

ТШРШ

ТШРШСОБРАРНШ

# Topography Typography: Detecting Glyphs and Creating Fonts from Satellite Imagery

Kara Lynn Bressler\*

Department of Computer Science, Princeton University

## Abstract

*I propose and implement a method for seeing the typographic forms in the topography of our physical worlds. I use image-based handwriting datasets to train neural networks which detect typographic glyphs in a satellite image, and I implement a pipeline for preparing these forms for use in a digitized font format. Thus far, I've generated several completed, vectorized fonts as well as a system for creating an infinite number of fonts from satellite imagery. This project serves to be at the fringe of computer science research as mimicked in this paper's writing style and structure.*

**Keywords:** typography, glyph detection, satellite imagery

## Introduction

The word **geography** stems from combining the Greek words *gē*—earth—and *graphia*—writing. The Topography Typography project serves to read and make legible land's writing. This project is a work in progress to be reframed and reconsidered; in this paper, I look through philosophical and technical lenses to understand the creation of these fonts. Let's first step through Topography Typography as the journey has played out so far.

### The Boot-Shaped Lake

I don't need entertainment on a plane as long as I have the window seat. At dawn or dusk, over sea or land, in rain or shine, I'll peer out the window and wonder about the forms and life below.

In November 2017, I was flying home to Naples, Florida for Thanksgiving Break, peering out from my window seat at the ever-changing landscape. Halfway through the flight, I settled my eyes on a large body of water in the shape of a cowboy boot with spurs. See *Figure 1*. Slowly, we flew past the lake. Even out of eyesight, the lake's form lingered in my brain. I could not help but continue to sit, transfixed. During that fall semester at Princeton, I was taking a Visual Arts class titled *T-y-p-o-g-r-a-p-h-y* taught by David Reinfurt. In my coursework, I was thinking about and working with the deconstruction of letterforms. Sitting in my window seat, I decided I wanted the ability to find typography in the land. I wanted to better investigate spatial structures and work with the striking forms of arbitrary, aerial landscape. I wrote this idea in my journal, returning to it for independent work starting in my undergraduate junior year.

### Initial Font Creation

Over the course of my junior spring at Princeton, I began creating this glyph detection algorithm. I iterated on places



**Figure 1:** Satellite imagery of a boot-shaped lake outside Sneads Ferry in North Carolina. Sourced from USGS Landsat imagery.

dear to me and my loved ones, places connected to my placement on Earth including my hometown (NAPLES) and my college town (PRINCETON). See *Figure 2*.

Spring turned into summer, and while at my internship, I created the SEATTLE font on site. In a work presentation, I used the SEATTLE font for the type, and my co-worker commented that he knew the exact location in downtown Seattle where I'd sourced the font's **P** character. See *Figure 3*. I became more interested in the field work aspect of this project, in visiting the locations of characters to understand the source of the indexical marks I was recording.

### Peruvian Geoglyphs

At the end of that same summer, I found myself backpacking alone in Peru, traveling from the country's southwest deserts to its northeastern rainforests. I was traveling in a space I'd only read and heard about, having sourced my visual understanding of the land from aerial satellite imagery stored in Google's omnipotent Cloud.

### Nazca Lines

Finding myself in the Nazca deserts, I visited the town's world-renowned geoglyphs. The term **geoglyph** refers to a grounded land design created from natural media like stone, water, sand, trees, or dirt. In imagining the Nazca Lines, think giant crop circles but preserved in the arid Peruvian desert sands for over two thousand years.

\*e-mail:kara.lynn.bressler@gmail.com

BRASOLETE, BRAZIL  
 BALTIMORE, MARYLAND  
 BROOKLYN, NEW YORK  
 BRUNNENBURG, GERMANY  
 INDIANAPOLIS, INDIANA  
 LRS FERRIS RIVER, PERU  
 WASHINGTON, DC  
 NAPLES, FLORIDA  
 NAPLES, ITALY  
 OXFORD, ENGLAND  
 PRINCETON, NEW JERSEY  
 REDWOOD CITY, CALIFORNIA  
 STAMFORD, CONNECTICUT  
 SPARTANBURG, SOUTH CAROLINA

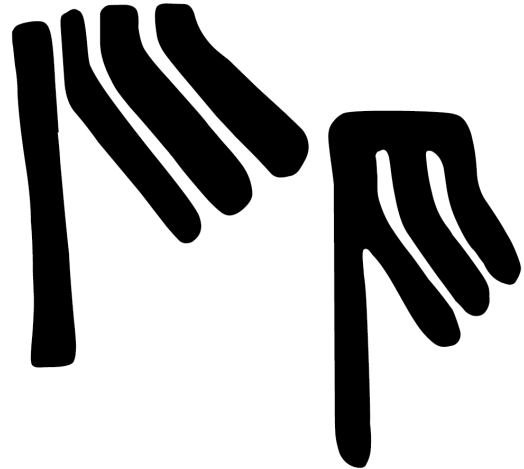
**Figure 2:** Names of the locations I used in initial trials as typeset in their respective fonts with original rendering.

This time in the window seat of a twelve-person plane, I settled into the continual rolling of the aircraft as the pilot gave passengers two opportunities to see the Lines, alternating to favor the right and left side windows. In ninety minutes, we flew over geoglyphs depicting twelve outlined graphics including la Ballena (the Whale), la Araña (the Spider), el Árbol (the Tree), and el Colibrí (the Hummingbird), the last of which we find on Peru's Nuevo Sol coinage. The sands were riddled with these surprising patterns, creating a graphic network in the otherwise uniform sands below. See *Figure 4*. Upon safe arrival back to the ground of the Pisco airport, I traveled to see the Candelabra geoglyph etched in the sands of the Paracas coast. Viewed from the coastal waters, the Candelabra loomed over me, graphically laying claim to the red cliffside. See *Figure 5*.

Today's anthropologists and scientists cannot agree on the creation methods behind these geoglyphs in Nazca and Paracas. Some think the lines were created by pressing down rope into the ground while others insist the Nazca people dragged a stick through the sand. Creation stories of the 1960s incorporated aliens and ancient astronauts. We too can only guess about the reasons for creating these grounded graphics; some propose the lines were created for rituals performed to improve chances of rain and crop fertility, while others propose origins relating to astronomy, calendar organization, and landmarking. [Golomb 2018]

### Aboard a River Cargo Boat

In the opposite corner of Peru, I had another encounter with grounded glyphs when I spent five days aboard a cargo boat. I found myself traveling from Yurimaguas, a quiet port town, to Iquitos, the largest city in the world not accessible by road and only reached by river or air. Our ship carried compost accelerator, potatoes, plantains, mattresses, and chickens—all for safe transport to Iquitos along el Marañón, a tributary to the Amazon River. See *Figure 6*. Around seventy other passengers boarded with me in Yurimaguas, and we set up our hammocks in parallel on the ship's middle, open-air deck.



**Figure 3:** A type sample of the letterforms P and p in SEATTLE, reminiscent of downtown Seattle's street plan.

Along the journey, I passed the time either reading the first edition of *The Serving Library* which regards time generally and libraries specifically or staring out over the ship's railing, entranced by the continually changing river banks. Over those long days aboard, I became acquainted with a group of passengers—a mix of backpackers, locals, and crew. With these folks, I started up a game to guess the letterform along which we were traveling. Over the course of an hour or so we would try to guess the letterforms which our captain had been maneuvering. I'd be swinging back and forth in my hammock, reading or sleeping or thinking, when a friendly face would walk by and comment, "Pienso que este es un S, no?" I'd nod or counter with "No, es un Z."

These cursive river glyphs fluidly flowed into one another; for me, it was unclear when a glyph would appropriately stop or start. Only with the waking from a nap or the sudden jolt of the boat nudging off a marooning moment on a sand dune would I be able to take a refreshing moment to reorient my internal typography.

This field work in Peru led me to focus on depth in this Topography Typography project. With these open questions about context from the Nazca Lines and this absurd time I'd spent marinating in el Marañón's glyphs, I was far less concerned with how many fonts I could accumulate—on which I'd focused that first spring when I'd cranking out over a hundred iterations—and far more interested in the stories and contexts behind the resulting sets of glyphs. I came into my undergraduate senior year with this lens of focusing on understanding my subject.

### Goal

The goal of this project is to create a system for generating typographic glyphs from a location's topography. Given satellite imagery, I want to algorithmically find letters, digits, and punctuation in the image. As a final result, I want the ability to type with these forms in a legible, complete typeface and understand the context behind these glyphs.



**Figure 4:** Photo taken over *el Mono (the Monkey)* geoglyph in the collection of Nazca Lines in Nazca, Peru. August 2018. Taken with my phone camera.

## Related Work

Next time you find yourself on the search engine of your choice, spend a couple minutes looking at search results for **pareidolia**. You'll find an incredible visual collection, mostly of faces where there is no living creature. This psychological phenomenon describes the ability to observe patterns in random data. We see pareidolia manifesting in the sightings of faces or common objects in impossible environments like the prints from Hermann Rorschach's inkblot test and the "Face on Mars" photograph imaged by *Viking 1* as seen in *Figure 7*. [Phillips 2001]

In 2004 in my home state of Florida, Diana Duyser sold on eBay for \$28,000 a ten-year-old grilled-cheese sandwich with the image of the Virgin Mary seared into the bread:

*Diana Duyser made the sandwich with white bread from Publix and Land O'Lakes American cheese in 1994. She took a bite, then looked down and saw the Virgin Mary staring up at her. Indeed, the image of a woman could be perceived in the charred bread, but it could have been a barroom portrait as much as the mother of G-d.* [Nolin 2015]

People today find entertainment in this phenomenon, spotting images of rabbits in the sky while cloud gazing or finding dogs in a plate of spaghetti while experimenting with Google's DeepDream algorithm which incorrectly detects and then exaggerates zoomorphic features in a given image. [Mordvintsev et al. 2015; Russon 2015]

### Paul Elliman's Found Font

Pareidolia is central to the life work of typographer, graphic designer, and artist **Paul Elliman** who situates himself at the cross-section of typography and found objects. In 1995, Elliman began curating his typeface *Found Font* (also



**Figure 5:** Photo taken of the *Candelabra* geoglyph from the perspective of a boat off the coast of Paracas, Peru. August 2018. Taken with my phone camera.



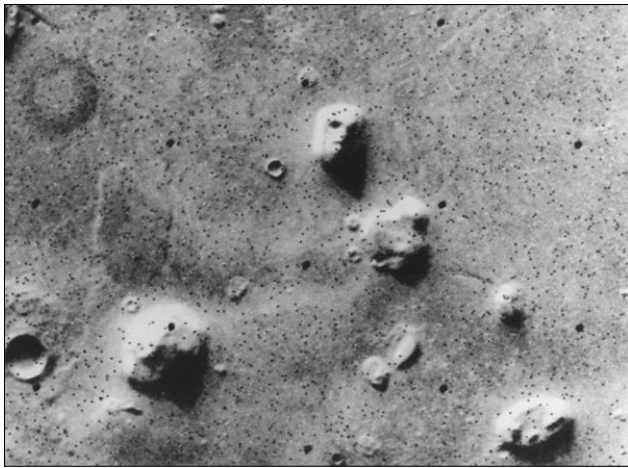
**Figure 6:** Satellite imagery of the cursive river forms of *el Marañón*, flowing from Yurimaguas (bottom left) into the Amazon River and toward Iquitos (top right). Sourced from USGS Landsat imagery.

known as *Bits*), a system of letters created from elements and castoffs of industrial production. As displayed in MoMA's *Ecstatic Alphabets / Heaps of Language* exhibit, the found letterforms comprise of zip ties, scissor handles, and hoop earrings, amongst other objects. See one iteration of this font in *Figure 8*. [Reinfurt et al. 2012; Wooldrage 2017]

Elliman's work dissects language's role in the world. *Found Font* addresses the human want to map outward environments to easily digestible understandings. By mapping language onto these objects, Elliman understands the objects in his environment via a typographic lens.

### The Aerial Bold Project

Benedikt Groß and Joey Lee conducted related research in the field of letterform detection from satellite imagery. After making their *Big Atlas of LA Pools*, these two designers "realize[d] that satellite and aerial imagery are rich with stories." In 2014, they organized the **Aerial Bold Project**, putting together a massive collaborative effort involving 140 people around the world (mostly living in North America



**Figure 7:** The “Face on Mars” photograph taken by Viking 1 in 1976. Sourced from the Wikipedia page’s visual fodder for “Cydonia (Mars).”

and Europe). These participants spent over two years using an app to manually detect and label over 11,000 letterforms from infrastructure. With the help of a type designer, Groß and Lee proceeded to parse the labeled images to find the forms which had the best “beauty and readability.” From this curated set, they made three vectorized fonts: Building, Suburbia, and Provence. While they commissioned machine-learning research for character recognition in satellite imagery, their final product did not implement the proposed algorithm. [Gross and Lee 2016; Arawal 2015]

## Data

While visiting my oldest brother Liam in Austin, Texas in January 2018, I began developing my blueprint. Over tacos from Torchy’s, my brother and I debated how to find the ‘best’ alphabetic forms of a landscape, discussing using human intelligence to manually pan Google Earth and create a test set of obvious letterforms. I would then test whether the proposed algorithm could detect and correctly label the same ‘obvious’ letterforms. This involved a lot of unnecessary hired help, and I quickly decided against this approach.

As I later researched in the Aerial Bold Project, Groß and Lee entirely crowd-sourced their repository of over 11,000 letterforms. This use of crowd-sourcing brings to light questions about global labor exploitation. Mechanisms in place today like Amazon Mechanical Turk outsource small microtasks to large populations of people on the Internet, streamlining the process to create a dataset from scratch. However, this process does not take into consideration edits to collected datapoints nor the ethics and integrity informing the practice of outsourcing the completion of these microtasks.

In order to curate a new, properly-sized dataset for fodder for this project, I would need to crowd-source the collection of the training and testing images to create any valid model. I instead choose to use preexisting datasets as source material for typographic character detection. Using a preexisting dataset allows this project to stand in conversation with the past and avoids issues of labor imbalance. Let’s now look at the history as well as the overall structure of the datasets used in the progression of Topography Typography.



**Figure 8:** A subset of glyphs in Paul Elliman’s Found Font project as traced in Adobe Illustrator. Sourced from the first Google Image result when searching for “Found Font Paul Elliman.” May 2019.

