
                          [-0.20421053, -0.18947368]],
                         [[-0.14526316, -0.13052632],
                          [-0.08631579, -0.07157895]],
                         [[-0.02736842, -0.01263158],
                          [ 0.03157895,  0.04631579]]],
                        [[[ 0.09052632,  0.10526316],
                          [ 0.14947368,  0.16421053]],
                         [[ 0.20842105,  0.22315789],
                          [ 0.26736842,  0.28210526]],
                         [[ 0.32631579,  0.34105263],
                          [ 0.38526316,  0.4       ]]]])
correct_out = np.transpose(correct_out, [0, 2, 3, 1])

# Compare your output with ours. Difference should be on the order of e-8.
print('Testing max_pool_forward_naive function:')
print('difference: ', rel_error(out, correct_out))
```

```
Testing max_pool_forward_naive function:
difference:  1.0
```

Multilayer Convolutional Network

You need to build a convolutional network with tensorflow operations: tf.nn.conv2d, tf.nn.relu, and tf.pool. You may want to do so by modifying the fully connected network provided in this assignment.

Overfit small data

A nice trick is to train your model with just a few training samples. You should be able to overfit small datasets, which will result in very high training accuracy and comparatively low validation accuracy.

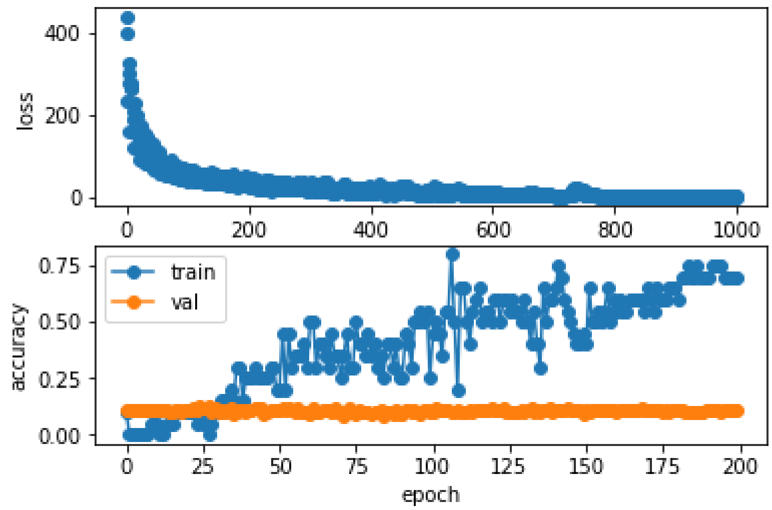
In [9]:
```
np.random.seed(15009)
tf.random.set_random_seed(15009)

from implementations.conv_net import ConvNet

num_train = 100
X_train = data['X_train'][:num_train].transpose([0, 2, 3, 1])
y_train = data['y_train'][:num_train]
X_val = data['X_val'].transpose([0, 2, 3, 1])
y_val = data['y_val']



model = ConvNet(input_size=[32, 32, 3],
                output_size=10,
                filter_size=[[3, 3, 5], [3, 3, 5], [3, 3, 5], [3, 3, 2]],
                pooling_schedule=[1, 3],
                fc_hidden_size=[50],
                use_bn = True,
                use_dropout = False)


trace = model.train(X_train, y_train, X_val, y_val,
            learning_rate=1e-3,
            reg=np.float32(5e-6),
            num_iters=1000,
            batch_size=20,
            verbose=True)
```

```
WARNING: The TensorFlow contrib module will not be included in TensorFlow
2.0.
For more information, please see:
  * https://github.com/tensorflow/community/blob/master/rfcs/20180907-con
trib-sunset.md (https://github.com/tensorflow/community/blob/master/rfcs/
20180907-contrib-sunset.md)
  * https://github.com/tensorflow/addons (https://github.com/tensorflow/a
ddons)
If you depend on functionality not listed there, please file an issue.

