Segmenting the Right-of-Way of San Francisco

Using VGG16-UNET on RGB Satellite Imagery

MUSA 650 Final Project – *Alexander Nelms*

For my final project, I will be performing right-of-way semantic segmentation of satellite imagery. I want to understand which areas of the City of San Francisco are roads/right-of-way. My training/mask dataset is a Right-of-Way polygons that define the drivable area in the city. The satellite imagery is from the National Agriculture Imagery Program and has 4 bands: Red, Green, Blue, & Infrared.

Introduction

It is financially and administratively difficult for the GIS departments of American cities to constantly update basic datasets. One large dataset that is rarely create or update is Right-of-Way polygons – even though many public and private stakeholders lean on that dataset to understand other urban trends. When looking at satellite imagery, it is easy for the human eye to classify what surfaces are asphalt, where the curb/sidewalk starts, and what isn't a road. With that in mind, I want to use semantic segmentation on satellite imagery to classify areas that are the right-of-way.

```
C:\Users\nelms\Documents\Penn\MUSA-650\FinalProject
```

When first thinking of this project, I was interested in covering more cities so that my model would be more generalizable. The issue is that most cities don't have available, updated Right-of-Way polygons. Instead of polygons, many studies use centerlines or vehicle/google steets images. Most projects, when trying to find RoW, will buffer centerlines (such as this Thesis or Journal Article). Although those two projects find secondary algorithms to balance out the centerlines, it is out of the scope of this project. But buffered centerlines alone will not accurately account for typically abnormal ends of the RoW (e.g. sidewalks, curbs). These projects (one, two) used google streets images or sensors from automated vehicles to aggregate a larger dataset.

Data

My data cleaning process is to (1) use multiband, higher resolution satellite imagery (.5 meter) as the input data of a neural network and (2) right-of-way polygons as the ground truth data. I will be focusing on San Francisco since the city's GIS team has a fairly clean and updated right-of-way polygon dataset. I will cut the right-of-way polygons then only select the fishnet cells that don't contain right-of-way polygons that are on freeways or in underground tunnels. The fishnet cells of right-of-way polygons will then be transformed to TIFs of equal size of the satellite imagery.

X Data: Satellite Images

My primary dataset is satellite images of San Francisco from the National Agriculture Imagery Program. This dataset is extremely valuable as it has:

1. 4 bands: Red, Green, Blue, & Infrared
2. a .5 meter resolution
3. Relatively low amounts of cloud cover
4. Images for every other year (2012-2020)

```
100%|████████████████████████████████████████| 42/42 [03:33<00:00,  5.07s/it]
```

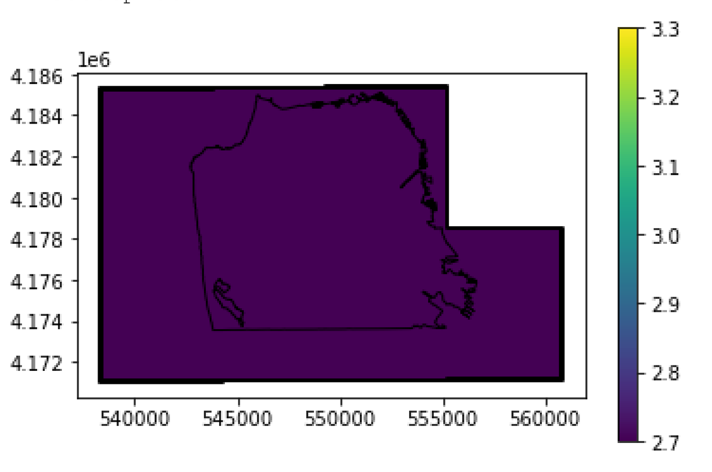
The narrow resolution will be helpful in getting accurate estimates of the RoW and being able to turn those predictions into polygons to be used.

