```
In [1]: from PIL import Image
   import numpy as np
   import math
   from scipy import signal
   import cv2
   import matplotlib.pyplot as plt
   import time
```

Part 2: Gaussian Filtering

Question 2.1

```
In [2]: def boxfilter(n):
            try:
                assert n \% 2 == 1
                array = np.ones((n,n))
                array = array / (n*n)
                return array
            except AssertionError as error:
                print("AssertionError: Dimension must be odd, dimension given is {}".f
        ormat(n))
        print(boxfilter(3))
        boxfilter 4 = boxfilter(4)
        print(boxfilter(5))
        [[0.1111111 0.1111111 0.1111111]
         [0.1111111 0.1111111 0.1111111]
         [0.1111111 0.1111111 0.1111111]]
        AssertionError: Dimension must be odd, dimension given is 4
        [[0.04 0.04 0.04 0.04 0.04]
         [0.04 0.04 0.04 0.04 0.04]
         [0.04 0.04 0.04 0.04 0.04]
         [0.04 0.04 0.04 0.04 0.04]
         [0.04 0.04 0.04 0.04 0.04]]
```

Question 2.2

```
In [3]: def gauss1d(sigma):
            # filter length is sigma*6 rounded up to the next odd int
            filter len = round(sigma * 6)
            if filter len % 2 == 0:
                filter len += 1
            # create 1D array, where x is distance away from center
            filter = np.arange(start=-np.floor(filter len/2), stop=np.ceil(filter len/
        2))
            # pass array through gaussian density function
            filter = np.exp(-filter**2 / (2*sigma**2))
            # normalize and return
            filter = filter/np.sum(filter)
            return filter
        print(gauss1d(0.3))
        print(gauss1d(0.5))
        print(gauss1d(1))
        print(gauss1d(2))
        [0.00383626 0.99232748 0.00383626]
        [0.10650698 0.78698604 0.10650698]
        [0.00443305 0.05400558 0.24203623 0.39905028 0.24203623 0.05400558
         0.00443305]
        [0.0022182  0.00877313  0.02702316  0.06482519  0.12110939  0.17621312
         0.19967563 0.17621312 0.12110939 0.06482519 0.02702316 0.00877313
         0.0022182 ]
```

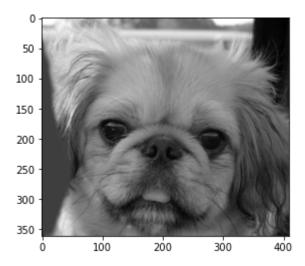
Question 2.3

```
In [4]: def gauss2d(sigma):
            # create 1D gaussian
            filter1d = gauss1d(sigma)[:,np.newaxis]
            # create 2D gaussian by convolution of 1D gaussian w/ its transpose
            filter2d = signal.convolve2d(filter1d, filter1d.T)
            return filter2d
        print(gauss2d(0.5))
        print(gauss2d(1))
        [[0.01134374 0.08381951 0.01134374]
         [0.08381951 0.61934703 0.08381951]
         [0.01134374 0.08381951 0.01134374]]
        [[1.96519161e-05 2.39409349e-04 1.07295826e-03 1.76900911e-03
          1.07295826e-03 2.39409349e-04 1.96519161e-05]
         [2.39409349e-04 2.91660295e-03 1.30713076e-02 2.15509428e-02
          1.30713076e-02 2.91660295e-03 2.39409349e-04]
         [1.07295826e-03 1.30713076e-02 5.85815363e-02 9.65846250e-02
          5.85815363e-02 1.30713076e-02 1.07295826e-03]
         [1.76900911e-03 2.15509428e-02 9.65846250e-02 1.59241126e-01
          9.65846250e-02 2.15509428e-02 1.76900911e-03]
         [1.07295826e-03 1.30713076e-02 5.85815363e-02 9.65846250e-02
          5.85815363e-02 1.30713076e-02 1.07295826e-03]
         [2.39409349e-04 2.91660295e-03 1.30713076e-02 2.15509428e-02
          1.30713076e-02 2.91660295e-03 2.39409349e-04]
         [1.96519161e-05 2.39409349e-04 1.07295826e-03 1.76900911e-03
          1.07295826e-03 2.39409349e-04 1.96519161e-05]]
```

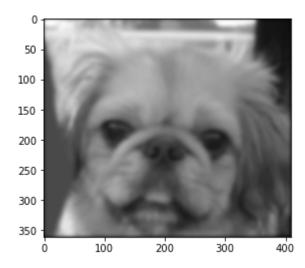
Question 2.4

```
In [5]: def convolve2d manual(array, filter):
            # Output image
            image out = np.zeros like(array)
            # Add zero padding to the input image
            padding = int(np.floor(filter.shape[0]/2))
            image_padded = np.zeros((array.shape[0] + 2*padding, array.shape[1] + 2*pa
        dding))
            image padded[padding:-padding, padding:-padding] = array
            # Loop through each neighbourhood and calculate new pixel value
            filtersz = filter.shape[0]
            for i in range(array.shape[1]):
                for j in range(array.shape[0]):
                     image_out[j, i] = np.sum(filter * image_padded[j:j+filtersz, i:i+f
        iltersz])
            return image out
        def gaussconvolve2d manual(array, sigma):
            # Create 2D gaussian filter and apply convolution
            filter = gauss2d(sigma)
            filtered_image = convolve2d_manual(array, filter)
            return filtered image
        # Load image and convert to grayscale
        coloured_image = cv2.imread("images/dog.jpg")
        grey image = cv2.cvtColor(coloured image, cv2.COLOR BGR2GRAY)
        filtered_image = gaussconvolve2d_manual(grey_image, 3)
        print("Original image:")
        plt.imshow(grey_image, cmap="gray")
        plt.show()
        print("Filtered image:")
        plt.imshow(filtered_image, cmap="gray")
        plt.show()
```

Original image:



Filtered image:



Question 2.5

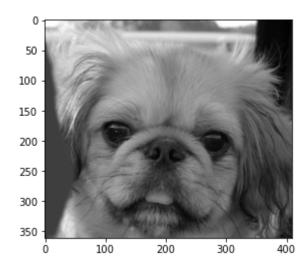
In this case, correlate2d and convolve2d return the same results because our 2D Gaussian filter is symmetric both horizontally and vertically. If the filter were not symmetric, the two functions would not return the same results.

```
In [6]: def gaussconvolve2d_scipy(array,sigma):
    filter = gauss2d(sigma)
    filtered_img = signal.convolve2d(array,filter,'same')
    return filtered_img

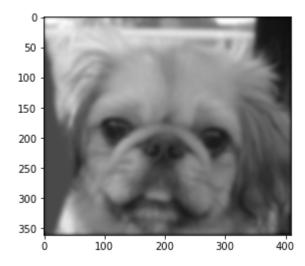
# Load image and convert to grayscale
    coloured_image = cv2.imread("images/dog.jpg")
    grey_image = cv2.cvtColor(coloured_image, cv2.COLOR_BGR2GRAY)
    filtered_image = gaussconvolve2d_scipy(grey_image, 3)

print("Original image:")
    plt.imshow(grey_image, cmap="gray")
    plt.show()
    print("Filtered image:")
    plt.imshow(filtered_image, cmap="gray")
    plt.show()
```

Original image:



Filtered image:



Question 2.6

The SciPy implementation is clearly faster when sigma=10. It may be possible that the scipy implementation uses various convolution speed-up techniques such as taking the logarithm so that multiplications become additions, or using Fourier transforms to reduce convolutions to complex multiplication. My manual implementation does not implement any of these techniques, and hence is likely why it runs slower.

```
In [7]: # Load image and convert to grayscale
    coloured_image = cv2.imread("images/dog.jpg")
    grey_image = cv2.cvtColor(coloured_image, cv2.COLOR_BGR2GRAY)

start_time = time.time() # start timestamp
    filtered_image = gaussconvolve2d_manual(grey_image, 10)
    duration_manual = time.time() - start_time # duration in seconds

start_time = time.time() # start timestamp
    filtered_image = gaussconvolve2d_scipy(grey_image, 10)
    duration_scipy = time.time() - start_time # duration in seconds

print("Manual implementation runtime: {} seconds".format(duration_manual))
    print("SciPy implementation runtime: {} seconds".format(duration_scipy))
```

Manual implementation runtime: 2.521883487701416 seconds SciPy implementation runtime: 1.7840995788574219 seconds

Question 2.7

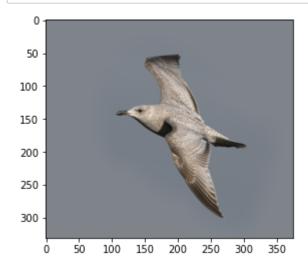
An implementation of the 2D Gaussian filter using convolution would be more efficient, because we can use 1D convolutions instead of 2D convolutions. We can first convolve each row with a 1D filter, and then convolve each column with a 1D filter. This works because the 2D Gaussian filter can be expressed as an outer product of two 1D filters (one as a function of x, the other as a function of y).

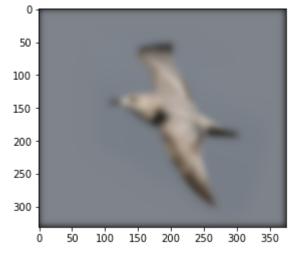
The naive implementation would need m^2 n^2 multiplications, where m is the size of the window and n is the size of the image. A separable implementation only needs 2m n^2 multiplications.

Part 3: Hybrid Images

Question 3.1

```
im a = cv2.imread("images/4a bird.bmp")
In [8]:
        im a = cv2.cvtColor(im a, cv2.COLOR BGR2RGB)
        plt.imshow(im a)
        plt.show()
        def blur_color_img(image, sigma):
            filtered channels = []
            # Split image into RGB channels
            red, green, blue = cv2.split(image)
            # Apply Gaussian blur filter to each channel separately
            for channel in [red, green, blue]:
                filtered_channel = gaussconvolve2d_scipy(channel, sigma)
                filtered_channels.append(filtered_channel.astype(int))
            # Merge channels back together and return filtered image
            filtered_color_img = cv2.merge(filtered_channels)
            return filtered_color_img
        low_freq_im_a = blur_color_img(im_a, sigma=5)
        plt.imshow(low_freq_im_a)
        plt.show()
```



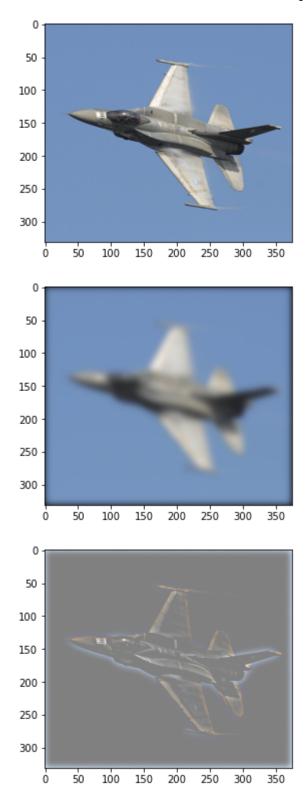


Question 3.2

```
In [9]: im_b = cv2.imread("images/4b_plane.bmp")
    im_b = cv2.cvtColor(im_b, cv2.COLOR_BGR2RGB)
    plt.imshow(im_b)
    plt.show()

    low_freq_im_b = blur_color_img(im_b, sigma=5)
    plt.imshow(low_freq_im_b)
    plt.show()

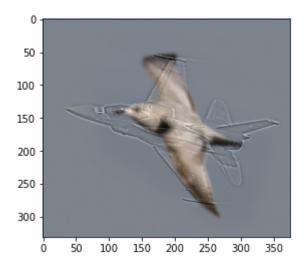
    high_freq_im = np.clip(im_b - low_freq_im_b, 0, 255)
    plt.imshow(np.clip(high_freq_im + 128, 0, 255))
    plt.show()
```



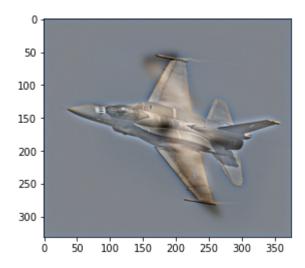
Question 3.3

```
In [10]: def merge images(im1 path, im2 path, sigma):
             im a = cv2.imread(im1 path)
             im a = cv2.cvtColor(im a, cv2.COLOR BGR2RGB)
             im b = cv2.imread(im2 path)
             im b = cv2.cvtColor(im b, cv2.COLOR BGR2RGB)
             low_freq_im_a = blur_color_img(im_a, sigma)
             low freq im b = blur color img(im b, sigma)
             high_freq_im = im_b - low_freq_im_b
             hybrid_image = np.clip(high_freq_im + low_freq_im_a, 0, 255)
             return hybrid image
         for sigma in [2,5,8]:
             print("Bird and plane at sigma={}".format(sigma))
             hybrid image = merge images("images/4a bird.bmp", "images/4b plane.bmp", s
         igma)
             plt.imshow(hybrid image)
             plt.show()
         for sigma in [2,5,8]:
             print("Cat and dog at sigma={}".format(sigma))
             hybrid_image = merge_images("images/0b_dog.bmp", "images/0a_cat.bmp", sigm
         a)
             plt.imshow(hybrid image)
             plt.show()
         for sigma in [2,5,8]:
             print("Bike and motorcycle at sigma={}".format(sigma))
             hybrid image = merge images("images/3a fish.bmp", "images/3b submarine.bm
         p", sigma)
             plt.imshow(hybrid_image)
             plt.show()
         for sigma in [2,5,8]:
             print("Einstein and Marilyn at sigma={}".format(sigma))
             hybrid_image = merge_images("images/2a_einstein.bmp", "images/2b_marilyn.b
         mp", sigma)
             plt.imshow(hybrid image)
             plt.show()
```

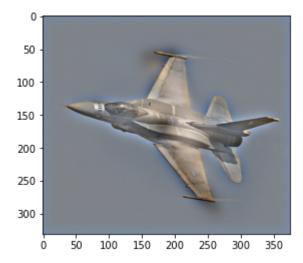
Bird and plane at sigma=2



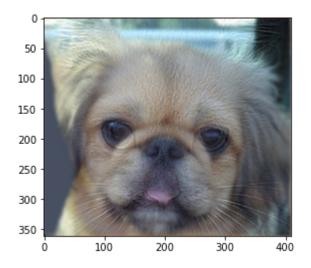
Bird and plane at sigma=5



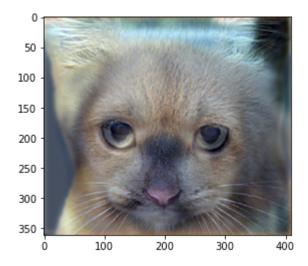
Bird and plane at sigma=8



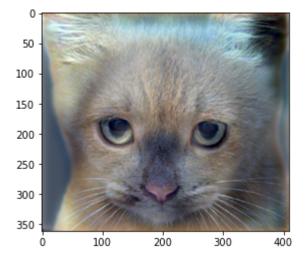
Cat and dog at sigma=2



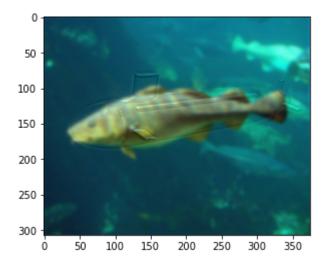
Cat and dog at sigma=5



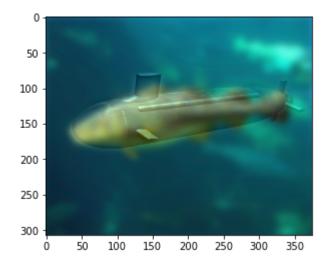
Cat and dog at sigma=8



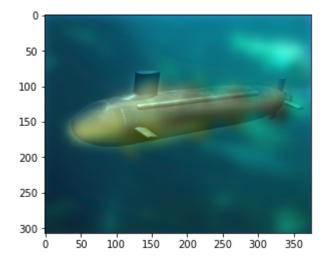
Bike and motorcycle at sigma=2



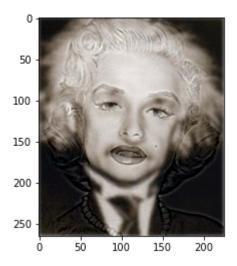
Bike and motorcycle at sigma=5



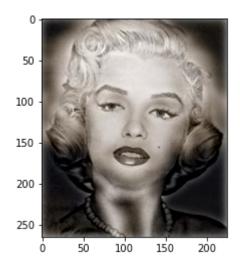
Bike and motorcycle at sigma=8



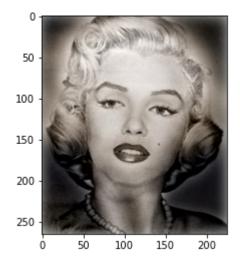
Einstein and Marilyn at sigma=2



Einstein and Marilyn at sigma=5



Einstein and Marilyn at sigma=8

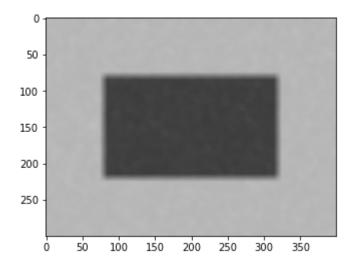


Part 4: Playing with Different Denoising Filters

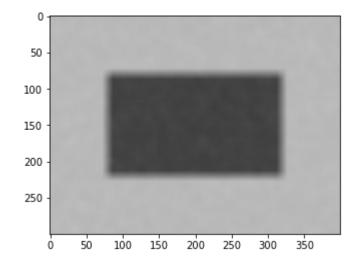
Question 4.1

```
box gauss = cv2.imread("images/box gauss.png")
box_speckle = cv2.imread("images/box_speckle.png")
print("GaussianBlur, box gauss: ksize=11, sigma=10")
plt.imshow(cv2.GaussianBlur(box gauss, ksize=(11,11), sigmaX=10, sigmaY=10))
plt.show()
print("GaussianBlur, box speckle: ksize=15, sigma=10")
plt.imshow(cv2.GaussianBlur(box speckle, ksize=(15,15), sigmaX=10, sigmaY=10))
plt.show()
print("BilateralFilter, box_gauss: d=25, sigma=225")
plt.imshow(cv2.bilateralFilter(box gauss, d=25, sigmaColor=225, sigmaSpace=225
))
plt.show()
print("BilateralFilter, box speckle: d=25, sigma=300")
plt.imshow(cv2.bilateralFilter(box speckle, d=25, sigmaColor=300, sigmaSpace=3
00))
plt.show()
print("MedianBlur, box_gauss: ksize=5")
plt.imshow(cv2.medianBlur(box_gauss, ksize=5))
print("MedianBlur, box speckle: ksize=7")
plt.imshow(cv2.medianBlur(box_speckle, ksize=7))
plt.show()
```

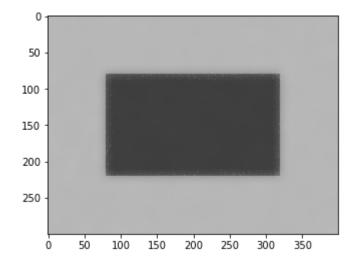
GaussianBlur, box_gauss: ksize=11, sigma=10



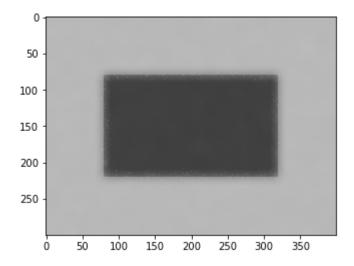
GaussianBlur, box_speckle: ksize=15, sigma=10



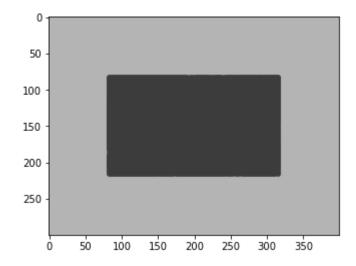
BilateralFilter, box_gauss: d=25, sigma=225



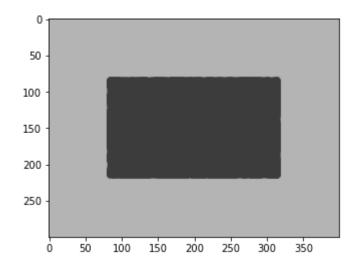
BilateralFilter, box_speckle: d=25, sigma=300



MedianBlur, box_gauss: ksize=5



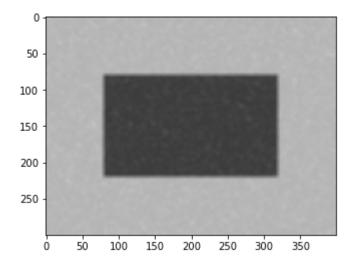
MedianBlur, box_speckle: ksize=7



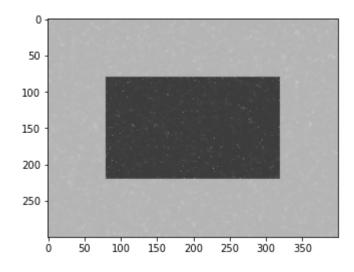
Question 4.2

```
In [12]: print("box gauss.png w/ gaussian blur:")
         plt.imshow(cv2.GaussianBlur(box_gauss, ksize=(7, 7), sigmaX=50))
         plt.show()
         print("box gauss.png w/ bilateral filter:")
         plt.imshow(cv2.bilateralFilter(box_gauss, 7, sigmaColor=150, sigmaSpace=150))
         plt.show()
         print("box_gauss.png w/ median blur:")
         plt.imshow(cv2.medianBlur(box gauss, 7))
         plt.show()
         print("box speckle.png w/ gaussian blur:")
         plt.imshow(cv2.GaussianBlur(box_speckle, ksize=(7, 7), sigmaX=50))
         plt.show()
         print("box speckle.png w/ bilateral filter:")
         plt.imshow(cv2.bilateralFilter(box_speckle, 7, sigmaColor=150, sigmaSpace=150
         ))
         plt.show()
         print("box_speckle.png w/ median blur:")
         plt.imshow(cv2.medianBlur(box_speckle, 7))
         plt.show()
```

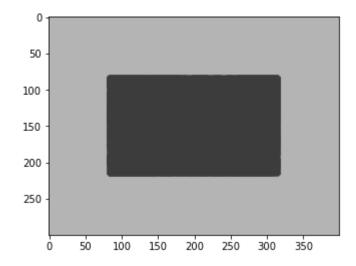
box_gauss.png w/ gaussian blur:



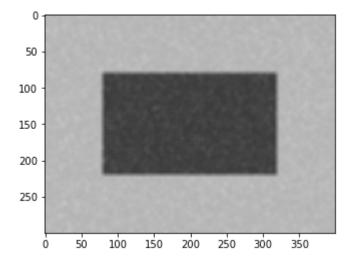
box_gauss.png w/ bilateral filter:



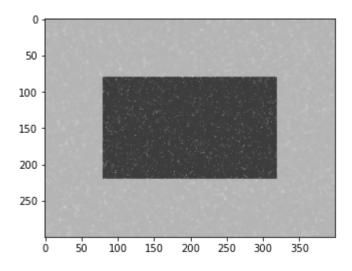
box_gauss.png w/ median blur:



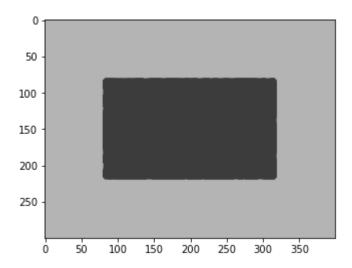
box_speckle.png w/ gaussian blur:



box_speckle.png w/ bilateral filter:



box_speckle.png w/ median blur:



Gaussian blur just tries to remove noise by blurring the image and the results are not impressive at all. In both images, the white artifacts arguably become more noticeable, since they cover larger areas. Additionally, the distinction between the outer and inner boxes are blurred as well.

With the bilateral filter, the line between the outer and inner box remains clear and distinct. This filter does a decent job with Gaussian noise. However, there is no noticeable improvement with speckle noise.

Evidently, for both images, the median blur filter works the best at removing noise. There are some remaining artifacts at the edge between the outer and inner box, but the rest of the image is much clearer than before. One con may be that the line between the outer and inner box does not remain straight.