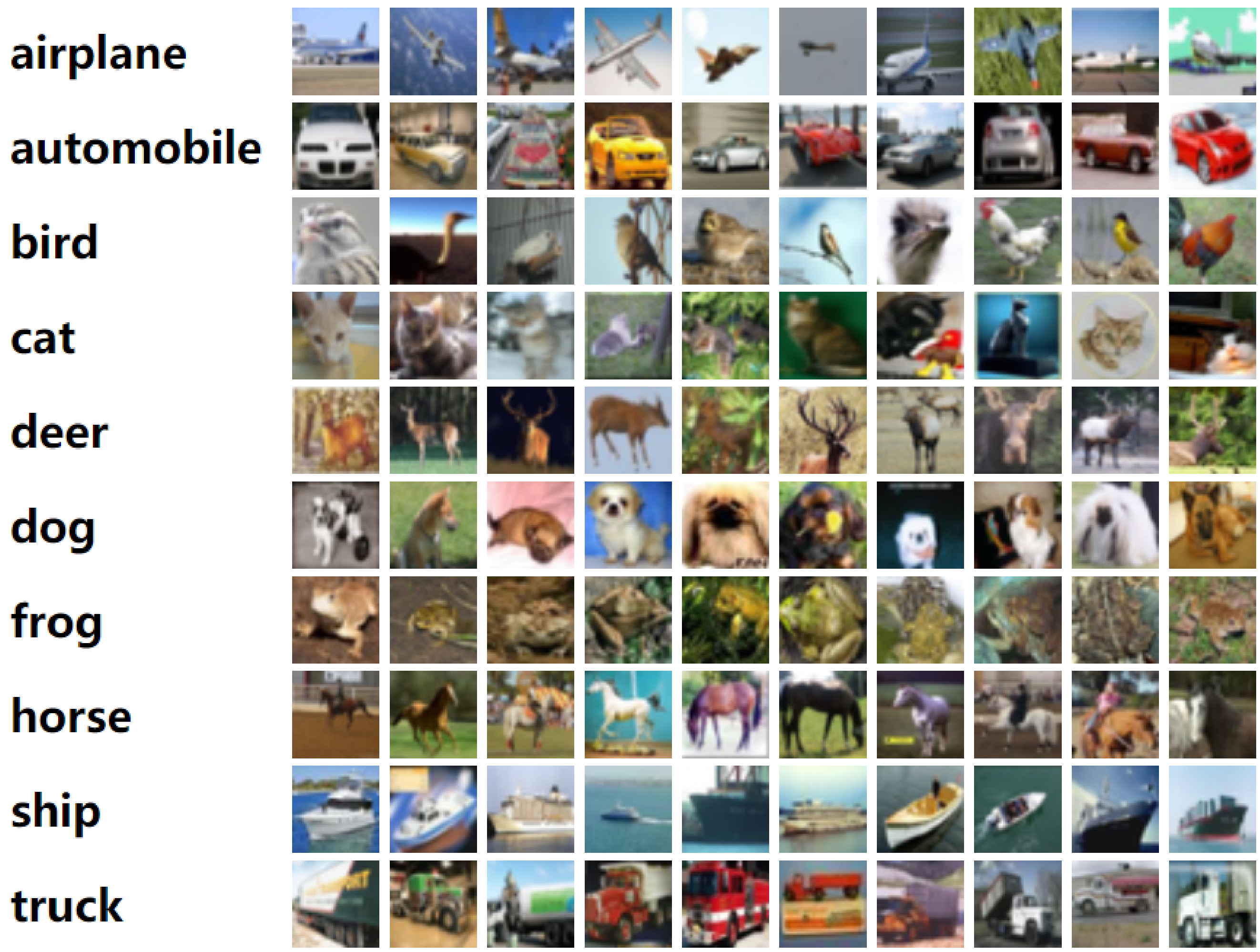
In [3]:

```python
import numpy as np
```

CIFAR-10 classifier with CNN



Task 1: Forward pass and Backward pass for Convolution

Implement a naive conv_forward function and apply the vertical and horizontal filter on example images

Implement a conv_forward using im2col and also apply the filter on example images