WARNING:tensorflow:From /Users/thomasklimek/anaconda3/lib/python3.7/site-
packages/tensorflow/python/framework/op_def_library.py:263: colocate_with
(from tensorflow.python.framework.ops) is deprecated and will be removed
 in a future version.
Instructions for updating:
Colocations handled automatically by placer.
8.0 8.0
before convolution (?, 32, 32, 3)
before add bias (?, 32, 32, 5)
after add bias (?, 32, 32, 5)
after convolution (?, 32, 32, 5)
WARNING:tensorflow:From /Users/thomasklimek/Downloads/comp150a2/implement
ations/conv_net.py:275: batch_normalization (from tensorflow.python.layer
s.normalization) is deprecated and will be removed in a future version.
Instructions for updating:
Use keras.layers.batch_normalization instead.
```

```
before convolution (?, 32, 32, 5)
before add bias (?, 32, 32, 5)
after add bias (?, 32, 32, 5)
after convolution (?, 32, 32, 5)
WARNING:tensorflow:From /Users/thomasklimek/Downloads/comp150a2/implement
ations/conv_net.py:269: max_pooling2d (from tensorflow.python.layers.pool
ing) is deprecated and will be removed in a future version.
Instructions for updating:
Use keras.layers.max_pooling2d instead.
before convolution (?, 16, 16, 5)
before add bias (?, 16, 16, 5)
after add bias (?, 16, 16, 5)
after convolution (?, 16, 16, 5)
before convolution (?, 16, 16, 5)
before add bias (?, 16, 16, 2)
after add bias (?, 16, 16, 2)
after convolution (?, 16, 16, 2)
128
WARNING:tensorflow:From /Users/thomasklimek/Downloads/comp150a2/implement
ations/conv_net.py:189: softmax_cross_entropy_with_logits (from tensorflo
w.python.ops.nn_ops) is deprecated and will be removed in a future versio
n.
Instructions for updating:

Future major versions of TensorFlow will allow gradients to flow
into the labels input on backprop by default.

See `tf.nn.softmax_cross_entropy_with_logits_v2`.

WARNING:tensorflow:From /Users/thomasklimek/anaconda3/lib/python3.7/site-
packages/tensorflow/python/ops/math_ops.py:3066: to_int32 (from tensorflo
w.python.ops.math_ops) is deprecated and will be removed in a future vers
ion.
Instructions for updating:
Use tf.cast instead.
iteration 0 / 1000: objective 437.744720
iteration 100 / 1000: objective 31.433693
iteration 200 / 1000: objective 21.286558
iteration 300 / 1000: objective 15.192031
iteration 400 / 1000: objective 12.231076
iteration 500 / 1000: objective 8.750280
iteration 600 / 1000: objective 10.414330
iteration 700 / 1000: objective 3.817036
iteration 800 / 1000: objective 3.073395
iteration 900 / 1000: objective 2.773842
```

Plotting the loss, training accuracy, and validation accuracy should show clear overfitting:

In [23]:
```
plt.subplot(2, 1, 1)
plt.plot(trace['objective_history'], 'o')
plt.xlabel('iteration')
plt.ylabel('loss')