	filename	raster	transform	proj	bounds	bands	shape	resolution	meta	mask	non_sf	water	hwy	roads	dat
0	m_3712212_se_10_060_20180804.tif	[[[42, 40, 38, 39, 43, 49, 42, 67, 94, 108, 84...	(0.6, 0.0, 538356.0, 0.0, -0.6, 4185282.0, 0.0...	epsg:26910	POLYGON ((544200 4185282, 544200 4178016, 5383...	(1, 2, 3, 4)	(12110, 9740)	(0.6, 0.6)	{'driver': 'GTiff', 'dtype': 'uint8', 'nodata'...	[[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,...	[[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,...	[[1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,...	[[0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0,...	[[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,...	2018 08-0
1	m_3712212_se_10_060_20200524.tif	[[[176, 181, 128, 129, 122, 134, 113, 75, 65, ...	(0.6, 0.0, 538308.0, 0.0, -0.6, 4185330.0, 0.0...	epsg:26910	POLYGON ((544248 4185330, 544248 4177968, 5383...	(1, 2, 3, 4)	(12270, 9900)	(0.6, 0.6)	{'driver': 'GTiff', 'dtype': 'uint8', 'nodata'...	[[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,...	[[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,...	[[1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,...	[[0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0,...	[[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,...	2020 05-2
2	m_3712212_se_10_h_20160625.tif	[[[39, 40, 40, 41, 42, 41, 41, 40, 39, 40, 40,...	(0.6, 0.0, 538356.0, 0.0, -0.6, 4185282.0, 0.0...	epsg:26910	POLYGON ((544200 4185282, 544200 4178016, 5383...	(1, 2, 3, 4)	(12110, 9740)	(0.6, 0.6)	{'driver': 'GTiff', 'dtype': 'uint8', 'nodata'...	[[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,...	[[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,...	[[1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,...	[[0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0,...	[[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,...	2016 06-2

I ultimately only used 2018 data as bringing also bringing in the 2016 & 2020 images would:

1. make processing even heavier
2. potentially make the model overfit on the same San Francisco streets

```
<AxesSubplot:>
```



Y Data: Right-of-Way Mask

The actual Right-of-Way (RoW) mask for the Deep Learning model is polygons of drivable streets in San Francisco. Originally from SF's Open Data Portal.

The dataset was hand made by the City of San Francisco over the course of 2016 and 2019. A single GIS Analyst or team handdrawing this dataset helps makes this dataset a fairly good quality overall. An issue with human error & team editing is that the definition of 'Right-of-Way' can slightly change throughtout the dataset. Most RoW polygons include the automobile traffic lanes; however, the polygons are *inconsistent* when considering:

- bike lanes,
- parking spots,
- highways, and
- sidewalks.

Because of the slight inconsistencies with the RoW polygons, I will bring in a road centerline dataset to sort of 'ground truth' the cut RoW polygons.

Filter & Data Quality Masks

Because of the slight variety in the RoW polygons and the fairly large satellite images, I will create geographic *masks* and *filters* that target certain cut areas that:

- have RoW polygons *when there is supposed to be*, and
- remove excess satellite images.

To accomplish this, I will bring in fiters that locate

1. unincorporated/non-SF land,
2. water *(primarily the Pacific Ocean)*,
3. highways & bridges *that aren't represented in the RoW polygons*, and
4. road centerlines *that will estimate how correct the RoW polygons are*.

1. Unincorporated Land

Determine which area of land is not in the city of san francisco (and won't have an RoW mask). The land polygon is Bay Area counties boundaries *(that aren't SF)* that are clipped by water, from the San Francisco Regional Open Data Portal.

2. Water

Water areas that cannot have RoW. It just considers areas that are not in the SF County boundary that is clipped by water, from the San Francisco Regional Open Data Portal.

