CSC420 Assignment2

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Question 1:

(a)

Harris

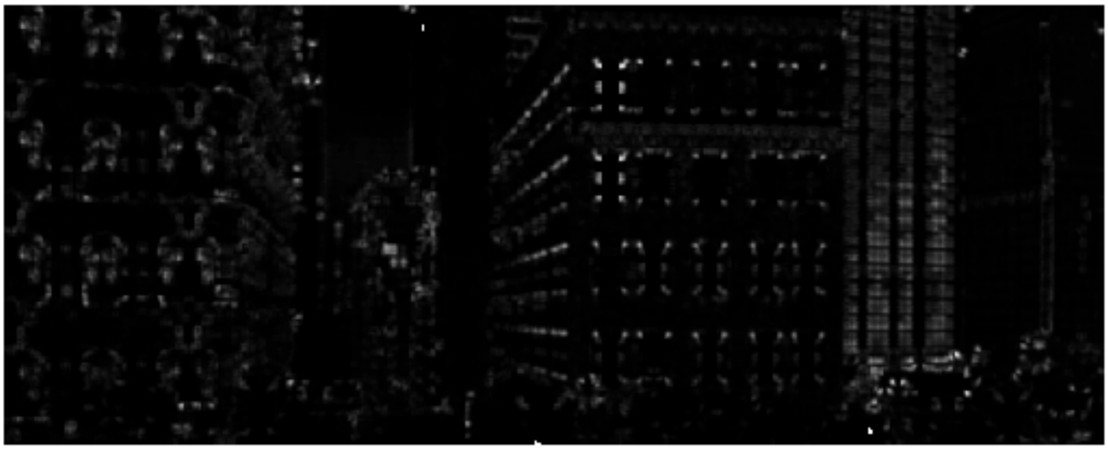
```
def Harris(img):
    gray = cv.cvtColor(img, cv.COLOR_BGR2GRAY)
    blur = cv.GaussianBlur(gray, (5, 5), 7)
    Ix = cv.Sobel(blur, cv.CV_64F, 1, 0, ksize=5)
    Iy = cv.Sobel(blur, cv.CV_64F, 0, 1, ksize=5)
    IxIy = np.multiply(Ix, Iy)
    Ix2  = np.multiply(Ix, Ix)
    Iy2 = np.multiply(Iy, Iy)

    Ix2_blur = cv.GaussianBlur(Ix2, (7, 7), 10)
    Iy2_blur = cv.GaussianBlur(Iy2, (7, 7), 10)
    IxIy_blur = cv.GaussianBlur(IxIy, (7, 7), 10)

    det = np.multiply(Ix2_blur, Iy2_blur) - np.multiply(IxIy_blur,
IxIy_blur)
    trace = Ix2_blur + Iy2_blur

    R = det - 0.05 * np.multiply(trace, trace)
    # plt.subplot(1, 2, 1), plt.imshow(img), plt.axis('off'),
plt.show()
    # plt.subplot(1, 2, 2), plt.imshow(R, cmap='gray'),
plt.axis('off'), plt.show()
    # adding threshold
    t = 0.01 * R.max()
```

```python
    for i in range(R.shape[0]):
        for j in range(R.shape[1]):
            if R[i, j] < t:
                R[i, j] = 0
    # adding threshold

    return R
```

Brown

```python
def Brown(img):
    gray = cv.cvtColor(img, cv.COLOR_BGR2GRAY)
    blur = cv.GaussianBlur(gray, (5, 5), 7)
    Ix = cv.Sobel(blur, cv.CV_64F, 1, 0, ksize=5)
    Iy = cv.Sobel(blur, cv.CV_64F, 0, 1, ksize=5)
    IxIy = np.multiply(Ix, Iy)
    Ix2 = np.multiply(Ix, Ix)
    Iy2 = np.multiply(Iy, Iy)

    Ix2_blur = cv.GaussianBlur(Ix2, (7, 7), 10)
    Iy2_blur = cv.GaussianBlur(Iy2, (7, 7), 10)
    IxIy_blur = cv.GaussianBlur(IxIy, (7, 7), 10)

    det = np.multiply(Ix2_blur, Iy2_blur) - np.multiply(IxIy_blur,
IxIy_blur)
```

```
    trace = Ix2_blur + Iy2_blur

    R = np.divide(det, trace)

    return R
```

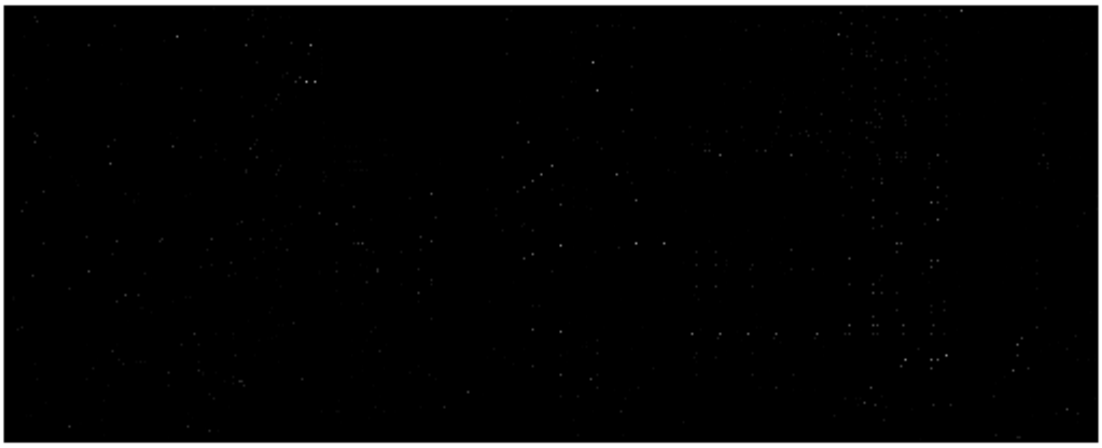


It seems that Brown will detect more keypoints than Harris. It is because in Harris we need to choose a threshold, while in Brown we only use the value of det(img) and trace(img), therefore the result won't be influenced by different thresholds.

(b)Non-Max-Suppression with circular-like kernel

```
def non_max_sup(img, r):

    img = Brown(img)

    Width, Height = img.shape[0], img.shape[1]
    padded = np.zeros((Width + 2*r, Height + 2*r))
    padded[r: Width+r, r:Height+r] = img[:, :]
    for i in range(Width):
        for j in range(Height):
            if img[i, j] != padded[i:i+2*r+1, j:j+2*r+1].max():
                img[i, j] = 0

    return img
```

R = 1



R = 3

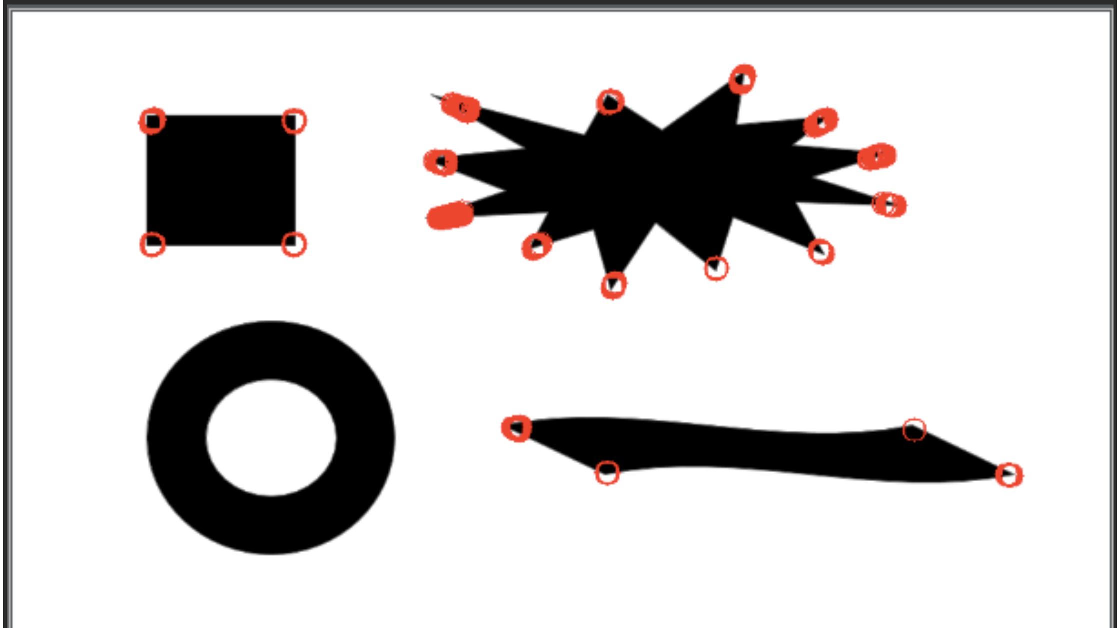
With the increasing of R value, we will detect a more wide space over our image, so the number of points is decreasing, meaning that they are more likely to be corners.

(c) Blob detection and draw keypoints

```
def blob_detector(name): #


    img = cv.imread(name, 0)
    img = img.astype(np.float32)
    M, N = img.shape
    image = np.zeros((M, N))
    Sigma_array, LoG_array = [], []
    sigma = 2
```

```
    number_of_layers = 15

    k = 2 ** 0.5
    Sigma_array.append(sigma)
    for i in range(number_of_layers - 1):
        Sigma_array.append(Sigma_array[-1] * k)
    for i in range(number_of_layers):
        blur = cv.GaussianBlur(img, (5, 5), Sigma_array[i])
        LoG_array.append(ndimage.gaussian_laplace(blur,
Sigma_array[i]))

    r = 1



    Width, Height = img.shape[0], img.shape[1]
    padded = np.zeros((Width + 2*r, Height + 2*r))
    padded[r: Width+r, r:Height+r] = img[:, :]
    Mm, Nn = padded.shape

    Pr_array = []

    Pr_array.append(np.zeros((Mm, Nn)))
    for image in LoG_array:
        Width, Height = image.shape[0], image.shape[1]
        padded = np.zeros((Width + 2 * r, Height + 2 * r))
        padded[r: Width + r, r:Height + r] = image[:, :]
        Pr_array.append(padded)

    Pr_array.append(np.zeros((Mm, Nn)))
    keypoints = {}
    for l in range(1, len(Pr_array) - 1):
        print(Pr_array[l].max(), Pr_array[l].min())
        for i in range(M):
```

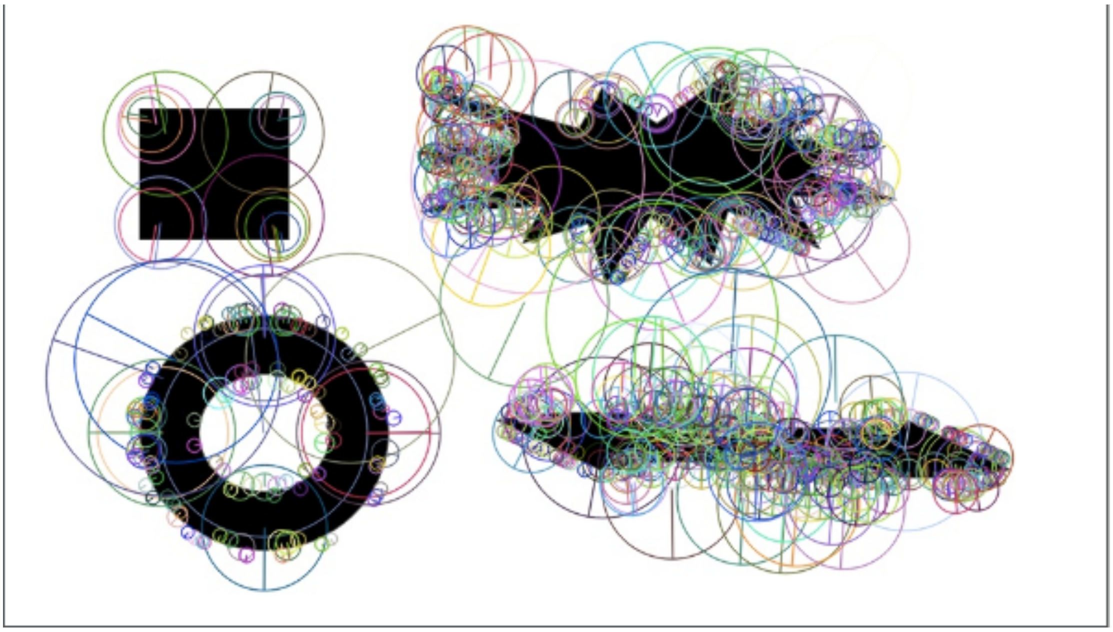
```
            for j in range(N):
                if Pr_array[l][i, j] == max(Pr_array[l][i:i+2 * r + 1,
j:j+2 * r + 1].max(), Pr_array[l-1][i:i+2 * r + 1, j:j+2 * r + 1].max(),
Pr_array[l+1][i:i+2 * r + 1, j:j+2 * r + 1].max()) and \
                         Pr_array[l][i, j] >= 11 and Pr_array[l][i, j]
<= 21:
                    if((j, i) not in keypoints):
                        keypoints[(j, i)] = Sigma_array[l-1]
    return keypoints

def drawkp(keypoints):
    image = cv.imread("synthetic.png")
    for item in keypoints.keys():
        cv.circle(image, (item[0], item[1]), radius= 5 *
int(keypoints[item]), color=(0, 0, 255), thickness=1)
    plt.subplot(1, 2, 2), plt.imshow(image, cmap='gray'),
plt.axis('off'), plt.show()
    cv.imwrite("q1c.png", image)
```



(d)

Use SURF detection:

```python
import cv2

def SURF_building(img):

    gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)
    surf = cv2.xfeatures2d.SURF_create()
    kp = surf.detect(gray, None)
    img = cv2.drawKeypoints(gray, kp, img,
flags=cv2.DRAW_MATCHES_FLAGS_DRAW_RICH_KEYPOINTS)
    cv2.imwrite('building_keypoints.jpg', img)

img2 = cv2.imread("building.jpg")
SURF_building(img2)

def SURF_synthetic(img):

    gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)
    surf = cv2.xfeatures2d.SURF_create()
    kp = surf.detect(gray, None)
    img = cv2.drawKeypoints(gray, kp, img,
flags=cv2.DRAW_MATCHES_FLAGS_DRAW_RICH_KEYPOINTS)
    cv2.imwrite('synthetic_keypoints.jpg', img)



# img1 = cv2.imread("synthetic.png", 0)
img3 = cv2.imread("synthetic.png")
SURF_synthetic(img3)
```



SURF works as follows:

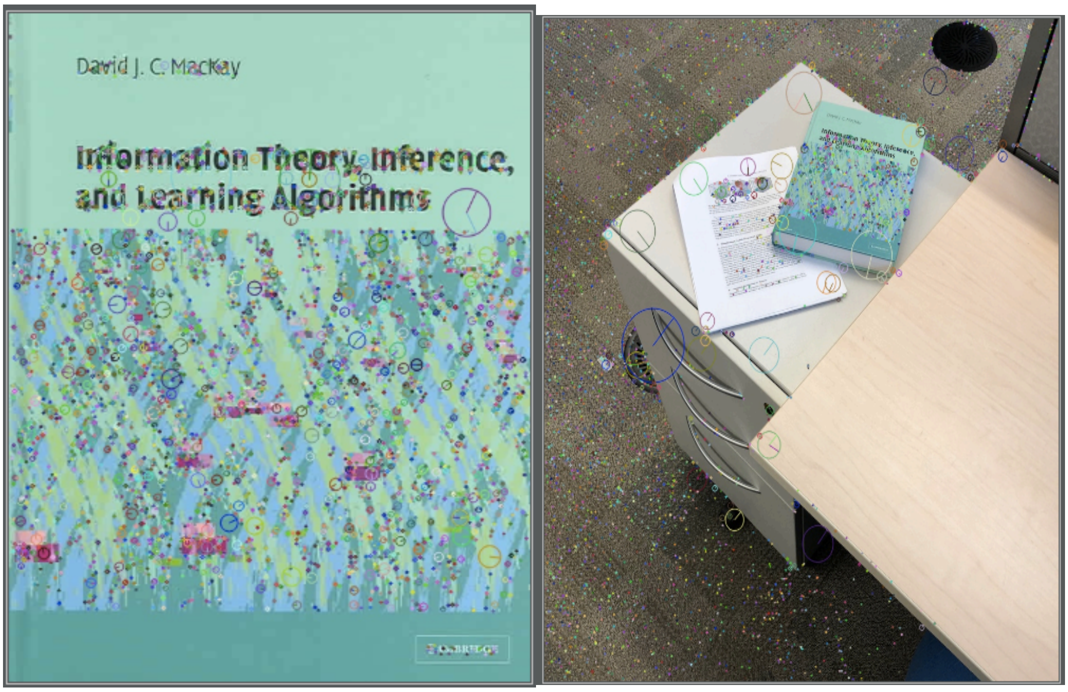
To detect interest points, SURF uses an integer approximation of the Hessian blob detector, which can be computed with 3 integer operations using a precomputed intergral image, Its feature descriptor is based on the sum of the Haar Wavelet response around the point of interest. These can also be computed with the aid of the integral image.

Question 2:

(a)

```
import cv2 as cv


def SIFT(name):
    img = cv.imread(name)
```

```
    gray = cv.cvtColor(img, cv.COLOR_BGR2GRAY)
    sift = cv.xfeatures2d_SIFT.create()
    kp = sift.detect(gray, None)
    img = cv.drawKeypoints(img, kp, img,
flags=cv.DRAW_MATCHES_FLAGS_DRAW_RICH_KEYPOINTS)
    cv.imwrite(name + '_q2_keypoints.jpg', img)

SIFT("book.jpeg")
SIFT("findBook.png")
```

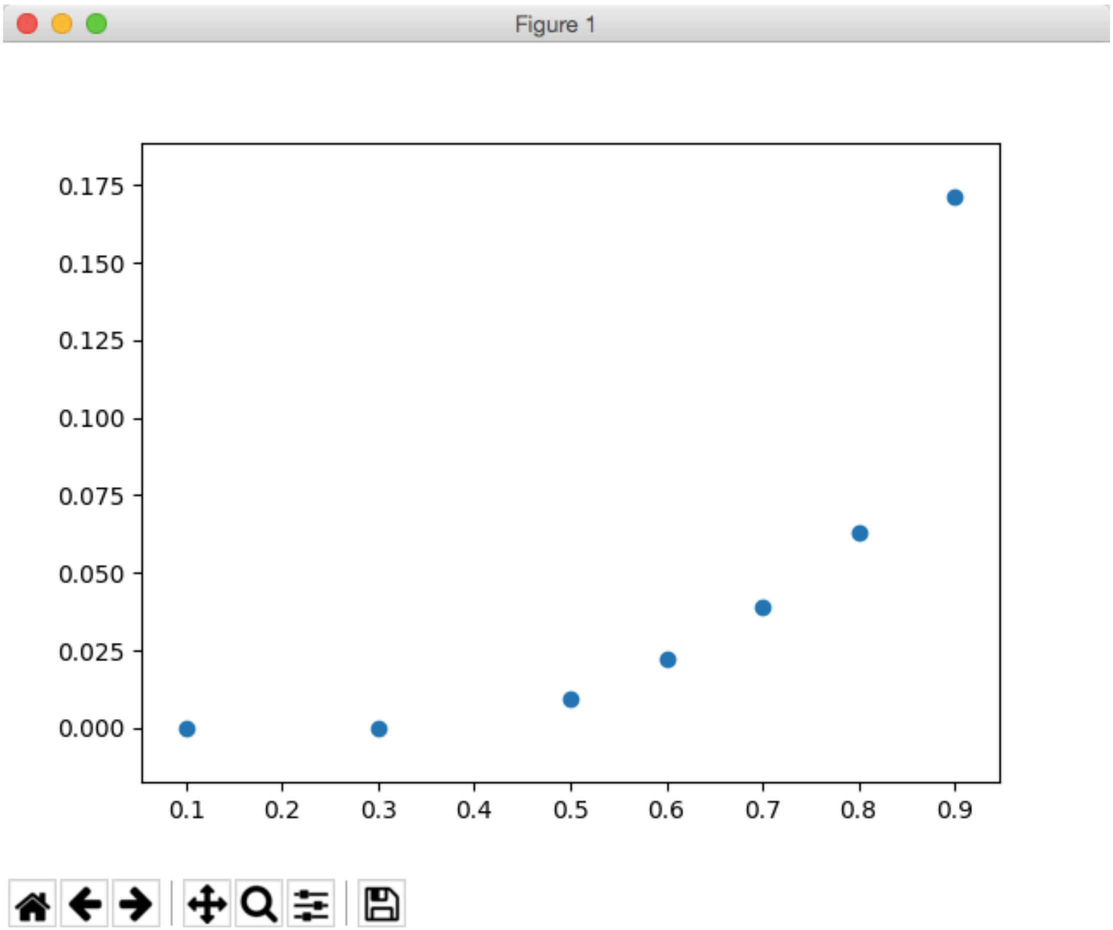


(b)

```
import numpy as np
import matplotlib
matplotlib.use('TkAgg')
import matplotlib.pyplot as plt
import cv2 as cv
```

```python
def dist(v1, v2):
    return np.linalg.norm(v1 - v2)


def SIFT_matching(name1, name2, threshold):
    img1 = cv.imread(name1)
    gray1 = cv.cvtColor(img1, cv.COLOR_BGR2GRAY)
    sift1 = cv.xfeatures2d.SIFT_create()

    img2 = cv.imread(name2)
    gray2 = cv.cvtColor(img2, cv.COLOR_BGR2GRAY)
    sift2 = cv.xfeatures2d.SIFT_create()

    kp1, des1 = sift1.detectAndCompute(gray1, None)
    kp2, des2 = sift2.detectAndCompute(gray2, None)
    # (_, axes) = plt.subplots(1, 2)
    # axes[0].set_title('threshold {}'.format(threshold))
    # axes[1].set_title('matches {}'.format(np.sum(actual_match >
-1)))

    result = np.zeros((len(kp1), 2)) # keep track of all distances
    pairs = np.zeros((len(kp1), 2))

    matched_kp1 = {}

    matches = 0
    for i in range(len(kp1)):
        temp = []
        for j in range(len(kp2)):
            # item = (distance, des1, des2, i, j)
            temp.append((dist(des1[i, :], des2[j, :]), (kp1[i].pt,
kp2[j].pt)))
```

```
        temp.sort()
        if temp[0][0] / temp[1][0] < threshold:
            matches += 1
            matched_kp1[temp[0][0] / temp[1][0]] = (temp[0][1][0],
temp[0][1][1])
    return matches / len(kp1), matched_kp1
```



Notice that: it seems the best value is around 0.8. Although the match rate for threshold=0.9 is higher, the actual matches contain some more “false” matches.

(c) Affine and

```python
# -----------Q2c----------
def affine(matched_kp1, k):
    order = sorted(matched_kp1.keys())
    # list of keys in order
    # print(matched[order[0]], matched[order[1]])
    # print(matched[order[0]][0][0], matched[order[0]][0][1])
    # print(matched[order[0]][1][0], matched[order[0]][1][1])
    P = np.array([[matched_kp1[order[0]][0][0],
matched_kp1[order[0]][0][1], 0, 0, 1, 0],
                 [0, 0, matched_kp1[order[0]][0][0],
matched_kp1[order[0]][0][1], 0, 1]])
    P_prime = np.array([[matched_kp1[order[0]][1][0],
matched_kp1[order[0]][1][1]]])
    # print(P, P_prime)

    for i in range(1, k):
        P = np.concatenate((P,
(np.array([[matched_kp1[order[i]][0][0],
matched_kp1[order[i]][0][1], 0, 0, 1, 0],
                                       [0, 0,
matched_kp1[order[i]][0][0], matched_kp1[order[i]][0][1], 0, 1]]))),
axis=0)
        P_prime = np.concatenate((P_prime,
np.array([[matched_kp1[order[i]][1][0],
matched_kp1[order[i]][1][1]]])),
                                axis=1)
    # print(P.shape, P_prime.shape)
    # Use pinv for inverse matrix
    P_prime = P_prime.reshape((2*k, 1))
    PP = np.linalg.pinv(P)
    return np.matmul(PP, P_prime)
# -----------Q2c----------
```

Minimum k is 3. Recall the format of Affine transformation, we have (a, b, c, d, e, f) 6 unknowns in total, which means we need at least 6 equations, implies we need to choose **3** different (xi, yi) and (xi', yi') to make the matrix invertible.

Also according to slides:

How many matches do we need to compute A?

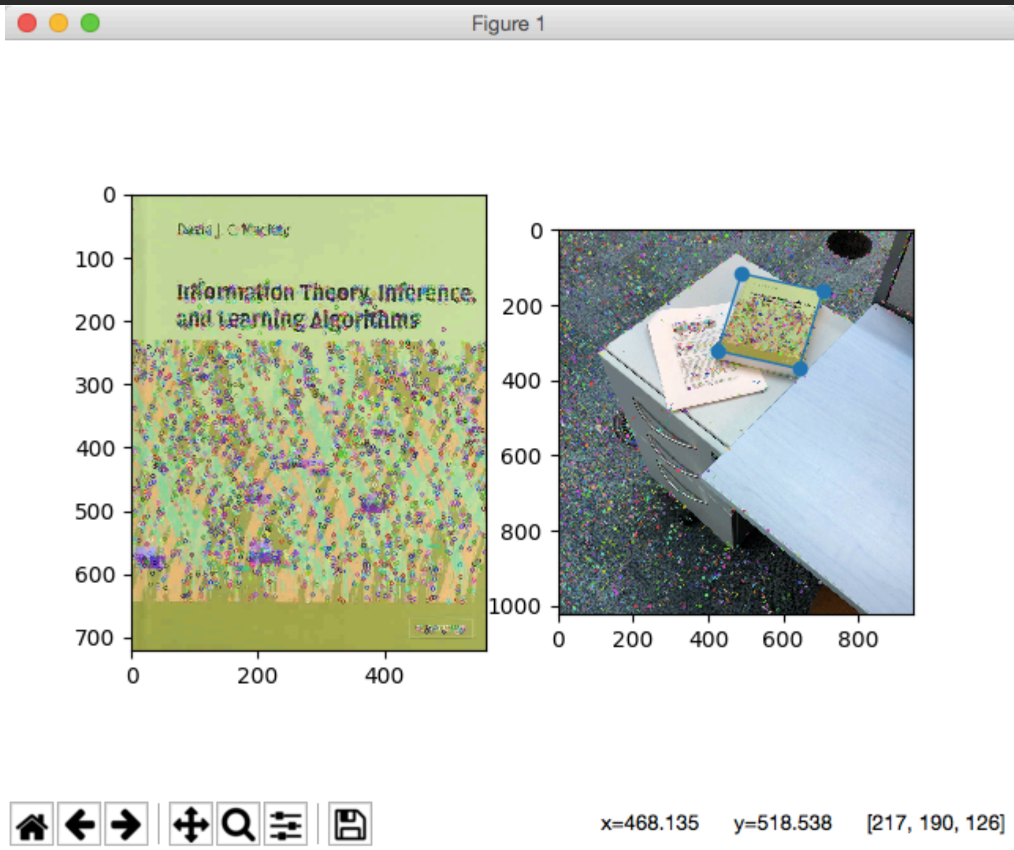
6 parameters $\rightarrow$ 3 matches

(d) Visualize affine

```
# ----------Q2d---------
def visualize_affine(name1, name2, mapping):
    image1 = cv.imread(name1)
    gray1 = cv.cvtColor(image1, cv.COLOR_BGR2GRAY)
    sift1 = cv.xfeatures2d.SIFT_create()

    image2 = cv.imread(name2)
    gray2 = cv.cvtColor(image2, cv.COLOR_BGR2GRAY)
    sift2 = cv.xfeatures2d.SIFT_create()

    kp1, des1 = sift1.detectAndCompute(gray1, None)
    kp2, des2 = sift2.detectAndCompute(gray2, None)

    M, N = image1.shape[0], image1.shape[1]
    fig = plt.figure()

    # reshape [a, b, c, d, e, f] to [[a, b, e],
    #                               [c, d, f]]
    # print(mapping)
    c, d, e = mapping.item(2), mapping.item(3), mapping.item(4)
    mapping[2] = e
    mapping[3] = c
```

```
    mapping[4] = d
    mapping = mapping.reshape(2, 3)
    # print(mapping)
    # reshape [a, b, c, d, e, f] to [[a, b, e],
    #                              [c, d, f]]

    ax2 = fig.add_subplot(122)
    ax1 = fig.add_subplot(121)
    ax1.imshow(image1, cmap='Greys_r')
    ax2.imshow(image2, cmap='Greys_r')

    template = cv.drawKeypoints(image1, kp1, None)
    image = cv.drawKeypoints(image2, kp2, None)
    ax1.imshow(template)
    ax2.imshow(image)

    x = np.array([[0, 0], [0, M - 1], [N - 1, 0], [N - 1, M - 1]])

    x = np.append(x, np.ones((4, 1)), axis=1)
    # print(x)
    transformed_x = np.dot(mapping, x.T)
    # print(transformed_x)
    ax2.scatter(transformed_x[0, :], transformed_x[1, :])

    line = matplotlib.lines.Line2D((transformed_x[0, 0],
transformed_x[0, 1]), (transformed_x[1, 0], transformed_x[1, 1]),
linewidth=1)
    ax2.add_line(line)
    line = matplotlib.lines.Line2D((transformed_x[0, 1],
transformed_x[0, 3]), (transformed_x[1, 1], transformed_x[1, 3]),
linewidth=1)
    ax2.add_line(line)
    line = matplotlib.lines.Line2D((transformed_x[0, 3],
```

```
transformed_x[0, 2]), (transformed_x[1, 3], transformed_x[1, 2]),
linewidth=1)
    ax2.add_line(line)
    line = matplotlib.lines.Line2D((transformed_x[0, 0],
transformed_x[0, 2]), (transformed_x[1, 0], transformed_x[1, 2]),
linewidth=1)
    ax2.add_line(line)

    plt.show()
# ----------Q2d---------
```



k = 3

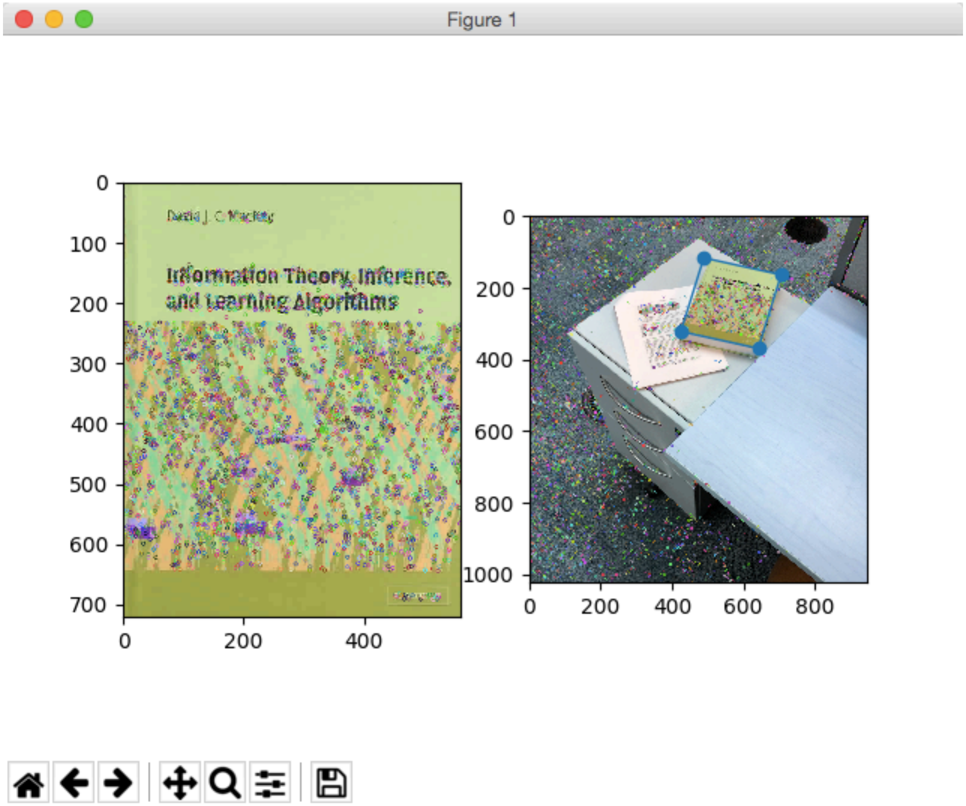


Figure 1
David J. C. MacKay
Information Theory, Inference, and Learning Algorithms
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100
200
300
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500
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700
0
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k = 10

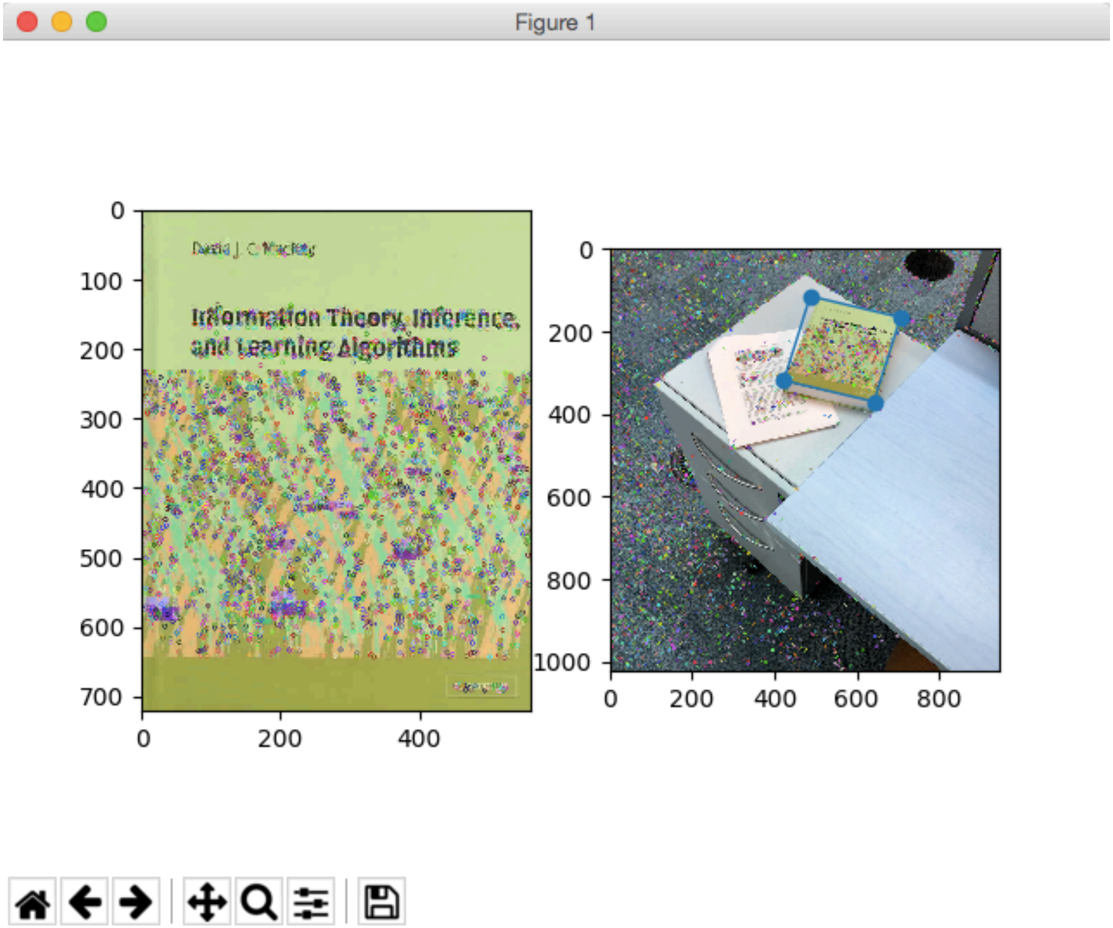
Figure 1
Information Theory, Inference, and Learning Algorithms
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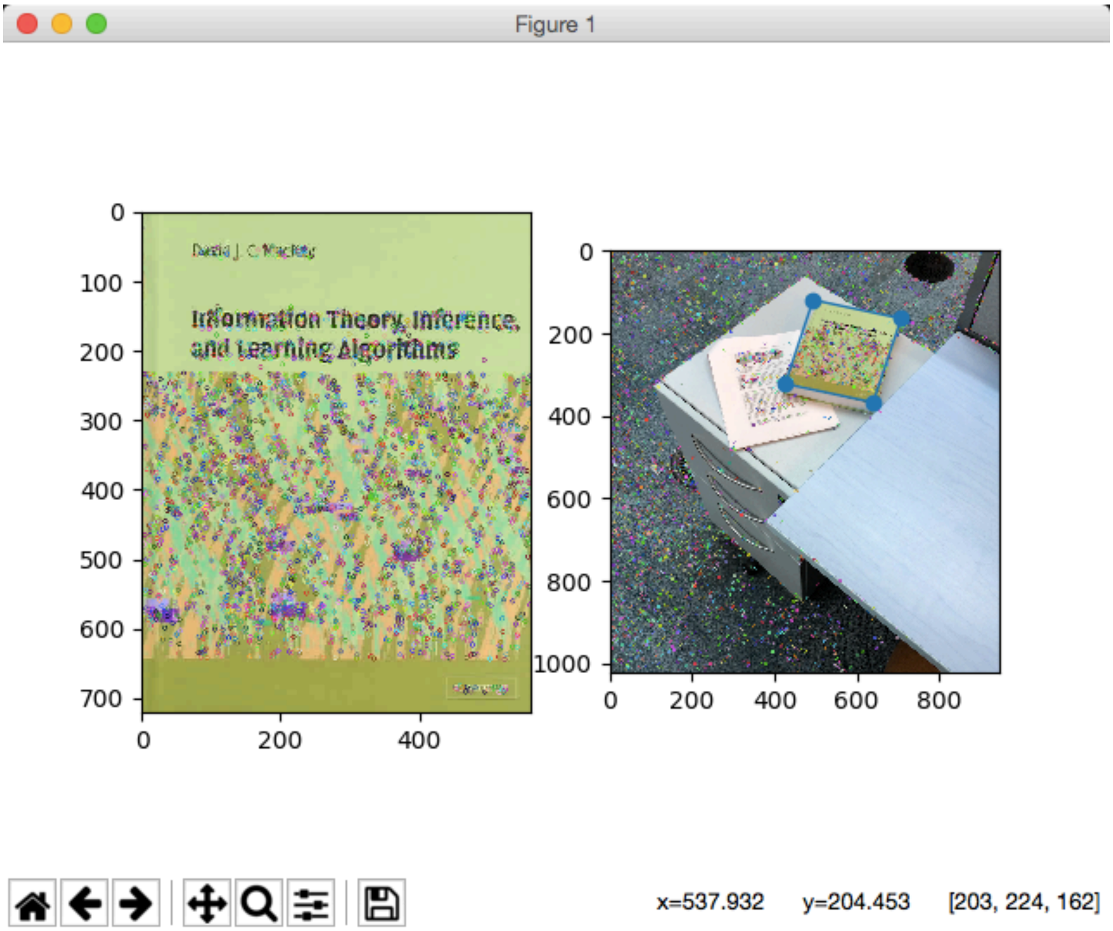
800

k = 20



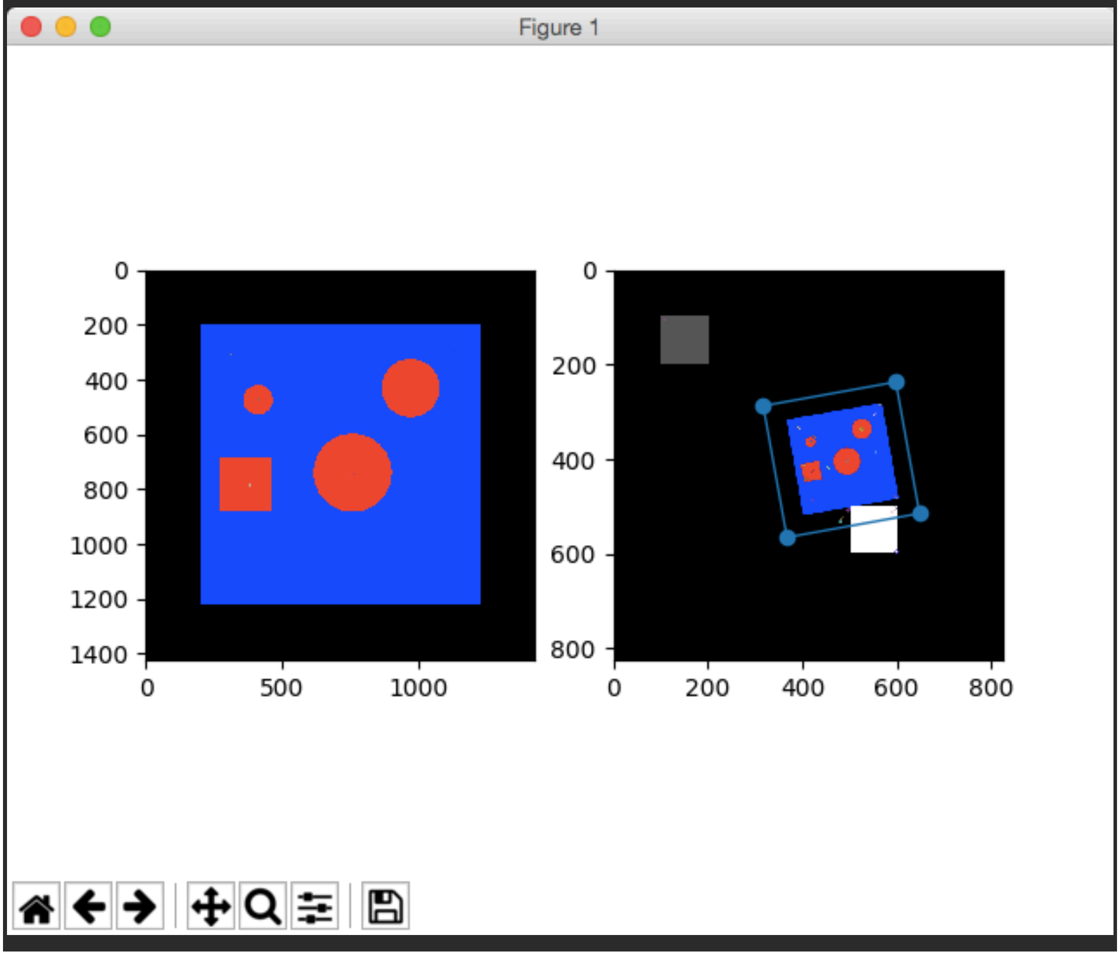
k = 30

(e) Color SIFT

```
# -----------Q2e----------
def color_SIFT(name1, name2):
    temp = cv.imread(name1)
    find = cv.imread(name2)

    M1, N1 = temp.shape[0], temp.shape[1]
    M2, N2 = find.shape[0], temp.shape[1]

    temp_g = cv.cvtColor(temp, cv.COLOR_BGR2GRAY)
    find_g = cv.cvtColor(find, cv.COLOR_BGR2GRAY)
    sift = cv.xfeatures2d.SIFT_create()
```

```
    kp_temp = sift.detectAndCompute(temp_g, None)[0]
    kp_find = sift.detectAndCompute(find_g, None)[0]

    temp_r, temp_g, temp_b = temp[0:, 0:, 2], temp[0:, 0:, 1], temp[0:,
0:, 0]
    find_r, find_g, find_b = find[0:, 0:, 2], find[0:, 0:, 1], find[0:,
0:, 0]

    tr = sift.compute(temp_r, kp_temp)[1]
    tg = sift.compute(temp_g, kp_temp)[1]
    tb = sift.compute(temp_b, kp_temp)[1]
    fr = sift.compute(find_r, kp_temp)[1]
    fg = sift.compute(find_g, kp_temp)[1]
    fb = sift.compute(find_b, kp_temp)[1]

    des1, des2 = [], []
    # init two descriptors
    for i in range(len(kp_temp)):
        aa = np.concatenate(tr[i], tg[i], 0)
        aa = np.concatenate(aa, tb[i], 0)
        des1.append(aa)

    matched_kp1 = {}
    for i in range(len(kp_find)):
        bb = np.concatenate(fr[i], fg[i], 0)
        bb = np.concatenate(bb, fb[i], 0)
        des1.append(bb)

    threshold = 0.8
    matches = 0
    for i in range(len(kp_temp)):
        temp = []
        for j in range(len(kp_find)):
```

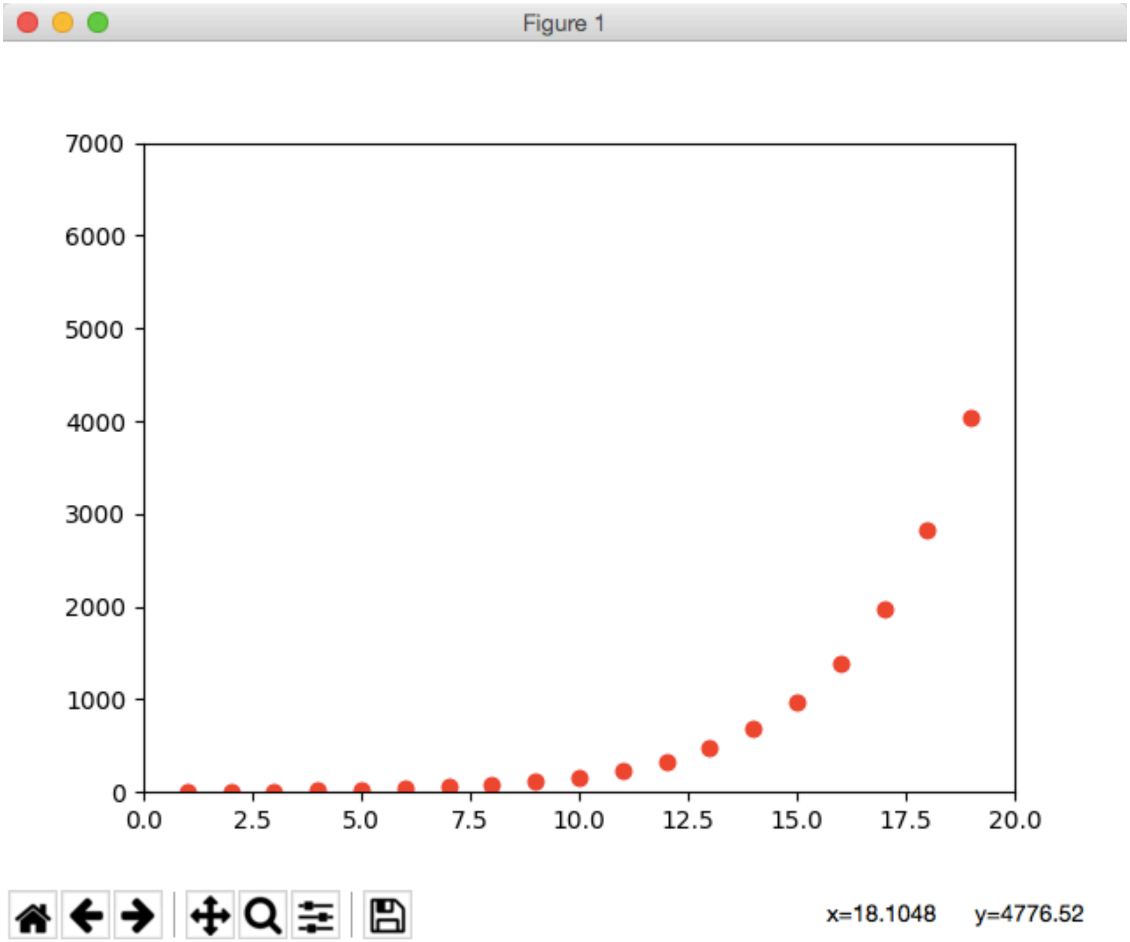
```
            # item = (distance, des1, des2, i, j)
            temp.append((dist(des1[i, :], des2[j, :]),
(kp_temp[i].pt, kp_find[j].pt)))
        temp.sort()
        if temp[0][0] / temp[1][0] < threshold:
            matches += 1
            matched_kp1[temp[0][0] / temp[1][0]] = (temp[0][1][0],
temp[0][1][1])

    result = affine(matched_kp1, k=5)
    visualize_affine(name1, name2, result)
# ----------Q2e---------
```



Main idea: First we find keypoints using SIFT on the grayscale image, then we isolate 3 colour channels from the template image and make a descriptor for each of them on every keyppint, then concatenate them back together(length = 128 * 3) and apply SIFT matching and affine transformation on the new-concatenated descriptor.

Question 3:

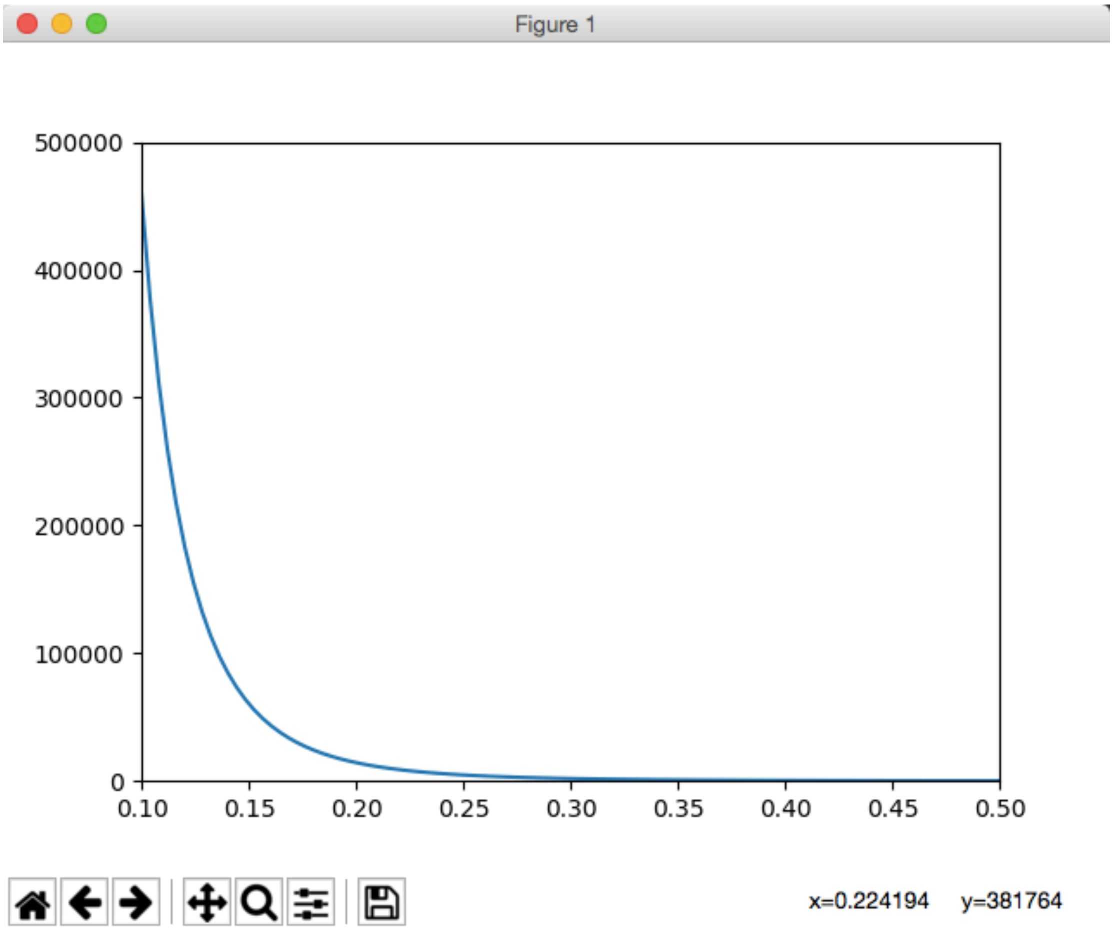
(a)




```
def Q3_a(x):
    return (np.log(0.01)) / (np.log(1 - pow(0.7, x)))
```

(b)

```python
def Q3_b(x):
    return (np.log(0.01)) / (np.log(1 - pow(x, 5)))
```



(c): Number of iterations with k = 5 and p = 0.2 is:

```
14389
```

And the number of required iterations won't change. Since k and p have been set and on one specific iteration, the number of agreed sample will not have actual adjustment on the parameters (i.e., k and p), so on the next iteration it will use the same k and p and continue randomly choosing points for comparison.

Therefore the number of iterations won't change.