plt.subplot(2, 1, 2)
plt.plot(trace['train_acc_history'], '-o')
plt.plot(trace['val_acc_history'], '-o')
plt.legend(['train', 'val'], loc='upper left')
plt.xlabel('epoch')
plt.ylabel('accuracy')
plt.show()
```



Train the net

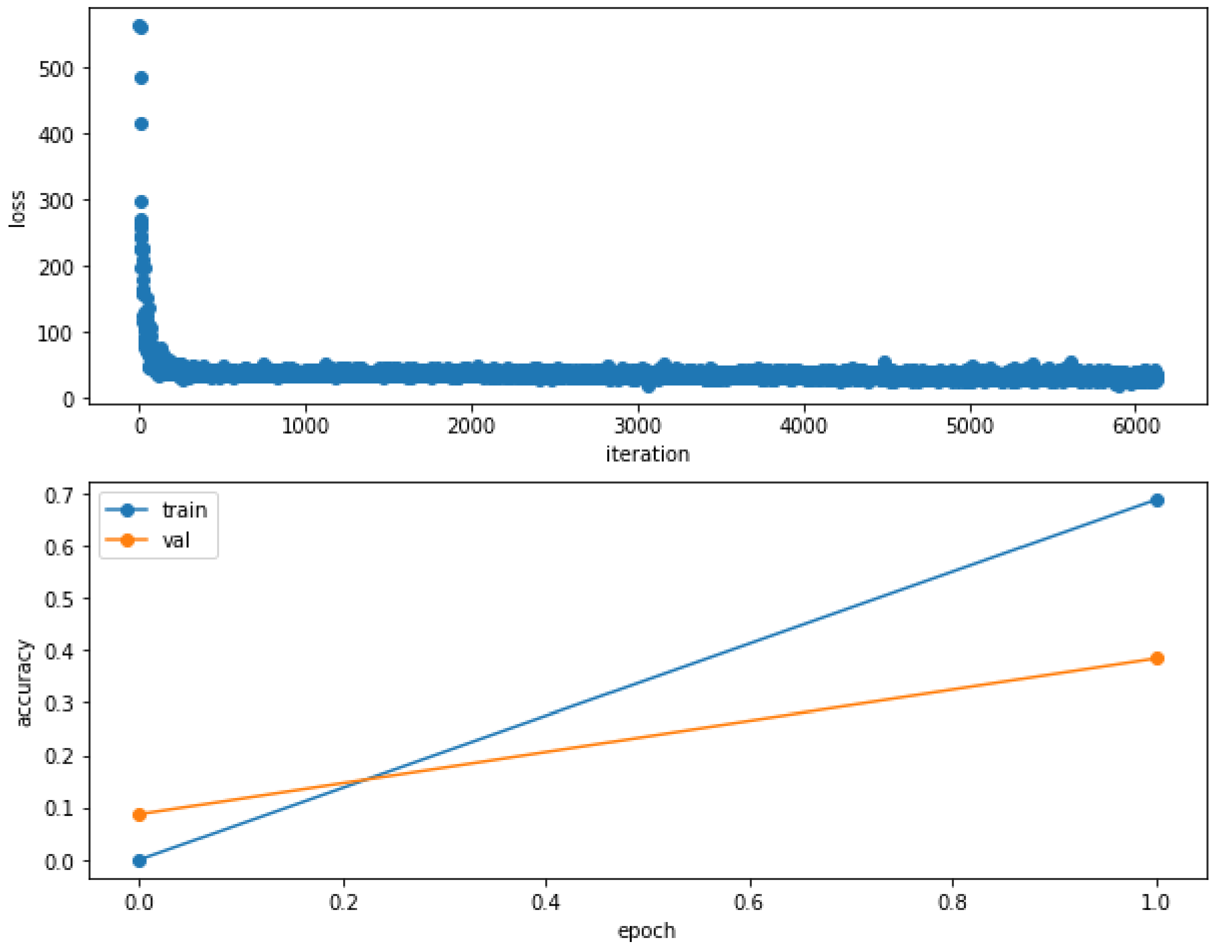
By training the three-layer convolutional network for one epoch, you should achieve greater than 40% accuracy on the training set:

In [19]:
```
X_train = data['X_train'].transpose([0, 2, 3, 1])
y_train = data['y_train']
X_val = data['X_val'].transpose([0, 2, 3, 1])
y_val = data['y_val']

num_train = X_train.shape[0]
batch_size = 16

model = ConvNet(input_size=[32, 32, 3],
                output_size=10,
                filter_size=[[9, 9, 8], [7, 7, 16], [5, 5, 32]],
                pooling_schedule=[0, 1, 2],
                fc_hidden_size=[32],
               use_bn=True)


trace = model.train(X_train, y_train, X_val, y_val,
            learning_rate=1e-3,
            reg=np.float32(5e-6),
            num_iters=(num_train * 2 // batch_size + 1),
            batch_size=batch_size,
            verbose=True)
```