3. Highways & Bridge Centerlines

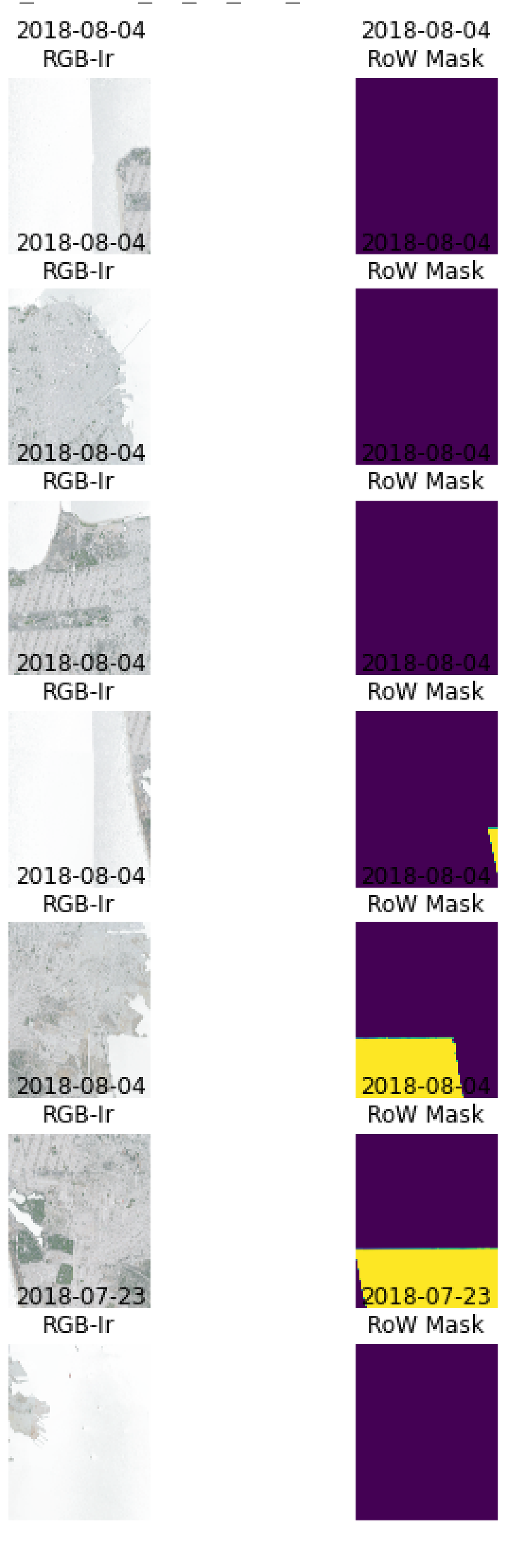
Highways & Bridges aren't in the RoW polygons. The centerlines are imported from Open Street Map *(via OSMnx)*, buffered by street lanes *(assuming ~12ft wide)*, then filtered by Highway & Bridge types.

4. Drivable Road Centerlines

I wanted to bring in road centerlines to detect defects in the RoW polygons. The centerlines are imported from Open Street Map *(via OSMnx)*, buffered by street lanes *(assuming ~12ft wide)*, then filtered by non-Highway, Bridge, & Tunnel road types.

The figures below show snippets of different satellites followed by a mask showing which lands are unincorporated. Notice that there is a lot of area that is in the ocean and outside of the city.

```
m_3712212_se_10_060_20180804.tif
m_3712213_se_10_060_20180804.tif
m_3712213_sw_10_060_20180804.tif
m_3712220_ne_10_060_20180804.tif
m_3712221_ne_10_060_20180804.tif
m_3712221_nw_10_060_20180804.tif
m_3712222_nw_10_060_20180723.tif
```