Implement a conv_backward using im2col and do some numerical gradient test

In [1]:

```python
from sklearn.datasets import load_sample_image
```

In [4]:

```python
china = load_sample_image('china.jpg')[150:220, 130:250] / 255
flower = load_sample_image("flower.jpg")[150:220, 130:250] / 255
images = np.array([china, flower])
batch_size, height, width, channels = images.shape
```

In [5]:

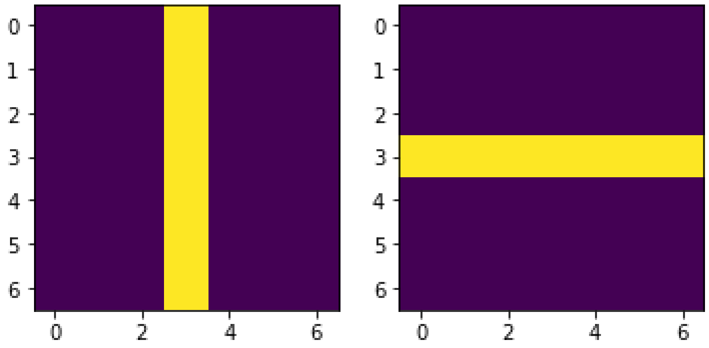
```
import sklearn
import matplotlib.pyplot as plt
```

In [6]:

```
# Create 2 filters
filters = np.zeros(shape=(7, 7, channels, 2), dtype=np.float32)
filters[:, 3, :, 0] = 1  # vertical line
filters[3, :, :, 1] = 1  # horizontal line
```

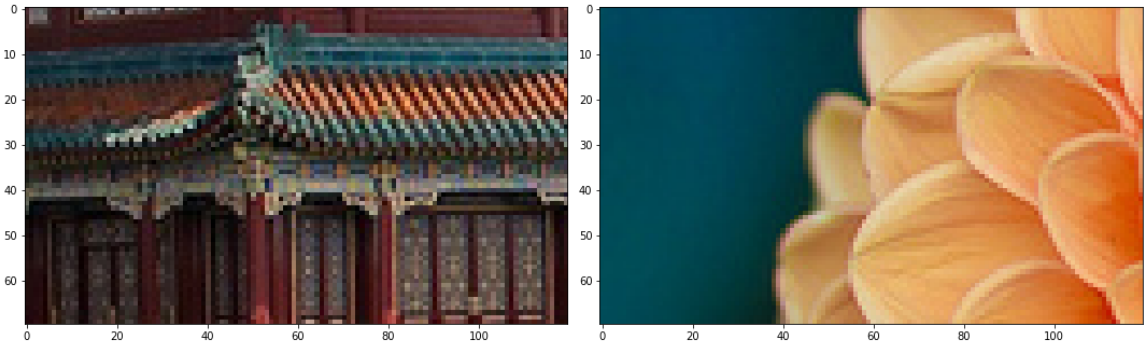
In [7]:

```
plt.subplot(1, 2, 1)
plt.imshow(filters[:, :, 0, 0])
plt.subplot(1, 2, 2)
plt.imshow(filters[:, :, 0, 1])
plt.show()
```



In [8]:

```
plt.figure(figsize=(15, 15))
plt.subplot(1, 2, 1)
plt.imshow(china)
plt.subplot(1, 2, 2)
plt.imshow(flower)
plt.tight_layout()
plt.show()
```



In [31]:

```
#!pip install torch torchvision -i https://pypi.douban.com/simple
```

In [9]:

```
# if you don't have torch and torchvision
# uncomment and run the above cell
import torch
import torch.nn.functional as F
```

In [12]:

```
filters = np.transpose(filters, (3, 2, 0, 1))
# We will want our image to be NCHW format for pytorch to process
images = np.transpose(images, (0, 3, 1, 2))
```

In [13]:

```
# Example on convolution using pytorch
images_tensor = torch.Tensor(images)
filters_tensor = torch.Tensor(filters)
outputs = F.conv2d(images_tensor, filters_tensor, )
```

In [14]:

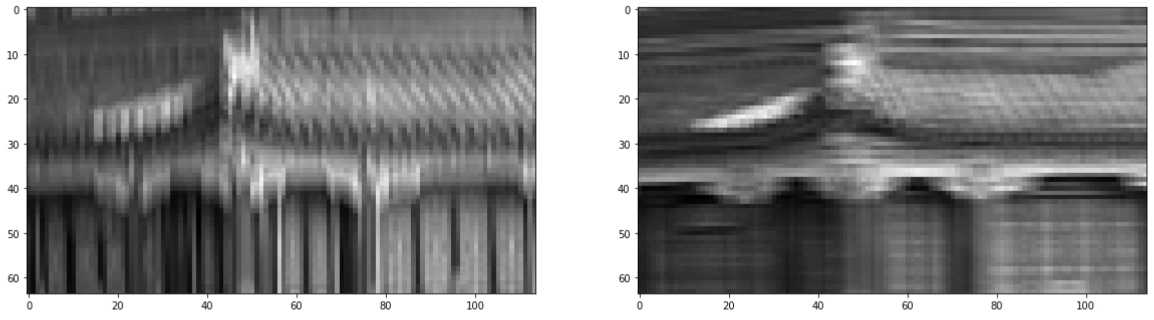
```
china_convolved = outputs[0].numpy()
flower_convolved = outputs[1].numpy()
```

In [15]:

```
china_convolved = np.transpose(china_convolved, (1, 2, 0))
flower_convolved = np.transpose(flower_convolved, (1, 2, 0))
```

In [16]:

```
plt.figure(figsize=(20, 20))
plt.subplot(1, 2, 1)
plt.imshow(china_convolved[:, :, 0], cmap='gray')
plt.subplot(1, 2, 2)
plt.imshow(china_convolved[:, :, 1], cmap='gray')
plt.show()
```



In [ ]:

```
def conv_forward_naive(x, w, b=None, pad=0, strides=1):
    """
    A naive implementation of the forward pass for a convolutional layer.
    The input consists of N data points, each with C channels, height H and width
    W. We convolve each input with F different filters, where each filter spans
    all C channels and has height HH and width HH.
    Input:
    - x: Input data of shape (N, C, H, W)
    - w: Filter weights of shape (F, C, HH, WW)
    - b: Biases, of shape (F,)
    - stride: The number of pixels between adjacent receptive fields in the
        horizontal and vertical directions.
    - pad: The number of pixels that will be used to zero-pad the input.
    Returns a tuple of:
    - out: Output data, of shape (N, F, H', W') where H' and W' are given by
      H' = 1 + (H + 2 * pad - HH) / stride
      W' = 1 + (W + 2 * pad - WW) / stride
    - cache: (x, w, b, pad, strides)
    """
    out = None
    N, C, H, W = x.shape
    F, C, HH, WW = w.shape
    S = strides
    P = pad

    if b is None:
        b = np.zeros((F))

    """
        TODO: write your code here
    """

    cache = (x, w, b, pad, strides)
    return out, cache
```

In [35]:

```
"""
    Here apply you implmentation of convolution on the sample images
    and show the result
"""
```