```
iteration 0 / 6126: objective 564.417847
iteration 100 / 6126: objective 58.476097
iteration 200 / 6126: objective 49.103870
iteration 300 / 6126: objective 38.214092
iteration 400 / 6126: objective 37.490974
iteration 500 / 6126: objective 36.985348
iteration 600 / 6126: objective 38.545746
iteration 700 / 6126: objective 42.438438
iteration 800 / 6126: objective 41.128532
iteration 900 / 6126: objective 35.569687
iteration 1000 / 6126: objective 42.883736
iteration 1100 / 6126: objective 38.087051
iteration 1200 / 6126: objective 38.985126
iteration 1300 / 6126: objective 37.515514
iteration 1400 / 6126: objective 37.102352
iteration 1500 / 6126: objective 34.994362
iteration 1600 / 6126: objective 42.087067
iteration 1700 / 6126: objective 36.731857
iteration 1800 / 6126: objective 35.863190
iteration 1900 / 6126: objective 33.324478
iteration 2000 / 6126: objective 38.110695
iteration 2100 / 6126: objective 42.799942
iteration 2200 / 6126: objective 35.978863
iteration 2300 / 6126: objective 37.596661
iteration 2400 / 6126: objective 35.440834
iteration 2500 / 6126: objective 31.667885
iteration 2600 / 6126: objective 38.450424
iteration 2700 / 6126: objective 35.932213
iteration 2800 / 6126: objective 32.386425
iteration 2900 / 6126: objective 34.231255
iteration 3000 / 6126: objective 37.434288
iteration 3100 / 6126: objective 35.995594
iteration 3200 / 6126: objective 33.596657
iteration 3300 / 6126: objective 30.809631
```

```
iteration 3400 / 6126: objective 37.208248
iteration 3500 / 6126: objective 33.014923
iteration 3600 / 6126: objective 32.022263
iteration 3700 / 6126: objective 37.906059
iteration 3800 / 6126: objective 37.241680
iteration 3900 / 6126: objective 31.426018
iteration 4000 / 6126: objective 30.822554
iteration 4100 / 6126: objective 39.956539
iteration 4200 / 6126: objective 39.257317
iteration 4300 / 6126: objective 31.160807
iteration 4400 / 6126: objective 34.096138
iteration 4500 / 6126: objective 31.431416
iteration 4600 / 6126: objective 39.975765
iteration 4700 / 6126: objective 29.645998
iteration 4800 / 6126: objective 32.865955
iteration 4900 / 6126: objective 32.707985
iteration 5000 / 6126: objective 32.246025
iteration 5100 / 6126: objective 35.088245
iteration 5200 / 6126: objective 29.250404
iteration 5300 / 6126: objective 29.136822
iteration 5400 / 6126: objective 28.385168
iteration 5500 / 6126: objective 31.430676
iteration 5600 / 6126: objective 27.866518
iteration 5700 / 6126: objective 35.185852
iteration 5800 / 6126: objective 30.769199
iteration 5900 / 6126: objective 30.053125
iteration 6000 / 6126: objective 30.943306
iteration 6100 / 6126: objective 35.488895
```

In [20]:
```
plt.subplot(2, 1, 1)
plt.plot(trace['objective_history'], 'o')
plt.xlabel('iteration')
plt.ylabel('loss')

plt.subplot(2, 1, 2)
plt.plot(trace['train_acc_history'], '-o')
plt.plot(trace['val_acc_history'], '-o')
plt.legend(['train', 'val'], loc='upper left')
plt.xlabel('epoch')
plt.ylabel('accuracy')
plt.show()
```



Visualize Filters

You can visualize the first-layer convolutional filters from the trained network by running the following:

In [23]:
```
from vis_utils import visualize_grid

grid = visualize_grid(model.get_params()['filter'][0].transpose(3, 0, 1, 2))
plt.imshow(grid.astype('uint8'))
plt.axis('off')
plt.gcf().set_size_inches(5, 5)
plt.show()
```

```
---------------------------------------------------------------------------
AttributeError                            Traceback (most recent call last)
<ipython-input-23-1eddac391d97> in <module>
      1 from vis_utils import visualize_grid
      2
----> 3 grid = visualize_grid(model.get_params()['filter'][0].transpose(3, 0, 1, 2))
      4 plt.imshow(grid.astype('uint8'))
      5 plt.axis('off')

AttributeError: 'RefVariable' object has no attribute 'transpose'
```

In [ ]: