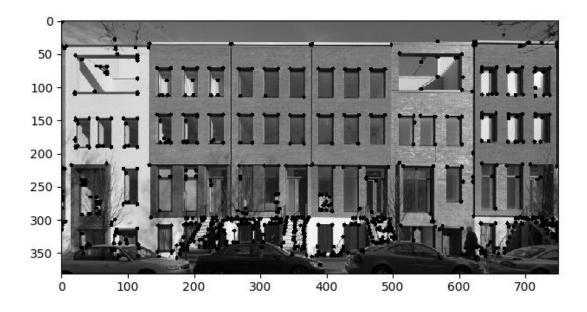
Yu-Chieh Wu

Q1 a)

```
def q1_a_harris_corner_detection(image):
    Mx = np.array([[-1, 0, 1], [-2, 0, 2], [-1, 0, 1]])
    My = np.array([[1, 2, 1], [0, 0, 0], [-1, -2, -1]])
    Ix = signal.convolve2d(image, Mx, mode='same')
    Iy = signal.convolve2d(image, My, mode='same')
    #calculate Ixx, Iyy, Ixy and perform gaussian with window size 3 to get M
    Ixx, Iyy, Ixy = np.square(Ix), np.square(Iy), Ix*Iy
    gaussian_filter = get_gaussian_filter(3, 2)
    Ixx = signal.convolve2d(Ixx, gaussian_filter, mode = 'same') # M[0][0]
    Iyy = signal.convolve2d(Iyy, gaussian_filter, mode = 'same') # M[1][1]
    Ixy = signal.convolve2d(Ixy, gaussian_filter, mode = 'same') # M[0][1] and M[1][0]
    R = (Ixx*Iyy - Ixy*Ixy) - 0.04*np.square(Ixx+Iyy)
    R = np.where(R>0.25, R, 0)
    num_row, num_col = R.shape
    non_max_suppress = np.zeros((num_row,num_col))
    for i in range(num_row):
        for j in range(num_col):
            right = i-1 if i>0 else 0
            left = i+2 if i<num_row-1 else i+1</pre>
            upper = j-1 if j>0 else 0
            bottom = j+2 if j<num_col-1 else j+1
            curr_max = np.max(R[right:left, upper:bottom])
            non_max_suppress[i,j] = 1 if R[i,j] == curr_max and R[i,j]>0.25 else 0
    return non_max_suppress
def get_gaussian_filter(kernel_size,sigma):
   x_values = np.linspace(-1* (kernel_size//2), kernel_size//2, kernel_size)
   gaussian = np.zeros(x_values.shape[0])
    for i in range(x_values.shape[0]):
       gaussian[i] = 1 / (sigma * math.sqrt(2*math.pi)) * np.exp(-1*pow(x_values[i],2)/(2*pow(sigma,2)))
   #2d gaussian is the outer product of the 1D gaussian
   kernel = np.outer(gaussian.T, gaussian)
   kernel = kernel / np.sum(kernel)
```

Q1 b)

return kernel



Q2 a)

```
# Reference: OpenCV SIFT documenation, link: https://docs.opencv.org/4.x/da/df5/tutorial_py_sift_intro.html

def q2_a_feature_extraction(image, image_name):
    sift = cv2.SIFT_create()
    keypoints, descriptors = sift.detectAndCompute(image,None)
    for i in range(0, 1000, 10):
        x, y = int(keypoints[i].pt[0]), int(keypoints[i].pt[1])
        r = int(keypoints[i].size/2)
        image = cv2.circle(image, (x,y), r, (random.randint(0, 255), random.randint(0, 255), random.randint(0, 255)), 2)
    cv2.imwrite('100_keypoints_{}.jpg'.format(image_name),image)
```

