

A2:CNN Report

Boxi Chen

Student ID:010671402

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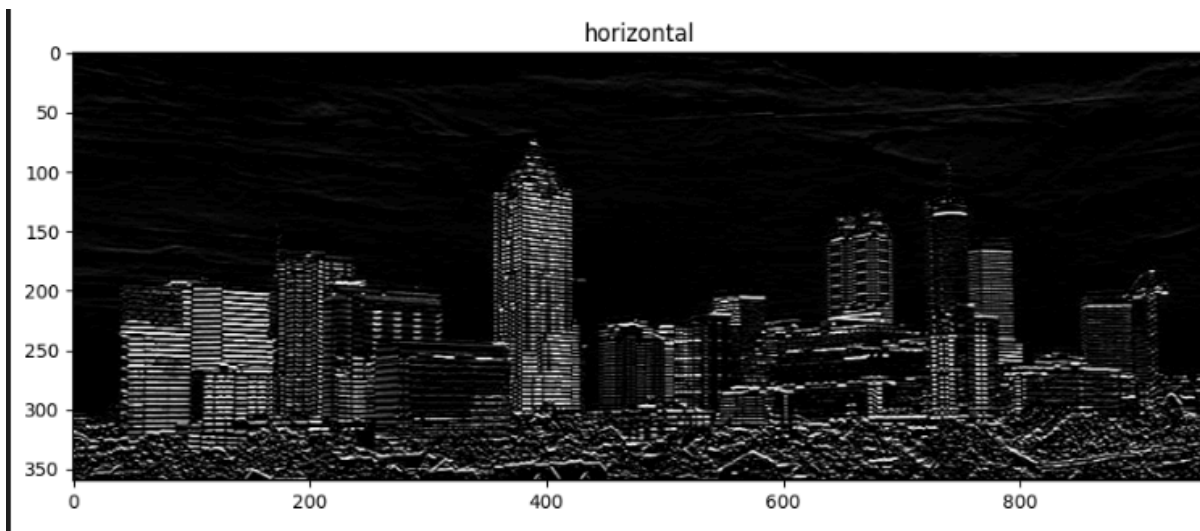
Professor:Prof. Bo Shen

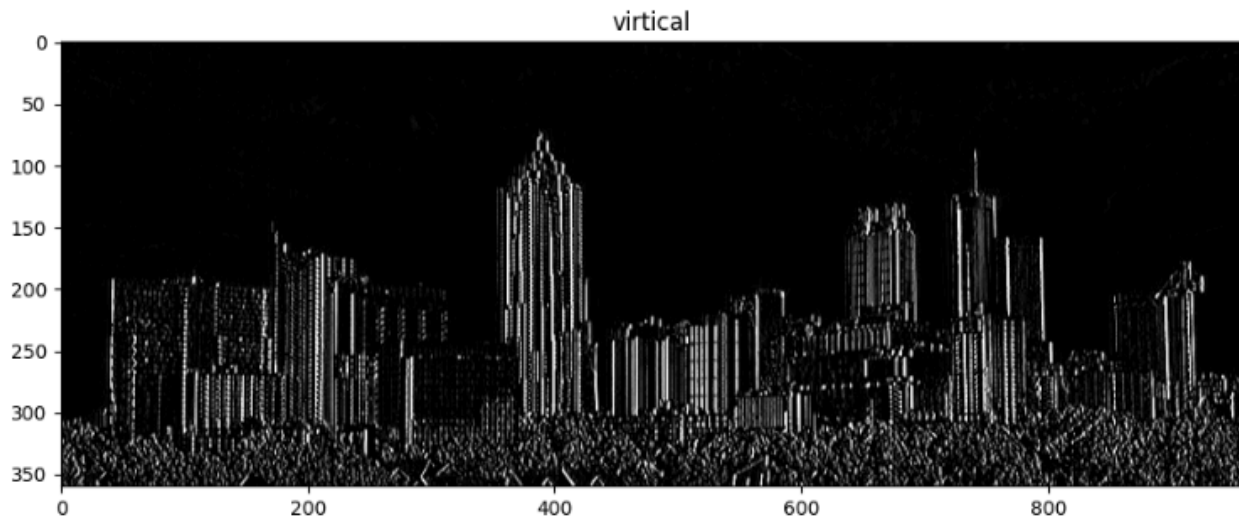
Department of Computer Science
California State University, Chico

Part 1 Image_Filter.zip:

```
## TODO: Create and apply a vertical edge detection operator
vertical = np.array([[ -1,  0,  1],
                    [ -1,  0,  1],
                    [ -1,  0,  1]])
```

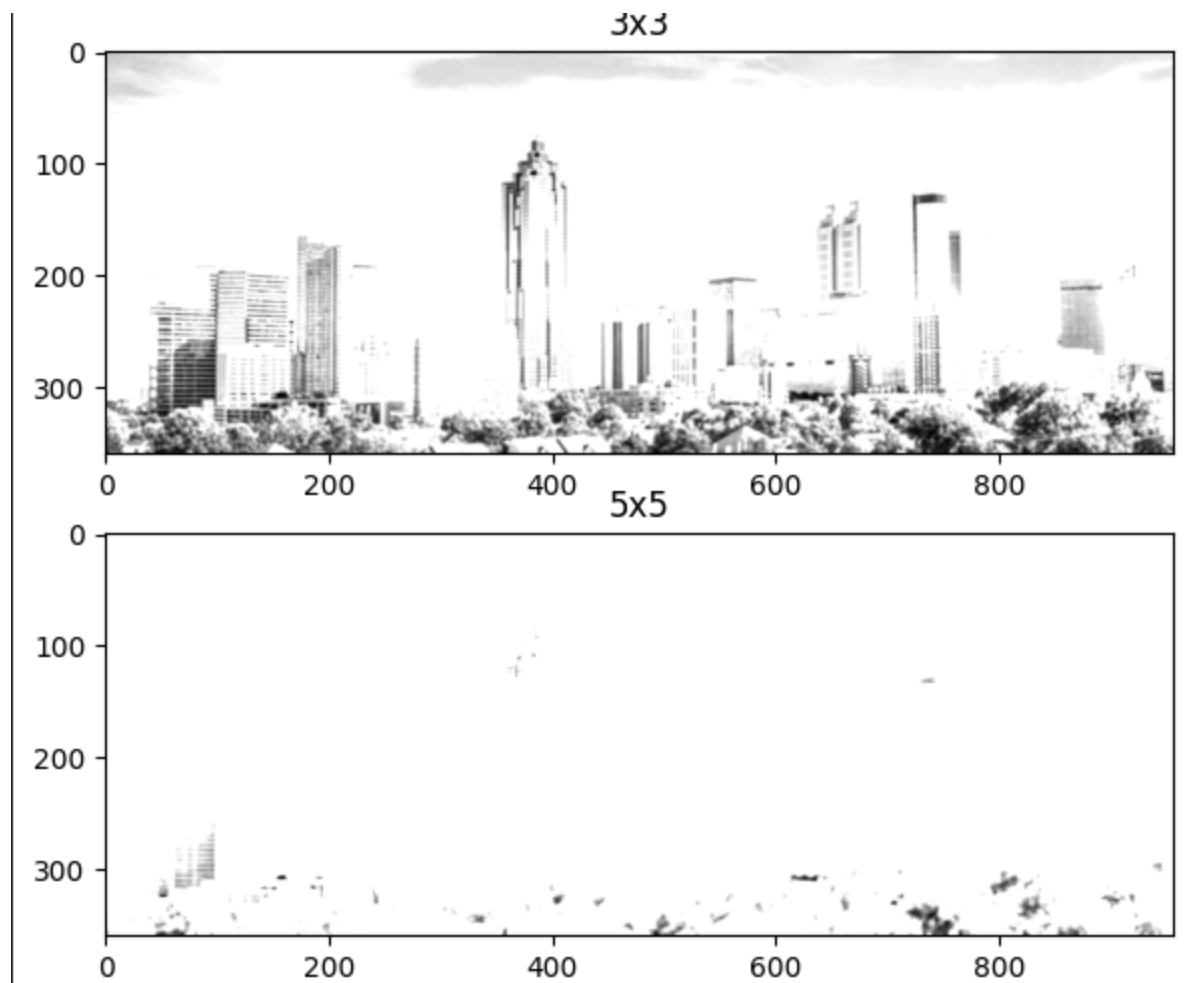
```
filtered_image2 = cv2.filter2D(gray, -1, vertical)
fig.add_subplot(2,2,2)
plt.imshow(filtered_image2, cmap='gray')
plt.title('vertical')
```





The answer of the code already given, we can compare the horizon filter, the picture is more focused on vertical lines/pixels.

```
# TODO: blur image using a 3x3 average
#fig.add_subplot(4,1,3)
#plt.title('3x3')
S3x3 = np.array([[ 1, 1, 1],
                  [ 1, 1, 1],
                  [ 1, 1, 1]])
blurred_image = cv2.filter2D(gray, -1, S3x3/4.0)
fig.add_subplot(4,1,3)
plt.imshow(blurred_image, cmap='gray')
plt.title('3x3')
# TODO: blur image using a 5x5 average
#fig.add_subplot(4,1,4)
#plt.title('5x5')
S5x5 = np.array([[ 1, 1, 1, 1, 1],
                  [ 1, 1, 1, 1, 1],
                  [ 1, 1, 1, 1, 1],
                  [ 1, 1, 1, 1, 1],
                  [ 1, 1, 1, 1, 1]])
blurred_image = cv2.filter2D(gray, -1, S5x5/4.0)
fig.add_subplot(4,1,4)
plt.imshow(blurred_image, cmap='gray')
plt.title('5x5')
plt.show()
```



Given the same value of 1 for different dimensions 3x3, 5x5 we can see different kernel filter impact to the picture, the bigger kernel filter the picture more blurred under all kernel filters divided by 4 for normalized weight.

TODO

Other image processing/filtering you can try:

- Other Edge Detector (e.g. Sobel Operator) A common 3×3 kernel for edge detection is the **Sobel operator**, which detects edges in a specific direction. Below are the Sobel kernels for detecting vertical and horizontal edges:

Vertical Edge Detection Kernel:

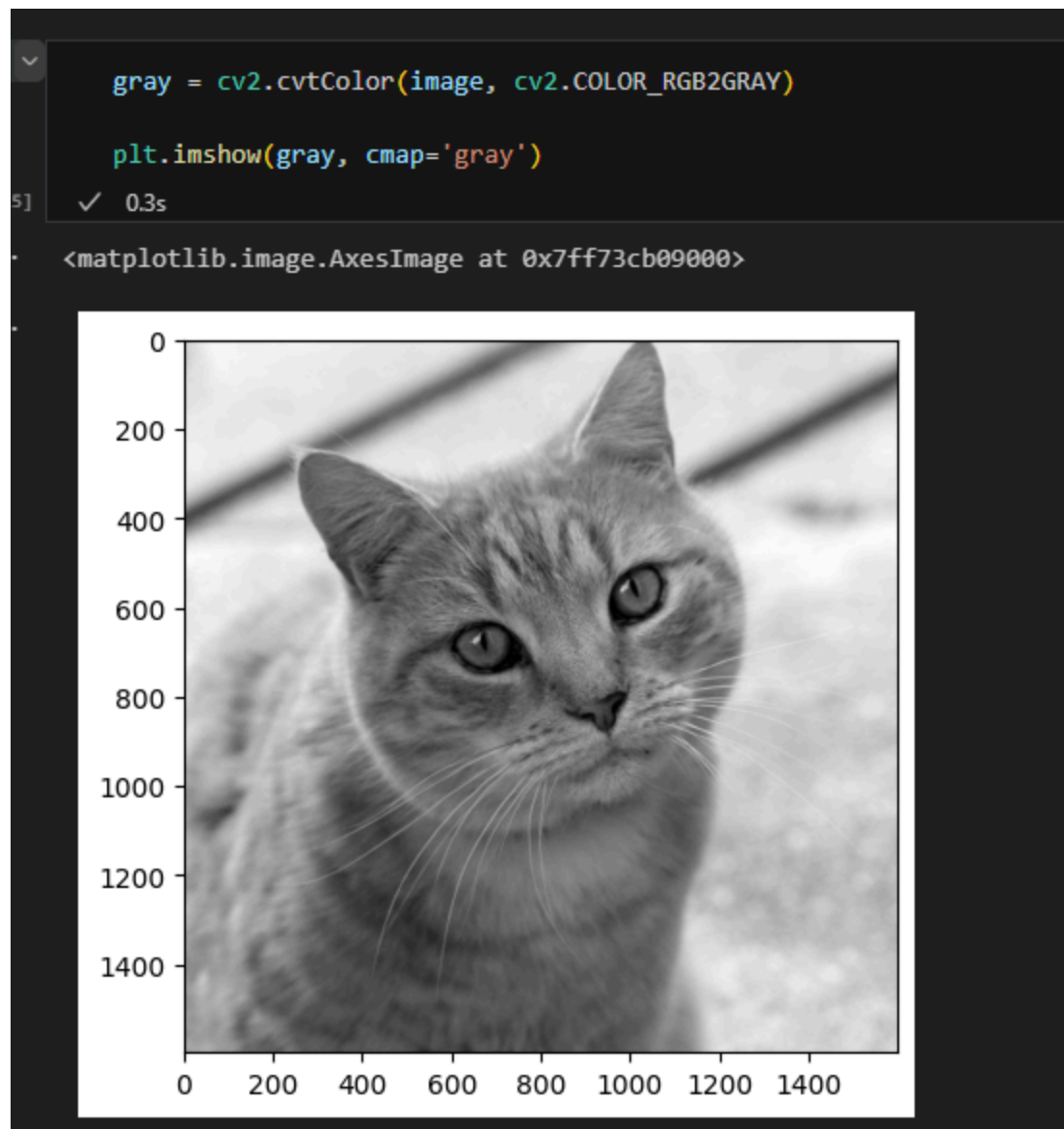
$$K_x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}$$

Horizontal Edge Detection Kernel:

$$K_y = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix}$$

These kernels are convolved with an image to highlight vertical and horizontal edges, respectively.

- Corner Detection (use the kernels we discussed in slides)
- Scaling (after the blurring, can you pick one pixel out of the following?)
 - 2×2
 - 4×4
- Use other images of your choice
- For a challenge, see if you can put the image through a series of filters: first one that blurs the image (takes an average of pixels), and then one that detects the edges.



Loading the cat gray picture

```

Kx = np.array([[ -1, 0, 1],
               [ -2, 0, 2],
               [ -1, 0, 1]])

Ky = np.array([[ -1, -2, -1],
               [ 0, 0, 0],
               [ 1, 2, 1]])

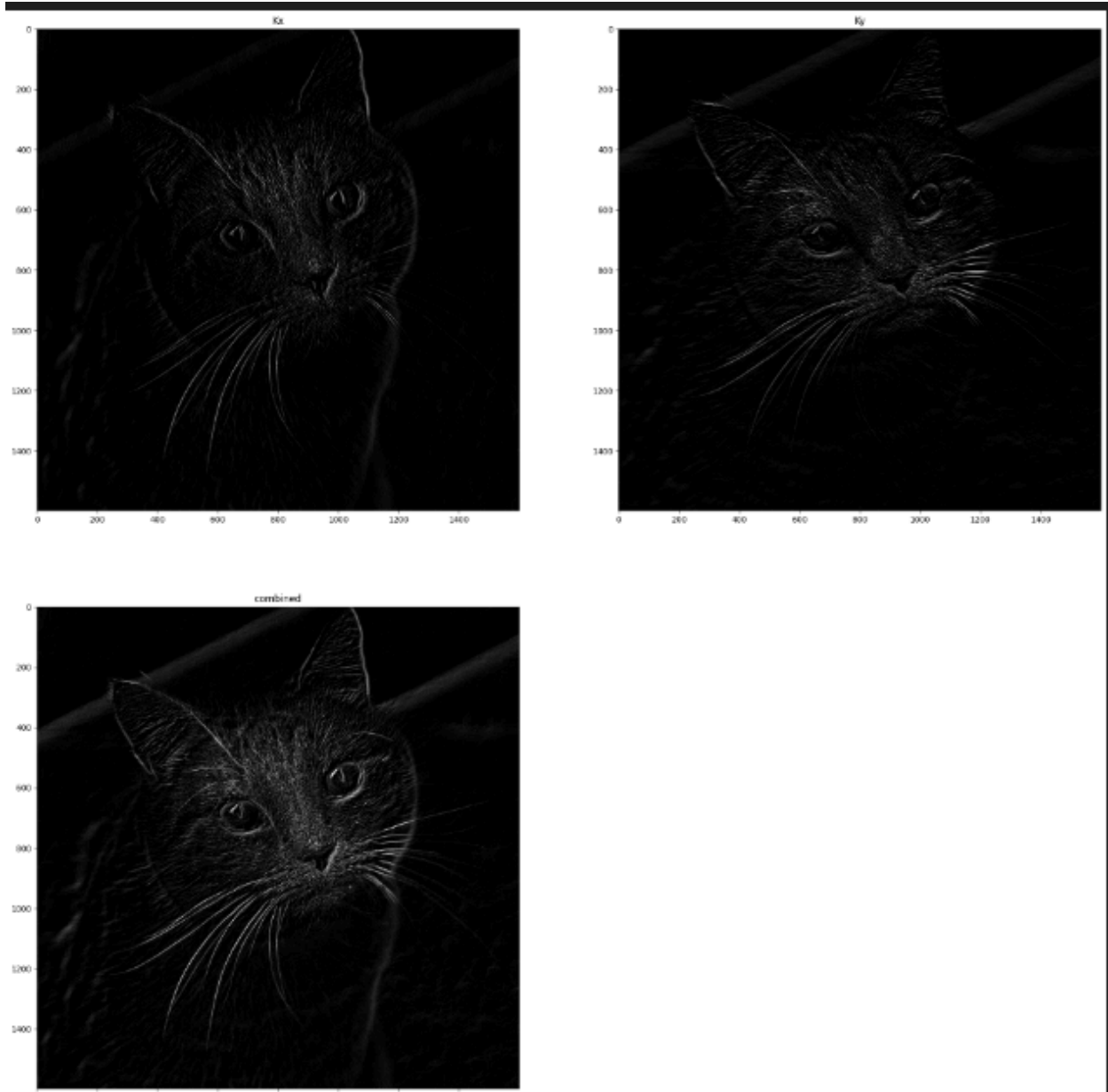
fig = plt.figure(figsize=(24,24))

filtered_image = cv2.filter2D(gray, -1, Kx)
fig.add_subplot(2,2,1)
plt.imshow(filtered_image, cmap='gray')
plt.title('Kx')

filtered_image2 = cv2.filter2D(gray, -1, Ky)
fig.add_subplot(2,2,2)
plt.imshow(filtered_image2, cmap='gray')
plt.title('Ky')

combined = cv2.addWeighted(filtered_image, 1, filtered_image2, 1, 0)
fig.add_subplot(2,2,3)
plt.imshow(combined, cmap='gray')
plt.title('combined')

```



```
combined = cv2.addWeighted(filtered_image, 1, filtered_image2, 1, 0)
```

We can see differences between the Kx and Yx, Kx is more focus vertical and Yx is more focus horizontal, then when i set combined x and y weight to 1 and mix them together to get a clear picture.

```
fig = plt.figure(figsize=(24,24))
```

```
S2x2 = np.array([[ 1, 1],
                  [ 1, 1]])
```

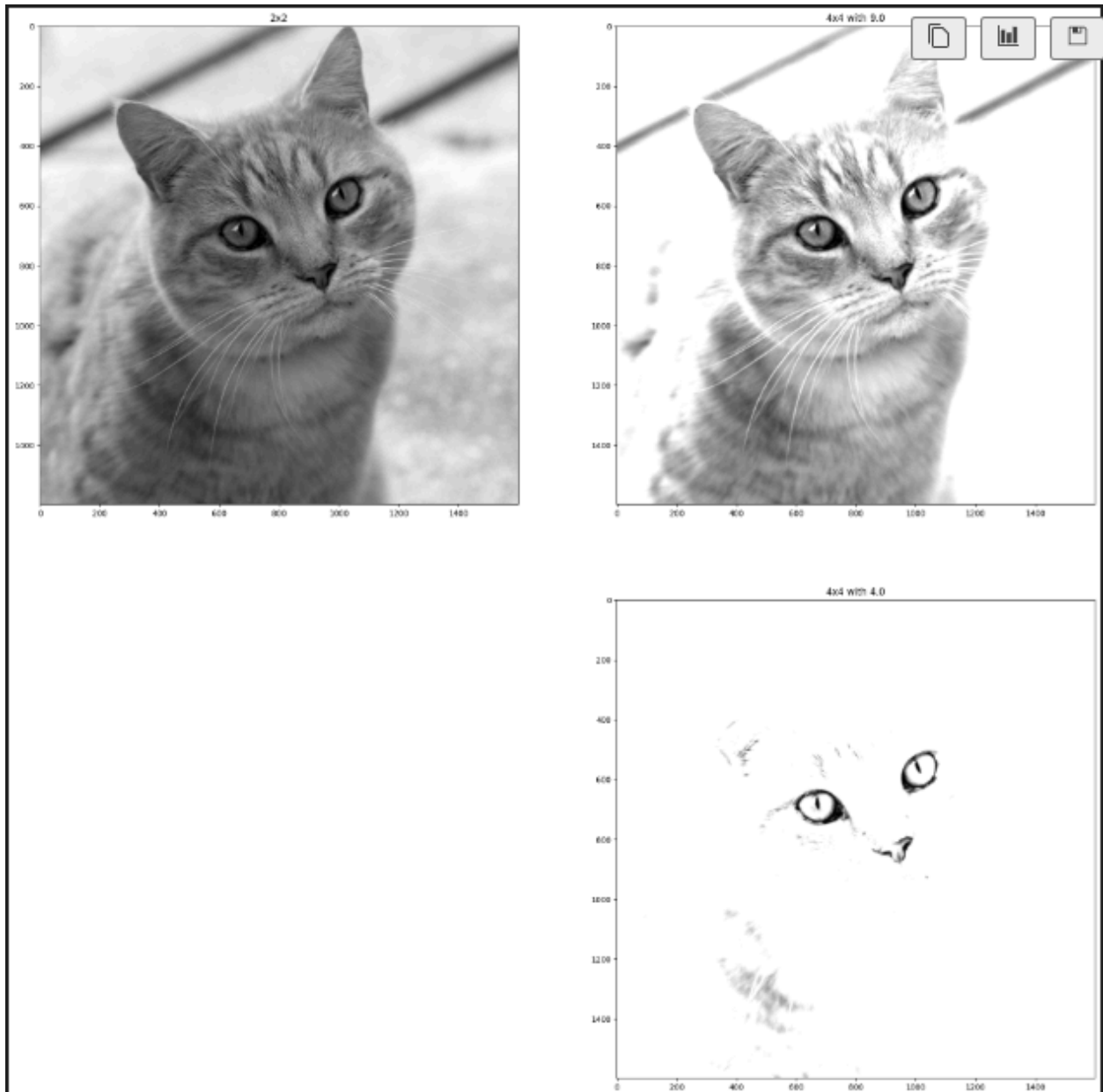
```
S4x4 = np.array([[ 1, 1, 1, 1],
                  [ 1, 1, 1, 1],
```

```
        [ 1, 1, 1, 1],
        [ 1, 1, 1, 1]])

blurred_image = cv2.filter2D(gray, -1, S2x2/9.0)
fig.add_subplot(2,2,1)
plt.imshow(blurred_image, cmap='gray')
plt.title('2x2')

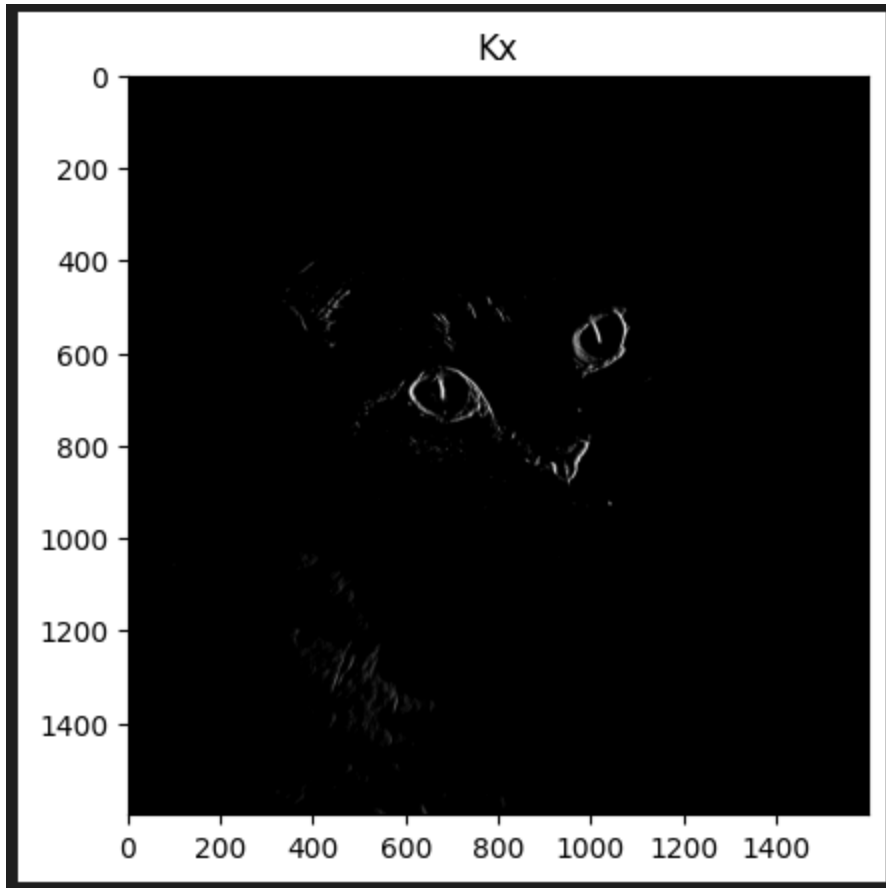
blurred_image = cv2.filter2D(gray, -1, S4x4/9.0)
fig.add_subplot(2,2,2)
plt.imshow(blurred_image, cmap='gray')
plt.title('4x4 with 9.0')

blurred_image = cv2.filter2D(gray, -1, S4x4/4.0)
fig.add_subplot(2,2,4)
plt.imshow(blurred_image, cmap='gray')
plt.title('4x4 with 4.0')
```

When we change the size of the kernel filter we can see the image is more blurred, more focus the detail, when size of filter weight/ 4, we can see the picture is much blurred than 9.0 which is more focus detail.

```
filtered_image = cv2.filter2D(blurred_image, -1, Kx)
plt.imshow(filtered_image, cmap='gray')
plt.title('Kx')
```



Using images that apply S4x4/4.0 to Kx edge detect, we can see there is not much difference due to the fact that all variables are detailed.

Part 2 Build_cnn.zip:

```
class Net(nn.Module):
    def __init__(self):
        super(Net, self).__init__()

        # TOTO: Build multiple convolutional layers (sees 32x32x3 image
        # tensor in the first hidden layer)
        # for example, conv1, conv2 and conv3
        self.conv1 = nn.Conv2d(in_channels=3, out_channels=32,
kernel_size=3, stride=1, padding=1)
        self.conv2 = nn.Conv2d(in_channels=32, out_channels=16,
kernel_size=3, stride=2, padding=0)
        self.conv3 = nn.Conv2d(in_channels=16, out_channels=32,
kernel_size=3, stride=1, padding=0)

        # max pooling layer
```

```

self.pool = nn.MaxPool2d(2, 2)

# TODO: Build some linear layers (fully connected)
# for example, fc1 and fc2
self.fc1 = nn.Linear(32 * 1 * 1, 100)
self.fc2 = nn.Linear(100, 10)

# TODO: dropout layer (p=0.25, you can adjust)
# example self.dropout = nn.Dropout(0.25)
self.dropout = nn.Dropout(0.25)

def forward(self, x):
    # add sequence of convolutional and max pooling layers
    # assume we have 2 convolutional layers defined above
    # and we do a maxpooling after each conv layer
    x = self.pool(F.relu(self.conv1(x)))
    x = self.pool(F.relu(self.conv2(x)))
    x = F.relu(self.conv3(x))

    #print(f"Shape before flatten: {x.shape}")
    # TODO: flatten x at this point to get it ready to feed into the
fully connected layer(s)
    # Can use this but need to figure out the actual value for a, b
and c
    # x = x.view(-1, a * b * c)
    x = x.view(-1, 32 * 1 * 1)
    #print(f"batch_size: {x.size(0)}")

    #x = x.view(x.size(0), -1)
    # optional add dropout layer
    x = self.dropout(x)

    # add 1st hidden layer, with relu activation function
    x = F.relu(self.fc1(x))
    # optional add dropout layer
    x = self.dropout(x)
    # add 2nd hidden layer, with relu activation function
    x = self.fc2(x)
    return x

```

$$H_{\text{out}} = \frac{H_{\text{in}} + 2P - K}{S} + 1$$

We have convolutional layer conv1 that input 3 channel sense RGB picture then output is 32 channel with 32*32 pixel picture.

$$(32+2(1)-3) / 1 + 1 = 32$$

We have convolutional layer conv2 need 32 channel which from conv1 and since padding and stride is not perfect, so we lost some pixel so picture which 15*15

$$(32+2(0)-3) / 2 + 1 = 15$$

Third convolutional layer con3 need 16 which from con2 and we lost some pixel because padding and stride, so it become 13*13

$$(15+2(0)-3) / 1 + 1 = 13$$

Then we have maxpool 2*2, so we eventually have 6*6 pixel picture

$$13 / 2 = 6.5 = 6$$

```
self.fc1 = nn.Linear(32 * 1 * 1, 100)
```

But reason why we using Linear 32*1*1 because of our forward function first two time call conv1 then will apply maxpool, so it cut the picture to half every time so math will change to below

```
x = self.pool(F.relu(self.conv1(x)))
x = self.pool(F.relu(self.conv2(x)))
x = F.relu(self.conv3(x))
```

$$(32+2(1)-3) / 1 + 1 = 32$$

$$32 / 2 = 16$$

$$(16+2(0)-3) / 2 + 1 = 7$$

$$7 / 2 = 3.5 = 3$$

$$(3+2(0)-3) / 1 + 1 = 1$$

So eventually we had 32 channel of 1*1 picture then we combine to train the model

```
Epoch: 1      Training Loss: 2.225502      Validation Loss: 2.031201
Validation loss decreased (inf --> 2.031201). Saving model ...
Epoch: 2      Training Loss: 1.977334      Validation Loss: 1.814740
Validation loss decreased (2.031201 --> 1.814740). Saving model ...
Epoch: 3      Training Loss: 1.802740      Validation Loss: 1.668203
Validation loss decreased (1.814740 --> 1.668203). Saving model ...
Epoch: 4      Training Loss: 1.695071      Validation Loss: 1.568709
Validation loss decreased (1.668203 --> 1.568709). Saving model ...
Epoch: 5      Training Loss: 1.623666      Validation Loss: 1.504402
Validation loss decreased (1.568709 --> 1.504402). Saving model ...
```

```
Test Loss: 1.495284
```

```
Test Accuracy of airplane: 43% (438/1000)
Test Accuracy of automobile: 60% (601/1000)
Test Accuracy of bird: 10% (100/1000)
Test Accuracy of cat: 5% (56/1000)
Test Accuracy of deer: 42% (425/1000)
Test Accuracy of dog: 61% (614/1000)
Test Accuracy of frog: 64% (641/1000)
Test Accuracy of horse: 53% (537/1000)
Test Accuracy of ship: 58% (585/1000)
Test Accuracy of truck: 51% (516/1000)
```

```
Test Accuracy (Overall): 45% (4513/10000)
```

We can see test loss is 1.5 and test accuracy is 45% using SGD with lr 0.01



Which is okay, but not really good.

Switch to Adam with lr 0.01 using code :

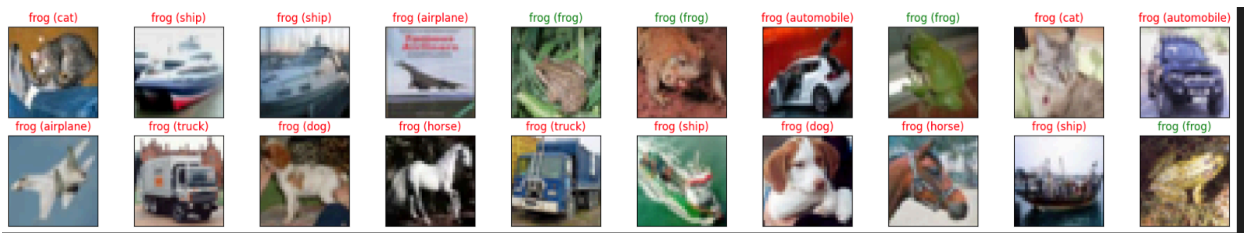
```
optimizer = optim.Adam(model.parameters(), lr=0.01)
```

```
Epoch: 1      Training Loss: 2.304510      Validation Loss: 2.305003
Validation loss decreased (inf --> 2.305003). Saving model ...
Epoch: 2      Training Loss: 2.304250      Validation Loss: 2.304262
Validation loss decreased (2.305003 --> 2.304262). Saving model ...
Epoch: 3      Training Loss: 2.304451      Validation Loss: 2.303670
Validation loss decreased (2.304262 --> 2.303670). Saving model ...
Epoch: 4      Training Loss: 2.304320      Validation Loss: 2.304309
Epoch: 5      Training Loss: 2.304205      Validation Loss: 2.303130
Validation loss decreased (2.303670 --> 2.303130). Saving model ...
```

Test Loss: 2.303204

Test Accuracy of airplane: 0% (0/1000)
Test Accuracy of automobile: 0% (0/1000)
Test Accuracy of bird: 0% (0/1000)
Test Accuracy of cat: 0% (0/1000)
Test Accuracy of deer: 0% (0/1000)
Test Accuracy of dog: 0% (0/1000)
Test Accuracy of frog: 100% (1000/1000)
Test Accuracy of horse: 0% (0/1000)
Test Accuracy of ship: 0% (0/1000)
Test Accuracy of truck: 0% (0/1000)

Test Accuracy (Overall): 10% (1000/10000)



For some reason it guesses all pictures as fog, and loss is 2.3, accuracy is 10% which is really bad, maybe Adam optimizer asking smaller lr than SGD causes this problem. So I used ADAM with lr with 0.001

```
Epoch: 1      Training Loss: 1.794639      Validation Loss: 1.559116
Validation loss decreased (inf --> 1.559116). Saving model ...
Epoch: 2      Training Loss: 1.561987      Validation Loss: 1.435943
Validation loss decreased (1.559116 --> 1.435943). Saving model ...
Epoch: 3      Training Loss: 1.479734      Validation Loss: 1.388820
Validation loss decreased (1.435943 --> 1.388820). Saving model ...
Epoch: 4      Training Loss: 1.425180      Validation Loss: 1.327199
Validation loss decreased (1.388820 --> 1.327199). Saving model ...
Epoch: 5      Training Loss: 1.384403      Validation Loss: 1.302884
Validation loss decreased (1.327199 --> 1.302884). Saving model ...
```

Test Loss: 1.301875

Test Accuracy of airplane: 66% (669/1000)
Test Accuracy of automobile: 65% (655/1000)
Test Accuracy of bird: 21% (210/1000)
Test Accuracy of cat: 32% (325/1000)
Test Accuracy of deer: 42% (423/1000)
Test Accuracy of dog: 58% (585/1000)
Test Accuracy of frog: 62% (629/1000)
Test Accuracy of horse: 64% (641/1000)
Test Accuracy of ship: 52% (523/1000)
Test Accuracy of truck: 64% (645/1000)

Test Accuracy (Overall): 53% (5305/10000)



We can see the result is much better, loss is 1.3, accuracy is 53% much better.

For summary of CNN file section, I think modify of hidden layer will help improve of accuracy, also adjust of learning step also improve accuracy, the reason why we having such low accuracy i think we used too much max layer in 16*16 picture which make it really small in the end which is 1*1.

Now we are focusing on improving the accuracy of the model. The first goal is to try to not make conventional layers cut our feature variances because everytime maxpool after conventional layer already halving a lot of feature variances, second we increase the channel of picture, 32 to 128 and make feature variances stay 8 * 8.

```
self.conv1 = nn.Conv2d(in_channels=3, out_channels=32,
kernel_size=3, stride=1, padding=1)

self.conv2 = nn.Conv2d(in_channels=32, out_channels=64,
kernel_size=3, stride=1, padding=1)
self.conv3 = nn.Conv2d(in_channels=64, out_channels=128,
kernel_size=3, stride=1, padding=1)
self.fc1 = nn.Linear(128 * 8 * 8, 100)
x = x.view(-1, 128 * 8 * 8)
```

```
Test Loss: 1.054625
```

```
Test Accuracy of airplane: 62% (629/1000)  
Test Accuracy of automobile: 72% (728/1000)  
Test Accuracy of bird: 53% (536/1000)  
Test Accuracy of cat: 44% (447/1000)  
Test Accuracy of deer: 43% (432/1000)  
Test Accuracy of dog: 51% (514/1000)  
Test Accuracy of frog: 74% (748/1000)  
Test Accuracy of horse: 63% (639/1000)  
Test Accuracy of ship: 86% (868/1000)  
Test Accuracy of truck: 69% (695/1000)
```

```
Test Accuracy (Overall): 62% (6236/10000)
```

We can see the result is much better.

Now I switch optim.SGD learning range to 0.01 to 0.001:

```
Test Loss: 1.724697
```

```
Test Accuracy of airplane: 50% (508/1000)  
Test Accuracy of automobile: 41% (419/1000)  
Test Accuracy of bird: 10% (101/1000)  
Test Accuracy of cat: 10% (101/1000)  
Test Accuracy of deer: 35% (358/1000)  
Test Accuracy of dog: 41% (414/1000)  
Test Accuracy of frog: 57% (574/1000)  
Test Accuracy of horse: 49% (495/1000)  
Test Accuracy of ship: 46% (460/1000)  
Test Accuracy of truck: 46% (469/1000)
```

```
Test Accuracy (Overall): 38% (3899/10000)
```

Using ADAM lr0.01


```
Test Loss: 0.781997
```

```
Test Accuracy of airplane: 75% (758/1000)
Test Accuracy of automobile: 88% (883/1000)
Test Accuracy of bird: 52% (529/1000)
Test Accuracy of cat: 53% (535/1000)
Test Accuracy of deer: 75% (759/1000)
Test Accuracy of dog: 58% (583/1000)
Test Accuracy of frog: 82% (823/1000)
Test Accuracy of horse: 80% (801/1000)
Test Accuracy of ship: 84% (846/1000)
Test Accuracy of truck: 81% (814/1000)
```

```
Test Accuracy (Overall): 73% (7331/10000)
```

The result getting worse, so when using SGD, higher learning range more worse accuray, Adam is opposite.

Last we can improve of accuracy is our number of epochs to train the model
I change 5 to 10

```
Test Loss: 0.731361
```

```
Test Accuracy of airplane: 85% (851/1000)
Test Accuracy of automobile: 84% (843/1000)
Test Accuracy of bird: 65% (656/1000)
Test Accuracy of cat: 64% (642/1000)
Test Accuracy of deer: 72% (727/1000)
Test Accuracy of dog: 53% (537/1000)
Test Accuracy of frog: 83% (830/1000)
Test Accuracy of horse: 78% (780/1000)
Test Accuracy of ship: 85% (851/1000)
Test Accuracy of truck: 85% (853/1000)
```

```
Test Accuracy (Overall): 75% (7570/10000)
```

Then there is the best result.