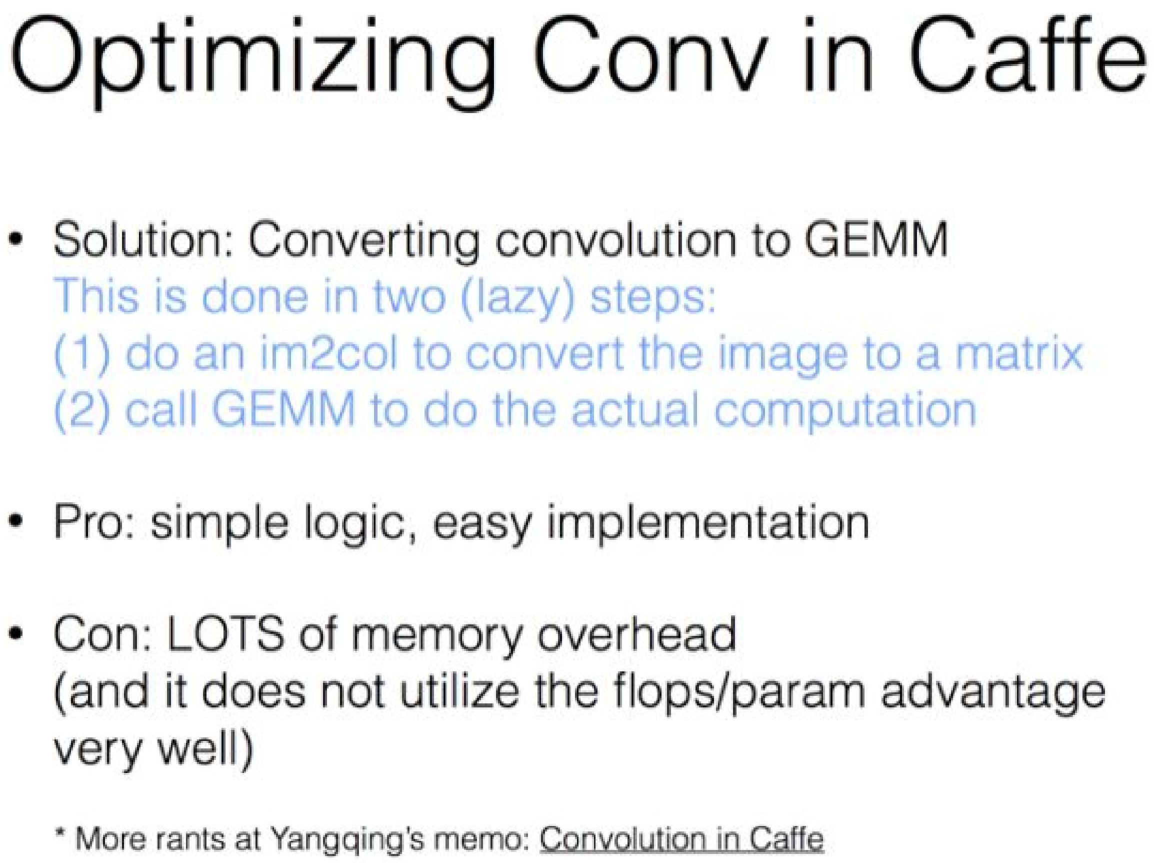
Out[35]:

```
'\n    Here apply you implmentation of convolution on the sample images\n    and s
how the result\n'
```

im2col

it turns out that we can use a clever algorithm called im2col to convert a image to a matrix and the convolution (which we naively implement using for-loops) will be a single matrix multiplication

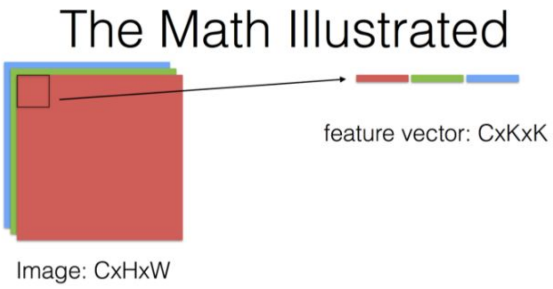
check this url (http://cs231n.github.io/convolutional-networks/#conv) and Yangqing's memo Conv in Caffe (https://github.com/Yangqing/caffe/wiki/Convolution-in-Caffe:-a-memo)



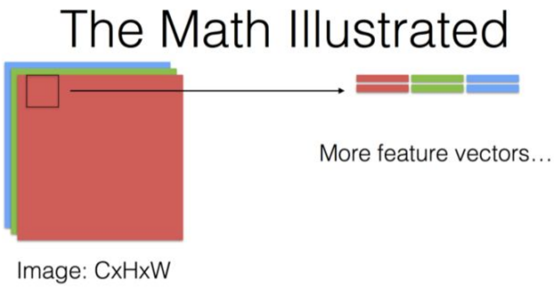
Optimizing Conv in Caffe

- Solution: Converting convolution to GEMM
  This is done in two (lazy) steps:
  (1) do an im2col to convert the image to a matrix
  (2) call GEMM to do the actual computation
- Pro: simple logic, easy implementation
- Con: LOTS of memory overhead
  (and it does not utilize the flops/param advantage very well)

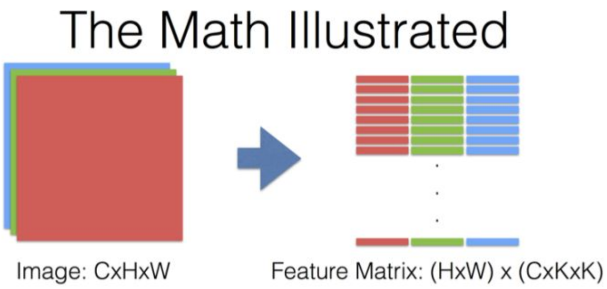
* More rants at Yangqing's memo: Convolution in Caffe

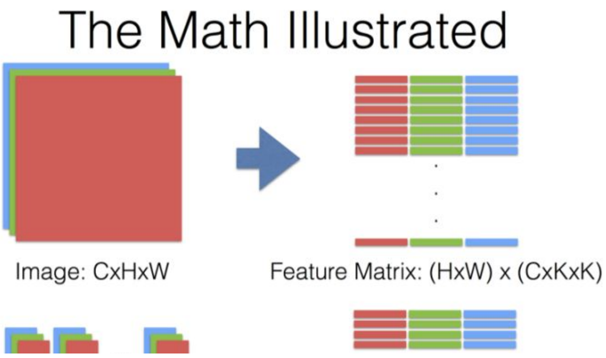


The Math Illustrated



The Math Illustrated





In [17]:

```
def im2col(image, ksize, stride):
    """
        TODO: Implement a im2col to NCHW format images
    """
    pass
```

In [18]:

```
def conv_forward_im2col(x, w, b=None, pad=0, strides=1):
    """
        TODO: Implement conv_forward using im2col
    """
    pass
```

In [36]:

```
"""
    Here apply you implmentation of convolution on the sample images
    and show the result
"""
```

Out[36]:

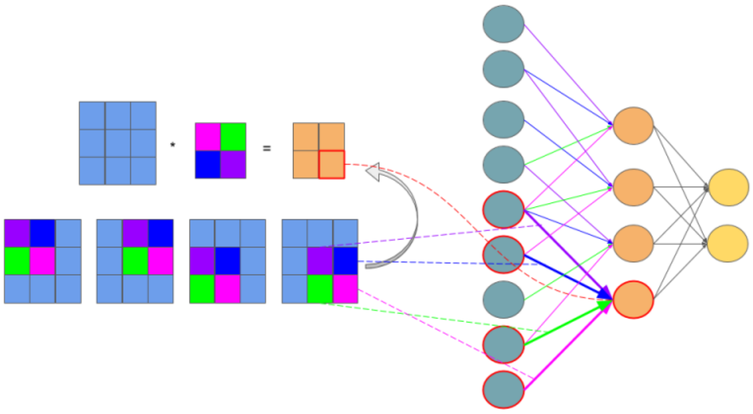
```
'\n    Here apply you implmentation of convolution on the sample images\n    and s
how the result\n'
```

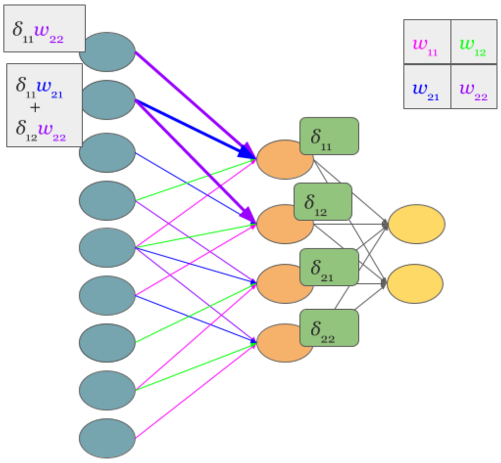
In [19]:

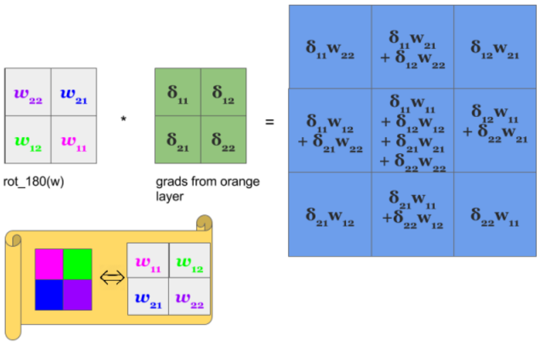
```
def conv_backward_im2col(dout, cache):
    """
        TODO
    """
    pass
```

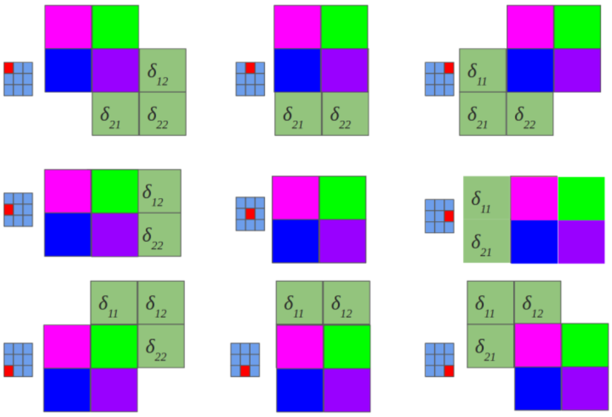
We can actually sees that the gradient through the convolution is the rotated kernel convolves over the error from later layer

(if you prefer solid math over this visual proof, check this (https://grzegorzgwardys.wordpress.com/2016/04/22/8/) this (https://www.jefkine.com/general/2016/09/05/backpropagation-in-convolutional-neural-networks/) and this lecture notes (http://courses.cs.tau.ac.il/Caffe_workshop/Bootcamp/pdf_lectures/Lecture%203%20CNN%20-%20backpropagation.pdf))






w_{22}
w_{21}
w_{12}
w_{11}
rot_180(w)
*
δ_{11}
δ_{12}
δ_{21}
δ_{22}
grads from orange layer
=
$\delta_{11} w_{22}$
$\delta_{11} w_{21} + \delta_{12} w_{22}$
$\delta_{12} w_{21}$
$\delta_{11} w_{12} + \delta_{21} w_{22}$
$\delta_{11} w_{11} + \delta_{12} w_{12} + \delta_{21} w_{21} + \delta_{22} w_{22}$
$\delta_{12} w_{11} + \delta_{22} w_{21}$
$\delta_{21} w_{12}$
$\delta_{21} w_{11} + \delta_{22} w_{12}$
$\delta_{22} w_{11}$
⇔
w_{11}
w_{12}
w_{21}
w_{22}



In [20]:

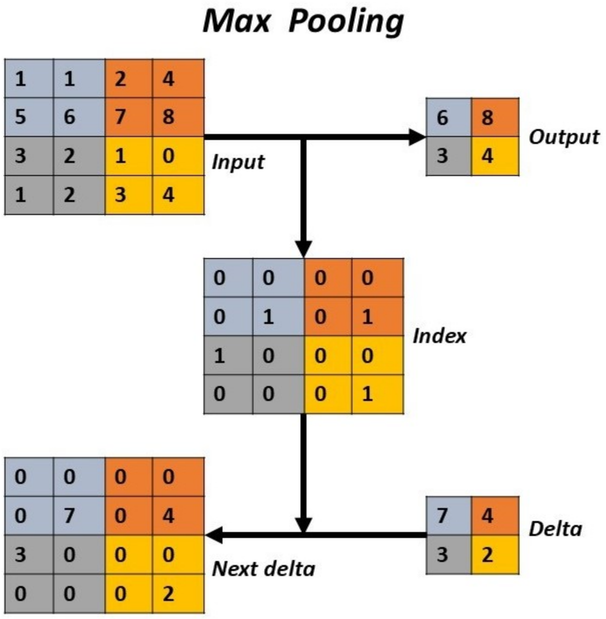
```
def eval_numerical_gradient_array(f, x, df, h=1e-5):
    """
    Evaluate a numeric gradient for a function that accepts a numpy
    array and returns a numpy array.
    """
    grad = np.zeros_like(x)
    it = np.nditer(x, flags=['multi_index'], op_flags=['readwrite'])
    while not it.finished:
        ix = it.multi_index

        oldval = x[ix]
        x[ix] = oldval + h
        pos = f(x).copy()
        x[ix] = oldval - h
        neg = f(x).copy()
        x[ix] = oldval

        grad[ix] = np.sum((pos - neg) * df) / (2 * h)
        it.iternext()
    return grad
```

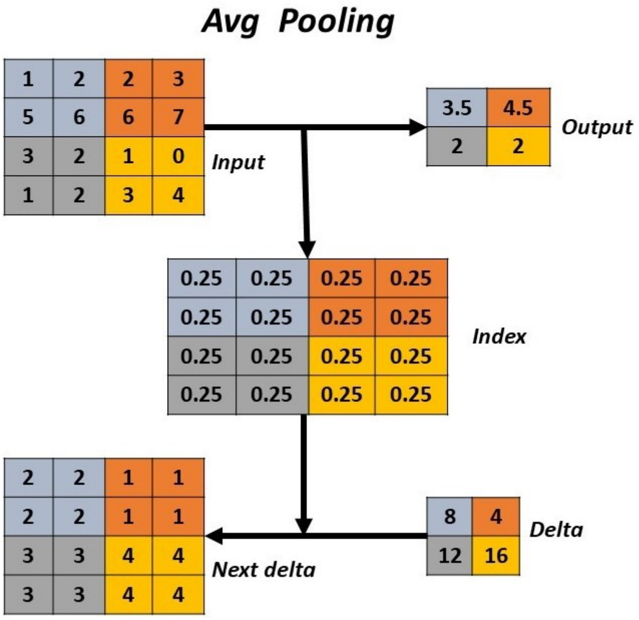
You relative error from the below cell output should be around 1e-9

In [ ]:

```
x = np.random.randn(4, 3, 5, 5)
w = np.random.randn(2, 3, 3, 3)
b = np.random.randn(2,)
dout = np.random.randn(4, 2, 5, 5)
stride, pad = 1, 1

dx_num = eval_numerical_gradient_array(lambda x: conv_forward_im2col(x, w, b, pad, stride)[0],
x, dout)
dw_num = eval_numerical_gradient_array(lambda w: conv_forward_im2col(x, w, b, pad, stride)[0],
w, dout)
db_num = eval_numerical_gradient_array(lambda b: conv_forward_im2col(x, w, b, pad, stride)[0],
b, dout)

out, cache = conv_forward_im2col(x, w, b, pad, stride)
dx, dw, db = conv_backward_im2col(dout, cache)

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))))

print("dx error: ", rel_error(dx, dx_num))
print("dw error: ", rel_error(dw, dw_num))
print("db error: ", rel_error(db, db_num))
```

Task 2: Forward pass and backward pass of other layers





you can choose either pool method and implement

In [22]:

```python
def pool_forward(x, height, width, ksize, method):
    """
        TODO
    """
    pass
def pool_backward(x, height, width, ksize, method):
    """
        TODO
    """
    pass
```

In [23]:

```python
def fc_forward(x, w, b):
    """
        TODO
    """
    pass

def fc_backward(dout, cache):
    """
        TODO
    """
    pass
```

In [24]:

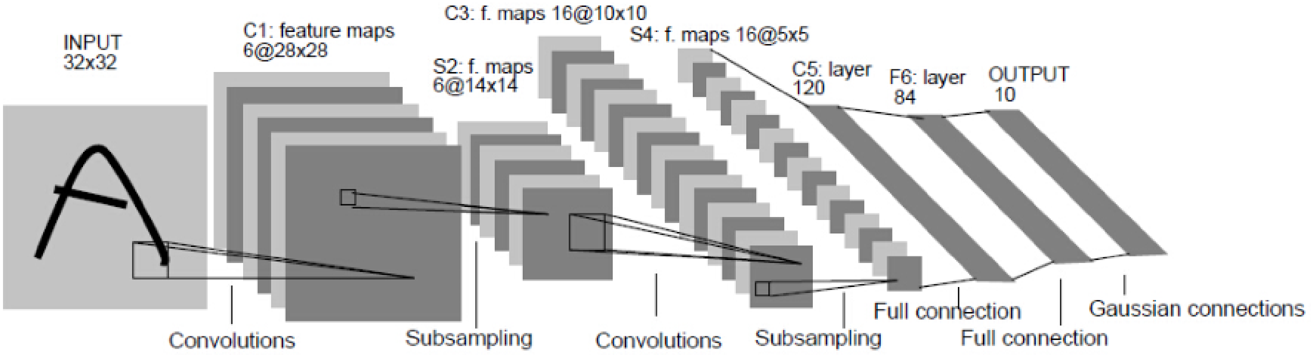
```
def relu_forward(x):
    """
        TODO
    """
    pass
def relu_backward(dout, cache):
    """
        TODO
    """
    pass
```

In [26]:

```
def softmax_loss(x, y):
    """
    Computes the loss and gradient for softmax classification.

    Inputs:
    - x: Input data, of shape (N, C) where x[i, j] is the score for the jth class
      for the ith input.
    - y: Vector of labels, of shape (N,) where y[i] is the label for x[i] and
      0 <= y[i] < C

    Returns a tuple of:
    - loss: Scalar giving the loss
    - probs: The predicted probability
    - dx: Gradient of the loss with respect to x
    """
    """
        TODO
    """
    pass
```

Task3: Combine all this together and train a CNN on CIFAR-10!