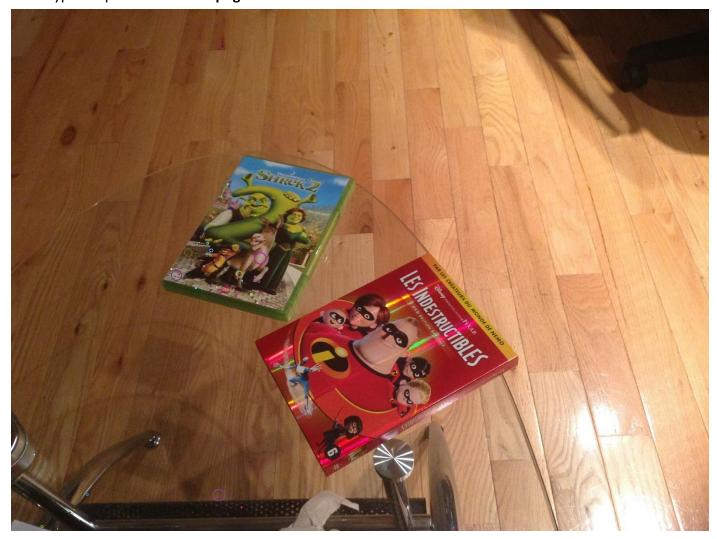
100 keypoints plotted for reference.png:



100 keypoints plotted for **test.png**:



100 keypoints plotted for **test2.png**:



Matching: The simple algorithm I'm using to find the top3 matches is the one described in the lecture. I compared the ratio = $||fi - f'i_1|| / ||fi - f'i_1||$, where

fi = the descriptor of keypoint i in reference.png

f'i_1 = the closest match to fi among the descriptors of the test image

f'i_2 = the second closest match to fi among the descriptors of the test image

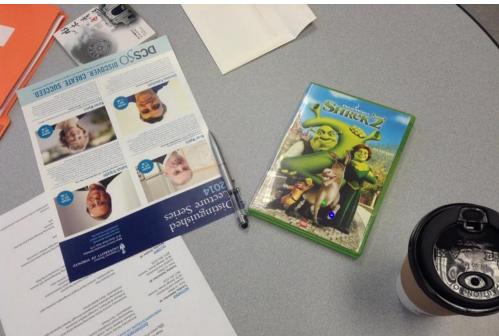
I pick the top3 minimum ratio to be the top 3 matches and make sure they are under the threshold, which I set to 0.8(as suggested in lecture slide).

```
def q2_b_matching(ref_img, test_img):
    sift = cv2.SIFT create()
    ref_keypoints, ref_descriptors = sift.detectAndCompute(ref_img,None)
    test_keypoints, test_descriptors = sift.detectAndCompute(test_img,None)
    top3_ratio = []
    top3 keypoints = []
    for i in range(ref_descriptors.shape[0]):
        distance = np.linalg.norm(ref_descriptors[i] - test_descriptors, axis=1)
        closest_idx = np.argmin(distance)
        closest = distance[closest idx]
        distance[closest_idx] = float('inf')
        sec_close_idx = np.argmin(distance)
        sec_close = distance[sec_close_idx]
        ratio = closest/sec_close
        if ratio > 0.8:
            continue
        if len(top3_ratio) < 3:</pre>
            top3_ratio.append(ratio)
            top3_keypoints.append([ref_keypoints[i], test_keypoints[closest_idx]])
        else:
            max_ratio = max(top3_ratio)
            if ratio <= max_ratio:</pre>
                index = top3 ratio.index(max ratio)
                top3_ratio.pop(index)
                top3_keypoints.pop(index)
                top3_ratio.append(ratio)
                top3_keypoints.append([ref_keypoints[i], test_keypoints[closest_idx]])
    color = [(0, 255, 0), (0, 0, 255), (255, 0, 0)]
    for i in range(len(top3_keypoints)):
        r_keypoint = top3_keypoints[i][0]
        t_keypoint = top3_keypoints[i][1]
        r_x, r_y = int(r_keypoint.pt[0]), int(r_keypoint.pt[1])
        r_radius = int(r_keypoint.size/2)
        t_x, t_y = int(t_keypoint.pt[0]), int(t_keypoint.pt[1])
        t_radius = int(t_keypoint.size/2)
        ref_img = cv2.circle(ref_img, (r_x,r_y), r_radius, color[i], 2)
        test_img = cv2.circle(test_img, (t_x,t_y), t_radius, color[i], 2)
    cv2.imwrite('ref_top3_keypoints.jpg',ref_img)
    cv2.imwrite('test_top3_keypoints.jpg',test_img)
    return top3_keypoints
```

Top3 matches between reference.png and test.png:

Note: the red point is a bit blocked by the blue one, but there are 3 points in total





Here is a zoom in version of test.png:



Top3 matches between reference.png and test2.png:





Here is a zoom in version of test2.png:



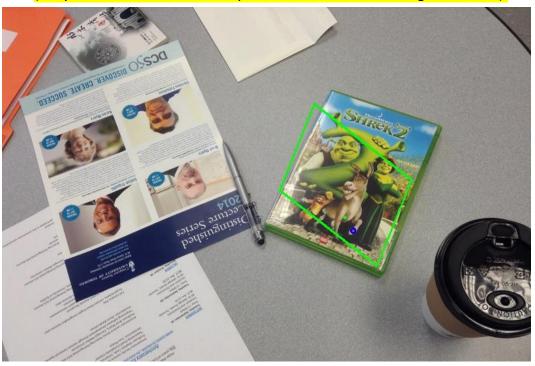
```
def q2_c_affine_transformation(ref_img, test_img):
    top3_keypoints = q2_b_matching(ref_img, test_img)
P, prime = [], []
    for kp in top3_keypoints:
        x_i, y_i = kp[0].pt[0], kp[0].pt[1]
        x_i_prime, y_i_prime = kp[1].pt[0], kp[1].pt[1]
        P += [[x_i, y_i, 0, 0, 1, 0], [0, 0, x_i, y_i, 0, 1]]
        prime += [x_i_prime, y_i_prime]
P, prime = np.array(P), np.array(prime)
AT_matrix_1D = np.dot(np.dot(np.linalg.inv(np.dot(P.T, P)), P.T), prime)
AT_matrix_2by3 = AT_matrix_1D[:4].reshape((2,2)).tolist()
AT_matrix_2by3[0].append(AT_matrix_1D[4])
AT_matrix_2by3[1].append(AT_matrix_1D[5])
AT_matrix_2by3 = np.array(AT_matrix_2by3)
    return AT_matrix_2by3
```

Q2 d)

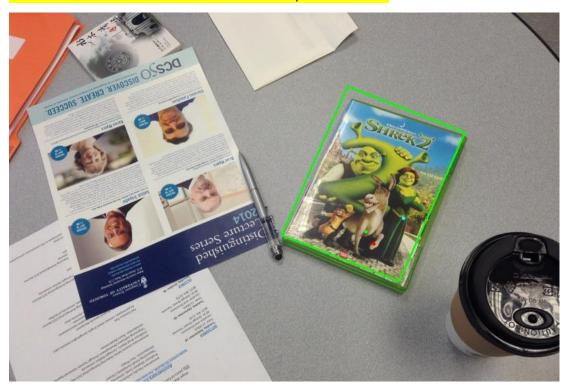
```
def q2_d_visualize_q2c(ref_img, test_img):
    AT_matrix = q2_c_affine_transformation(ref_img, test_img)
    # get the 4 corners of ref image
    ul = np.dot(AT_matrix, np.array([0, 0, 1]))
    ur = np.dot(AT_matrix, np.array([ref_img.shape[1]-1, 0, 1]))
    ll = np.dot(AT_matrix, np.array([0, ref_img.shape[0]-1, 1]))
    lr = np.dot(AT_matrix, np.array([ref_img.shape[1]-1, ref_img.shape[0]-1, 1]))
    # plot the affine transformed corners on test img
    test_img = cv2.line(test_img, (int(ur[0]), int(ur[1])), (int(ul[0]), int(ul[1])), (0, 255, 0), thickness=2)
    test_img = cv2.line(test_img, (int(ur[0]), int(ur[1])), (int(lr[0]), int(lr[1])), (0, 255, 0), thickness=2)
    test_img = cv2.line(test_img, (int(ll[0]), int(ll[1])), (int(ul[0]), int(ul[1])), (0, 255, 0), thickness=2)
    cv2.line(test_img, (int(ll[0]), int(ll[1])), (int(ul[0]), int(ul[1])), (0, 255, 0), thickness=2)
    cv2.imwrite('test_AT.jpg',test_img)
```

Visualize affine transform with reference.png and test.png:

Note: By using the top3 keypoints I previously obtained in q2b does not give an accurate transformation (picture below). I believe this is because there are two keypoints that are very close to each other (red and blue are really close), which does not give me an accurate transformation matrix (They are too close and basically contribute the same during calculation).



Therefore, I discarded the blue keypoint and picked the keypoint that has the 4th smallest ratio meaning the top 4th match (colored in light blue). I performed affine transformation again and got a more accurate transformation shown in the picture below:



Visualize affine transform with reference.png and test2.png:

