Project 3: Stitching Photo Mosaics

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This project focuses on creating panoramas! In **part A**, we focus on computing homographies, using them to warp images, and compositing images together. To compute homographies, we will manually select point correspondences across 2 images. In **part B**, we will focus on automatic feature matching and use a RANSAC algorithm to compute homographies.

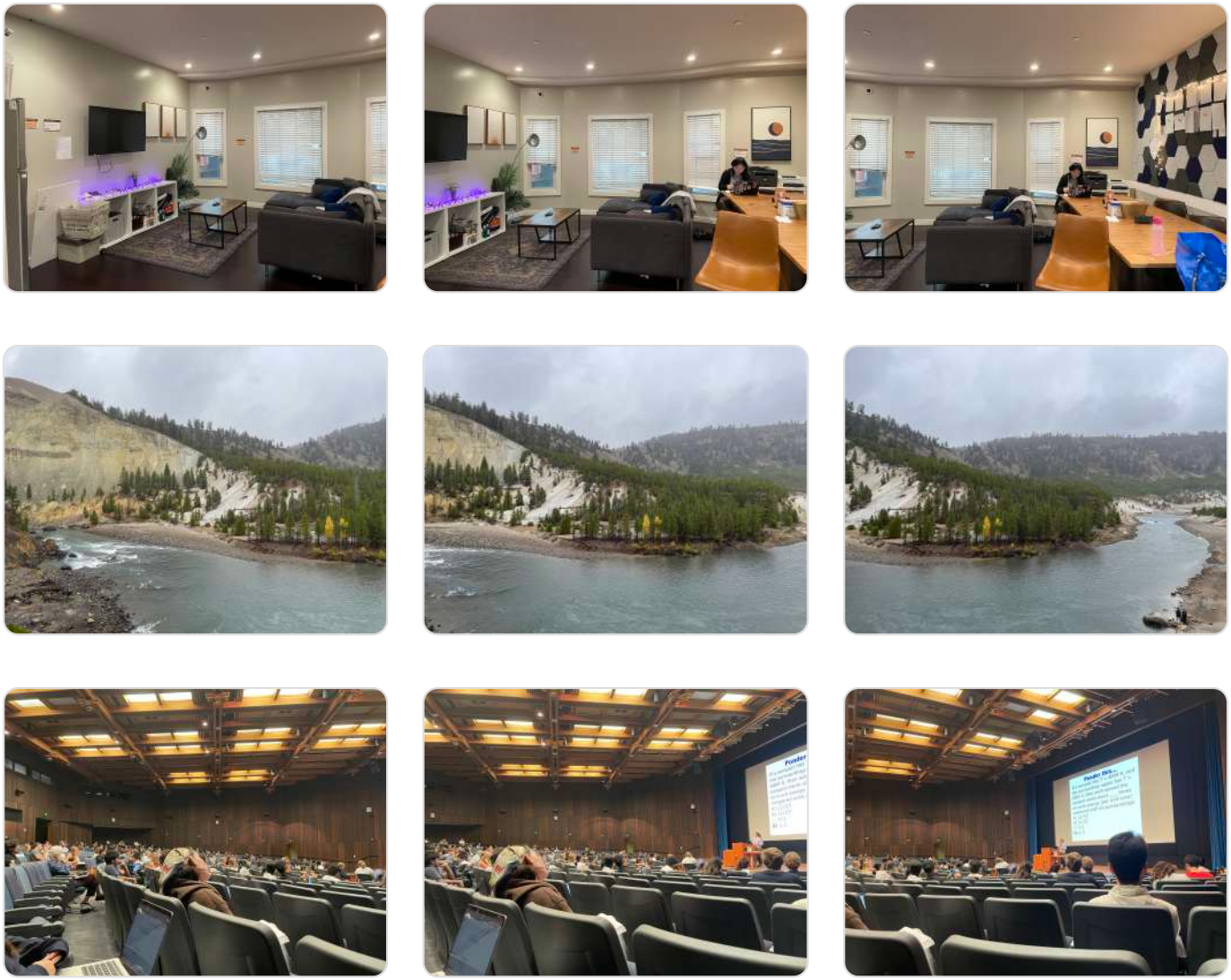
Table of Contents

Part A: Image Mosaicing and Warping

A.1: Raw Pictures

The following pictures were taken by fixing the center of projection (COP) and rotating the camera. They feature (1) my living room, (2) my hike at Yellowstone, and (3) Wheeler

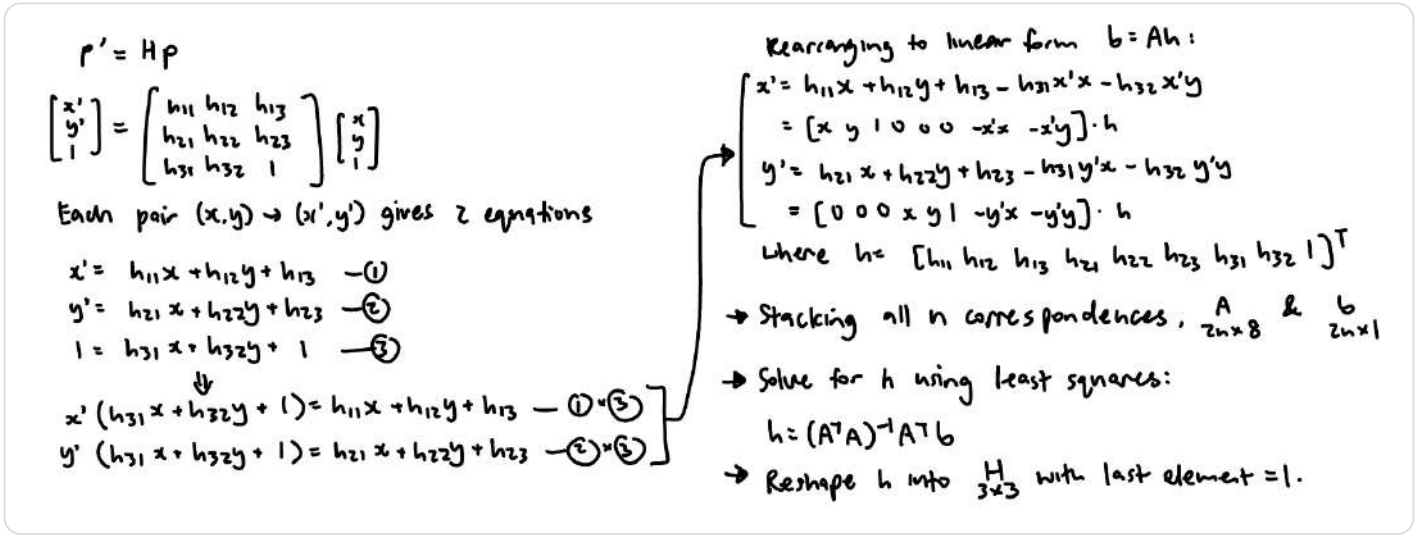
Auditorium. They will each be stitched into a panorama!



A.2: Calculating Homographies

First, we will recover the parameters of the transformation between each pair of images. The transformation is a homography: p'=Hp, where H is a 3x3 matrix with 8 degrees of freedom that transforms a point p in image 1 to p' in image 2. In order to compute the entries in the matrix H, we set up a linear system using n=12 pairs of points p and p'. These are correspondences, manually selected using matplotlib's `ginput` function.

Here is the math and system of linear equations:



Stacking n correspondences gives us a matrix equation `Ah = b`, where A is a 2nx8 matrix, b is a 2nx1 vector, and h is `[h11,h12,h13,h21,h22,h23,h31,h32^]T`. From this matrix equation, we solve for h using least squares: `h=((A^TA)^-1)(A^T)b` and convert it back to a 3x3 homography matrix H.

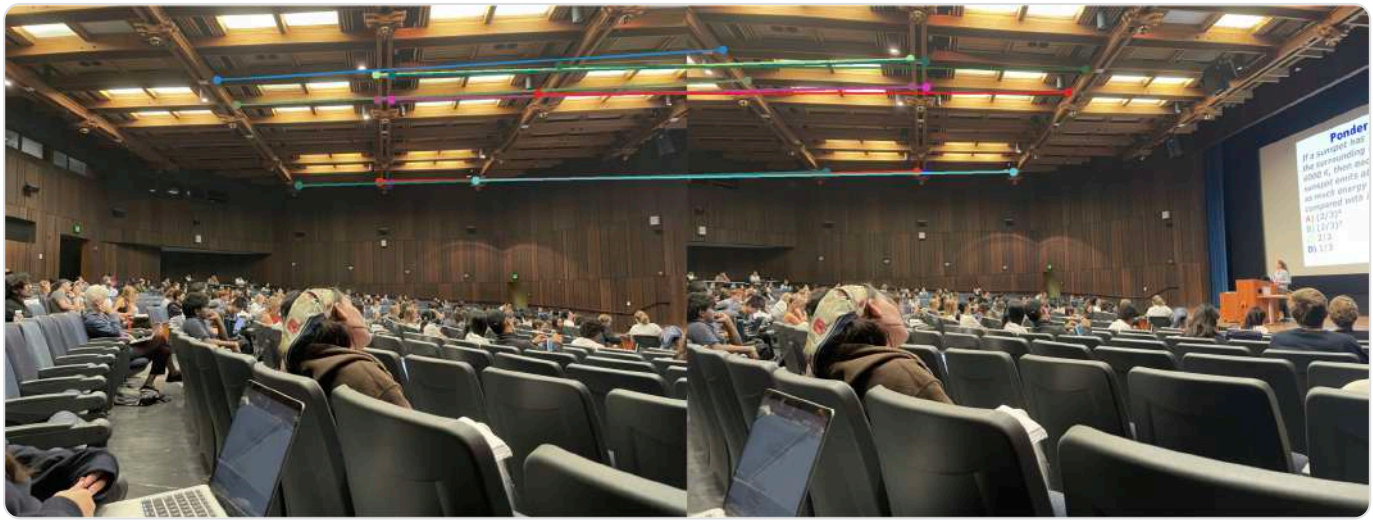
Below, we display the correspondence points and homographies for the set of Wheeler Auditorium photos.

H1to2

```
[[ 1.53900e+00  2.40000e-02 -6.81714e+02]
 [ 1.67000e-01  1.31300e+00 -1.94857e+02]
 [ 0.00000e+00 -0.00000e+00  1.00000e+00]]
```

H2to3

```
[[ 1.68800e+00 -3.60000e-02 -8.50662e+02]
 [ 2.80000e-01  1.42500e+00 -2.89783e+02]
 [ 0.00000e+00 -0.00000e+00  1.00000e+00]]
```

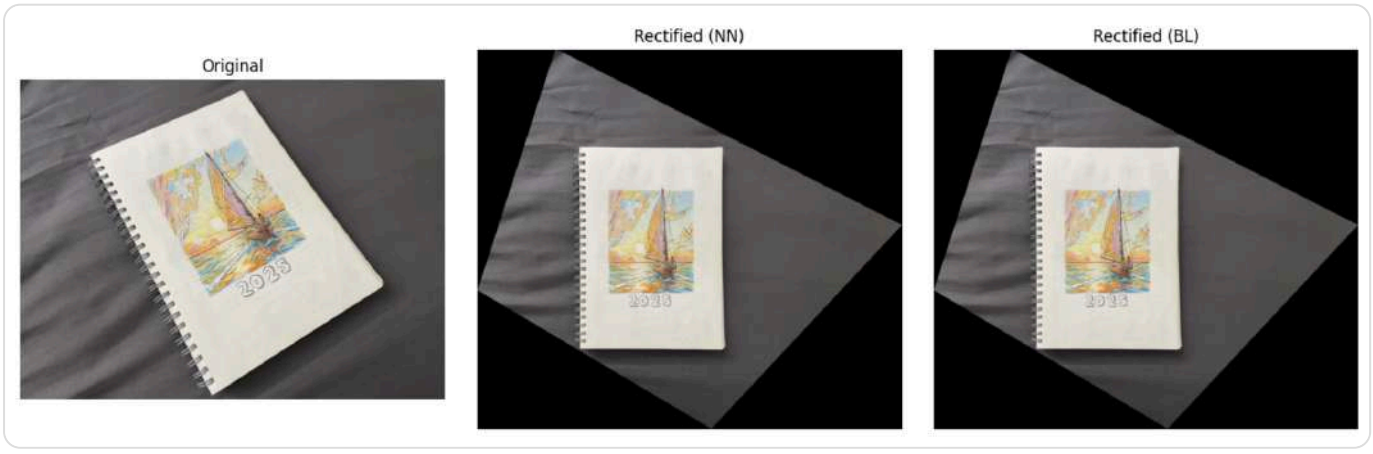


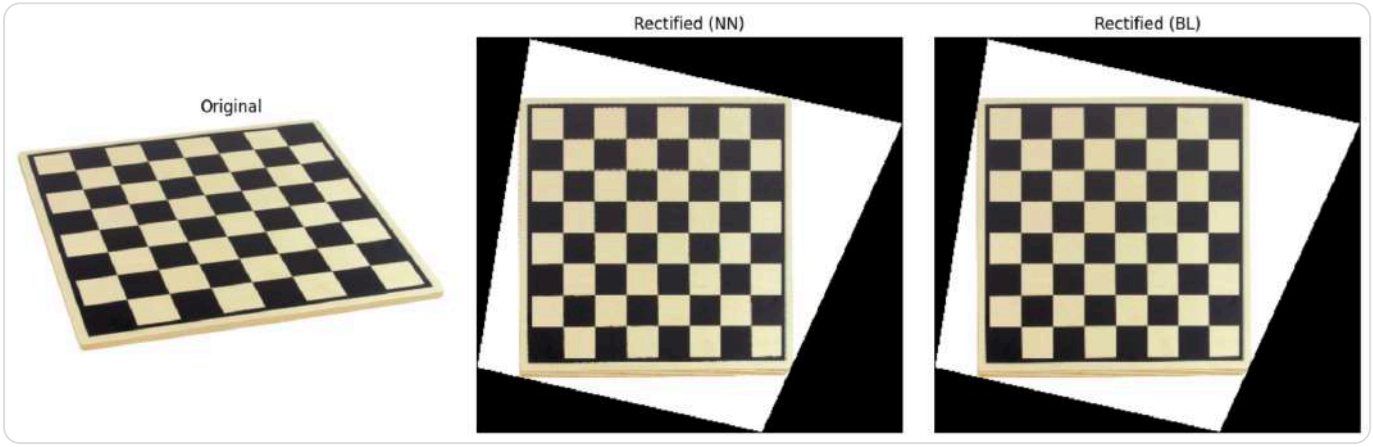
A.3: Warping

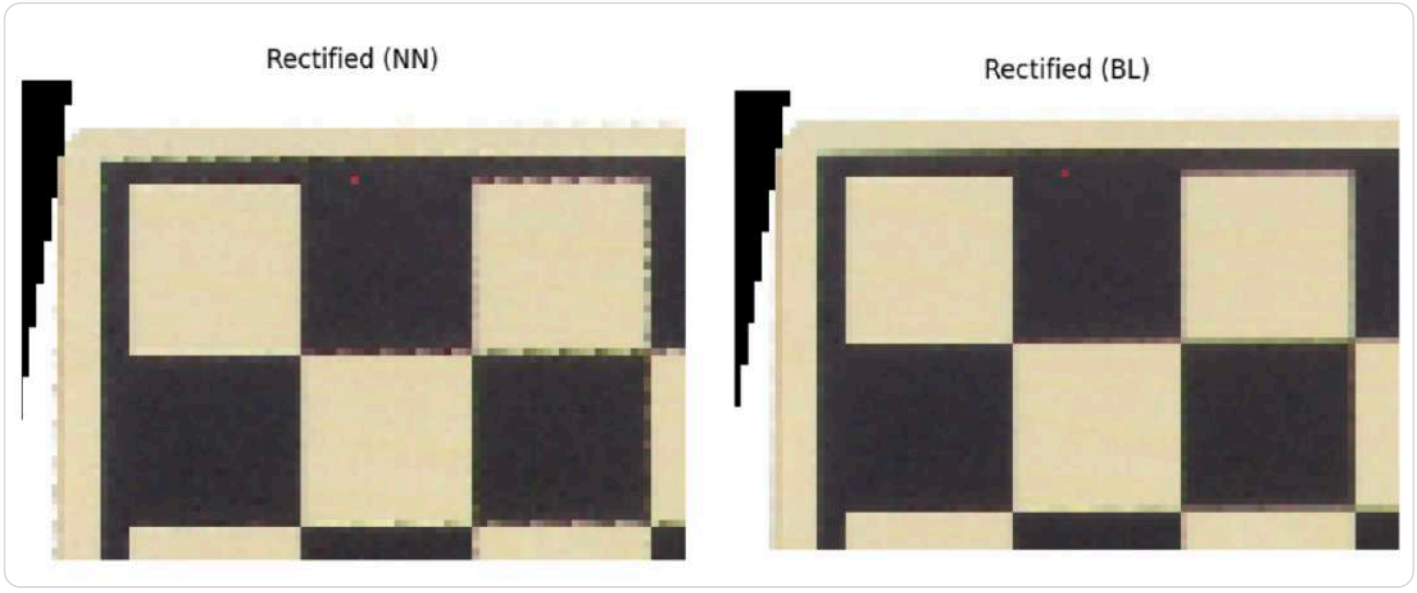
Now, we will implement warping using homographies. First, we predict the boundaries of the destination image by applying homography H on the 4 corners of the source image. We then initialise the destination image grid. Next, we do **inverse warping**, where for each destination pixel (xd, yd), we compute the corresponding source coordinates using `(xs, ys) = H_inverse*[xd, yd, 1]^T`. This avoids holes (the usual problem of forward-warp).

When we get the source coordinates, it may not land directly on a whole pixel. Hence, we explore 2 methods to determine what pixel value to map over. The first is **Nearest Neighbor Interpolation**, where we round the source coordinates to the nearest pixel and take its value. The second is **Bilinear Interpolation**, where we take the weighted average of four neighboring pixel values.

We test out these 2 interpolation methods to perform “rectification” on the following images.







Nearest Neighbour (NN) VS Bilinear (BL) interpolation:

Quality wise, comparing the zoomed-in versions of NN and BL, we see that NN introduces jaggers/pixelated edges, while BL has less staircasing. This is because BL smooths and slightly blends values as it takes a weighted average of neighbouring pixels. However, in terms of **speed**, NN is faster as it involves just a rounding and fetch, while BN involves calculating weights, multiplication and addition on the pixel values of 4 neighbours.

Overall, in the trade off between quality and speed, BN still is preferred as it still is relatively cheap and usually real-time for moderate image sizes. Visually, it also yields better results. We will use BN in our next panorama stitching stages.

A.4: Mosaicing

Finally, we will use all of the above to warp and combine 3 images create an image mosaic (panorama). The procedure is as follows:

Step 1: Compute homographies to reference frame

Each adjacent image pair has manually chosen point correspondences. We compute pairwise homographies H1to2 and H2to3, each describing how to map image i to image i+1's coordinate frame. Next, we make homographies to express every image relative to image 2. We have `H1to2 = H1to2; H2to2 = np.eye(3); H3to2 = np.linalg.inv(H2to3)`

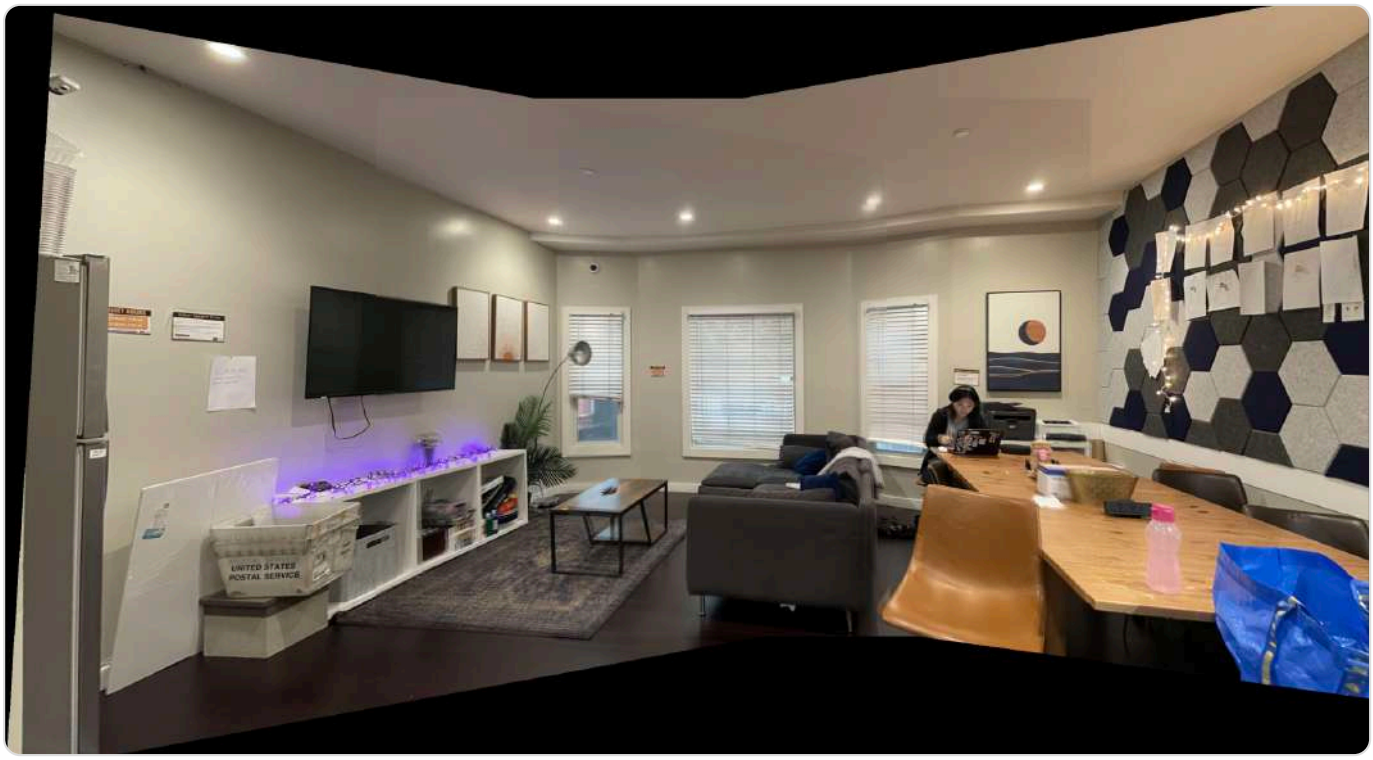
Step 2: Find bounding box of final mosaic

Now we set a bounding box for our final mosaic by first seeing where all image corners land in the 2nd image's frame. We take the 4 corners of all images and pass them through their homography Hxto2, and find the collective xmin, x mas, ymin and ymax that gives us the bounding box for all images. The final panorama's width and height are $W = \lceil x_{max} - x_{min} \rceil$, $H = \lceil y_{max} - y_{min} \rceil$. Then we build a small translation homography T that shifts everything by (-xmin, -ymin) so that the top left corner aligns with (0,0) to ensure all warped images fit in the canvas.

Step 3: Wrap each image onto canvas

The final homography for image x will be `Hx = T @ Hxto2` . We wrap the image using **bilinear interpolation** `im_warped, mask = warpImageBilinear(im, H_final, out_shape=(H, W))`, producing a warped image that fits in the bounding box and a binary mask indicating which pixels in the panorama are filled by the warped image (HxW). We then convert the single-channel mask into three identical copies (H×W×3) — one per color channel. Finally, we **blend the images via weighted averaging**. For each pixel, the warped image contributions are summed (`num += im_warped * m3`) and divided by the total number of overlapping images (`den += m3`), yielding the average color value per pixel in the final mosaic.

Results below!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We observe that the final panoramas can appear slightly blurry, likely due to errors in manual selection of our point correspondences. In part 3B, we will look at how to fix this by automating feature matching across images!

Part B: Feature Matching for Autostitching

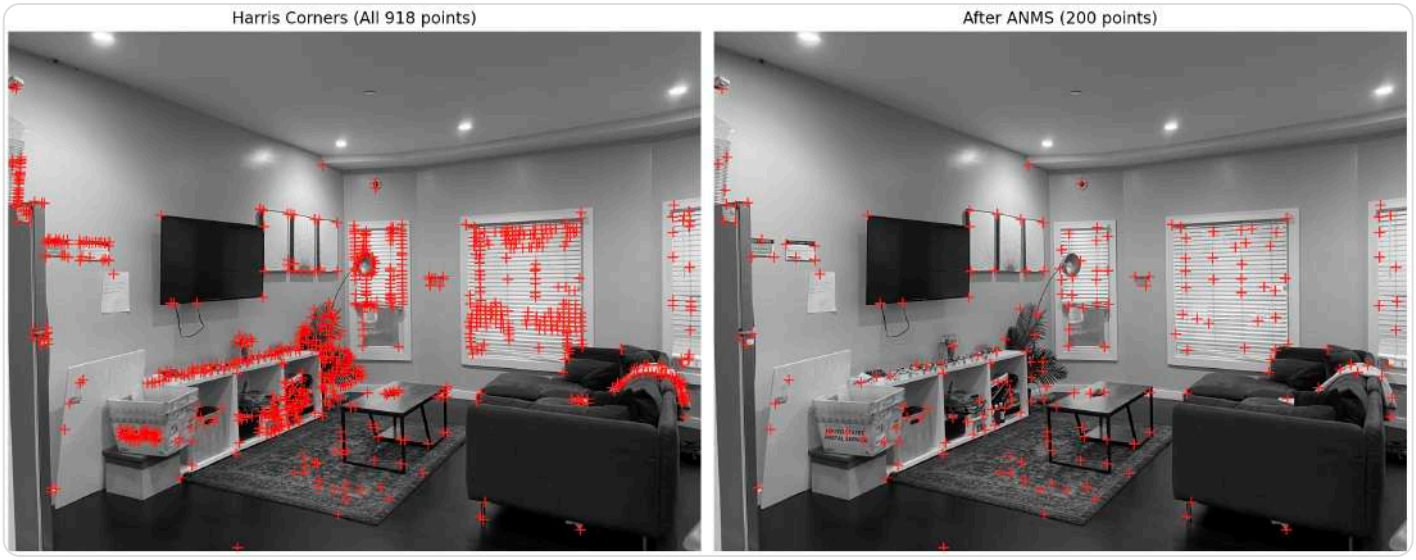
B.1: Harris Corner Detection

In this section, we create a system for automatically stitching images into a mosaic.

First, we will implement **Harris Corner Detection**. We use skimage's `corner_harris` to compute the Harris response map h, which assigns a corner strength value to each pixel, indicating how likely it is to be a corner. We then find local maxima in this map using skimage's `peak_local_max`, ensuring that detected corners are spaced at least `min_dist`=10 pixels apart and exceed a `threshold`=0.1 (basically, only shortlist corners with h values > h.max() * threshold). We remove points that lie within `edge_discard`=20 pixels of the image edges. We return both the full Harris response map h and the coordinates of valid corners.

Next, we apply **Adaptive Non-Maximal Suppression** which refines these detected corners to keep only spatially well-distributed and distinctive ones. For each corner, it finds the distance to the nearest corner that has a stronger Harris response. This distance, called the

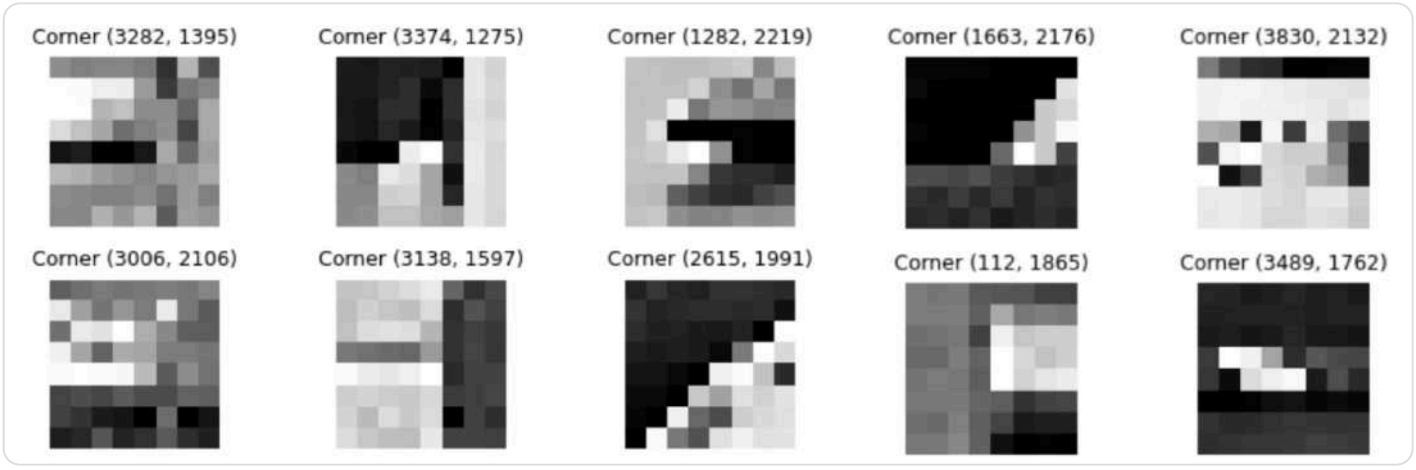
suppression radius, indicates how isolated a corner is among stronger points. Corners with larger radii are more valuable since they represent locally unique and prominent features. Finally, we select `num_points`=200 corners with the largest suppression radii, producing a set of strong, evenly spaced points suitable for robust feature matching and image alignment.



B.2: Feature Descriptor Extraction

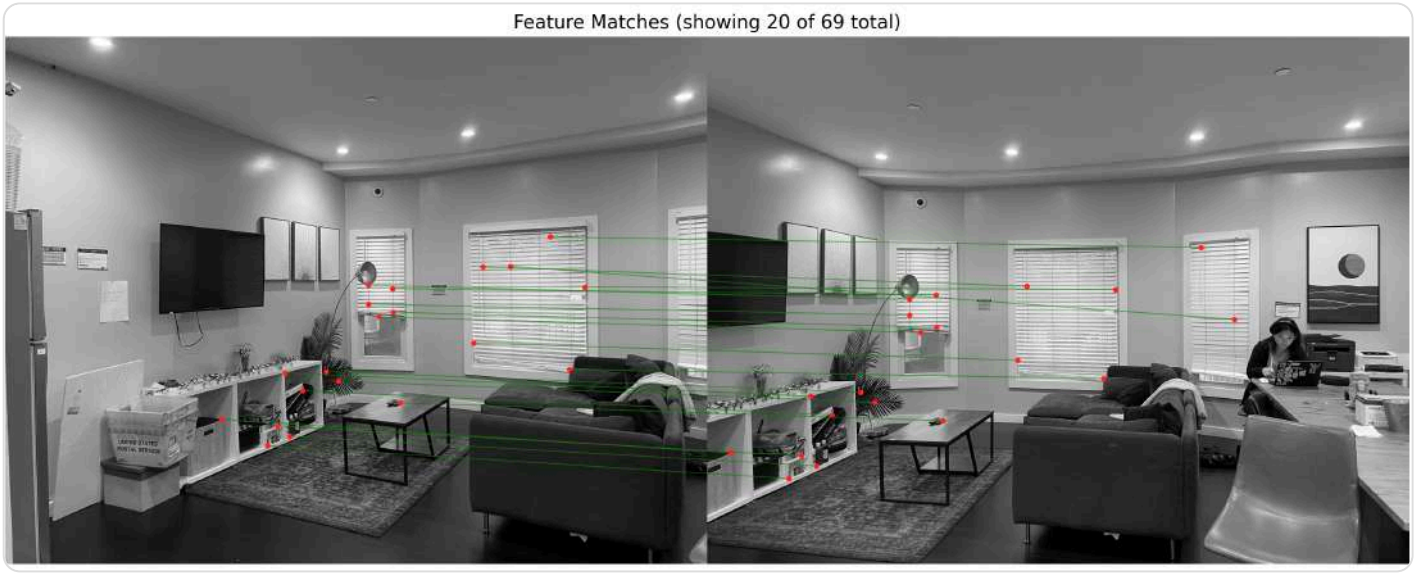
Next, we create feature descriptors around previously detected corner points. For each corner, we sample a 40×40 window centered on the corner to capture local image structure. In each window, we extract an 8×8 patch by sampling pixels at fixed intervals of `sample_spacing`=5, which downsamples the window while retaining key texture information.

Each 8x8 patch is then flattened into a 1D feature vector and normalized to ensure the descriptor is insensitive to changes in overall brightness or contrast. Patches with near-zero variance (flat regions) are discarded because they lack meaningful structure. Finally, we return an array of all valid descriptors (N x (patch_size*patch_size)), along with their corresponding corner coordinates (2xN). This is a set of feature descriptors that represent the local appearance around strong, well-distributed corners — suitable for feature matching between images.



B.3: Feature Matching

Now, we match features across 2 images together by computing the euclidean distances between all the descriptors and using the **Lowe's ratio test**. Lowe's ratio = (distance for the best match)/(distance for the second best match). A high ratio means that we have a clear match with little confusion, and we consider only matches with ratio above `ratio_thresh = 0.8` as valid matches. This returns a list of all matched points between 2 images.



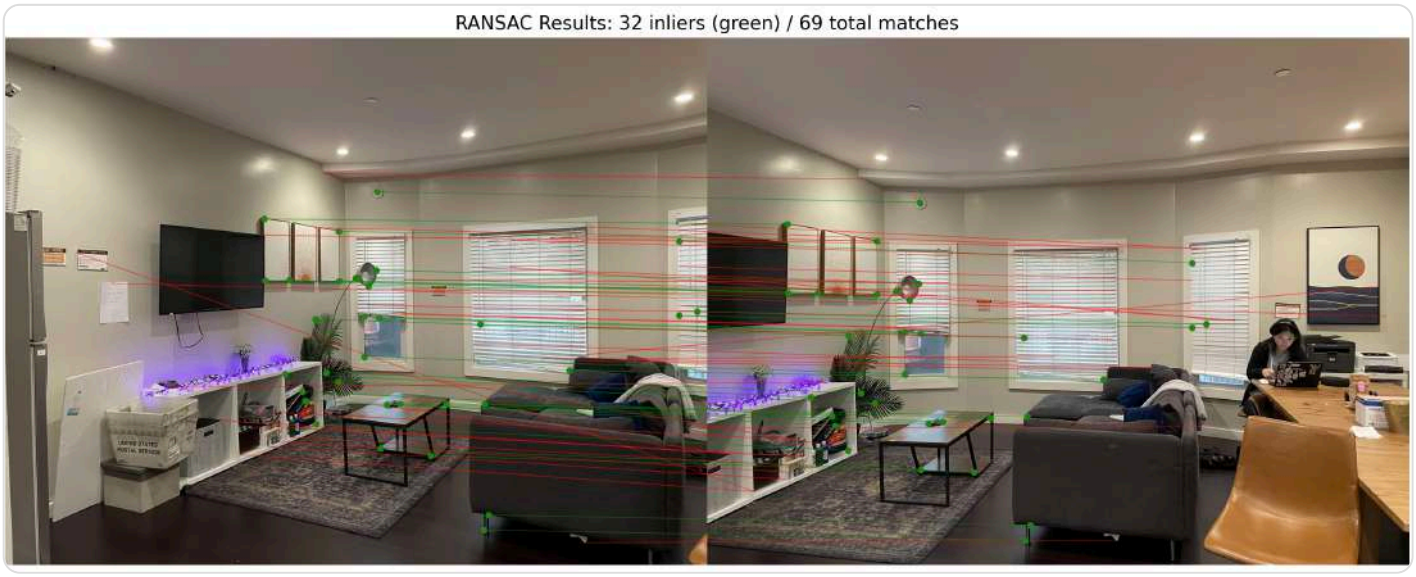
B.4: RANSAC for Robust Homography

In this last section, we use 4-point RANSAC to compute our homography. It starts with the matched points from both images. We first randomly sample 4 matched point pairs to compute a candidate homography H. Then we project all image1 points to image2 using this H, and compute a reprojection error — the distance between the projected point and the true match point — for all matches. Matches with errors below the inlier_threshold are considered

inliers, representing matches that agree with the estimated transformation.

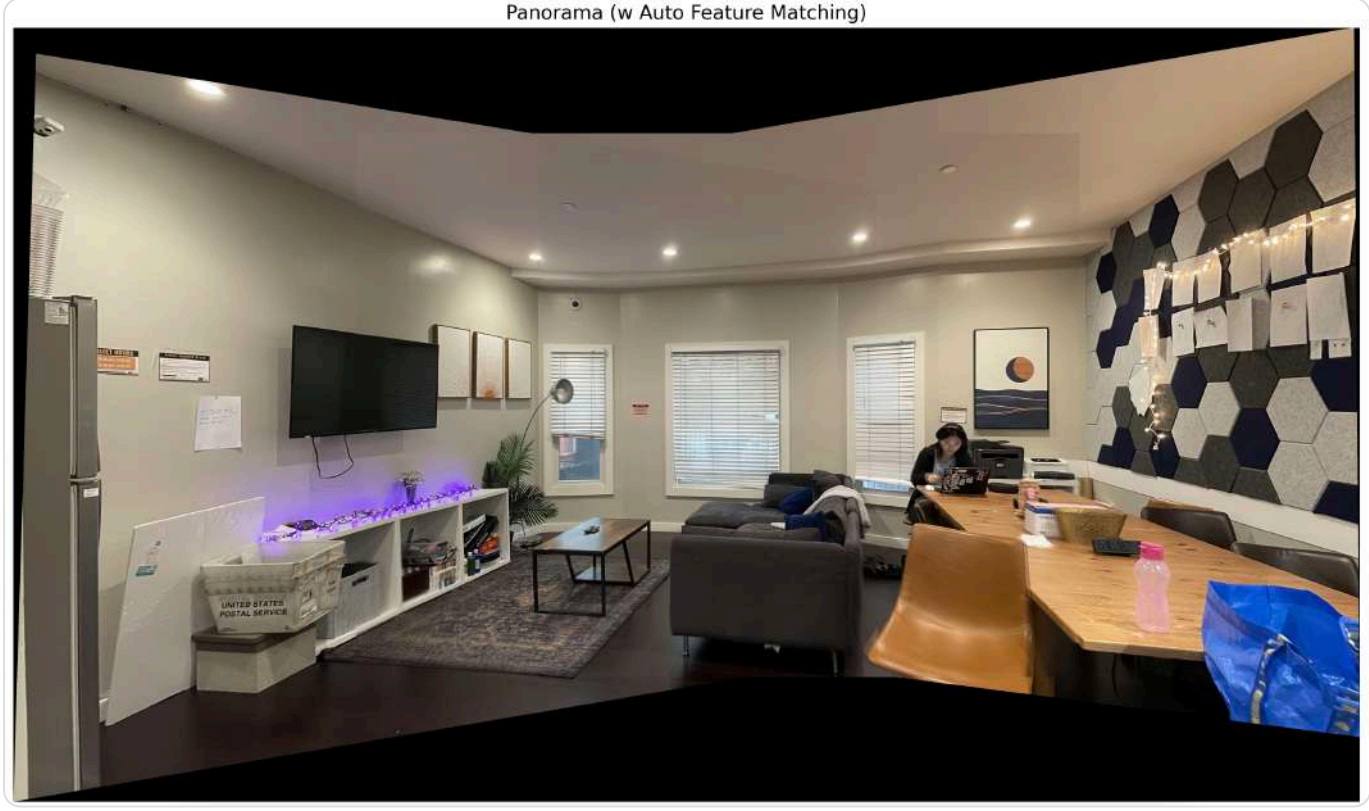
Over `n_iters`=2000 iterations, the function keeps track of the candidate H with the most inliers, representing the best geometric fit. Finally, from the best candidate H, it recomputes a final homography using all of that H's inliers. The resulting best_H matrix encodes the optimal perspective warp aligning image 1 to image 2, while best_inliers identifies which matches were geometrically consistent under that transformation.

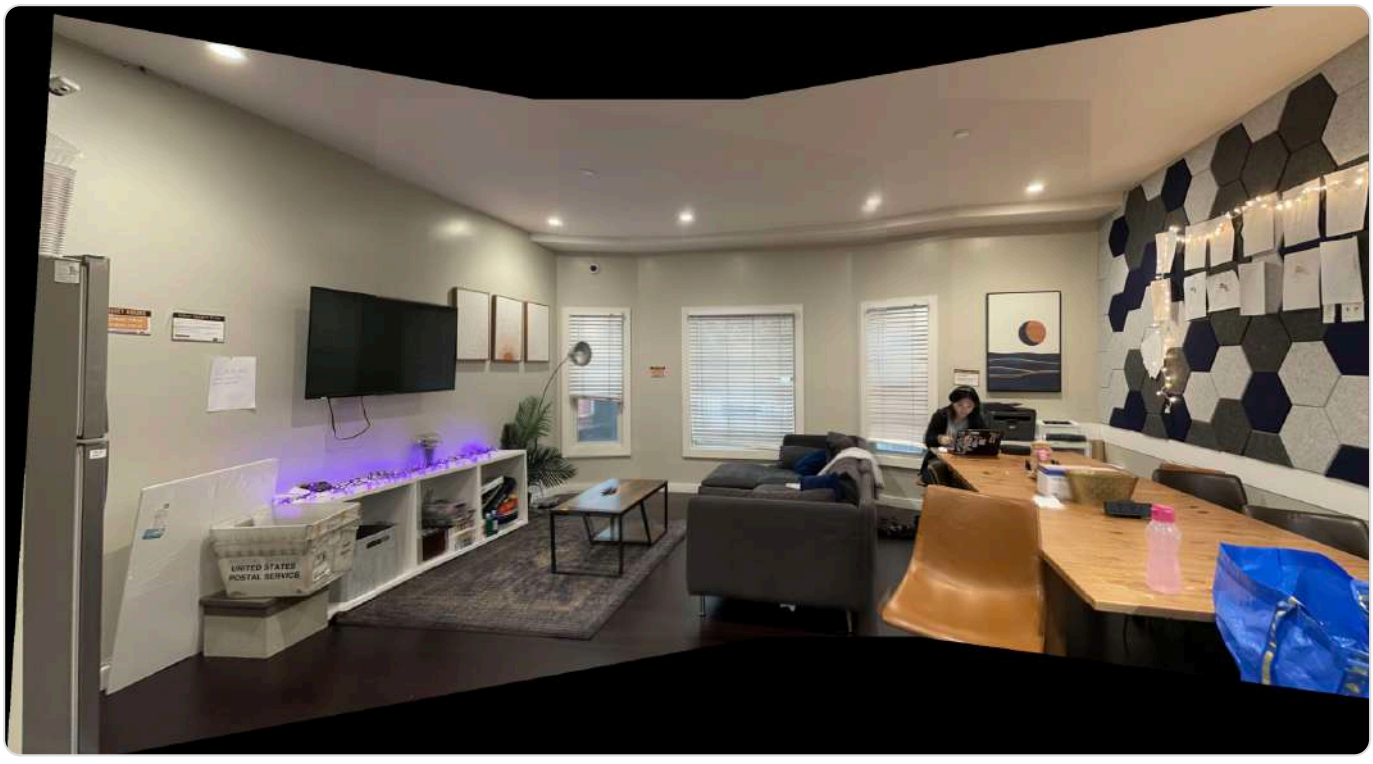
The below image shows the results of RANSAC (inliers = green, outliers = red). Looking at the placements of the green dots across the 2 images, we see that they do indeed match!



With the best_H homographies computed from RANSAC, we can stitch together panoramas using the techniques in part A. Here are the results! We first show the new panoramas with auto feature matching, then the old panoramas from Part 3A (with manual matching) below for comparison. We see that for the Yellowstone and Wheeler Auditorium images that have lots of details, auto feature matching improves the clarity of the panoramas significantly.

Panorama (w Auto Feature Matching)





Panorama (w Auto Feature Matching)

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