Examples_20200224

February 23, 2020

1 Goal

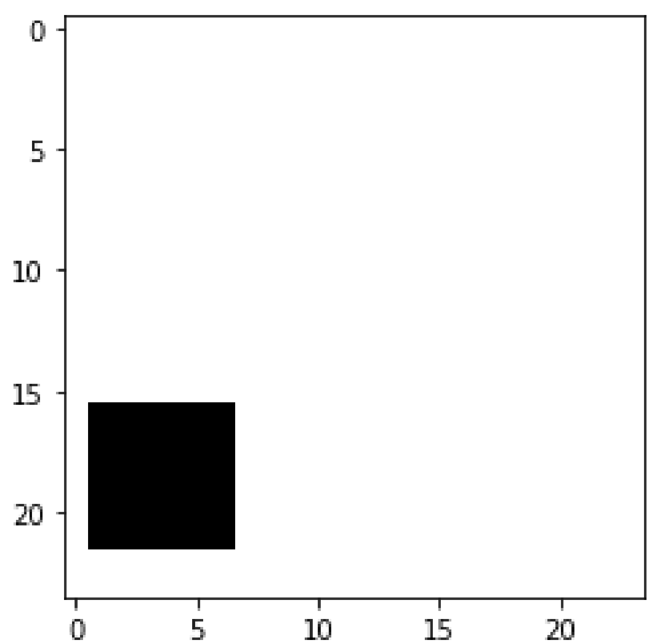
We want to take greyscale images that contain either a square or a triangle, and classify them.

2 Square and Triangle

[0]:
```
np.random.seed(4381)
sq = sim_square(24, 3)
print(sq.shape)
plt.imshow(sq[:,:,0], cmap = "gray")
```

```
(24, 24, 1)
```

[0]:
```
<matplotlib.image.AxesImage at 0x7f5a7b89c1d0>
```



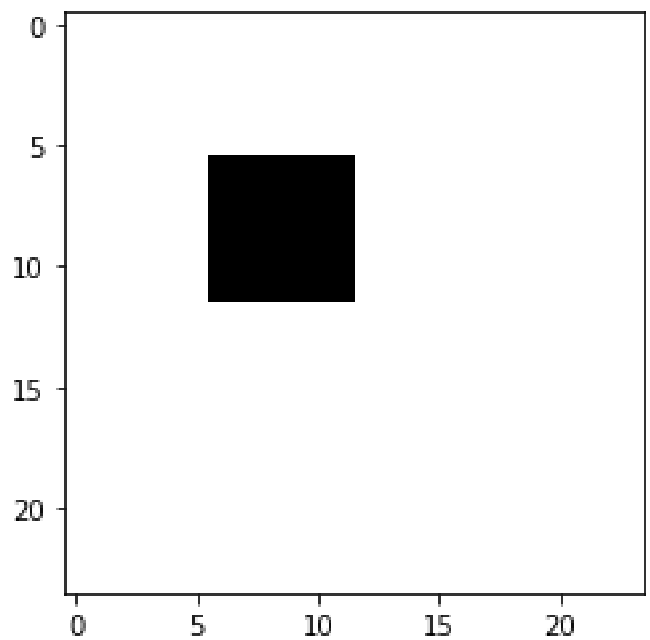
[0]:
```
sq[:,:,0]
```

[0]:
```
array([[255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255,
        255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255],
       [255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255,
        255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255],
       [255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255,
        255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255],
       [255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255,
        255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255],
       [255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255,
        255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255],
       [255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255,
        255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255],
       [255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255,
        255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255],
       [255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255,
        255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255],
       [255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255,
        255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255],
       [255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255,
        255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255],
       [255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255,
        255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255],
       [255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255,
        255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255],
       [255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255,
        255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255],
       [255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255,
        255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255],
       [255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255,
        255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255],
       [255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255,
        255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255],
       [255,   0,   0,   0,   0,   0,   0, 255, 255, 255, 255, 255, 255,
        255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255],
       [255,   0,   0,   0,   0,   0,   0, 255, 255, 255, 255, 255, 255,
        255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255],
       [255,   0,   0,   0,   0,   0,   0, 255, 255, 255, 255, 255, 255,
        255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255],
       [255,   0,   0,   0,   0,   0,   0, 255, 255, 255, 255, 255, 255,
        255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255],
       [255,   0,   0,   0,   0,   0,   0, 255, 255, 255, 255, 255, 255,
        255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255],
       [255,   0,   0,   0,   0,   0,   0, 255, 255, 255, 255, 255, 255,
```

```
        255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255],
       [255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255,
        255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255],
       [255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255,
        255, 255, 255, 255, 255, 255, 255, 255, 255, 255, 255]])
```