## MNIST and Extended MNIST

In 1995, the United States’ National Institute of Standards and Technology (NIST) created a novel database of hand-written characters called *NIST Special Database 19*. The characters were curated from nearly 3700 instances of the *Handwriting Sample Form* filled out by both employees of the American Census Bureau and American high school students. See *Figure A1* for an example of a completed form. Each of the 800,000+ characters in *Database 19* is represented by a binary black-and-white 128×128 pixel image fulfilling membership in one of the sixty-two following classes:

- Uppercase letters: {A, B, C, ... , Z}
- Lowercase letters: {a, b, c, ... , z}
- Digits: {0, 1, 2, ... , 9}

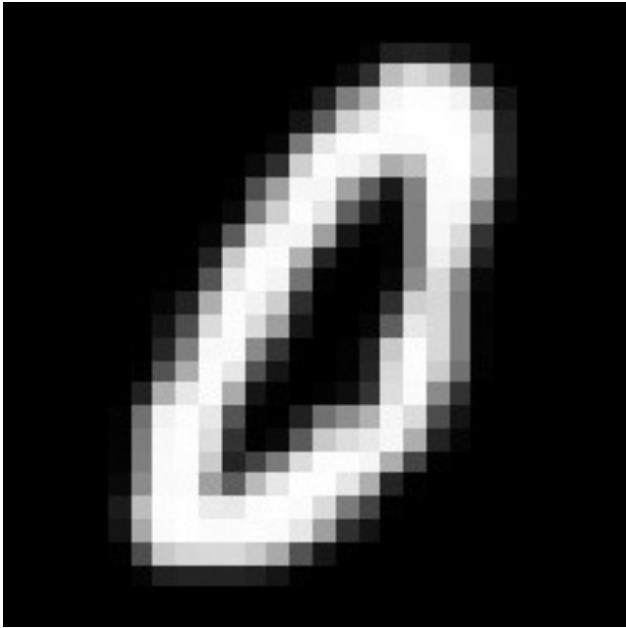
*Database 19* splits its training data into characters written by American Census Bureau workers and testing data into characters written by the high school students. [Grother 1995] In an effort to create a representative testing set accommodating for the potential biases in between these training and testing sets, *LeCun et al.* curated the MNIST dataset from *Database 19*.

**MNIST** (the Modified National Institute of Standards and Technology database) is the canonical machine learning (ML) dataset. In my undergraduate junior fall, I encountered MNIST in two different computer science assignments introducing ML topics. Each of the 70,000 characters in



**Figure 9:** Designer and technologist Joey Lee stands behind a poster featuring the Aerial Bold Building font. Sourced from Lee’s personal website. [Lee 2019]

MNIST are represented as smaller, more compressed versions of those in the NIST database, depicted by an anti-aliased grayscale  $28 \times 28$  pixel image fulfilling membership in one of ten classes:  $\{0, 1, 2, \dots, 9\}$ . See Figure 10. MNIST is split into training and testing sets, sized 60,000 and 10,000 samples respectively, which scramble together *NIST Special Database 19*’s training and testing data. [LeCun et al. 2013]



**Figure 10:**  $28 \times 28$  pixel sample from the 0 class in the canonical MNIST dataset.

In 2017, Cohen et al. published an extended version of the MNIST dataset known as **EMNIST** (Extended MNIST). The two are, of course, pronounced the same. Samples in EMNIST are based in the same anti-aliased grayscale  $28 \times 28$  pixel format as MNIST, all with a grayscale character on a black background. This extension functions as another variant on *Database 19*, now containing all of the original sixty-two classes cleaned and arranged in multiple datasets

including: ByClass, ByMerge, Balanced, Letters, Digits, and the original MNIST. The four later classes are **balanced**, meaning there is an equal number of samples in each class. For this project I use two of these clean balanced datasets:

- Letters:  $\{A \text{ and } a, B \text{ and } b, C \text{ and } c, \dots, Z \text{ and } z\}$
- Digits:  $\{0, 1, 2, \dots, 9\}$



**Figure 11:**  $28 \times 28$  pixel letterform samples from each of the twenty-six letterform classes in EMNIST’s Letter dataset.

The Letters dataset contains 5600 instances for each of its twenty-six classes, and the Digits dataset contains 28,000 instances for each of its ten classes. The Digits class represents a smaller set of the original MNIST dataset, and I use this more manageable size without a statistically significant difference in testing error. [Cohen et al. 2017]

## UNIPEN

We just looked at Extended MNIST—the alphanumeric handwriting dataset—where each datapoint is separated from the rest and packaged in a pixelated format. This dataset is said to be an **offline** handwriting dataset because its information is already stored in the written images. In *Topography Typography*, I also use the **UNIPEN** online handwriting dataset to create a dataset of non-alphanumeric glyph samples. UNIPEN is **online** in the sense that the information is saved as points along a vectorized curve in the graphical space of  $(x, y)$  coordinates, not in the form of pixels in an image. Online handwriting data is pertinent in understanding real-time handwriting, as in the case of writing with a stylus on a tablet.

Imagine this offline versus online difference as similar to my experiences with the Nazca Lines and el Marañón’s cursive glyphs. Both of these information systems encode graphical information. However, my experiences encountering these glyphs change what I understood about this information. The Nazca geoglyphs relate to offline handwriting—I see the glyph all at once in its entirety from the plane’s window. On the other hand, traveling along the river allows me to understand the present glyph as I experience it over the course of time.

To use the UNIPEN dataset like I use the alphanumeric information from Extended MNIST, I need this online handwritten data to be offline. UNIPEN’s vectorized coordinates should be converted into pixelated images. I need to see the river from above. Thanks for the work of Sueiras et al., I have access to a free offline version of the UNIPEN dataset. This rendition is hand-curated, resulting in over 62,000 character samples categorized in one of ninety-three categories. From this UNIPEN dataset, I use 6014 samples which act in one of thirty-one categories of punctuation: [Sueiras 2017]

- Punctuation:  $\{-, !, ", \#, \$, \%, \&, ', (, ), *, +, ,, ., /, :, ;, i, =, \grave{a}, ? , @, [, ], \hat{, }-, \backslash\}$

## Normalization

When data is **normalized**, each sample on the dataset conforms to certain standards which make salient the universal similarities present in the collection. For normalized data, all of the images should be of the same relative size and subject matter. For a dataset on handwriting samples, the forms of a particular category should take up about the same space in the image field and should all be oriented similarly.

Unlike the samples from MNIST, the samples from this offline UNIPEN dataset are not normalized. As curated by *Sueiras et al.*, each sample is a  $64 \times 64$  pixel image with a black background and a grayscale glyph in the pixel grid, spatially oriented as if placed in a line of type. Some punctuation glyphs only fall in the superscript region—the top third—of the pixel grid including the apostrophe (’), quotation mark (”), and circumflex or caret (^) symbols; other glyphs including the period (.) and comma (,) fall within the subscript region—the bottom third—of the pixel grid. The detection of glyphs in a landscape is not relevant to relative spatial placement inside the sliding window, and thus I center all handwriting samples. This maximizes the amount of relevant detail taught to the neural network about the relatively smaller glyphs which fall in these constrained superscript and subscript regions.

In order to center these images, I first detect where the glyph is in the pixel grid and find the smallest rectangular bounding box which cuts off the totally black background, taking away any black trim found around the pixelated grayscale glyph. For each  $64 \times 64$  pixel sample, I convert all non-black pixels to white, creating a **binary image** where pixels are no longer in grayscale but now exclusively black or white. I re-size this trimmed, binary sample to be  $22 \times 22$  pixels without misshaping the glyph. I then calculate the **center of mass** of this image, weighting each pixel by its density; the whiter the pixel, the heavier the pixel, and thus the closer this pixel is to the image’s center of mass. I put this calculated center of mass as the direct center of the black  $28 \times 28$  pixel image field, thus centering the handwriting sample on a black canvas and providing an approximate three pixels of padding on all sides of the handwritten glyph. Adjusted for its center of mass, each sample now lies in the same general area as do other members of the same class.

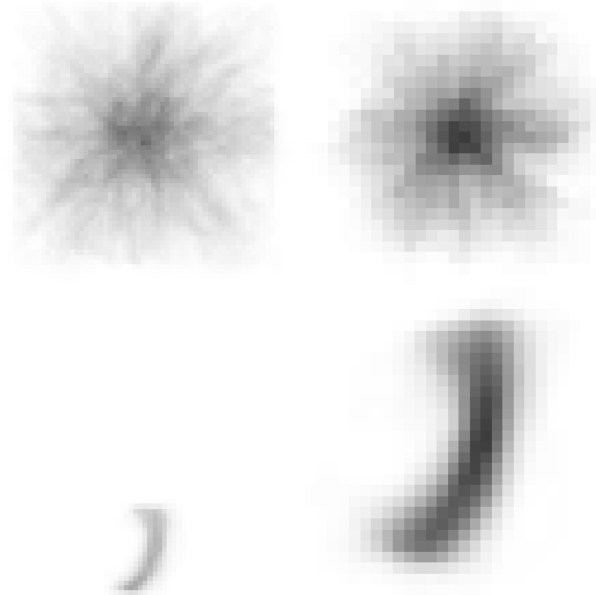
## Visualizing AVERAGE Data

To visualize the normalization of the offline UNIPEN dataset, I refer to the **AVERAGE** font’s punctuation glyphs. In AVERAGE, I make the ‘average’ mean sample from all instances of the glyph in the respective dataset—either Extended MNIST or UNIPEN—by stacking and equally weighting each sample. See *Figure 12*. Note the grayscale inversion in visualizing AVERAGE. In the case of AVERAGE punctuation, the output represents the ‘average’ glyph in the adjusted UNIPEN dataset. [Kröger 2015]

As an example, let’s specifically look at the normalization of a single character class in the UNIPEN dataset—our cephalopodic friend, the asterisk (\*). In this case, the center of mass corresponds to a point in the middle of the symmetrical asterisk where the arms of the symbol converge. By centering with respect to the center of mass, the arms of the asterisk lie near, if not on top, other asterisks’ similarly aligned arms, and the centers of all the asterisks should be within the range of a handful of pixels. See the AVERAGE

**Figure 12:** A type sample of the AVERAGE font. Like all AVERAGE samples shown in this paper, the results are graphically inverted (black on white) to differentiate them from single samples (white on black) as we see in *Figure 11*.

asterisk, pre- and post-normalization, in *Figure 13*. The center of the new normalized data is darker and thus indicates more overlap at the center of the glyph. The concentrated center of the asterisk is more universal to the form than the spatial placement of its arms which appear in the AVERAGE context as lighter and less dense than the center.



**Figure 13:** The AVERAGE asterisk (top) and the AVERAGE comma (bottom), on a  $64 \times 64$  pixel grid straight from online to offline conversions of the UNIPEN dataset (left) and on a  $28 \times 28$  pixel grid after normalization for center of mass and binary pixel value (right).

## Data Augmentation

Compared to MNIST which had over 5600 samples per class, the offline UNIPEN dataset has far fewer samples, averaging at about 200 samples for each punctuation class. I have the most in the hyphen (–) and period (.) classes with just under 500 examples per class while I’m limited to just over 80 samples of the grave diacritic (˘) and the tilde (˜). For many of the punctuation glyphs I want to detect, this is not enough data to properly teach a neural network. There isn’t enough variation in the given samples to understand which features of the glyph samples are universal to that class and which happen to be unique to the samples at hand. As will be discussed in the next section, we are trying to ‘fit’ a model and have a neural network classify an image sample as a member of one of the thirty-one classes of punctuation. The

problem with having too little data involves **overfitting** the model where the model has too narrow of an understanding of a form and therefore slight variation on a relevant sample will be wrongly classified and assigned to a less strict class.

To fix this problem of a lack of sufficient data, I augment the normalized offline UNIPEN samples, adjusting the given samples and using them as fodder to produce plausible variations on the given class. Here are a handful of mapping techniques I used to alter the given dataset and produce more fodder for teaching the neural network:

- **Rotate:** I rotate a sample about the center of the  $28 \times 28$  pixel grid—and thus the sample’s center of mass—within a range of  $[-5^\circ, 5^\circ]$  from its initial position.
- **Stretch:** I stretch the sample vertically and horizontally within a range of three pixels outside the closest rectangular bounding box of the glyph.
- **Shear:** I warp the rectangular bounding box of the glyph into a parallelogram, slightly shifting the glyph diagonally.
- **Add Noise:** I add grayscale noise to the sample, adjusting the values for an arbitrary collection of ten percent of the pixels in the sample’s  $28 \times 28$  pixel grid.

These basic techniques allow enough variation to create thousands of samples for each punctuation class—plenty on which to train the neural network. Other more advanced techniques for data augmentation—including elastic distortions and perspective transformation—can also be employed to create more training and testing fodder. [Bloice 2019]

## Satellite Imagery

In December 1972, astronauts of the Apollo 17 mission captured the “Blue Marble” image on their way to the moon. This image showcases the world as a blue marble floating in black space, marking the first human-photographed image to capture a fully illuminated Earth. The “Blue Marble” image circulated broadly, framing global eco-political conversation and understanding in the 1970s. This self-portrait helped create a world consciousness around humans’ impact on the Earth. See *Figure 14*.

This eco-political framing came at the same time Secretary of the Interior Stewart Udall pushed to fully document the surface of the earth and provide unambiguous documentation of human land use. Udall urged Lyndon Johnson to form an “Earth-observing program” which would employ space-based satellites. From this push emerged NASA’s Earth Resources Technology Satellite (ERTS) which would later to be known as Landsat. Since 1972, the **Landsat** missions—eight to date—have run continuously. Landsat’s data archive aims to provide a record of broad satellite imagery of Earth’s surface. Today run by the United States Geological Survey (**USGS**), each functioning Landsat satellite has a ninety-nine minute orbit, and every sixteen days, the satellite completely documents our Earth. Today, the USGS provides this satellite imagery free via the Internet, allowing everyone on the world access to this information. Most publically available satellite imagery, including that on Google Maps, is acquired by the USGS and their Landsat missions. In this project, I use satellite imagery curated by Google Maps and available through the Landsat missions run by USGS. [Shurkin 2012]



**Figure 14:** *AS17-148-22727*, commonly known as the “Blue Marble” photo. The original label read: “View of the Earth as seen by the Apollo 17 crew traveling toward the moon. This translunar coast photograph extends from the Mediterranean Sea area to the Antarctica south polar ice cap. This is the first time the Apollo trajectory made it possible to photograph the south polar ice cap. Note the heavy cloud cover in the Southern Hemisphere. Almost the entire coastline of Africa is clearly visible. The Arabian Peninsula can be seen at the northeastern edge of Africa. The large island off the coast of Africa is the Malagasy Republic. The Asian mainland is on the horizon toward the northeast.” The image was originally taken with Antarctica at the top of the image; I’ve flipped the image to show how it commonly appears in graphic circulation. [NASA 2001]

## Sourcing Imagery for a Location

As discussed in the *Introduction*, I curate the satellite imagery for a location specifically with respect to my memory and understanding of the place. With a specific place in mind—a neighborhood, town, city, or back-country site—I use the desktop application Google Earth Pro to find the rectangular bounds for the space and save a single image with the rough dimensions of  $1200 \times 700$  pixels. I make slight adjustments to the image in order to emphasize the difference between foreground and background. In images of mostly uniform color density and tone, I increase contrast and slightly adjust the highlights and shadow properties in a basic photo processing application like Mac’s default Photo. For all images, I crop out the Google Earth watermark. See an example of this transformation in *Figures A2* and *A3*. For other images with relatively good contrast throughout the topography, I leave these images in their raw states.

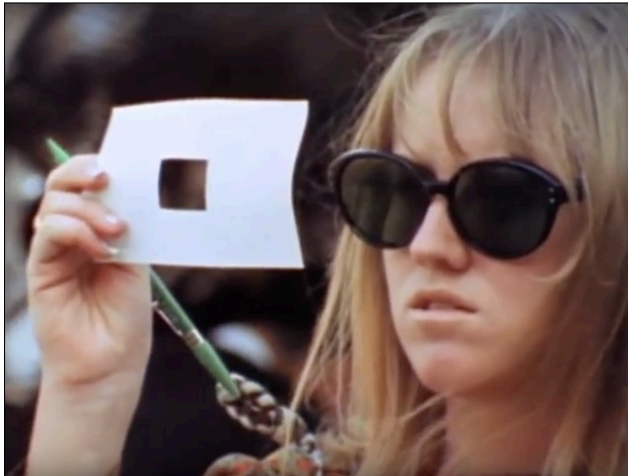
## Corita Kent’s Finder

As an artist and nun, Sister Corita Kent taught at Los Angeles-based Immaculate Heart College, the school where my maternal grandmother received her degree in sociology. Kent often instructed her students to interact with the world



through what she named a **finder**—a piece of paper with a small rectangle cut out from the middle. See *Figure 15*. The finder privileges a perspective of the world where content is isolated from context and where forms are highlighted. [Rose 2009]

*The finder became integral to Kent’s curriculum, inspiring the close study of objects—like cars—that might normally be passed without consideration of their aesthetic value. Any car becomes a thing of beauty when viewed through a finder,” reads one prompt. “View the facade of the nearest building through the finder and isolate 10 details to draw on the spot” instructs another. [Gotthardt 2017]*



**Figure 15:** *Looking through Sister Corita Kent’s finder. Sourced from a YouTube excerpt of 2009 film “Become a Microscope” directed by Aaron Rose which centers around Kent’s life, art, and teachings. [Rose 2009]*

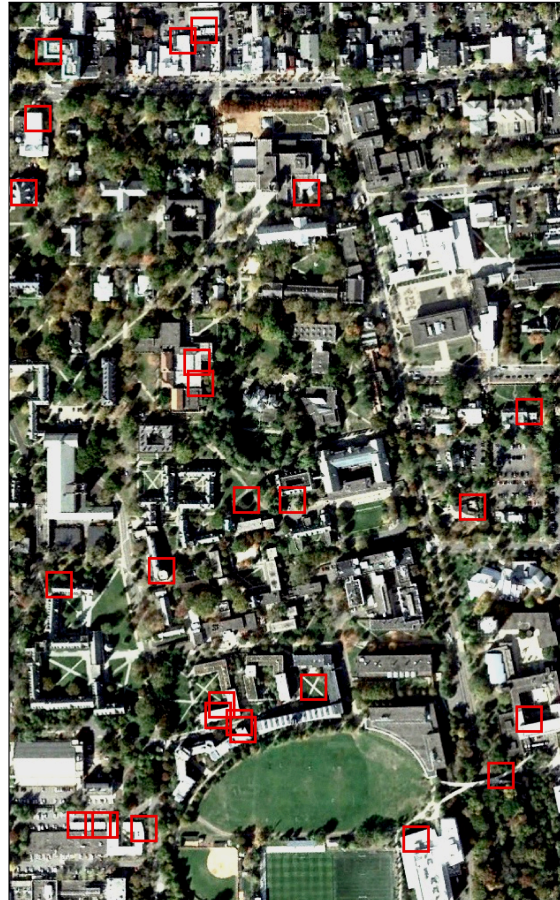
Sister Corita Kent taught others to examine their environments in much the same way my algorithm maneuvers through an image. My glyph detection algorithm uses the idea of a sliding window through which to look and investigate a landscape. With my own algorithmic finder, I look at the topography one small section at a time, trying to make sense of that little chunk without distractions from the larger landscape. Below, I develop an algorithm for processing the satellite imagery from the USGS’s Landsat feed to create the set of samples for eventual glyph detection.

### Sample Curation from a Single Resolution

Before I give the neural network the input image for glyph detection, I preprocess the image and curate a set of grayscale,  $28 \times 28$  pixel samples. I first convert the image to grayscale from RGB. This allows the input to the neural network to be in the same form as the offline UNIPEN and EMNIST samples. The satellite imagery now has one layer of information per pixel—its grayscale value in the range  $[0, 255]$ —instead of three separate layers for the red, green, and blue channels in the initial full-color image.

After preprocessing, I curate samples by **stepping through** the image. Stepping through an image means something different than splitting an image into a grid and iterating through each element. Instead, imagine I have a  $28 \times 28$  pixel window—like Kent’s finder—which I slide across the rows

and columns of the image to take samples. For this example, let my reference location be the top left of the  $28 \times 28$  pixel window—I’ll start the sample curation at the top left of the image, and thus my reference location starts at  $(0,0)$ . With a step size = 4, I move the window to the right, sliding over four columns of pixels. The reference point moves from  $(0,0) \rightarrow (4,0) \rightarrow (8,0) \rightarrow$  etc. Once my window reaches the end of the row, I restart at the beginning of the row and shift down by the step size of 4. My reference point proceeds to move across the row from  $(0,4) \rightarrow (4,4) \rightarrow (8,4) \rightarrow$  etc. In this manner, I step through the pixels in the image. I have found a step size = 4 to be most effective in terms of trading off between speed and content traversed.



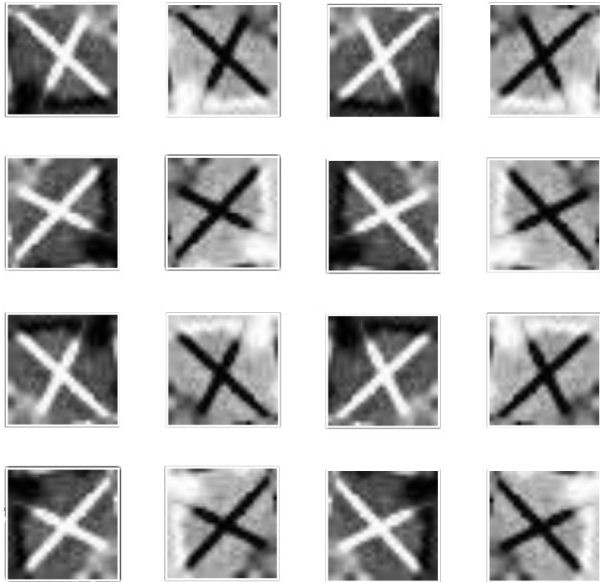
**Figure 16:** *Letterform detection algorithm applied to aerial image of Princeton, New Jersey circa February 2018.*

### Sample Transformations

Having generated a  $28 \times 28$  pixel sample from the image, I transform that sample, providing more variation from this single viewpoint. I use three methods for transforming the curated sample: **rotation**, **reflection**, and **grayscale inversion**. I perform the sixteen possible combinations of these transformations in order to create a diverse representation of the set. See *Figure 17* for a visual example of these sixteen combinations of transformations.

Grayscale inversion is especially important in this project. All training and testing data presents grayscale depictions of light characters on a black background, and the neural net-

work learns to predict a light form on a respectively darker background. Therefore if the satellite sample's glyph happens to be of a dark form on a lighter background, I want to feed the neural net an image of this glyph in an inverted context. Inverting the grayscale values of all of the sample's pixels efficiently performed this desired transformation.



**Figure 17:** The sixteen possible combinations of the three transformations—rotating, flipping, and inverting—performed on a grayscale,  $28 \times 28$  pixel sample. This sample is an image of the sidewalk in front of Scully Hall on Princeton University's campus; I walked along this X detected outside Scully every day to eat dinner in my food co-op.

### Image Pyramids

A large glyph and a relatively small glyph both from the landscape have the same presence in the final resulting font, and the combination of the two in concert with one another provides a more complete story of the land. Therefore, my algorithm detects glyphs in the landscape which appear at varying scales. In order to not only find letterforms in the  $28 \times 28$  pixel form of the original image, I create an **image pyramid** of the  $1200 \times 700$  pixel original image. This means downsampling and resizing the original image to multiple smaller pictures as visualized in *Figure 18* including images of the following dimensions:

- (1) ↓  
**1200 × 700**
- (2) ↓  
**600 × 350**
- (3) ↓  
**300 × 175**
- (4) ↓  
**150 × 87**
- (5) ↓  
**75 × 43**



**Figure 18:** A five-tier image pyramid as visualized on a satellite photo of Naples, Florida where I grew up. The detection algorithm starts from the version of the image with the highest resolution (top) and proceeds until it reaches that with the lowest resolution (bottom).

For this algorithm, I step through each of these differently-sized images, looking at  $28 \times 28$  pixel samples in the method detailed before. I save the most confidently detected sample per character class; by the end of the script, one result for a glyph class may be at a different resolution than another. In the computer-generated output from the neural network, one letter may be  $56 \times 56$  pixels in the original image while another letter could be  $28 \times 28$ . See an example of multi-scale letterform detection in *Figure 25*.

### Setup

I write the scripts for this project in a set of Jupyter Notebooks ([jupyter.org](http://jupyter.org)), an open-source project which easily runs my Python 3 scripts. I host these notebooks directly on my computer.

Using a preexisting dataset allows for guidance from previous work. Especially using a dataset in the canonical MNIST

family, I found plenty of online interest and experimentation on the code-sharing website Github ([github.com](https://github.com)), used commonly by developers for version control and code distribution. I found Ryan Cooper’s off-the-shelf solution for object detection of EMNIST characters using a neural network, and I use this code as a template for a portion of my algorithm. [Cooper 2017]

## Teaching a Computer to Classify Glyphs

Using the Extended MNIST and UNIPEN datasets of handwritten glyphs, I train three separate neural networks to understand the universal elements of these categorized glyphs. Each neural network specializes in one of three types of glyphs: letterforms, number forms, and punctuation. Let’s walk through the basic intuition for the course of this project and then delve into technical aspects of implementation.

### Typography as a Set of Signs

Typography is a set of glyphs, and a glyph is a symbol which itself is a type of sign. To understand a sign, let’s first take the **referent** which refers to the thing itself; in our example, let’s take me—Kara Lynn Bressler, the actual living person—as the referent.

The sign stands in place of the referent and is made up of two components: the signifier and the signified. The **signified** embodies the sign’s meaning and concept, while the **signifier** is a manifestation of the sign. In our example, the signified is me—Kara Lynn Bressler. There are three types of signifiers: iconic, indexical, and symbolic. The **iconic sign** references and mimics the physical appearance of the referent; a drawing of tall stick figure functions as an iconic sign for myself in that it incorporates my physical traits. The **indexical sign** refers to something showing ‘proof’ of existence; a voicemail I leave on your phone serves as testament to my presence on the other side of the line and my past action of calling you. Finally, the **symbolic sign** is culturally learned, and the manifestation of the symbol is not connected with the reality of the signified. A glyph in the Latin alphabet is a symbol; its existence does not refer to the glyph’s respective sound or elemental meaning. Without cultural context and previous knowledge of the written script, symbols have no stake in reality. My family grew up with English and thus understands the written letter **K** refers to me; meanwhile, someone unfamiliar with my presence or the script has no clue to decipher that the lines forming the **K** reference myself. As symbols, Latin glyphs do not embody the phenomena they wish to reference. [Bradley 2016]

### Teaching a Human to Classify Glyphs

Since glyphs are symbols, the forms must be learned. With repeated exposure in different environments, I understand the universal traits of the **K**. If you write a **K** on a chalkboard, I do not have to have previously seen this exact rendition of the glyph, but it should look close enough to what I’ve seen before that I can properly classify it.

Humans are able to learn these universal traits of typographic forms, but there is not a hard-defined list of rules defining the universal traits of specific glyphs. There are more convincing and legible versions of letterforms, but we are able to create and identify unique forms which still serve as members of a traditional glyph class. Without a hard

set of rules formally defining the typographic glyphs, we are unable to explicitly teach an algorithmic typography classifier. Therefore, we must show the computer program many examples of each class of glyphs in order for the computer to understand how to classify a form, no matter how unique the encounter.

### What is a Neural Network?

Modern computers have a mind-boggling capacity for computational power, but there is no program today that can independently think and make associations without a human programmer initiating these decisions.

The phenomenon of pareidolia shows that the human brain can detect patterns in random data. Psychologists hypothesize that pareidolia—particularly seeing human faces in inanimate forms—stems from an infant’s necessity to identify its parents as well as potential predators. [Coolidge and Coolidge 2016] We compare this ability to that of the modern computer and see that unlike the human brain, the computer can only do what it is told. In an effort to create more computational complexity, we create artificial neural networks to simulate connected neurons in the human brain, attempting to mimic the brain’s ability to form pros and cons about a situation and then make decisions. [Woodford 2018]

A multi-class neural network is a structure of connected nodes with different respective weights. As a network sees different examples of the various classes it wants to distinguish amongst, the network assigns different weights to the nodes, adjusting its judgment scale. As more information passes through the network, the weights are reevaluated, and when a critical mass of examples have passed through, the model can properly make its decision in classifying an input.

### Training the Neural Network

Each of the three neural networks I implement—detecting letters, numbers, or punctuation—is a model. As used here, a **model** describes a literal mapping from an input to an output; each network takes a  $28 \times 28$  pixel input and outputs an educated guess about the present glyph. The network can receive a  $28 \times 28$  pixel sample from satellite imagery and guess the pictured typographic form. Some sections of satellite imagery will be better than others, but we want to be able to classify any given section in order to create a complete typeface.

I use the architecture of a recurrent convolutional neural network (**RCNN**) to organize the functionality of my network. This architecture allows for the output of a given node to act as input for the same node; recurrence and back-filtering both help the network adjust its nodes’ weights to learn from successes and failures in detection. I decided to run a RCNN due to its limited parameters compared to a basic convolutional neural network and the RCNN’s recent success and speed in object detection. [Liang and Hu 2015; Cooper 2017]

To **train** this neural network, I show it many examples from a variety of glyph classes. These initial samples come from a training dataset, different than the samples I use later for testing. I pass the pre-labeled sample images through the network one-by-one. Each handwriting sample image is assigned a label for its relevant class: {**A** and **a**, **B** and **b**, **C** and **c**, ... , **Z** and **z**} for letters, {**0**, **1**, **2**, ... , **9**} for numbers, {**-**, **!**, **”**, **#**, **\$**, ...} for punctuation. As images trickle through the network, the predictive quality improves.

As the network’s programmer and teacher, I set up the guard rails to facilitate a positive learning environment. To do so, one tactic I employ is to use multiple **epochs**, where in each epoch I feed the neural network all of the training data through once. I’ve found running each of my networks through ten epochs is appropriate in properly training the three distinct models.

To test the efficiency of training, I show the neural network variations on glyphs that it has not seen before. I take new pre-labeled testing samples and see how well they perform on the trained net. For the punctuation dataset, I manually separated training and testing samples, assigning just under a quarter of images from the dataset as testing data. Extended MNIST’s alphanumeric samples are already separated into training and testing data. Here, I’m not testing rote memorization. The model is forced to make an educated guess and classify forms it has not been explicitly trained to recognize. This is good practice for the world in which very few landforms which form ‘perfect’ glyphs, and resulting forms are bound to be more varied relative to the more uniform, normalized figures in the Extended MNIST and UNIPEN datasets.

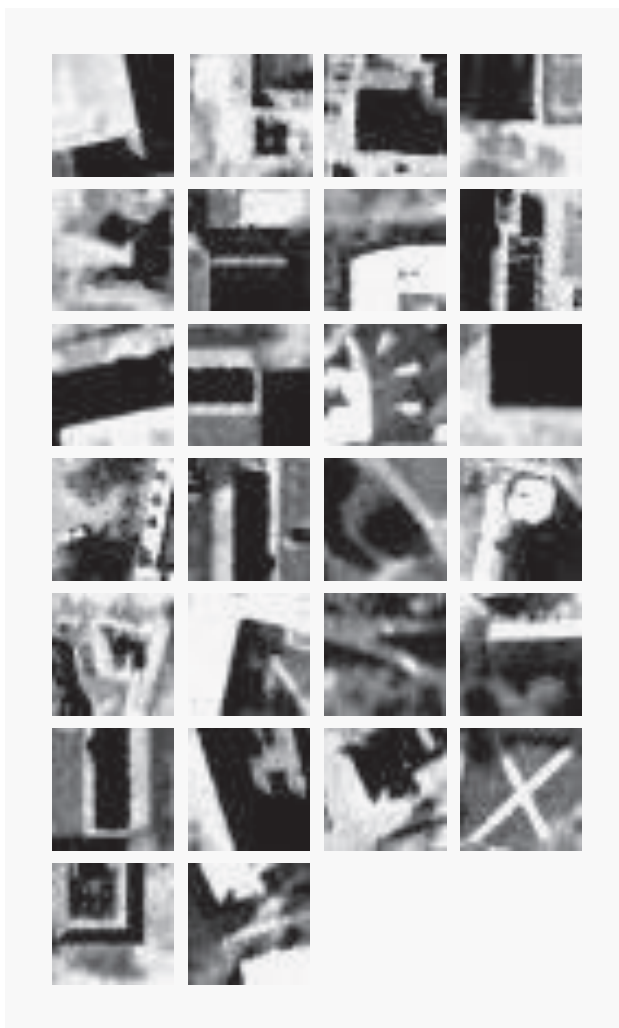
With EMNIST’s Digits dataset, I train the network to a testing accuracy of over 99 percent; for EMNIST’s Letters dataset—over 93 percent, and for the UNIPEN dataset—92 percent. Regarding timing, it takes about twenty minutes to train the RCNN with ten epochs on EMNIST’s Letters dataset and about half an hour for Digits. Training the neural net on the normalized offline UNIPEN punctuation dataset takes about ten minutes for ten epochs.

## Detecting Glyphs

After training the network, I then **test** the network on the curated  $28 \times 28$  pixel samples, simulating **typographic pareidolia**. To do so, I feed the set of curated  $28 \times 28$  pixel samples harvested from the satellite imagery to the neural network. From the network, I receive a prediction and thus a detection of the glyph label **A**, **B**, **C**, etc. as well as the network’s percent confidence in the prediction. The prediction comes from the **softmax** function which takes as input  $n$  numbers ( $n = 26$  in the case of the letterform detection,  $= 10$  for the digit detection, and  $= 31$  for punctuation detection) and outputs a set of  $n$  respective probabilities from the network’s learned probability distribution function. For a given input sample of satellite imagery, the network might output 94% confidence in the presence of a **C**, 3% confidence in an **O**, 2% confidence in an **L**, and 1% confidence spread throughout the other twenty-three letterform classes. Each  $28 \times 28$  sample from satellite imagery is classified as a glyph class, and I save the ‘best’ sample per class as determined by the largest respective confidence from the softmax confidence; at any given time during detection, I am saving no more than  $n$  samples for output from the algorithm. Detecting glyphs in a  $1200 \times 700$  original image takes about twenty minutes to complete.

## Extensions to Improve Legibility

Seeing early renderings, people often commented on the ‘hieroglyphic’ and ‘blocky’ qualities of the resulting glyphs; many also stated that the forms were quite difficult to read. This feedback demonstrated poor legibility of the networks’ outputted predictions.



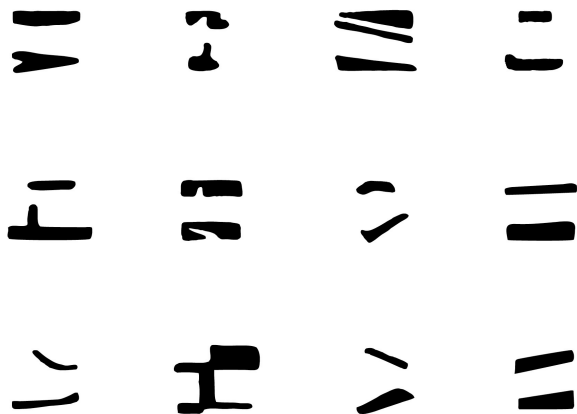
**Figure 19:** Computer-detected letterforms for Princeton, New Jersey. The output grid should be read in alphabetic order starting from the top left, proceeding across and down.

Let’s look at some glyph-specific problems in initial detection trials. Upon examination, illegibility primarily stems from the absence of a **stem**—the main vertical stroke—in the **I**, **J**, **L**, and **T** characters. Instead, the algorithm detects different combinations of horizontal strokes for these four problematic letterforms. The **I** is often represented by two horizontal strokes of equal length on the top and bottom, the **J** by two horizontal strokes with a longer top and shorter bottom, the **L** by one horizontal stroke on the bottom, and the **T** by one horizontal stroke on the top. See *Figure 20*.

## Clustering of Similar Forms

From the available training data, I can selectively show forms to the neural network. If the network only encounters glyphs of a specific class with curated traits, that is all the network will learn about that form. I can limit the shown variation, intentionally limiting the network’s perspective.

In order to improve the legibility for the problematic classes of **I** and **J**, I algorithmically group members of each class which are visually similar to one another. I perform this



**Figure 20:** Collection of vectorized **I** letterforms, many of which lack complete stems and are instead represented by two horizontal strokes.

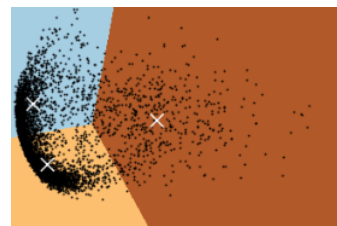
grouping using **k-means clustering** on all the samples of a class. I input a value for  $k$ , say  $k = 3$ , and the  $k$ -means clustering algorithm creates three mutually exclusive groups which group together similarly drawn letters. See *Figure 21*. I've found  $k = 3$  to be appropriate for the **I** class and  $k = 10$  appropriate for the **J** class.

Before I conduct this clustering, I reduce a glyph class' sample data down to its most distinct parts using principal component analysis (**PCA**). This is dimension reduction and speeds up the necessary processing in the clustering algorithm. Using PCA, I reduce the number of relevant 'features'—pixels—from  $28 \times 28 = 784$  pixels per sample to 330. From this reduction, I take the two most variable pixels as determined by PCA—the two pixels whose grayscale values are hardest to predict across all the samples—and for each sample I graph these pixel values in a Cartesian graph. On this graph as seen in *Figure 22*, I then conduct  $k$ -means clustering as detailed above.



**Figure 21:** On the left, the **AVERAGE** of all 5600 samples in the **I** class and, on the right, the **AVERAGE** of each of the  $k$ -means clusters with  $k = 3$  as performed under **PCA**. Wanting to ignore horizontal strokes for legibility reasons, I only train the neural network on samples from the first two clusters in order to guarantee a detected stem.

After clustering the respective **I** and **J** classes, I choose the clusters which do not have horizontal strokes. For example, I ignore the third cluster in *Figure 21* which prominently includes top and bottom horizontal strokes, taking the samples instead for the first two clusters. I selectively curate the samples for the legibly problematic **I** and **J** classes as well as all the data from the rest of the glyph classes to train the neural network.



**Figure 22:** Visualizing  $k$ -means clustering on all 5600 samples in the **I** class of the Extended MNIST dataset as organized by the class' two principal components. The first component maps to the  $x$ -axis, the second to the  $y$ -axis. Each cluster's centroid is marked by a white crisscross.

### Calculating Legibility

In determining the 'best' glyph from the highest probability outputted by the softmax function, I am determining the *most unique* form found in the landscape that is a member of the given glyph class. That is, this form has the resulting property that it definitely is not a member of any of the other classes. I find this to be a convincing argument for the creation of a site-specific glyph; this ensures different locations result in a unique collection of forms corresponding to the space's hyper-specific landforms.

However, this criteria for determining the 'best' glyph does not take into account the legibility of the resulting form—how close this form is to the 'true' form of the corresponding class. The definitely-not-any-other-glyph form is not necessarily the remaining possible glyph. There are other possible forms other than the forms of the 26 letters, 10 digits, or 31 punctuation marks. Therefore, for the legibly problematic letterforms **I**, **J**, **L**, and **T** as well as the sometimes fickle **V**, **X**, and **7**, I calculate how close the 'detected' form is to the **AVERAGE** sample of the respective class. To calculate this legibility, I perform a per-pixel calculation, subtracting the grayscale pixel value of the detected sample from the corresponding pixel value in the **AVERAGE** sample. I calculate a *uniqueness quotient* to measure respective legibility by using the **L2 loss** function—summing up the squares of these respective differences; the smaller the uniqueness quotient, the more legible and close-to-the-detected-form the result is. I save the 'best' glyph in the class as the result with the smallest uniqueness quotient.

### Font Creation

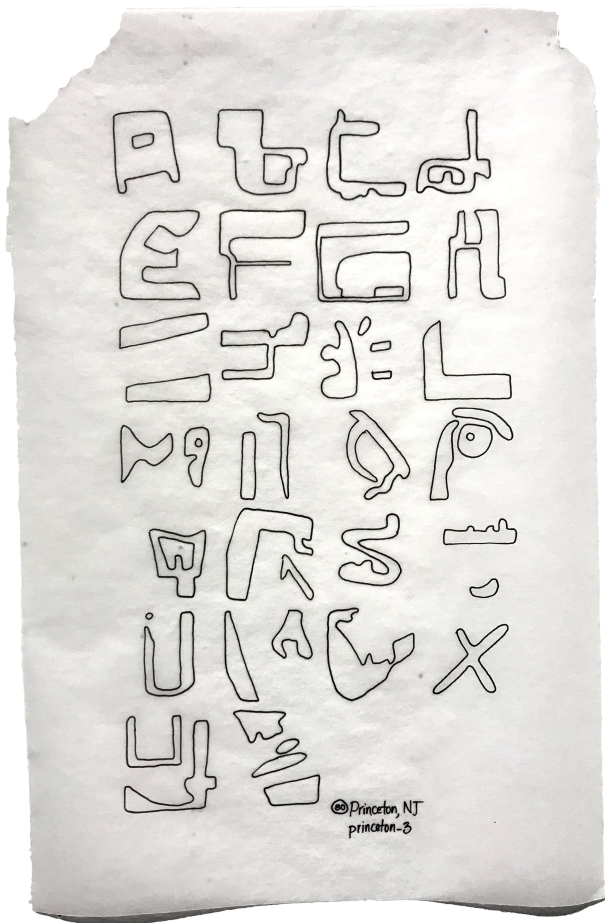
A central focus of this project is to create a typeable font for a given location, a font able to properly circulate and function as a graphic design tool. I need to create a proper font, not one whose glyphs are based in highly pixelated images as are outputted by the neural network as see in *Figure 23*.

### Simplifying the Glyphs

From the  $28 \times 28$  pixel output of the algorithm, I hand-trace the forms of the glyphs. I overlay a roll of tracing paper atop the grid of outputted images, and, with an ink pen, I trace the outlines of the glyphs. I try to stay as true to the present forms as possible while still projecting typographic pareidolia on the pixelated samples. See a traced output from Princeton, New Jersey in *Figure 19*.

Having finished tracing the glyphs, I vectorize them. I import a high contrast picture of the inscribed tracing paper into Adobe Illustrator, where I make a *Live Trace* of the image (accessed under *Object* → *Live Trace* → *Make*). This function turns the pixelated images of the forms into vectorized outlines.

These outlines from Illustrator copy and paste directly into the **Glyphs App** ([glyphsapp.com](http://glyphsapp.com)), where each of the forms are entered in as individual characters in the alphabet. The vectorized font is then exported directly from the app as a TrueType (.*ttf*) or OpenType (.*otf*) file. These files open up directly on a computer via an application like Font-Book to be instantly downloaded and used on any computer. Throughout the process, I attempted different ways of approaching the tracing and vectorizing procedure. I traced the letterforms digitally in Illustrator with Bèzier curves as well as exported high-resolution computer-generated outputs as bitmaps for vectorization directly in Illustrator. However, the hand-drawn outlines on physical tracing paper feel right for this project; this technique gives me the best result in terms of smoothness of a character's form and control over the font's overall weight. Aptly, the handwritten quality visually references the handwritten samples training the detection algorithm.



**Figure 23:** *Hand-traced letterforms from Princeton, New Jersey as seen on a section of a roll of tracing paper.*

## Selecting from Options

In an effort to make the fonts more legible, I perform *k*-means clustering in curating fodder for the network as well as calculate the relative distance from glyph samples as I described before. However, even these resulting forms can be questionable in legibility. Therefore, I run the algorithm on multiple input images to increase the likelihood of a 'legible' glyph for a given category. From each of these images, I can receive a different output from the network.

I trace each of the forms and put them side by side, horizontally lining up all the **As**, all the **Bs**, etc. from a given place. See *Figures A5–A9*. I curate the 'best' letters for the final vectorized font. I've tried out different techniques for choosing these final forms. One technique involves marking the most legible uppercase and lowercase results myself. Another process involves sitting with a group of people and, without pointing, debating which form is the 'best.' In discussion I find myself learning about different differentiators in determining what is 'best,' and this last crowd-sourcing approach mimics the structure of the crowd-sourcing of samples in the EMNIST and UNIPEN handwritten datasets.

## Case Studies

With a complete typeface, I am able to try out my fonts in a range of applications. Here are a few case studies looking at the most developed sights of intelligibility of Topography Topography to date—July 11, 2019.

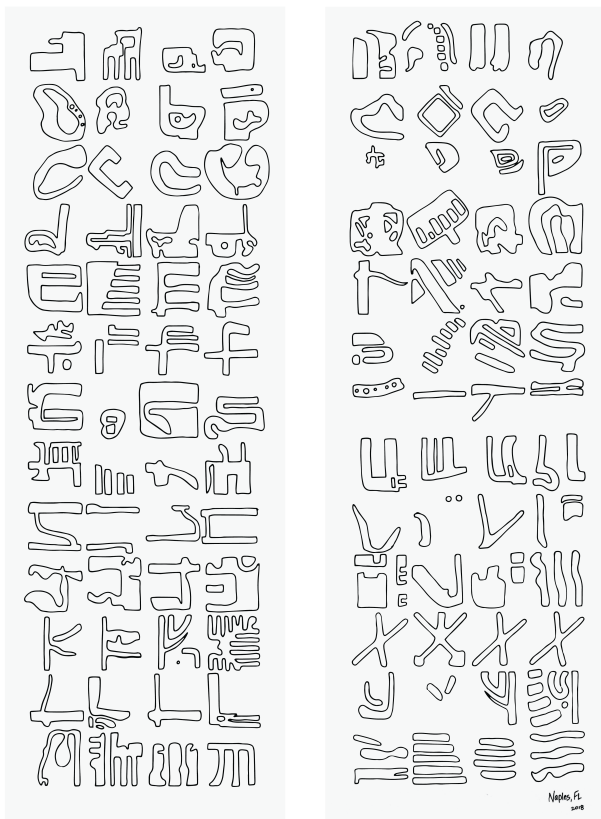
### Initial Testing with NAPLES

I'm bothered by computer graphics research when I see researchers using an arbitrary test set. Using a preexisting dataset of test images like ImageNet or COCO (Common Objects in Context) from related work studies is understandably helpful in the search for comparison and reproducibility. However, without constraints of a large curated dataset or randomized content, I feel novel research should be initially tested on images hand-selected by the researcher, not Internet stock images. This creates a more unique, handwritten quality to the work and presents context behind the creation of the eventual algorithm or application. [Deng et al. 2009; Lin et al. 2015]

For this project, I intentionally first tested my algorithm on two specific locations: Naples, Florida and Naples, Italy. I lived my first eighteen years in **Naples**, Florida. In aerial imagery of Southwest Florida, there is stark contrast in the dark bodies of water weaving around the light-colored infrastructure of roads and neighborhoods. See the spatial detection of letterforms in Naples, Florida in *Figure 25* and some of its traced letterforms in *Figure 24*. On the other hand, Naples, Italy presents a dense port city whose aerial imagery is comparatively flat in color. Both locations provide unique challenges which helped develop the algorithm, especially the preprocessing of the satellite imagery.

### PRINCETON Visual Arts

In the context of the fourth floor junior's studio in 185 Nassau on Princeton's campus, I started to run my algorithm and trace the resulting outputs. I hung up the tracing paper with the initial blocky forms on the walls of my open studio, and week after week, my collection grew. As a junior



**Figure 24:** Hand-traced letterforms from Naples, Florida as seen on split-up sections of a roll of tracing paper. Each column shows the result from a different satellite image as vectorized by *Illustrator's Live Trace*.

in Princeton's Visual Arts (**VIS**) Department, I started to test my fonts as fodder for graphic design projects.

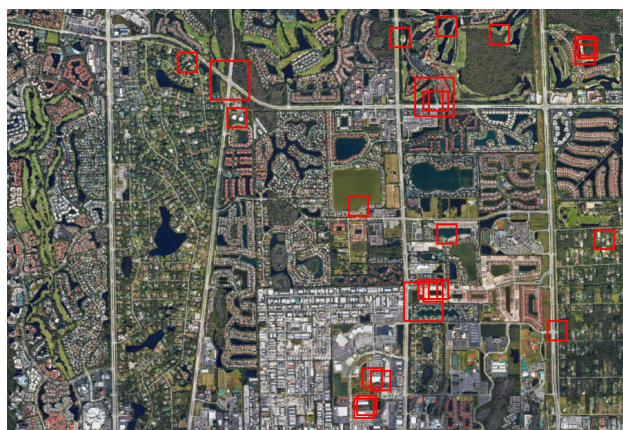
### VIS Logo

In response to Eric Li's design for a department logo which initially employed Times Italic, I created the current VIS logo as typeset in PRINCETON. To date, a large 3'×3' printout of the logo can be found outside 185 Nassau in an informational display case. Members of the Princeton community, including many people in the Computer Science department, walk by this sign every day on their way to grab lunch on Nassau Street.

### Art Show Posters

While developing this algorithm for glyph detection, I was also creating printed matter for the Princeton Visual Arts Department's Junior Independent Work Show, known around campus as *The VIS Junior Show*.

I decided to incorporate my font system in a poster campaign for the show, asking each of the twenty artists exhibiting work for a physical place in the world which has greatly impacted their artistic practice. This question resulted in an array of answers, from Midtown Sacramento to I-95 to Southern Norway. See the final result of the posters series in *Figure A12* and *Figure 27*.



**Figure 25:** Letterform detection algorithm applied to a satellite image of Naples, Florida circa March 2018. I grew up in a house at the center of this image.

A year after *The VIS Junior Show* and the debut of Princeton's contentious type (see *Figure A13*), I returned to PRINCETON to create the poster for the final senior show titled *Final Runnings Before the After*, a student group show exhibiting pieces from VIS seniors. See *Figure A17*. [Rivitz 2018]

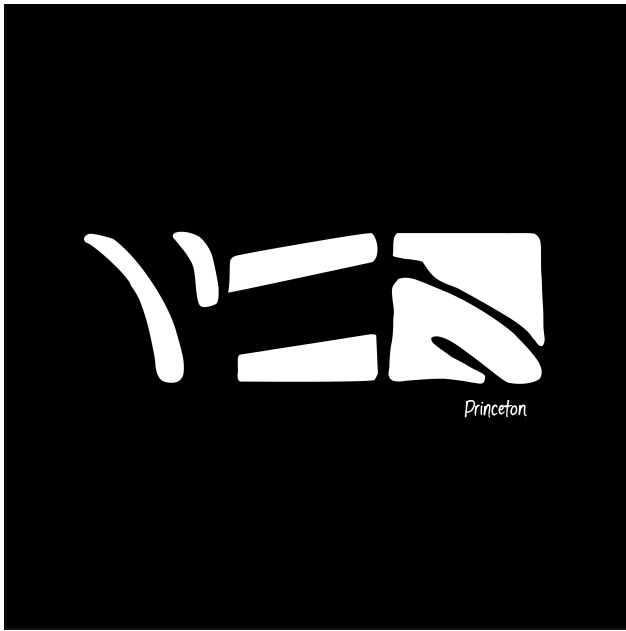
### Mapping Campus

In my four years on campus, I've tried to explore every nook and cranny, looking to understand the space by absorbing spatial relations and details of light. In an effort to better understand the source of my glyphs and present a more cohesive visual story for the viewer, I took up the task of visiting the PRINCETON glyphs at their respective sources. By mapping the alphanumeric glyphs of PRINCETON to their geographic locations and doing so by hand, I was able to internalize where and in what context these forms are located. This too helped me to understand the formal relationships between different glyphs sourced from overlapping sections of satellite imagery. See PRINCETON's map in *Figure 28*.

### Princeton Visual Arts 2019 Catalogue

I wrapped up my stint in Princeton's Visual Arts Department by editing and designing a catalogue of work of the Visual Arts Department's Class of 2019. Solely typeset in PRINCETON and AVERAGE, I included printed matter created in Topography Typography fonts including the VIS logo, various art show posters, and the map of PRINCETON. With the help of Eric Li and Nazlı Ercan, I printed 500 copies of this book. On the last page of the book, I include "A Note on the Type" in PRINCETON:

*This catalogue is printed using Kara Bressler's Topography Typography, a typeface made from the aerial forms of a place. Character forms are detected from satellite imagery using an algorithm trained on the extended form of the 1995 MNIST handwriting dataset as visualized in the AVERAGE font. Each glyph illustrates an indexical trace of the referent landscape. 185 Nassau lies between PRINCETON's q & a. Written in PRINCETON.*



**Figure 26:** Princeton Visual Arts' VIS logo as seen in PRINCETON. This iteration manifests as a circulating lap-top sticker distributed by the department.

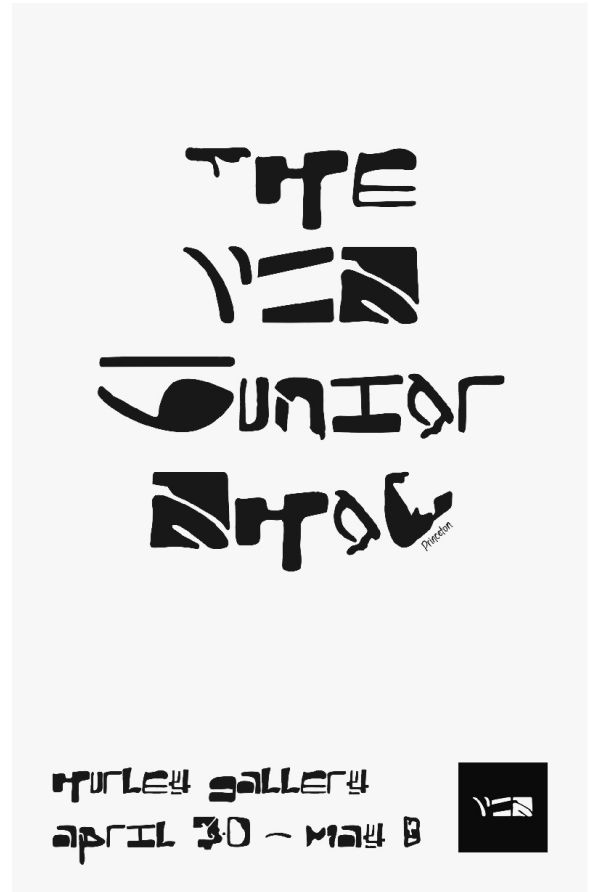
## BEARS EARS

In the spring semester of my senior year, I took the opportunity to travel to southeastern Utah and study native and public land use in the area. As part of a class field trip, I met and listened to people who live in the area. I spoke with natives whose people had lived in the Four Corners region (present-day Utah, Colorado, Arizona, and New Mexico) for thousands of years; these are storied landscapes, and in the little time I spent in the area to date, I learned a lot about the interplay between land and language.

### A Proclamation

In graphic design, Lorem ipsum is the canonical text serving as a placeholder to test typesetting layout before finalizing a piece's content. Just as I dislike the mode of graphics research which unnecessarily tests algorithms on impersonal fodder, I believe typesetting a font from Topography Typography with the 'neutral' Lorem ipsum strips the font from its indexical context. Especially in the context of auratic and sacred Bears Ears, I did not want to test the work on just any body of text.

Instead, I chose meaningful content relevant to the land—the Land Proclamation deeming Bears Ears a National Monument. In 2016, President Barack Obama established Bears Ears National Monument, a 1.35 million acre space granted as public land under a presidential proclamation via the Antiquities Act. I used an abridged form of this text to test BEARS EARS. I continued to return to this text, ultimately creating a circulating pamphlet, a printed manifestation of Topography Typography. See this pamphlet in *Figure A9*. I also scaled up the Proclamation to serve as an 8'x8' piece printed as black wall vinyl in *Public Lands, Private Hands*, an art exhibition in Princeton's Nulu (Lewis Arts Complex).



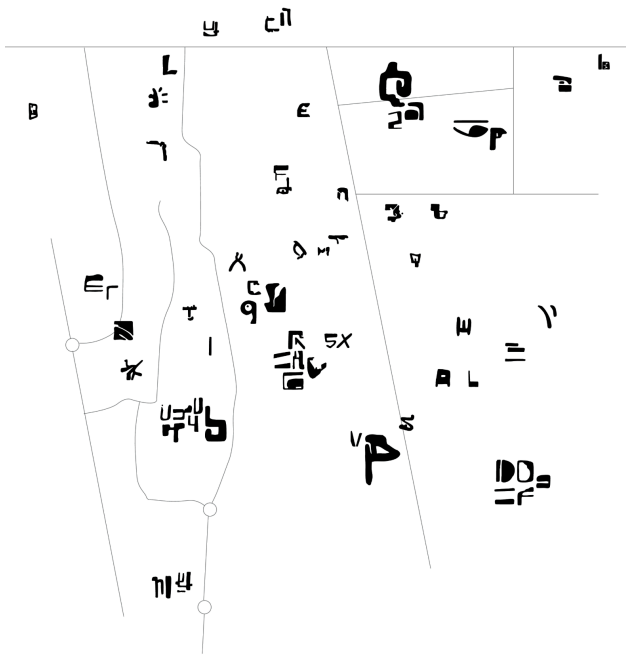
**Figure 27:** Circulating poster for The VIS Junior Show, April 2018. The entire poster is in the font PRINCETON, New Jersey. This poster was posted on screens and signs at Princeton University. It also appeared on the graphic design is my passion Facebook meme page in April 2018.

### BEARS EARS Bounded

Less than two years after Obama established Bears Ears National Monument, Donald Trump, in an executive order, cut the monument's acreage by eighty-five percent, thus choosing to ignore the boundaries as they were originally drawn.

When I traveled to the Four Corners region to visit Bears Ears, I started to run the detection algorithm on the landscape with boundaries that had been verbally described to me, using broad rectangular satellite images of the land. As I do not use political boundaries when curating satellite imagery, I was only using rough estimates of the monument's boundaries. After vectorizing the font and testing the typeface on the Proclamation, I returned to the geo-coordinates of the individual glyphs and mapped them to their referential locations. Due to some extremely legible river forms in both the Canyonlands (northwest of Bears Ears) and Monument Valley (south of Bears Ears), over half of the glyphs' referential locations were positioned outside the boundaries of the Monument as designated under Obama. By spatially mapping out the forms, I am able to better understand the context of the storied forms I am curating. In the case of BEARS EARS, it is essential to the font that the geoglyphic forms lie within the boundaries. These lines were meticu-





**Figure 28:** Uppercase letters, lowercase letters, and digits of PRINCETON mapped to their respective locations on campus. Find Nassau Street at top of the map. This graphic appears on the back of the Class of 2019 VIS shirt and in the Princeton Visual Arts 2019 Catalogue of senior work.

lously drawn by those familiar with and invested in the area in order to encompass spaces sacred to the native peoples of the region. To be true to the naming of the font, I need to respect this containment. Upon understanding which glyphs lay outside the bounds, I curated another batch of satellite imagery well within the boundaries of Bears Ears and conducted another pass of glyph detection and vectorization to create the final result—proper BEARS EARS.

### Revisiting the Glyphs Remotely

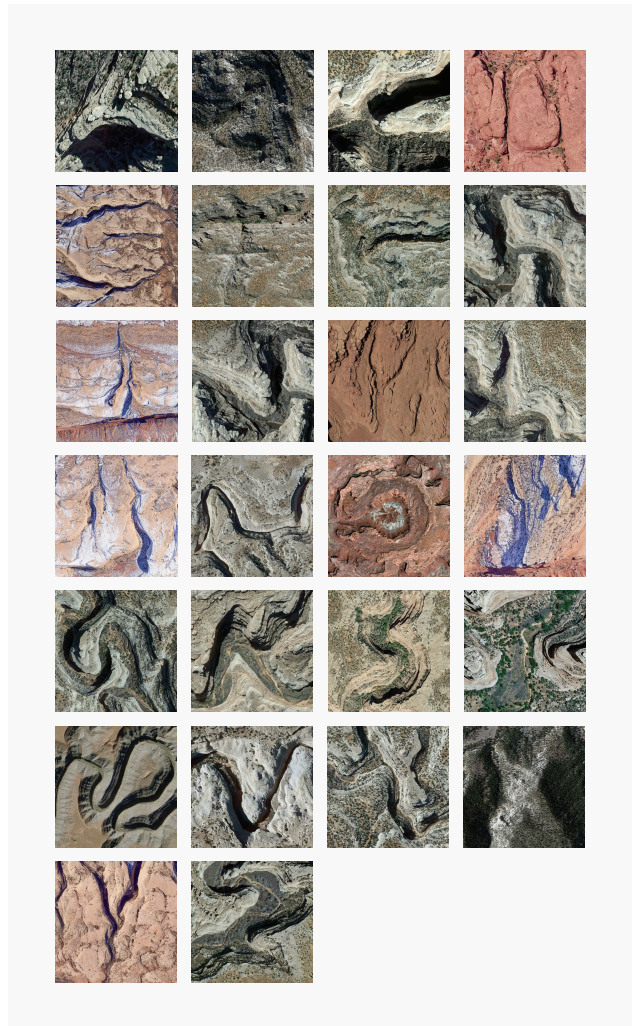
In creating the properly-bounded BEARS EARS Proclamation wall piece, I remotely revisited each of the glyphs via Google Earth. I used the geo-coordinates and orientation of the ‘best’ detected samples to curate a set of images depicting the range of the topographic knowledge of the land and the context of each glyph. See these high resolution images in *Figure 29* and compare them to their corresponding detection samples outputted from the detection algorithm in *Figure 30*.

### Future Steps

As I’ve mentioned in the text, this project stands to be re-framed and reconsidered for years to come. Here are some aspects of the Topography Typography project which lie on the horizon.

#### Autokerning

As I continue to work on this project, I would like to implement a system for **autokerning** my fonts where I can input the glyphs and algorithmically generate the spacing in be-



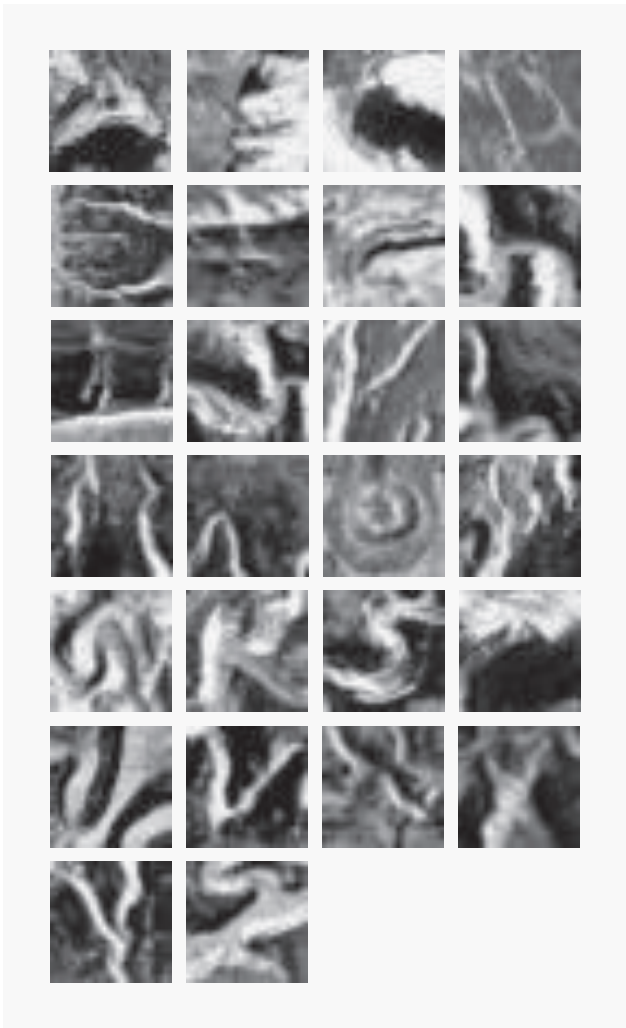
**Figure 29:** Revisited landforms at the sites of the BEARS EARS glyphs’ referential locations. These high resolution images are hand-curated from Google Earth Pro.

tween character forms. In order to kern my fonts for proper spacing, I currently adjust the spacing in between pairs of letterforms by hand in the Glyphs App, and this can take me up over twelve hours per font. Even the final result of my hand-kerning as embedded in the circulatable TrueType or OpenType file is sub-optimal, as I am kerning for a relatively tight letter spacing. I am skeptical of removing the designer’s eye from the final result, but it would be helpful to ask for technology’s assistance in taking an initial stab at this arduous task.

Currently I typeset with the autokerning feature of Adobe’s *Optical Kerning* to autokern text in-place—a solution fine for me today but not okay in a widely circulating font where many will not have access to the Adobe Suite.

#### Free, Open, and Available to the Public

**Google Fonts** curates the widely accepted standard for free font distribution, currently circulating just over 900 font families. Many web developers and designers use Google Fonts as their go-to place for font fodder. I would like to



**Figure 30:** *A curated set of computer-detected letterforms for the region of Bears Ears National Monument as designated in 2016. Each is a  $28 \times 28$  grayscale sample.*

add BEARS EARS to Google Fonts for global usage. Paired with written context and the glyphs' geographic locations, a curated set of Topography Typography fonts will also exist at [topography-typography.info](http://topography-typography.info), free for download and circulation.

### Visiting and Revisiting

As I continue to understand this project, I would like to continue on-site work. I plan to visit more detected landforms and create an interplay between visiting one of these geoglyphs and illustrating it for circulation.

I have developed my font creation pipeline substantially over the past year, and I would like to revisit many of the initial locations I quickly saw in my 100+ glyph detection trails, this time in depth for each place. I would like to spend time reconsidering imagery over time and understanding the bounds of these areas, mapping where glyphs come from and understanding the landforms that particular glyph classes tend toward.

### Conclusion

In its conception, I meant this project to lie at the fringe of computer science research. Unlike Groß and Lee with their Aerial Bold Project, I am not necessarily searching for the most legible and clean letterforms; I want to keep some index of the topography in the final vectorized version of the typefaces. As I iterate on different aspects of this project, I continue to learn from the results, helping me reframe how I'm thinking about land, language, and everything in between. More to come!

## References

- ANONYMOUS, 2018. Terrace email. Gmail, personal communication, 4.
- ARAWAL, A. 2015. *Character Recognition in Satellite Images using Machine Learning*. Master’s thesis, Ravensburg-Weingarten University of Applied Sciences.
- BLOICE, M. D., 2019. Augmentor. <https://github.com/mbloice/Augmentor>.
- BRADLEY, S. 2016. Icon, index, and symbol three categories of signs.
- COHEN, G., AFSHAR, S., TAPSON, J., AND VAN SCHAİK, A. 2017. EMNIST: an extension of MNIST to handwritten letters.
- COOLIDGE, F. L., AND COOLIDGE, M. L. 2016. Why People See Faces When There Are None: Pareidolia. *Psychology Today*.
- COOPER, R., 2017. EMNIST. <https://github.com/Coopss/EMNIST>.
- DENG, J., DONG, W., SOCHER, R., LI, L.-J., LI, K., AND FEI-FEI, L. 2009. ImageNet: A Large- Scale Hierarchical Image Database. In *CVPR09*.
- GOLOMB, J. 2018. Nasca Lines. *National Geographic*.
- GOTTHARDT, A. 2017. How to Free Your Creative Spirit, According to Sister Corita Kent. *Artsy*.
- GROSS, B., AND LEE, J., 2016. The Aerial Bold Project. <http://type.aerial-bold.com/process/>.
- GROTHER, P. J. 1995. NIST Special Database 19 Handprinted Forms and Characters Database. *National Institute of Standards and Technology*.
- KRÖGER, O. 2015. Tensorflow, MNIST and your own handwritten digits.
- LECUN, Y., CORTES, C., AND BURGESS, C. J., 2013. The MNIST database of handwritten digits. <http://yann.lecun.com/exdb/mnist/>.
- LEE, J., 2019. The Aerial Bold Project. <https://jk-lee.com/aerial-bold-project/>.
- LIANG, M., AND HU, X. 2015. Recurrent Convolutional Neural Network for Object Recognition.
- LIN, T.-Y., MAIRE, M., BELONGIE, S., BOURDEV, L., GIRSHICK, R., HAYS, J., PERONA, P., RAMANAN, D., ZITNICK, C. L., AND DOLL, P. 2015. Microsoft COCO: Common Objects in Context.
- MORDVINTSEV, A., OLAH, C., AND TYKA, M. 2015. Inceptionism: Going Deeper into Neural Networks. *Google Research Blog*.
- NASA. 2001. The Blue Marble from Apollo 17. *NASA: Earth Observatory*.
- NOLIN, R. 2015. Woman on a roll, gets big bread for cheesy sandwich. *Sun Sentinel*.
- PHILLIPS, T., 2001. Unmasking the Face on Mars. [https://science.nasa.gov/science-news/science-at-nasa/2001/ast24may\\_1](https://science.nasa.gov/science-news/science-at-nasa/2001/ast24may_1).
- REINFURT, D., BAILEY, S., AND KEEFER, A. 2012. *Ecstatic Alphabets/Heaps of Language*. The Serving Library.
- RIVITZ, W., 2018. graphic design is my passion. Facebook, personal communication, 4.
- ROSE, A., 2009. Become a Microscope. <https://www.youtube.com/watch?v=3x4HgonSW6k>.
- RUSSON, M. A. 2015. Google DeepDream robot: 10 weirdest images produced by AI ‘inceptionism’ and users online. *International Business Times*.
- SCIKIT-LEARN DEVELOPERS, 2017. A demo of K-Means clustering on the handwritten digits data. [http://scikit-learn.org/stable/auto\\_examples/cluster/plot\\_kmeans\\_digits.html](http://scikit-learn.org/stable/auto_examples/cluster/plot_kmeans_digits.html).
- SHURKIN, J. N. 2012. Landsat Looks and Sees. *NASA: Earth Observatory*.
- SINISTER, D. 2010. A Note on the Type. *The Serving Library*.
- SUEIRAS, J., 2017. Handwriting characters database. [https://github.com/sueiras/handwriting\\_characters\\_database](https://github.com/sueiras/handwriting_characters_database).
- WOODFORD, C., 2018. Neural networks. *Explain that Stuff*.
- WOOLDRAGE, C. 2017. Found Font (1995 – present). *Medium*.

## Acknowledgements

Time is the greatest gift to give someone. I’d like to thank my advisors—formal and informal—for your time and empathetic feedback.

Thank you, Hemani—my other half. You analyze light bouncing off space rocks; I analyze light bouncing off animated rocks. Name a more iconic duo. I’ll wait.

Thank you, Andie, for teaching me the right way to ask questions and talk to strangers.

Thanks to all the members of the Visual Arts community who have helped create an incredibly inclusive space in 185 Nassau and let me circulate these funky fonts. As well, thank you for the opportunity to experience and better understand Peruvian geoglyphs.

This list has no proper order, so here’s a huge thanks to my family—Mom, Dad, Max, Liam, Blue Belle, Nate, and Oscar—for your encouragement of me doing weird things and being cool with it. Each glyph I traced in NAPLES has a part of you.

A last thank you to Light, Land, and Language—LA!

## HANDWRITING SAMPLE FORM

NAME	DATE	CITY	STATE	ZIP
[REDACTED]	8-3-89	MINDEN CITY	MI	48452

This sample of handwriting is being collected for use in testing computer recognition of hand printed numbers and letters. Please print the following characters in the boxes that appear below.

0 1 2 3 4 5 6 7 8 9			0 1 2 3 4 5 6 7 8 9			0 1 2 3 4 5 6 7 8 9		
0123456789			0123456789			0123456789		
87	701	3752	80759	960941				
87	701	3752	80759	960941				
158	4586	32123	832656		82			
158	4586	32123	832656		82			
7481	80539	419219		67	904			
7481	80539	419219		67	904			
61738	729658	75	390	5716				
61738	729658	75	390	5716				
109334	40	625	4234	46002				
109334	40	625	4234	46002				

g y x l a k p d s b t z i r u m w f q j e n h o c v

g y x l a k p d s b t z i r u m w f q j e n h o c v
Z X S B N G E C M Y W Q T K F L U O H P I R V D J A
Z X S B N G E C M Y W Q T K F L U O H P I R V D J A

Please print the following text in the box below:  
 We, the People of the United States, in order to form a more perfect Union, establish Justice, insure domestic Tranquility, provide for the common Defense, promote the general Welfare, and secure the Blessings of Liberty to ourselves and our posterity, do ordain and establish this CONSTITUTION for the United States of America

<p>We, the people of the United States, in order to form a more perfect Union, establish Justice, insure domestic Tranquility, provide for the common Defense, promote the general Welfare, and secure the Blessings of Liberty to ourselves and our posterity, do ordain and establish this CONSTITUTION for the United States of America.</p>
---

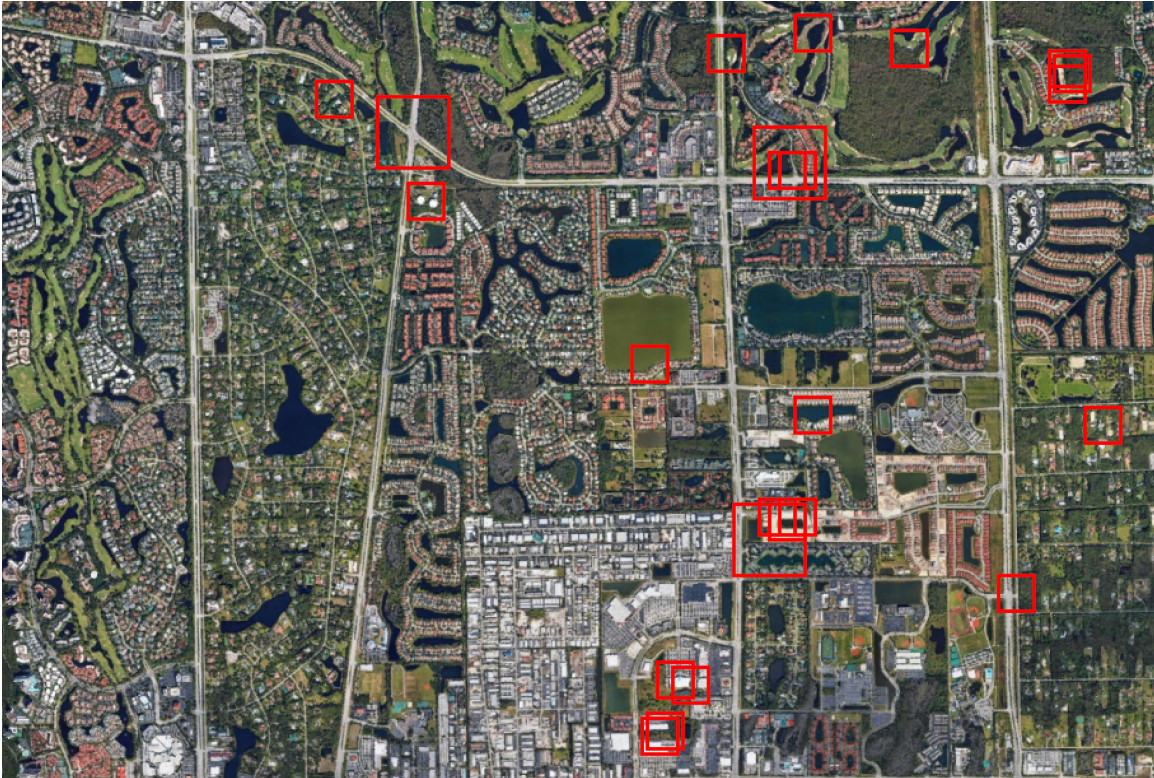
Figure A1: NIST Handwritten Sample Form. August 1989. Image courtesy of Patrick Grother. [Grother 1995]



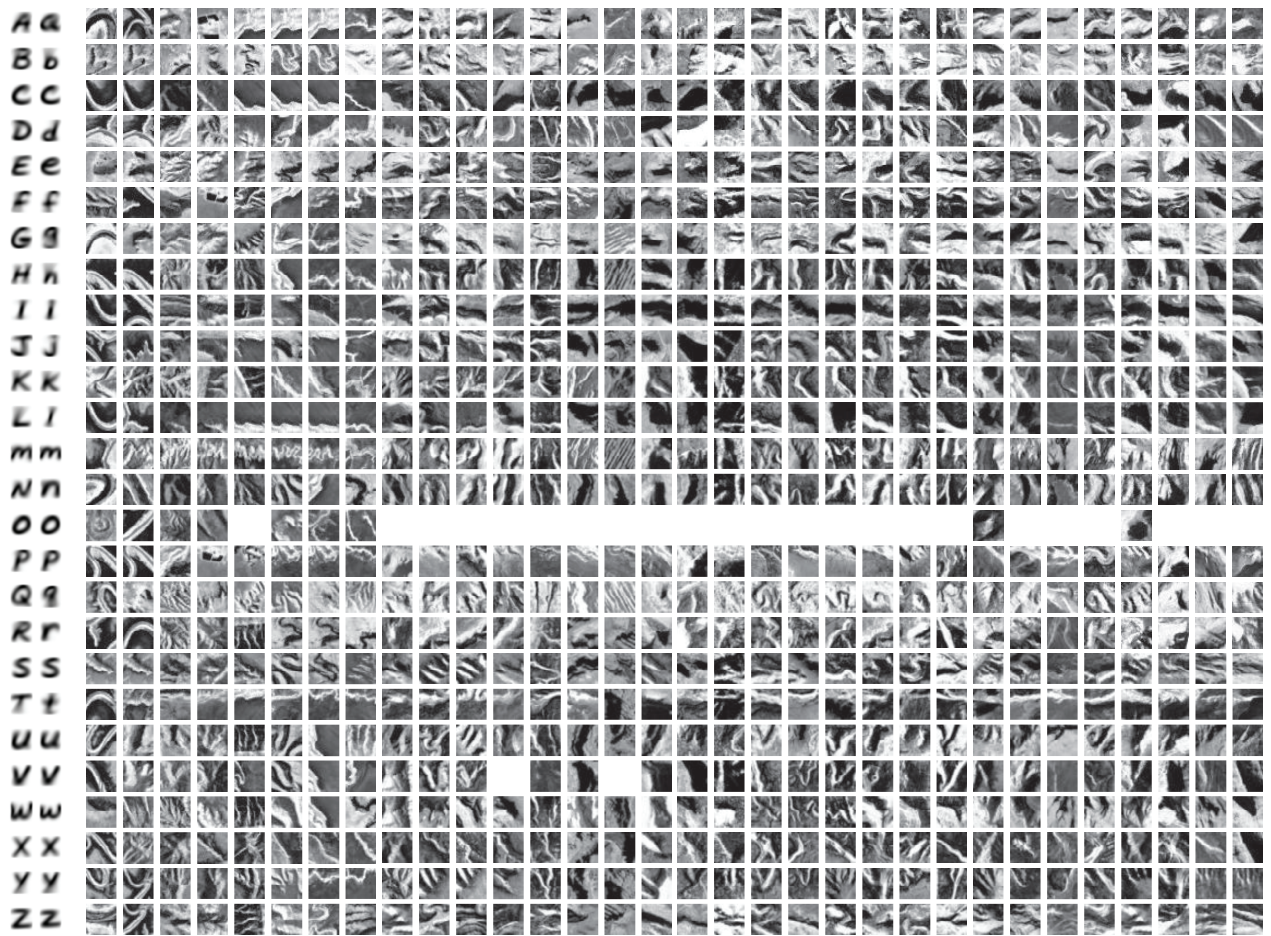
**Figure A2:** *Raw satellite imagery of Princeton, New Jersey circa February 2018.*



**Figure A3:** *Cropped satellite image of Princeton, New Jersey adjusted for contrast, highlights, and shadows.*



**Figure A4:** Letterform detection algorithm applied to satellite image of Naples, Florida circa March 2018. This output shows character detection of both  $28 \times 28$  and  $56 \times 56$  pixel samples. For this image, the algorithm produced a five-tier image pyramid.

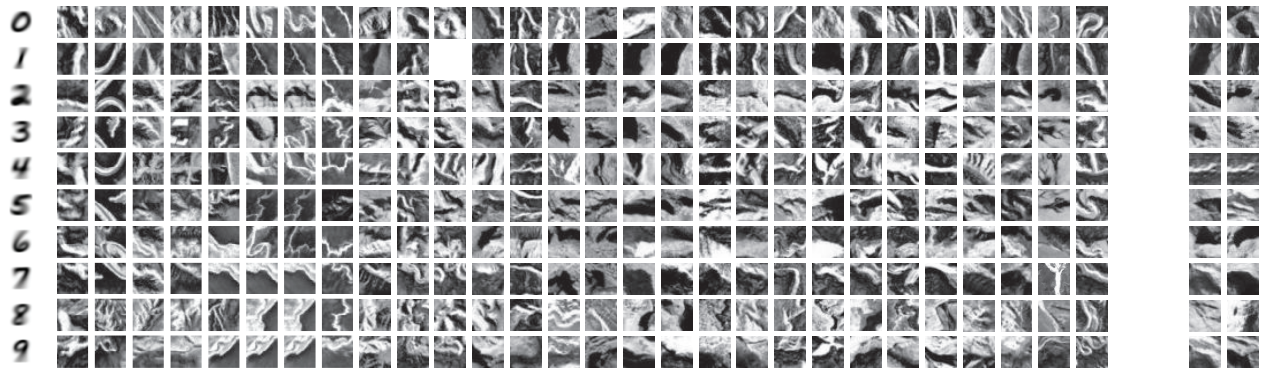


**Figure A5:** Computer-detected letterforms from the Bears Ears region. The corresponding AVERAGE uppercase and lowercase characters (left) label the output of the row.

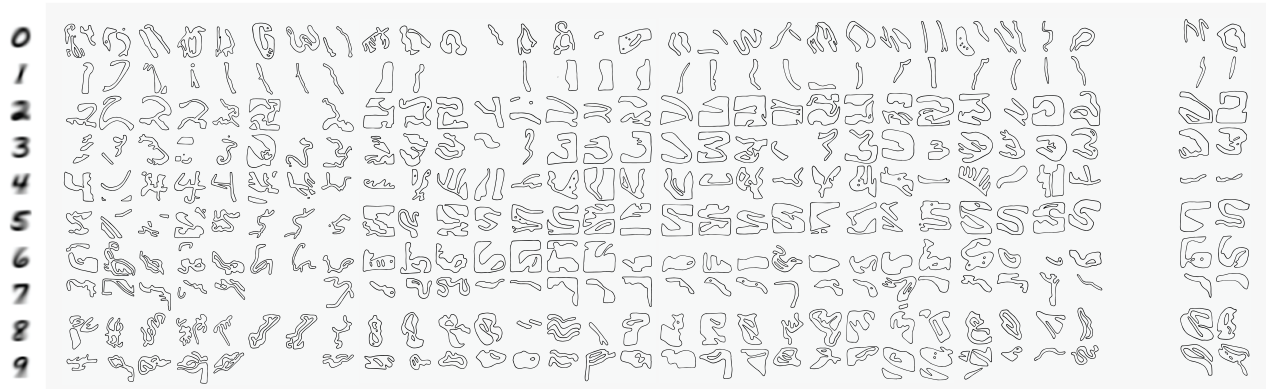


**Figure A6:** Computer-detected punctuation from the Bears Ears region. Each row is labeled by its respective class of punctuation as seen in the corresponding non-normalized  $64 \times 64$  pixel and normalized  $28 \times 28$  pixel AVERAGE characters.





**Figure A7:** Computer-detected digits from the Bears Ears region.



**Figure A8:** Traced results of thirty trials of digit detection in the Bears Ears region accompanying the computer-detected samples (above).



## Establishment of the Bears Ears National Monument By the President of the United States of America

### A Proclamation

Rising from the center of the southeastern Utah landscape and visible from every direction are ruin terraces so distinctive that in each of the native languages of the region their name is the same: Moenkampi, Shash Uza, Kuyacate, Navuzochi, Ansh An, Lasherville, or Bears Ears. For hundreds of generations, native peoples lived in the astonishing deep sandstone canyons, desert mesas, and majestic mountain tops, which constitute one of the richest and most significant cultural landscapes in the United States. Abundant rock art, ancient cliff dwellings, ceremonial sites, and countless other structures provide an extraordinary archaeological and cultural record that is important to us all, but most notably the land is historically sacred to many Native American tribes, including the Ute, Hopai, Ute, Navajo, Northern Ute, Indian Pueblo of the Ute, Grand, Hopi, Navajo, and Zuni Pueblo.

The area's human history is as vibrant and diverse as the incredibly beautiful landscape. From the earliest occupation, native peoples left traces of their presence. Clovis people hunted across the cliffs and canyons of Cedar Mesa as early as 13,000 years ago, leaving behind tools and projectile points in places like the Lime Ridge Clovis Site, one of the oldest known archaeological sites in Utah. Archaeologists believe that these early people hunted mammoths, deer, sloths, and other now-extinct megafauna; a narrative echoed by native creation stories. Hunters and gatherers continued to live in this region in the Anchaic period with sites dating as far back as 8500 years ago.

Ancestral Puebloans followed beginning to occupy the area at least 2500 years ago, leaving behind items from their daily life such as baskets, pottery, and weapons. These early makers of Basketmaker II and III and builders of Pueblo I, II, and III left their marks on the land. The remains of small family dwellings, granaries, river terraces, and large villages and roads linking them together reveal a complex cultural history. Most steps, hand and toe holds carved into steep canyon walls by the Ancestral Puebloans illustrate the early people's ingenuity and perseverance and are still used today to access dwellings along cliff walls. Other, distinct cultures have thrived here as well—the Fremont People, Navajo, and Archaic-period hunter-gatherers, and Ute and Navajo. Residences such as the Wolf, Horse, and Elk Canyon Villages and the Aspen House Ruin on Cedar Mesa allow visitors to marvel at humanity and architecture that have withstood thousands of seasons in this harsh climate.

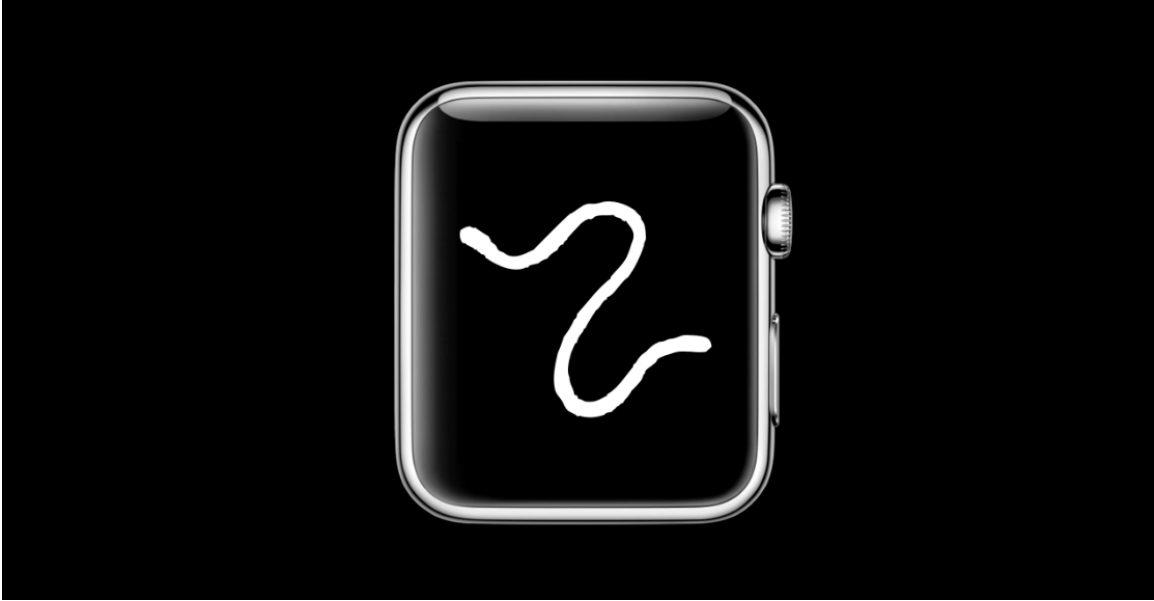
The landscape is a mirror of the accessible and observable together with the inaccessible and hidden. The area's petroglyphs and pictographs capture the imagination with images dating back at least 5000 years and spanning a range of styles and traditions. From life-size chestlike figures that defy categorization, to the more literal depictions of bighorn sheep, birds, and lizards, these images enable us to feel the humanity of these ancient artists. The Indian Creek area contains spectacular rock art, including hundreds of petroglyphs at Newspaper Rock. Visitors to Bears Ears can also discover more recent rock art left by the Ute, Navajo, and Paiute peoples. It is also the less visible sites, however—those that witnessed the food, ceremony, subsistence, and ceremony of daily life—that tell the story of the people who lived here. Historic remnants of Native American sheep-herding and ranching are scattered throughout the area, and pottery and Navajo hogans record the lifeways of native peoples in the 19th and 20th centuries.

For thousands of years, humans have occupied and stewarded this land. With respect to most of these people, their contribution to the historical record is minimal, but some have played a more public role. Famous Navajo headman Koyahjué was born around 1800 near the ruin Bears Ears terraces. His land used the area's remote canyons to elude capture by the U.S. Army and avoid the fate that befell many other Navajo lands, including the Long Walk, and forced relocation to Ganado, Arizona. Another renowned 19th century Navajo leader, Hatanii Chihabaji Anshelino, was also born near the Bears Ears.

The area's cultural importance to Native American tribes continues to this day. As they have for generations, these tribes and their members come here for ceremonies and to visit sacred sites. Throughout the region, many landscape features, such as Bent, Kuce, the San Juan River, and Cedar Mesa, are closely tied to native stories of creation, human protection, and healing. The volcanic sites in the Valley of the Gods are sacred to the Navajo, representing ancient Navajo warriors frozen in stone. Traditions of hunting, fishing, gathering, and food curing are still practiced by tribal members, as is collection of medicinal and ceremonial plants, wildlife, herbs, and minerals for curative treats. Live baskets and medicines. The traditional ecological knowledge passed by the Native Americans whose ancestors inhabited this region passed down from generation to generation, offers critical insight into the historic and scientific significance of the area. Such knowledge is irreplaceable and must be protected and used in understanding and managing this landscape sustainably for generations to come.

Barack Obama  
December 23, 2016

Figure A9: Circulating pamphlet with an abridged version of the Bears Ears National Monument Proclamation (bottom) as signed by President Barack Obama and the traced results of thirty-two trials of letterform detection in the Bears Ears region (top).



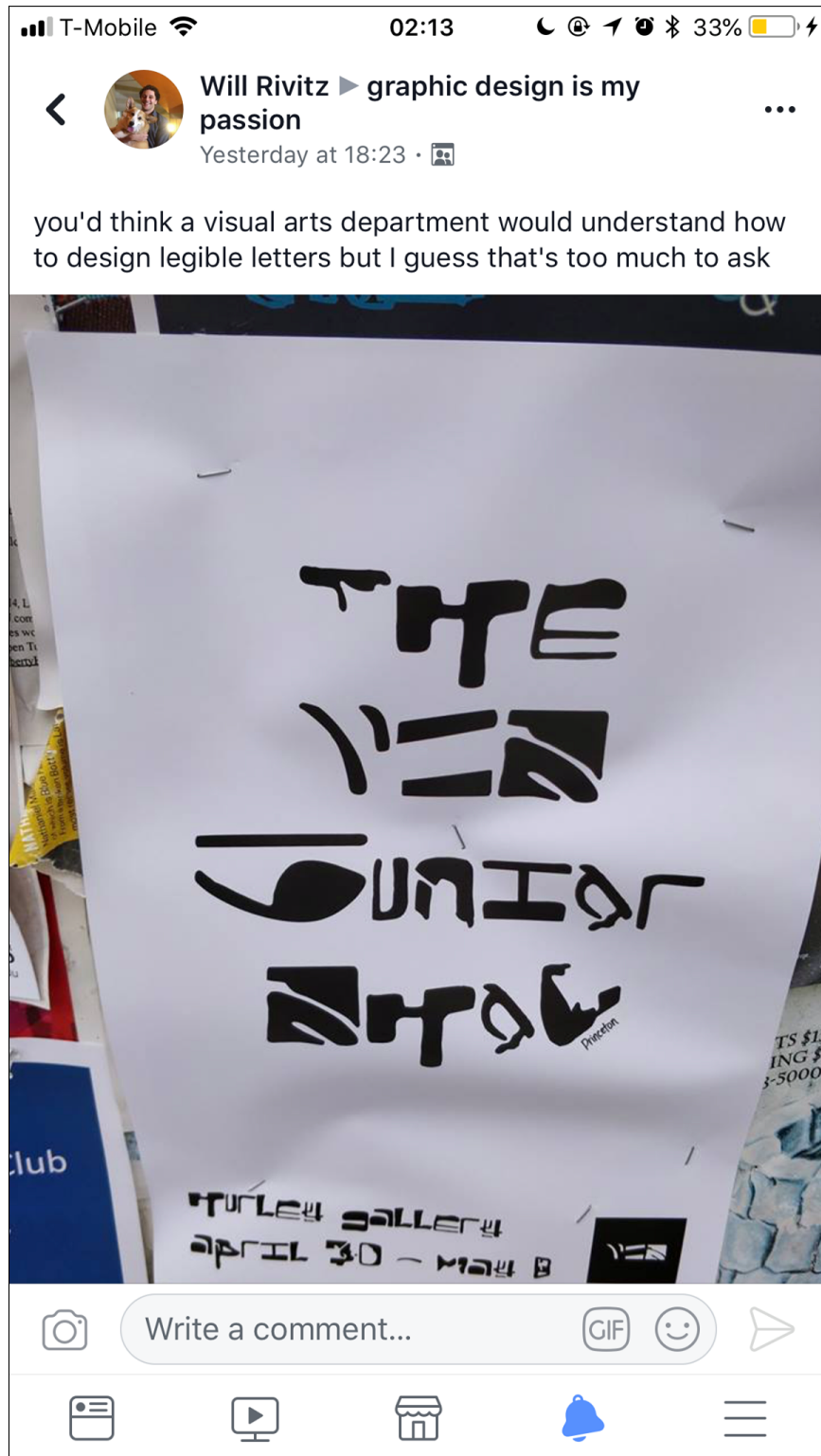
**Figure A10:** Design for an Apple Watch clock interface. Typeset in LAS PIEDRAS—derived from the namesake river in Peru. The watch currently presents the number 2.



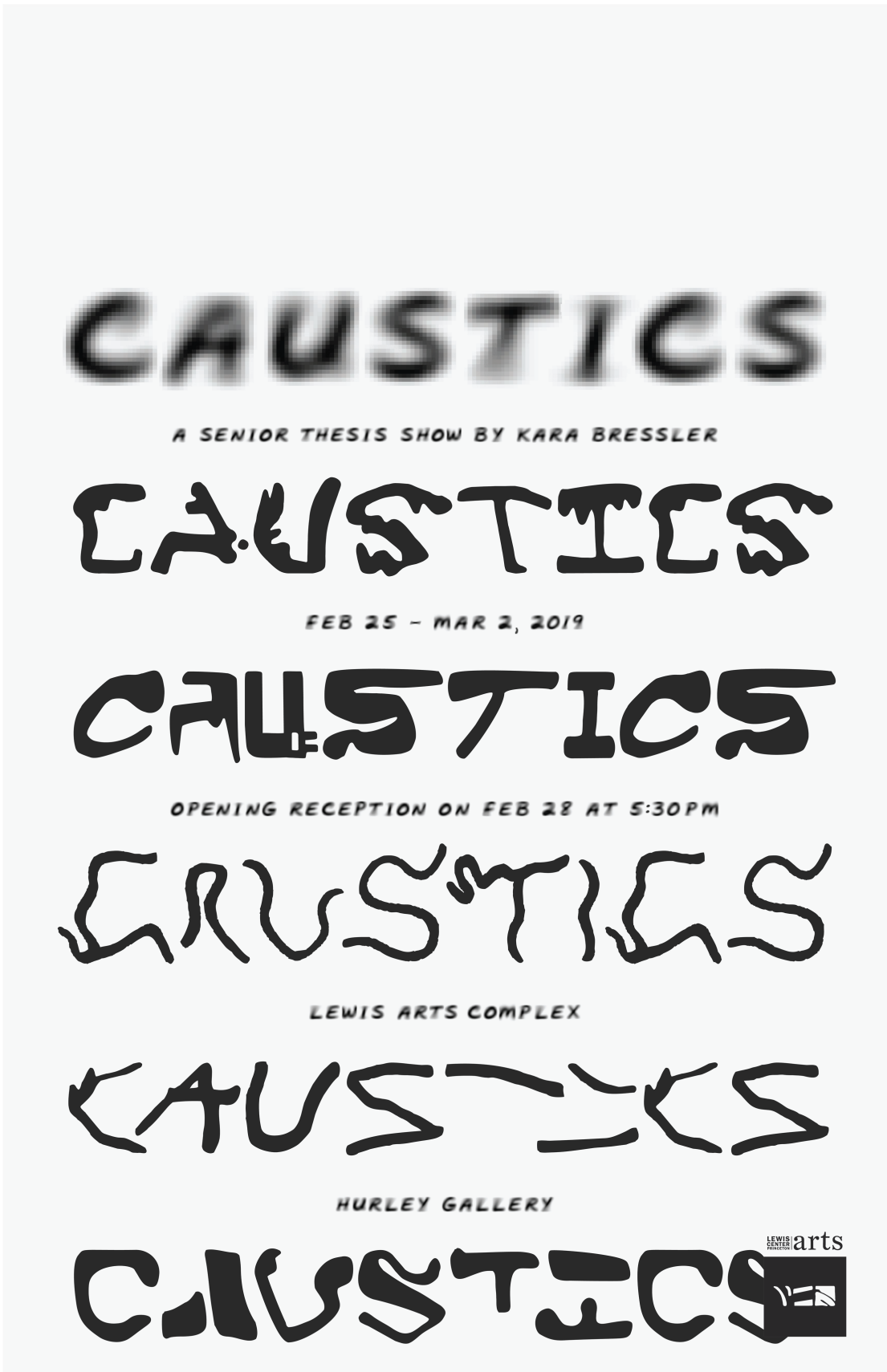
**Figure A11:** Continuous river of numbers using LAS PIEDRAS.



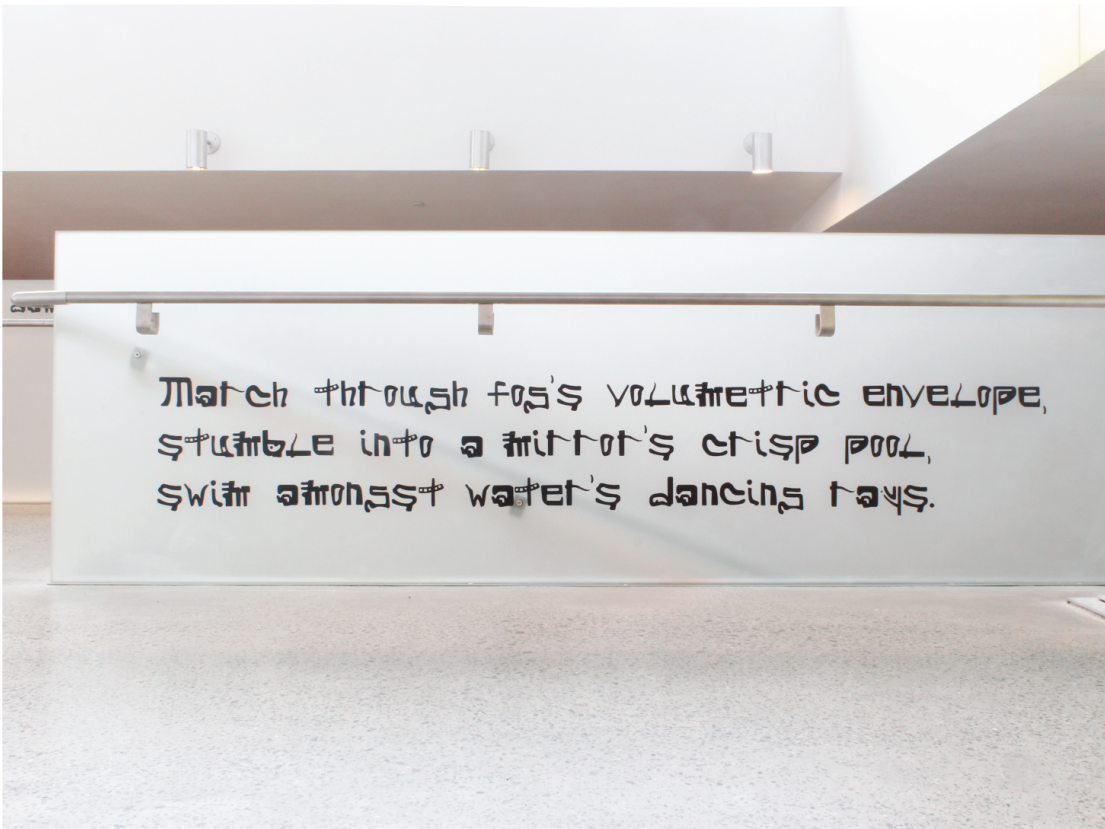
**Figure A12:** Poster series with individual names for The VIS Junior Show as circulated in Spring 2018. Each student was prompted for the place which has inspired their artistic practice the most. Typeset in CUPERTINO, GUANGZHOU, VILNIUS, ARACAJU, ZAPOTLÁN DEL REY, NORWAY, MIDTOWN SACRAMENTO, BROOKLYN, PATERSON, PLANO, NAPLES, BRIDGEWATER, I-95, MANHATTAN, LOS ANGELES, BALTIMORE, REDWOOD CITY, ENGLAND, NAOSHIMA, and PRINCETON. April 2018.



**Figure A13:** The main circulating poster for The VIS Junior Show appeared on a popular Facebook meme page. I received this screenshot from a friend before the post was deleted soon after. At the time, the meme group circulated to over 45,000 individual accounts.



**Figure A14:** Informational circulating poster for my Princeton Visual Arts undergraduate senior thesis titled *CAUSTICS*. Typeset in *AVERAGE*, *SEATTLE*, *NAPLES*, *LAS PIEDRAS*, *1-95*, and *CORNWALL*. February 2019.



**Figure A15:** Vinyl wall text introducing *CAUSTICS*, my undergraduate senior thesis show for Princeton's Visual Arts department. Typeset in NAPLES. February 2019.



**Figure A16:** Vinyl wall text defining *CAUSTICS*, a computer graphics term to describe a particular manifestation of light and namesake of my undergraduate senior thesis show for Princeton's Visual Arts department. Typeset in NAPLES. February 2019.





**Figure A17:** Circulating poster for “Final Runnings Before the After”—an end-of-year show of seniors’ work in Princeton’s Visual Arts Department. Typeset in PRINCETON. April 2019.



**Figure A18:** *VIS logo displayed outside 185 Nassau. Photo courtesy of Jonathan Zong and his exploration with the Nikon COOLPIX 885.*