Cutting Satellite Images, RoW Masks, & Filters into Samples

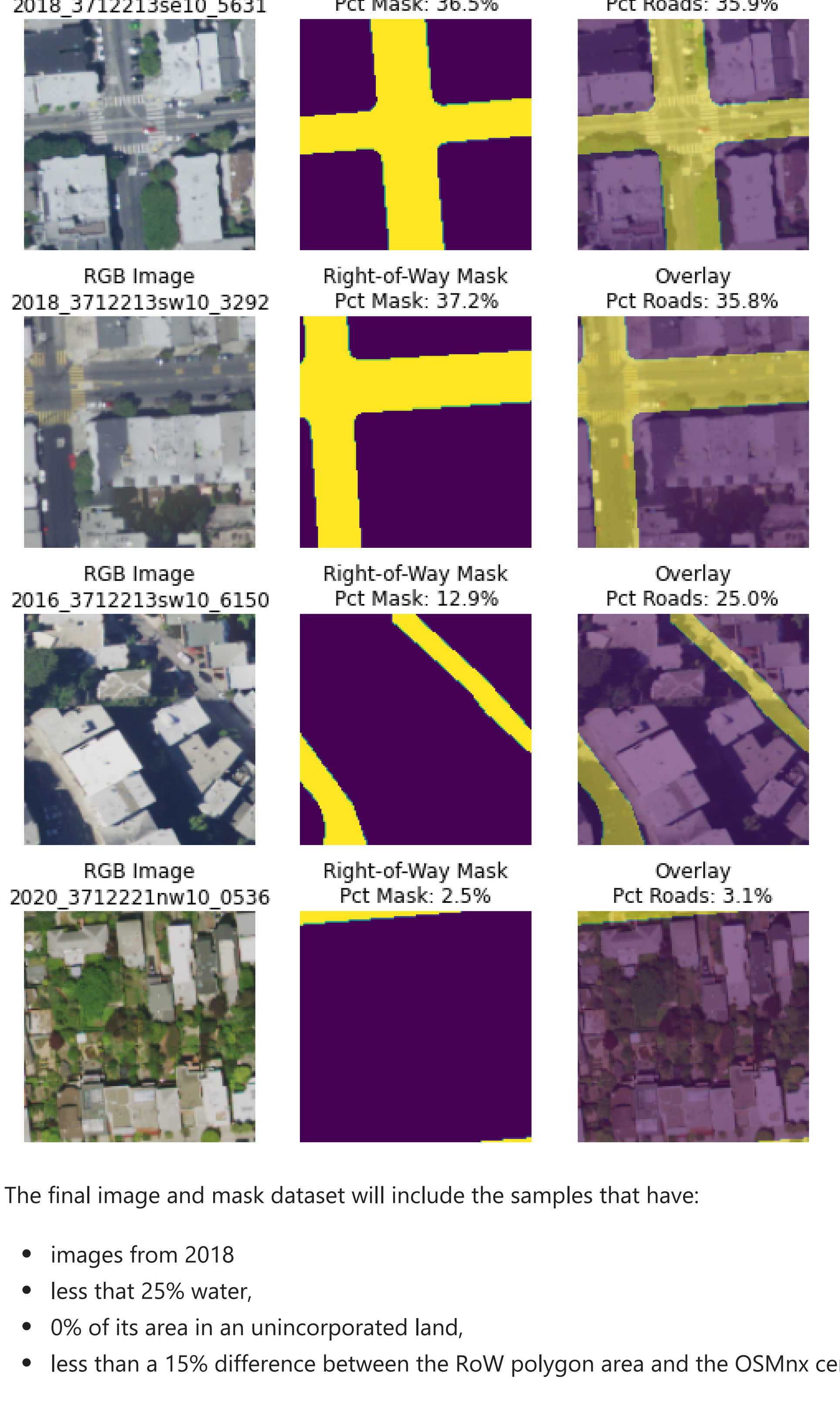
The dataset will now need to be cut up into equal sized images. I chose 128 x 128 squares because it will be 64 meters *(or ~210 feet)* wide. Olivier Rukundo, in his paper *Effects of Image Size on Deep Learning*, suggests that U-Nets that use images of size 256 x 256 wil lead to better outcomes than those of 128 x 128 – but at the cost of longer training times. I wanted to use 256 x 256 but my data cleaning and training was taking hours at a time. I had to commit to 128 x 128 at a certain point because it took to much time to transfer the data to google colab.

To make these sample cuts, I followed a process of:

1. finding which part of the larger image should be left out,
2. measuring how many samples could be cut from the image, and
3. cutting the image, mask, and filter arrays.

After cutting the arrays, I then *pool* the filter samples (i.e. water, unincorporated land, highways, & buffered street centerlines) into "what percentage of their cut area is the filter". With this percentage, I can then filter out cuts with too high of a percentage of water, *for example*.

The figures below show samples of the RGB satellites, the RoW Mask, and them overlayed each other. Roughly 78% of the samples have the Right-Of-Way in them. On average, a sample has 17.5% of its area covered by Right-of-Way polygons. What is concerning is that the OSMnx street centerlines will, on average, comprise of 22% of the sample areas. This difference between the RoW polygons and the buffered centerlines is a tad concerning. Most samples have little area difference between the RoW polygons and the OSMnx centers. But then there's some samples with alot of difference.



The final image and mask dataset will include the samples that have:

- images from 2018
- less that 25% water,
- 0% of its area in an unincorporated land,
- less than a 15% difference between the RoW polygon area and the OSMnx centerline area

The final count of 2018 samples is 18,811. Before filtering out just 2018, there were around 56,000 samples. So if I want to return to this project later, I can also include 2016 & 2020.