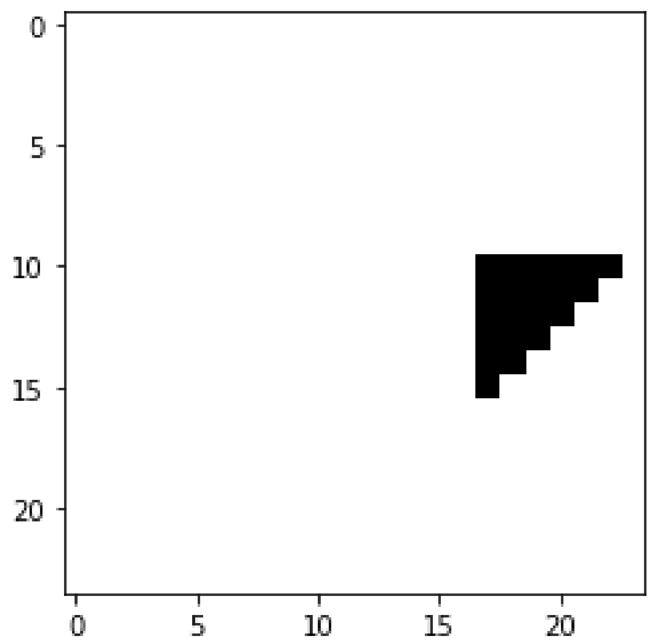
[0]:
```
sq = sim_square(24, 3)
plt.imshow(sq[:,:,0], cmap = "gray")
```

[0]: <matplotlib.image.AxesImage at 0x7f5a7b3d7ba8>



[0]:
```
tri = sim_triangle(24, 3)
plt.imshow(tri[:,:,0], cmap = "gray")
```

[0]: <matplotlib.image.AxesImage at 0x7f5a7b33d630>


0
5
10
15
20
0
5
10
15
20

3 Manual Neural Network

3.1 First Hidden Layer: Convolutional, Edge Detection

I manually specify five different 5 by 5 filters:

[0]:
```
W_vert_left = np.array([[1, 1, 0, -1, -1],
                        [1, 1, 0, -1, -1],
                        [1, 1, 0, -1, -1],
                        [1, 1, 0, -1, -1],
                        [1, 1, 0, -1, -1]]).reshape((5,5,1))
b_vert_left = -2100

W_vert_right = np.array([[-1, -1, 0, 1, 1],
                        [-1, -1, 0, 1, 1],
                        [-1, -1, 0, 1, 1],
                        [-1, -1, 0, 1, 1],
                        [-1, -1, 0, 1, 1]]).reshape((5,5,1))
b_vert_right = -2100

W_horiz_top = np.array([[1, 1, 1, 1, 1],
                        [1, 1, 1, 1, 1],
                        [0, 0, 0, 0, 0],
                        [-1, -1, -1, -1, -1],
                        [-1, -1, -1, -1, -1]]).reshape((5,5,1))
b_horiz_top = -2100

W_horiz_bottom = np.array([[-1, -1, -1, -1, -1],
                           [-1, -1, -1, -1, -1],
                         [0, 0, 0, 0, 0],
                         [1, 1, 1, 1, 1],
                         [1, 1, 1, 1, 1]]).reshape((5,5,1))
b_horiz_bottom = -2100

W_45_lower_right = np.array([[-1, -1, -1, -1, 0],
                      [-1, -1, -1, 0, 1],
                      [-1, -1, 0, 1, 1],
                      [-1, 0, 1, 1, 1],
                      [0, 1, 1, 1, 1]]).reshape((5,5,1))
b_45_lower_right = -2100

all_W1 = [W_vert_left, W_vert_right, W_horiz_top, W_horiz_bottom,␣
 ↪W_45_lower_right]
all_b1 = np.array([b_vert_left, b_vert_right, b_horiz_top, b_horiz_bottom,␣
 ↪b_45_lower_right]).reshape(1, 1, 5)
```

Calculating the activation outputs for the square and for the triangle:

```
[0]: sq_z_no_b1 = do_convolutions(sq, all_W1)
sq_z1 = sq_z_no_b1 + all_b1
sq_a1 = relu(sq_z1)
print("shape = " + str(sq_a1.shape))

tri_z_no_b1 = do_convolutions(tri, all_W1)
tri_z1 = tri_z_no_b1 + all_b1
tri_a1 = relu(tri_z1)
print("shape = " + str(tri_a1.shape))
```

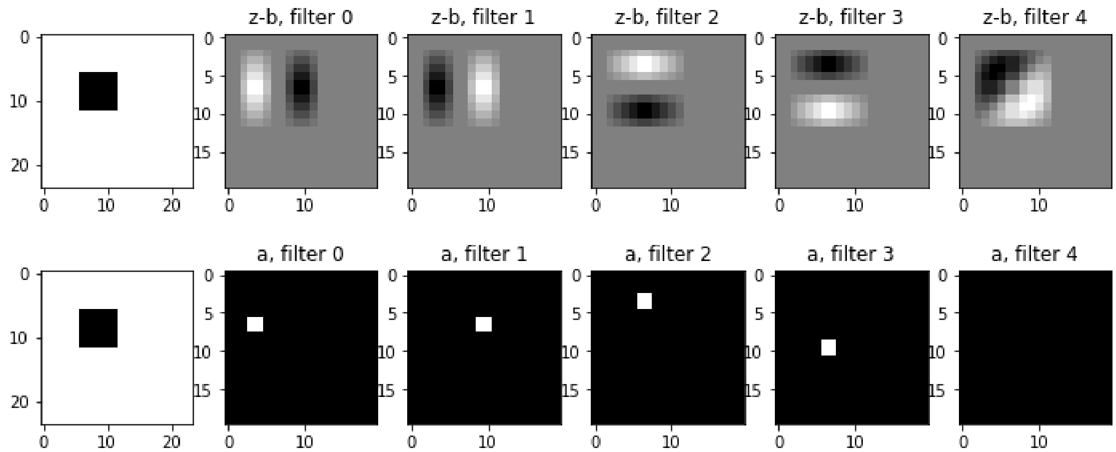
```
shape = (20, 20, 5)
shape = (20, 20, 5)
```

Here's a display of the filter outputs for the square image:

```
[0]: fig, axs = plt.subplots(2, 6, figsize=(12, 5))
axs[0,0].imshow(sq[:, :, 0], cmap = "gray")
axs[1,0].imshow(sq[:, :, 0], cmap = "gray")

b = -2100.0

for i in range(5):
  print("\nfilter " + str(i))
  print("largest z value before adding b = " + str(np.max(sq_z_no_b1[:,:,i])))
  print("largest a value = " + str(np.max(sq_a1[:,:,i])))

  axs[0, i+1].imshow(sq_z_no_b1[:,:,i], cmap = "gray")
  axs[0, i+1].set_title("z-b, filter " + str(i))
  axs[1, i+1].imshow(sq_a1[:,:,i], cmap = "gray")
  axs[1, i+1].set_title("a, filter " + str(i))
```

```
filter 0
largest z value before adding b = 2550.0
largest a value = 450.0

filter 1
largest z value before adding b = 2550.0
largest a value = 450.0

filter 2
largest z value before adding b = 2550.0
largest a value = 450.0

filter 3
largest z value before adding b = 2550.0
largest a value = 450.0
```

```
filter 4
largest z value before adding b = 2040.0
largest a value = 0.0
```

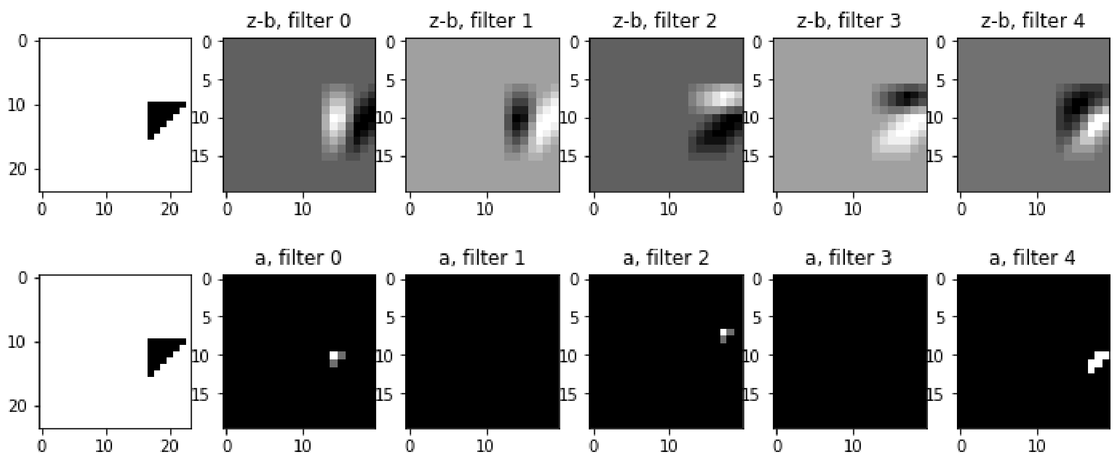


Here's a display of the filter outputs for the triangle image:

[0]:
```
fig, axs = plt.subplots(2, 6, figsize=(12, 5))
axs[0,0].imshow(tri[:, :, 0], cmap = "gray")
axs[1,0].imshow(tri[:, :, 0], cmap = "gray")

b = -2100.0

for i in range(5):
  print("\nfilter " + str(i))
  print("largest z value before adding b = " + str(np.max(tri_z_no_b1[:,:,i])))
  print("largest a value = " + str(np.max(tri_a1[:,:,i])))

  axs[0, i+1].imshow(tri_z_no_b1[:,:,i], cmap = "gray")
  axs[0, i+1].set_title("z-b, filter " + str(i))
  axs[1, i+1].imshow(tri_a1[:,:,i], cmap = "gray")
  axs[1, i+1].set_title("a, filter " + str(i))
```

```
filter 0
largest z value before adding b = 2550.0
largest a value = 450.0

filter 1
largest z value before adding b = 1530.0
largest a value = 0.0
```

```
filter 2
largest z value before adding b = 2550.0
largest a value = 450.0

filter 3
largest z value before adding b = 1530.0
largest a value = 0.0

filter 4
largest z value before adding b = 2550.0
largest a value = 450.0
```



[0]:
```
np.where(sq_a1[:,:,0] > 0)
```

[0]: (array([6, 6, 7, 7]), array([3, 4, 3, 4]))

[0]:
```
np.where(sq_a1[:,:,1] > 0)
```

[0]: (array([6, 6, 7, 7]), array([9, 10, 9, 10]))

[0]:
```
np.where(sq_a1[:,:,2] > 0)
```

[0]: (array([3, 3, 4, 4]), array([6, 7, 6, 7]))

[0]:
```
np.where(sq_a1[:,:,3] > 0)
```

[0]: (array([9, 9, 10, 10]), array([6, 7, 6, 7]))

[0]:
```
sq_a1.shape
```

[0]: (20, 20, 5)

3.2 Second Hidden Layer: Max Pooling, Size Reduction

[0]:
```
sq_a2 = max_pool(sq_a1, 2)
tri_a2 = max_pool(tri_a1, 2)
print(sq_a2.shape)
print(np.where(sq_a2[:,:,0] > 0))
print(np.where(sq_a2[:,:,1] > 0))
print(np.where(sq_a2[:,:,2] > 0))
print(np.where(sq_a2[:,:,3] > 0))
```

```
(10, 10, 5)
(array([3, 3]), array([1, 2]))
(array([3, 3]), array([4, 5]))
(array([1, 2]), array([3, 3]))
(array([4, 5]), array([3, 3]))
```

3.3 Third Hidden Layer: Convolutional, Corner Detection

[0]:
```
# Filter to detect a top left square (or triangle) corner
W_90_corner_top_left = np.zeros((3, 3, 5)) # mostly irrelevant

# vertical left edge (channel 0 of previous layer) exists
# in lower-left corner of this 3 by 3 patch of previous layer's activations
W_90_corner_top_left[[1,1,2,2], [0,1,0,1], 0] = 1.0

# horizontal top edge (channel 2 of previous layer) exists
# in upper-right corner of this 3 by 3 patch of previous layer's activations
W_90_corner_top_left[[0,0,1,1], [1,2,1,2], 2] = 1.0

b_90_corner_top_left = -1000


# Filter to detect a top right square corner
W_90_corner_top_right = np.zeros((3, 3, 5)) # mostly irrelevant

# vertical right edge (channel 1 of previous layer) exists
# in lower-right corner of this 3 by 3 patch of previous layer's activations
W_90_corner_top_right[[1,1,2,2], [1,2,1,2], 1] = 1.0

# horizontal top edge (channel 2 of previous layer) exists
# in upper-left corner of this 3 by 3 patch of previous layer's activations
W_90_corner_top_right[[0,0,1,1], [0,1,0,1], 2] = 1.0

b_90_corner_top_right = -1000
```

```python
# Filter to detect a bottom left square corner
W_90_corner_bottom_left = np.zeros((3, 3, 5)) # mostly irrelevant

# vertical left edge (channel 0 of previous layer) exists
# in upper-left corner of this 3 by 3 patch of previous layer's activations
W_90_corner_bottom_left[[0,0,1,1], [0,1,0,1], 0] = 1.0

# horizontal bottom edge (channel 3 of previous layer) exists
# in lower-right corner of this 3 by 3 patch of previous layer's activations
W_90_corner_bottom_left[[1,1,2,2], [1,2,1,2], 3] = 1.0

b_90_corner_bottom_left = -1000


# Filter to detect a bottom right square corner
W_90_corner_bottom_right = np.zeros((3, 3, 5)) # mostly irrelevant

# vertical right edge (channel 1 of previous layer) exists
# in upper-right corner of this 3 by 3 patch of previous layer's activations
W_90_corner_bottom_right[[0,0,1,1], [1,2,1,2], 1] = 1.0

# horizontal bottom edge (channel 3 of previous layer) exists
# in lower-left corner of this 3 by 3 patch of previous layer's activations
W_90_corner_bottom_right[[1,1,2,2], [0,1,0,1], 3] = 1.0

b_90_corner_bottom_right = -1000


# Filter to detect a top right triangle corner
W_45_corner_top_right = np.zeros((3, 3, 5)) # mostly irrelevant

# vertical left edge (channel 0 of previous layer) exists
# in lower-left corner of this 3 by 3 patch of previous layer's activations
W_45_corner_top_right[[1,1,2,2], [0,1,0,1], 0] = 1.0

# diagonal edge (channel 4 of previous layer) exists
# in middle-to-lower part of this 3 by 3 patch of previous layer's activations
W_45_corner_top_right[[1,1,1,2,2,2], [0,1,2,0,1,2], 4] = 1.0

b_45_corner_top_right = -1000


# Filter to detect a bottom left triangle corner
W_45_corner_bottom_left = np.zeros((3, 3, 5)) # mostly irrelevant

# vertical left edge (channel 0 of previous layer) exists
# in upper-left corner of this 3 by 3 patch of previous layer's activations
```

```
W_45_corner_bottom_left[[0,0,1,1], [0,1,0,1], 0] = 1.0

# diagonal edge (channel 4 of previous layer) exists
# in middle-to-right side of this 3 by 3 patch of previous layer's activations
W_45_corner_bottom_left[[0,0,1,1,2,2], [1,2,1,2,1,2], 4] = 1.0

b_45_corner_bottom_left = -1000


all_W3 = [W_90_corner_top_left, W_90_corner_top_right,
          W_90_corner_bottom_left, W_90_corner_bottom_right,
          W_45_corner_top_right, W_45_corner_bottom_left]
all_b3 = np.array([b_90_corner_top_left, b_90_corner_top_right,
          b_90_corner_bottom_left, b_90_corner_bottom_right,
          b_45_corner_top_right, b_45_corner_bottom_left]).reshape(1, 1, 6)
```

Calculating the activation outputs:

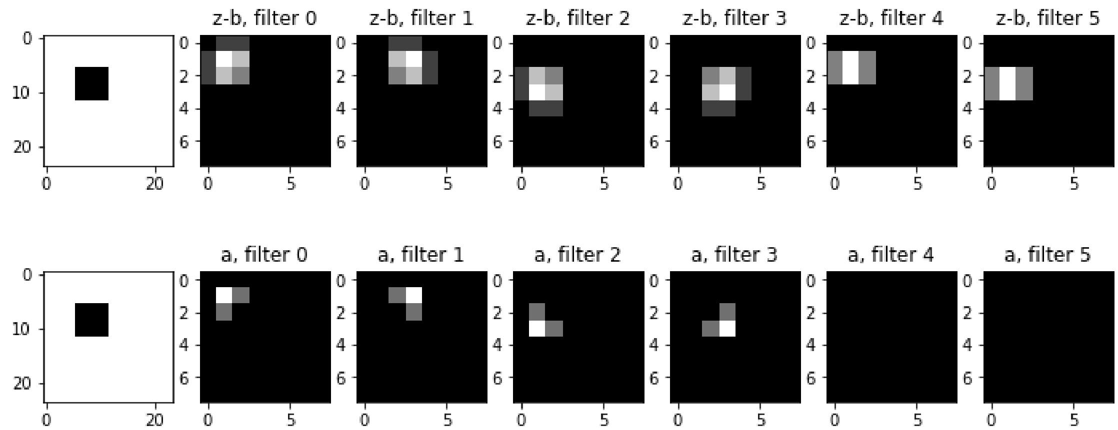
[0]:
```
sq_z_no_b3 = do_convolutions(sq_a2, all_W3)
sq_z3 = sq_z_no_b3 + all_b3
sq_a3 = relu(sq_z3)
print("shape = " + str(sq_a3.shape))

tri_z_no_b3 = do_convolutions(tri_a2, all_W3)
tri_z3 = tri_z_no_b3 + all_b3
tri_a3 = relu(tri_z3)
print("shape = " + str(tri_a3.shape))
```

```
shape = (8, 8, 6)
shape = (8, 8, 6)
```

Here's a display of the filter outputs for the square image:

[0]:
```
fig, axs = plt.subplots(2, 7, figsize=(12, 5))
axs[0,0].imshow(sq[:, :, 0], cmap = "gray")
axs[1,0].imshow(sq[:, :, 0], cmap = "gray")

for i in range(6):
  print("\nfilter " + str(i))
  print("largest z value before adding b = " + str(np.max(sq_z_no_b3[:,:,i])))
  print("largest a value = " + str(np.max(sq_a3[:,:,i])))

  axs[0, i+1].imshow(sq_z_no_b3[:,:,i], cmap = "gray")
  axs[0, i+1].set_title("z-b, filter " + str(i))
  axs[1, i+1].imshow(sq_a3[:,:,i], cmap = "gray")
  axs[1, i+1].set_title("a, filter " + str(i))
```

```
filter 0
largest z value before adding b = 1800.0
largest a value = 800.0

filter 1
largest z value before adding b = 1800.0
largest a value = 800.0

filter 2
largest z value before adding b = 1800.0
largest a value = 800.0

filter 3
largest z value before adding b = 1800.0
largest a value = 800.0

filter 4
largest z value before adding b = 900.0
largest a value = 0.0

filter 5
largest z value before adding b = 900.0
largest a value = 0.0
```

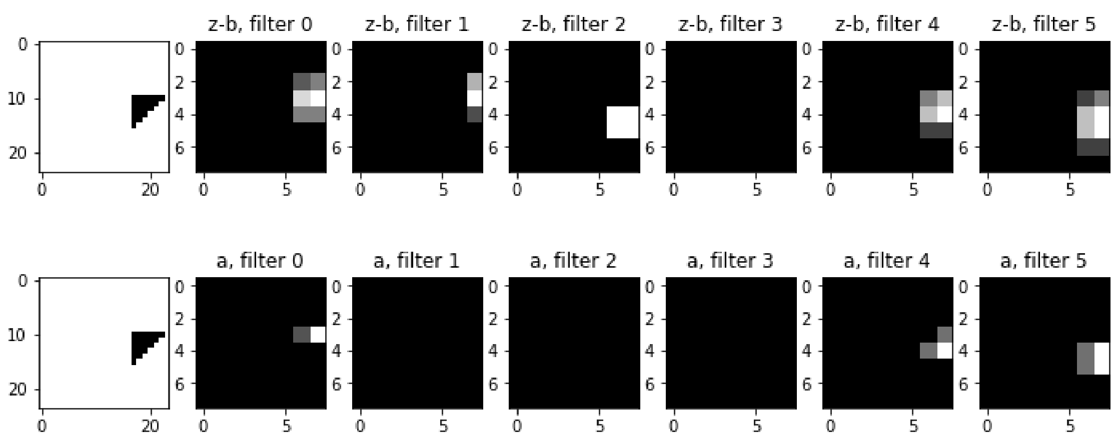


[0]:

```
fig, axs = plt.subplots(2, 7, figsize=(12, 5))
axs[0,0].imshow(tri[:, :, 0], cmap = "gray")
axs[1,0].imshow(tri[:, :, 0], cmap = "gray")

for i in range(6):
  print("\nfilter " + str(i))
  print("largest z value before adding b = " + str(np.max(tri_z_no_b3[:,:,i])))
  print("largest a value = " + str(np.max(tri_a3[:,:,i])))
```

```
axs[0, i+1].imshow(tri_z_no_b3[:,:,i], cmap = "gray")
axs[0, i+1].set_title("z-b, filter " + str(i))
axs[1, i+1].imshow(tri_a3[:,:,i], cmap = "gray")
axs[1, i+1].set_title("a, filter " + str(i))
```

```
filter 0
largest z value before adding b = 1290.0
largest a value = 290.0

filter 1
largest z value before adding b = 645.0
largest a value = 0.0

filter 2
largest z value before adding b = 450.0
largest a value = 0.0

filter 3
largest z value before adding b = 0.0
largest a value = 0.0

filter 4
largest z value before adding b = 1800.0
largest a value = 800.0

filter 5
largest z value before adding b = 1800.0
largest a value = 800.0
```



3.4 Output Layer: Fully Connected, Probability of Square

[0]:
```
W4 = np.concatenate(
    (np.zeros((8,8,1)), # detection of upper left square corner irrelevant
    np.ones((8,8,1)), # detection of upper right square corner indicates square
    np.ones((8,8,1)), # detection of lower left square corner indicates square
    np.ones((8,8,1)), # detection of lower right square corner indicates square
    -1*np.ones((8,8,1)), # detection of upper left triangle corner indicates not␣
 ↪square
    -1*np.ones((8,8,1))), # detection of lower left triangle corner indicates␣
 ↪not square
    axis = 2
).reshape(-1, 1)
b4 = 0

print(W4.shape)
```

```
(384, 1)
```

[0]:
```
sq_a3_vec = sq_a3.reshape(-1, 1)
print(sq_a3_vec.shape)
sq_a4 = sigmoid(b4 + np.dot(W4.T, sq_a3_vec))
print(sq_a4)
```

```
(384, 1)
[[1.]]
```

[0]:
```
tri_a3_vec = tri_a3.reshape(-1, 1)
tri_a4 = sigmoid(b4 + np.dot(W4.T, tri_a3_vec))
print(tri_a4)
```

```
[[0.]]
```

3.5 Function to predict from this model

[0]:
```
def predict_my_nn(X):
  # layer 1
  z1 = do_convolutions(X, all_W1) + all_b1
  a1 = relu(z1)

  # layer2
  a2 = max_pool(a1, 2)

  # layer 3
  z3 = do_convolutions(a2, all_W3) + all_b3
  a3 = relu(z3)
```

```
# layer 4
a3_vec = a3.reshape(-1, 1)
a4 = sigmoid(b4 + np.dot(W4.T, a3_vec))

return(a4)
```

4 Model in Keras

We just manually specified all the weight matrices for the convolutional layers and the dense layer, but it would be better to treat these as model parameters to estimate from data.

4.1 Generate a bunch of images

Let's make a training data set with 50 images of squares and 50 images of triangles.

[0]:
```
np.random.seed(5434)
(train_x, train_y) = sim_data(n = 50, img_dim = 24, radius = 3)
(val_x, val_y) = sim_data(n = 50, img_dim = 24, radius = 3)
print(train_x.shape)
print(train_y.shape)
```

```
(100, 24, 24, 1)
(100, 1)
```

For estimation to work, we need to standardize the data. For image data, the most common way to do this is to just divide everything by 255 to values between 0 and 1.

[0]:
```
train_x_scaled = train_x.astype(float) / 255
val_x_scaled = val_x.astype(float) / 255
```

4.1.1 First Keras Model

Exactly the same structure as our hand-made model above.

[0]:
```
model1 = models.Sequential()
model1.add(layers.Conv2D(5, (5, 5), activation = 'relu', input_shape = (24, 24,␣
↪1)))
model1.add(layers.MaxPooling2D((2, 2)))
model1.add(layers.Conv2D(6, (3, 3), activation = 'relu'))
model1.add(layers.Flatten())
model1.add(layers.Dense(1, activation = 'sigmoid'))

model1.compile(optimizer = 'adam', loss = 'binary_crossentropy', metrics =␣
↪['accuracy'])

model1.fit(train_x_scaled, train_y, epochs = 250, batch_size = 100,␣
↪validation_data = (val_x_scaled, val_y))
```

```
Train on 100 samples, validate on 100 samples
Epoch 1/250
100/100 [==============================] - 0s 5ms/step - loss: 0.6937 - acc:
0.4800 - val_loss: 0.6880 - val_acc: 0.5200
```

```
... all the epochs ...


Epoch 250/250
100/100 [==============================] - 0s 441us/step - loss: 0.0358 - acc:
1.0000 - val_loss: 0.1949 - val_acc: 0.9400
```

[0]: <keras.callbacks.History at 0x7f5a736580f0>

[0]:
```
model1.summary()
```

```
Model: "sequential_3"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_5 (Conv2D)            (None, 20, 20, 5)         130
_________________________________________________________________
max_pooling2d_4 (MaxPooling2 (None, 10, 10, 5)         0
_________________________________________________________________
conv2d_6 (Conv2D)            (None, 8, 8, 6)           276
_________________________________________________________________
flatten_3 (Flatten)          (None, 384)               0
_________________________________________________________________
dense_3 (Dense)              (None, 1)                 385
=================================================================
Total params: 791
Trainable params: 791
Non-trainable params: 0
_________________________________________________________________
```

4.2 Validation set accuracy for our hand-made model

[0]:
```
yhat = np.ndarray((100,1))
for i in range(100):
  yhat[i,0] = predict_my_nn(val_x[i, ...]).astype(int)

np.mean(yhat == val_y)
```

[0]: 1.0

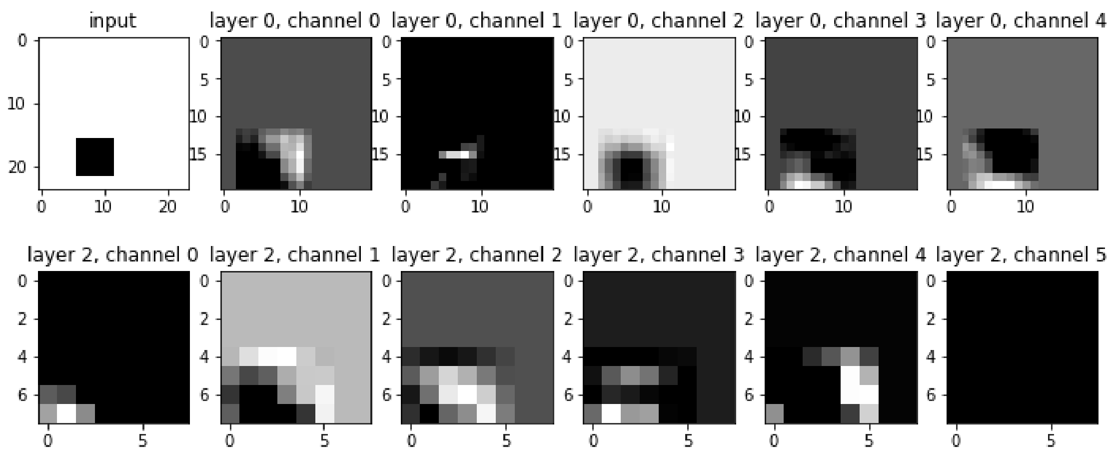
4.3 Visualizing Keras Model Activations

We can plot the activation outputs from each unit (or a selection of units) in a Keras model using the following code (adapted from Chapter 5 of Chollet). This is what we did with our regression models last week, and with our hand-made model above.

[0]:
```
# extract a list with the outputs from all layers in the model
layer_outputs = [layer.output for layer in model1.layers]
print(layer_outputs)

# create a new model with all these layers as outputs
# instead of 1 output layer at the end, we get to see the outputs from every␣
↪layer
activation_model = models.Model(inputs = model1.input, outputs = layer_outputs)
```

```
[<tf.Tensor 'conv2d_5/Relu:0' shape=(?, 20, 20, 5) dtype=float32>, <tf.Tensor
'max_pooling2d_4/MaxPool:0' shape=(?, 10, 10, 5) dtype=float32>, <tf.Tensor
'conv2d_6/Relu:0' shape=(?, 8, 8, 6) dtype=float32>, <tf.Tensor
'flatten_3/Reshape:0' shape=(?, ?) dtype=float32>, <tf.Tensor
'dense_3/Sigmoid:0' shape=(?, 1) dtype=float32>]
```

[0]:
```
# call predict to get the activations for a square and a triangle
input_img = val_x[0:1,...]
activations = activation_model.predict(input_img)
#tri_activations = activation_model.predict(val_x[1:2,...])

fig, axs = plt.subplots(2, 6, figsize=(12, 5))
axs[0,0].imshow(input_img[0, :, :, 0], cmap = "gray")
axs[0,0].set_title("input")

# layer 0 activations
for i in range(5):
  axs[0, i+1].imshow(activations[0][0,:,:,i], cmap = "gray")
  axs[0, i+1].set_title("layer 0, channel " + str(i))

# layer 2 activations
for i in range(6):
  axs[1, i].imshow(activations[2][0,:,:,i], cmap = "gray")
  axs[1, i].set_title("layer 2, channel " + str(i))
```



[0]:
```python
# call predict to get the activations for a square and a triangle
input_img = val_x[50:51,...]
activations = activation_model.predict(input_img)
#tri_activations = activation_model.predict(val_x[1:2,...])

fig, axs = plt.subplots(2, 6, figsize=(12, 5))
axs[0,0].imshow(input_img[0, :, :, 0], cmap = "gray")
axs[0,0].set_title("input")

# layer 0 activations
for i in range(5):
  axs[0, i+1].imshow(activations[0][0,:,:,i], cmap = "gray")
  axs[0, i+1].set_title("layer 0, channel " + str(i))

# layer 2 activations
for i in range(6):
  axs[1, i].imshow(activations[2][0,:,:,i], cmap = "gray")
  axs[1, i].set_title("layer 2, channel " + str(i))
```