

# Seeing the Past: A Computer Vision Approach to University-led Gentrification

Ronnie Shashoua   Seehanah Tang

## Motivation

Brown's campus expansion and university-led gentrification has drastically changed the landscape of College Hill by demolishing family homes and businesses to make way for university housing and academic buildings.



As Brown continues to grow, there are few avenues for students to learn about the communities that preceded them.

## Define the problem

We aimed to create a program that can take in an image of signage on a modern day building on Brown's campus and have it output images of that area prior to Brown's demolition of those historic buildings. First, we needed to build a dataset of images of historical buildings, and a set of images of signage on those buildings. Then, we utilized optical character recognition (OCR) to identify the building to match it with the corresponding historical images.

## Goal

1. Build dataset of images of historical buildings and research to understand where each one is located.
2. Find the current day buildings in those physical locations and photograph signage in order to build a dataset of modern images—to test accuracy, and to have if we would like to train a more complicated model in the future.
3. Build model using OCR and adjust it until it is 60% accurate at least.

## Dataset Building

**John Hay Library.** First, we pulled boxes of archival data to look through in the John Hay library, such as the Wriston Papers. We researched the exact locations of old images, which involved cross-referencing with other images of buildings and aerial photos, official university correspondences, and historic registries and ownership records.

**Non-University sources.** We also found images and reference sources from Rhode Island Historical Society directories, Providence Public Library digital photo collections, and the Brown University repository. Using this knowledge, we worked to match the sites of our historic images to the sites of current day buildings. Then we went to build up a dataset of images of the signage on these buildings, which just involved going to every single one to take images of the signs with their names from several different angles.

## Data Acquired

We were able to acquire images for many buildings, especially within Wriston Quadrangle. We wanted to emphasize the disorientation we felt looking through images of a completely different landscape that once stood on College Hill. Below are two images, side by side with the current sites today. On the left is a view down Benevolent Street from Thayer, a look into a bustling commercial street that no longer exists after being demolished for the construction of Wriston Quad. On the right is a view from further up Thayer Street, depicting the life that once existed in this neighborhood. Now, these businesses have been replaced by a brick wall and the Sharpe Refectory.



## References

- [1] Kirkpatrick, Finn. Pickens, Katy. "We didn't choose to be neighbors": A history of Brown's property impact on the East Side." Brown Daily Herald, 2020.
- [2] Pettit, Nathaniel. "A Home for the Liberal Ideal: Brown University Housing Policy & the East Side of Providence, 1937-1997". Thesis (Honors)--Brown University, 2020., 2020.
- [3] Schermerhorn, Peter. "Competing Visions : Historic Preservation and Institutional Expansion on Providence's East Side, 1937-1966". Thesis (Honors)--Brown University, 2005., 2005.

## Model Creation and Adjustment

**Preprocessing.** To get better results, we tried various combinations of filters and preprocessing techniques. The final model performs preprocessing by converting the image to black and white, applying median and Gaussian blur, and inverting the final image.

**Matching sign to building.** Building off of the python library pytesseract, extracted characters and words from the signs. To map words to the building, we created a dictionary of building to its characteristics (e.g. name, year it was built, location).



"Perkins": {"Perkins", "Power", "1960"},



## Results of Model

Building	Accuracy
Barbour	0.6
Buxton	0.25
Chapin	0
Diman	0.4
Goddard	1
Harkness	0.17
Hegeman	1
Keeney	0.86
Macmillan	1

Building	Accuracy
Marcy	0.75
Nelson	0
Newpem	0.6
Olney	0.83
Perkins	0.8
Ratty	1
Rock	0.5
Sears	0.4
Wayland	0.4
Total	0.62

Our final model was able to achieve an accuracy of 62% on our dataset of 94 images of 18 campus buildings.

In general, it performs well on direct, close-up photos of signs, especially signs that are the standard brown signs with white letters.

We found the pytesseract algorithm to be quite unreliable, so next steps would be to train our own model (e.g. using CNNs).

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