You can use an arch samiliar to LeNet



1. overfit a small data(achieve 100% accuracy on a small data)
2. train on the whole training data, validation on validation data, finally test on test data

In [30]:

```
#!pip install torch torchvision -i https://pypi.douban.com/simple
```

In [29]:

```
import torchvision

# I'm using torchvision to load the CIFAR10 dataset
# if you don't have torch and torchvision
# uncomment and run the above cell
def load_cifar(path='./data'):
    cifar_train = torchvision.datasets.cifar.CIFAR10(path, download=True)
    cifar_test = torchvision.datasets.cifar.CIFAR10(path, download=True, train=False)

    cifar_train_img_list, cifar_train_label_list = [], []
    for train_example in cifar_train:
        img = np.array(train_example[0])[np.newaxis, :]
        label = train_example[1]
        cifar_train_img_list.append(img)
        cifar_train_label_list.append(label)
    cifar_train_img = np.concatenate(cifar_train_img_list, axis=0).astype(np.float) / 255
    cifar_train_label = np.array(cifar_train_label_list).astype(np.int)

    cifar_test_img_list, cifar_test_label_list = [], []
    for test_example in cifar_test:
        img = np.array(test_example[0])[np.newaxis, :]
        label = test_example[1]
        cifar_test_img_list.append(img)
        cifar_test_label_list.append(label)
    cifar_test_img = np.concatenate(cifar_test_img_list, axis=0).astype(np.float) / 255
    cifar_test_label = np.array(cifar_test_label_list).astype(np.int)

    return cifar_train_img[:49000], cifar_train_label[:49000], \
          cifar_train_img[49000:], cifar_train_label[49000:], \
          cifar_test_img, cifar_test_label
```

In [32]:

```
X, y, X_val, y_val, X_test, y_test = load_cifar()
X = np.transpose(X, (0, 3, 1, 2))
X_val = np.transpose(X_val, (0, 3, 1, 2))
X_test = np.transpose(X_test, (0, 3, 1, 2))
batch_size = 64
X_mini_batches = [X[k:k+batch_size] for k in range(0, len(X), batch_size)]
y_mini_batches = [y[k:k+batch_size] for k in range(0, len(y), batch_size)]
X_dummy = X[:100]
y_dummy = y[:100]
```

```
Files already downloaded and verified
Files already downloaded and verified
```

In [33]:

```
X.shape, y.shape, X_val.shape, y_val.shape, X_test.shape, y_test.shape
```

Out[33]:

```
((49000, 3, 32, 32),
 (49000,),
 (1000, 3, 32, 32),
 (1000,),
 (10000, 3, 32, 32),
 (10000,))
```

Check if you have any bug by overfitting a small dat

In [34]:

```
X_dummy.shape, y_dummy.shape
```

Out[34]:

```
((100, 3, 32, 32), (100,))
```

In [ ]:

```
for epoch in range(200):
    alpha = 0.1
    reg = 0.01
    # forward pass through network using X_dummy
    """
        TODO
    """
    #from ipdb import set_trace; set_trace()
    # Calculate the loss
    """
        TODO
    """




    acc = np.mean(np.argmax(pred, axis=1) == y_dummy)
    if epoch % 20 == 0:
        #print('dloss: ', dloss)
        print('epoch:', epoch, 'loss:', loss)
        print('epoch:', epoch, 'reg_loss:', reg_loss)
        print('epoch:', epoch, 'acc:', acc)

    # backward pass through network
    """
        TODO
    """

    # update parameter
    """
        TODO
    """
```

Train on the whole dataset

```
for epoch in range(num_epoch):
    for X_batch, y_batch in zip(X_batches, y_batches)
        forward(X_batch)
        loss(pred, y_batch)
        backward()
        update()
    if epoch % interval == 0:
        validate(X_val, y_val)

test(X_test, y_test)
```

In [ ]: