GEODOME MIDS Capstone Project

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Background

- Earth observation (EO) data allows to understand and plan around infrastructure system and flow of resources at global scale
- Access to labeled satellite imagery is expensive and public datasets are rare.
- Deep learning models do not generalize well when trained on images with limited geographical diversity


Imagery Source: Google Maps - Maxar Technologies

Project Objectives

- Create a tool to develop and expand a training dataset for EO data with **existing infrastructure labels**
- Create a new benchmark dataset for the EO computer vision community
- Stretch goal: Design and execute domain adaptation experiments

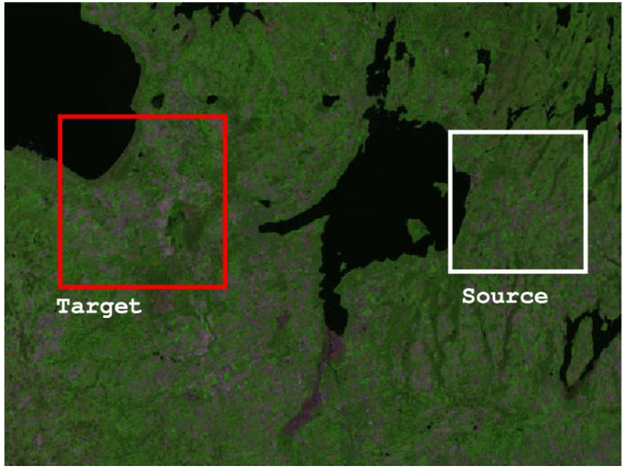
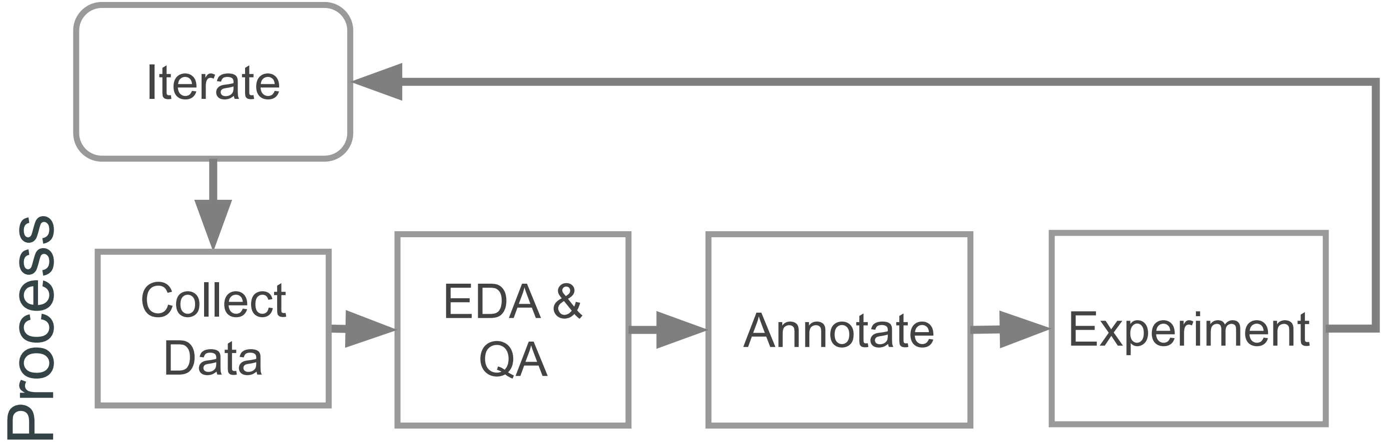


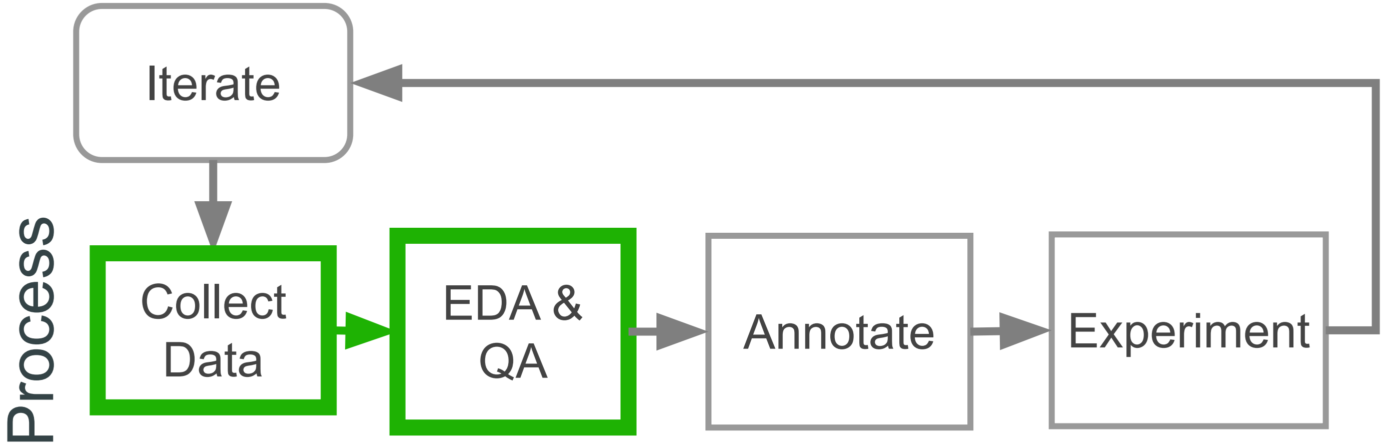
Image source: Elshamli, Ahmed et al. “Domain Adaptation Using Representation Learning for the Classification of Remote Sensing Images.” *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 10 (2017): 4198-4209.

Process


Process
Iterate
Collect Data
EDA & QA
Annotate
Experiment


Location ID: developed_id_24837
Image
Raster
KEEP
UNSURE
DISCARD
SAVE

Data Sources



Data Source: NAIP

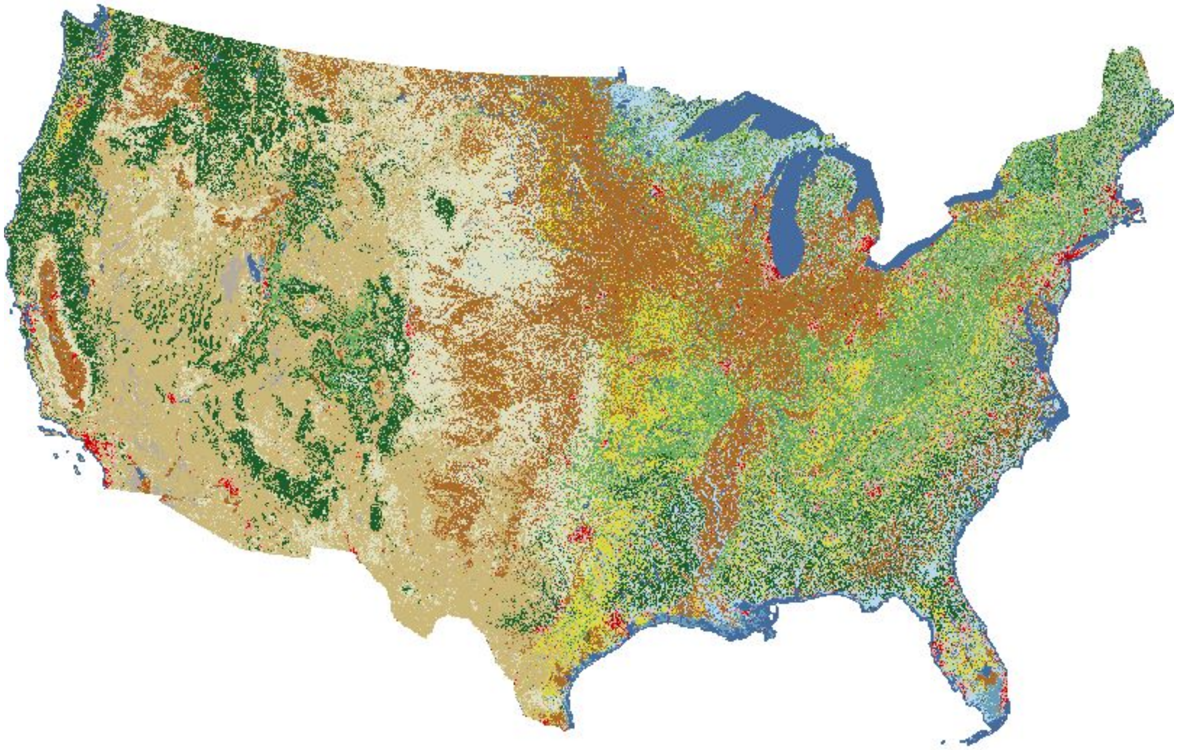
- USDA program
- High image resolution (<1 m)
- 4 bands
  - Natural Color (RGB)
  - Near infrared (N)
- There is plenty geographical diversity within the US

Data Source: NLCD

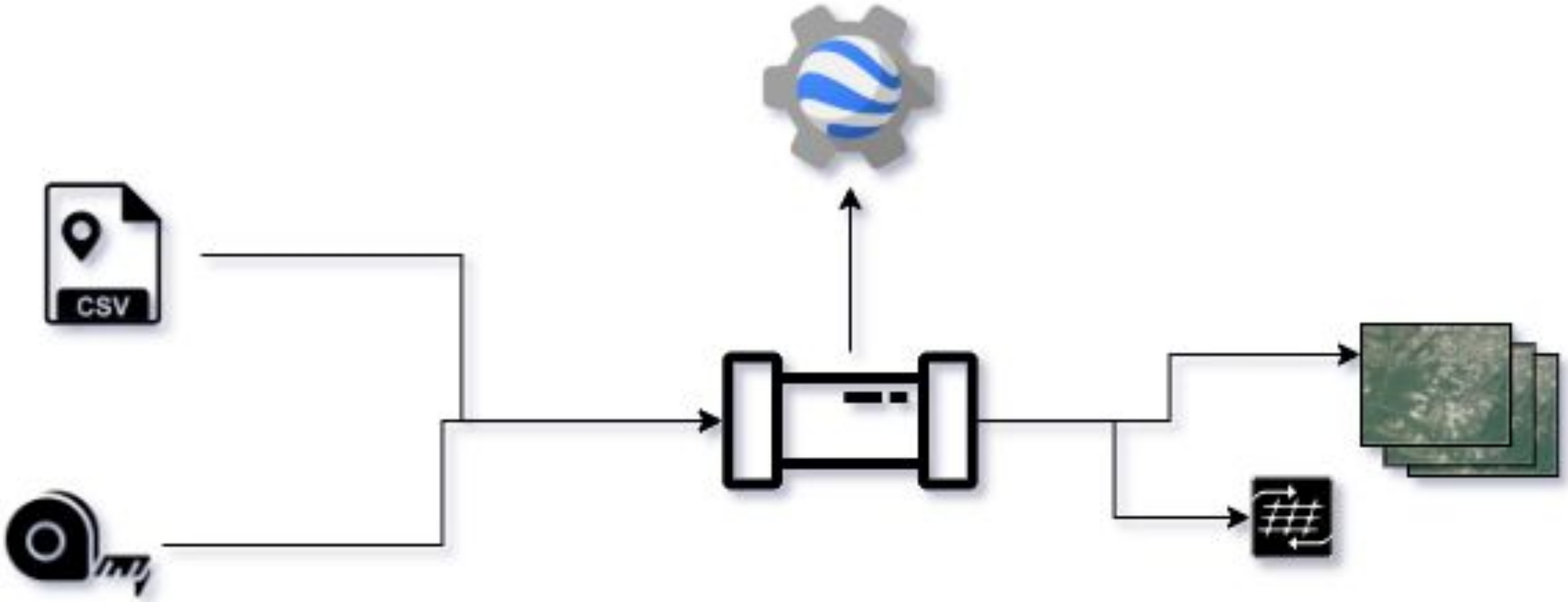
NLCD Land Cover Classification Legend

- 11 Open Water
- 12 Perennial Ice/ Snow
- 21 Developed, Open Space
- 22 Developed, Low Intensity
- 23 Developed, Medium Intensity
- 24 Developed, High Intensity
- 31 Barren Land (Rock/Sand/Clay)
- 41 Deciduous Forest
- 42 Evergreen Forest
- 43 Mixed Forest
- 51 Dwarf Scrub*
- 52 Shrub/Scrub
- 71 Grassland/Herbaceous
- 72 Sedge/Herbaceous*
- 73 Lichens*
- 74 Moss*
- 81 Pasture/Hay
- 82 Cultivated Crops
- 90 Woody Wetlands
- 95 Emergent Herbaceous Wetlands

* Alaska only

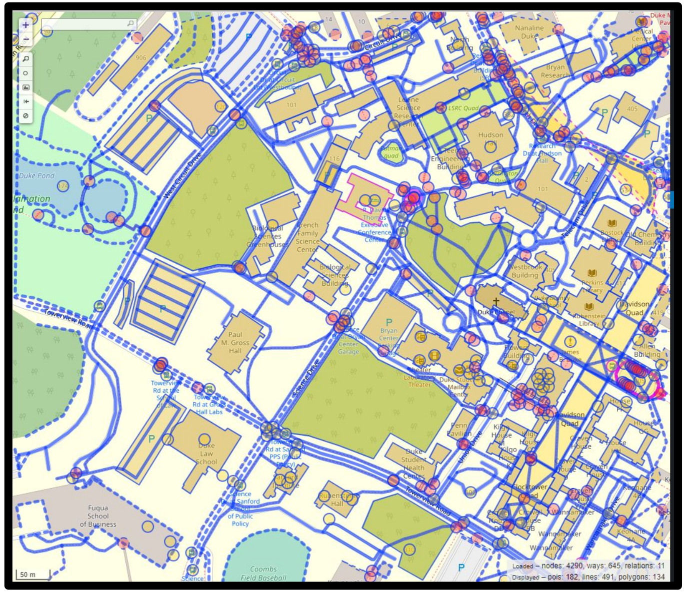


TOOL: Satellite Imagery Download



Data Sources: OpenStreetMaps

- Open and collaborative project to create a publicly available and editable map of the world

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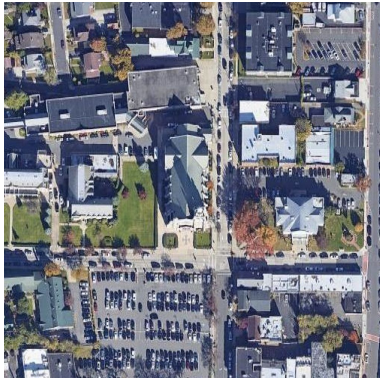
OpenStreetMaps Labels

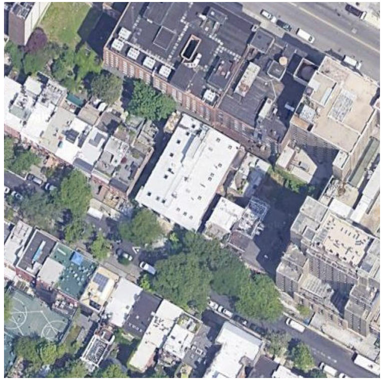
- Analyzed each one of the 682 labels to
  - discard those that are not relevant
  - discard those that are not visible
  - merge those that refer to the same or very similar features
- Created a new ‘taxonomy’: a dictionary to translate the original labels into our new classification

OpenStreetMaps Labels

Merged Labels



church



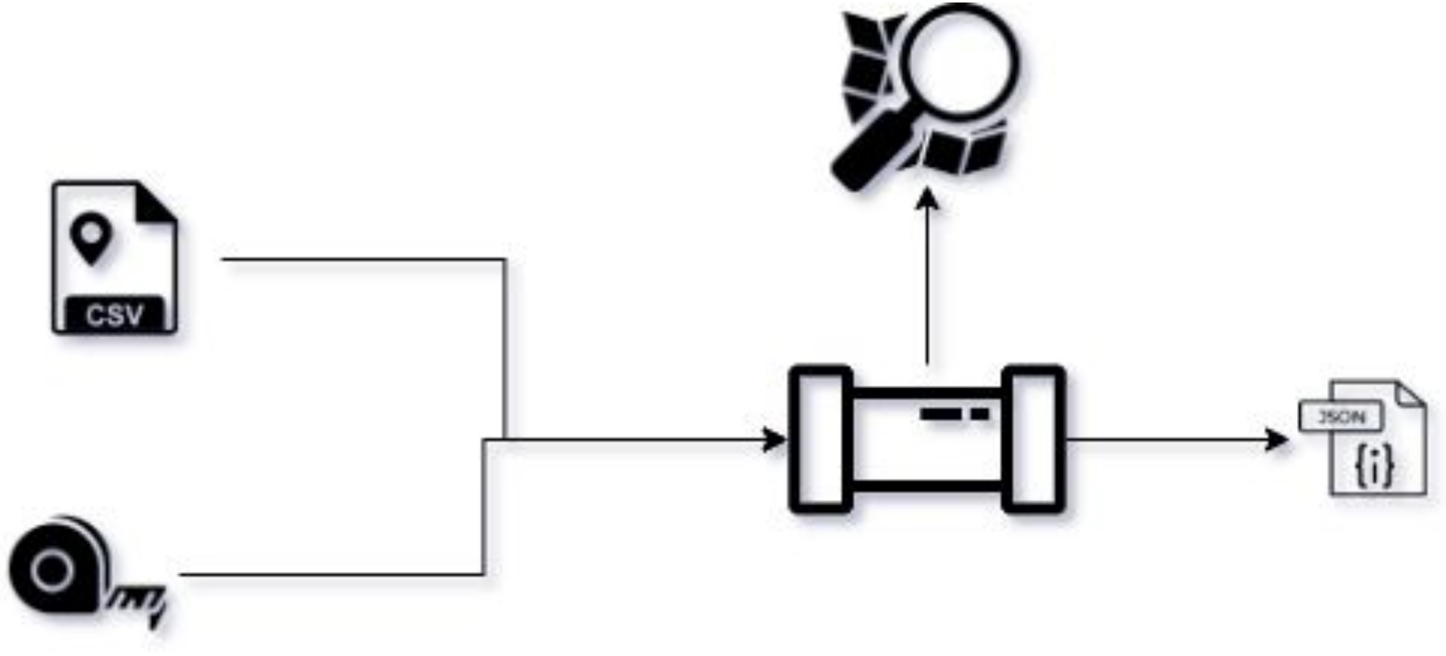
place of worship

university

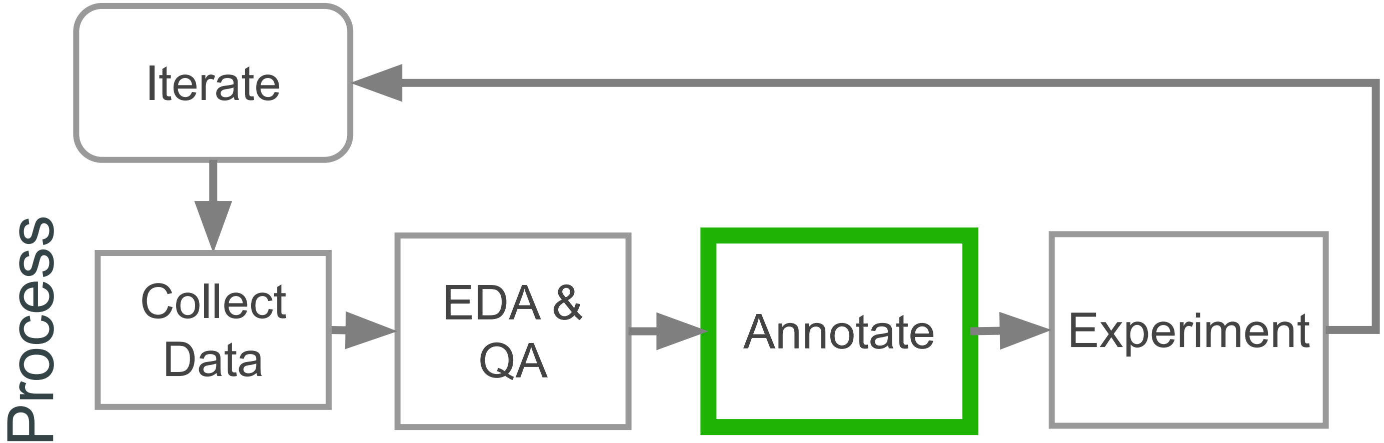
college

building

TOOL: OSM Label Pipeline



Annotation

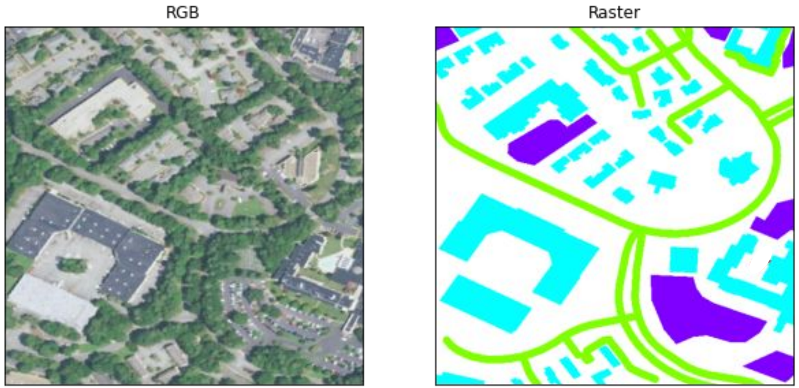


Annotation

- Aerial imagery is not always an orthogonal top-down view
- Developed tools that align the orthogonal label layout to match the view of the aerial image
- Turn the labels from vectors into pixels (rasterize)
- Verified that the structure coordinates aligned correctly from both sources

TOOL: Rasterization Pipeline

- Takes the output of the first 2 tools
- Collapses them into the labels of interest
- Assigns a ‘depth’ value for each polygon
- Uses the meta information to align the shapefile with the satellite image
- Burns the polygons as pixels to use as labels



Experiments

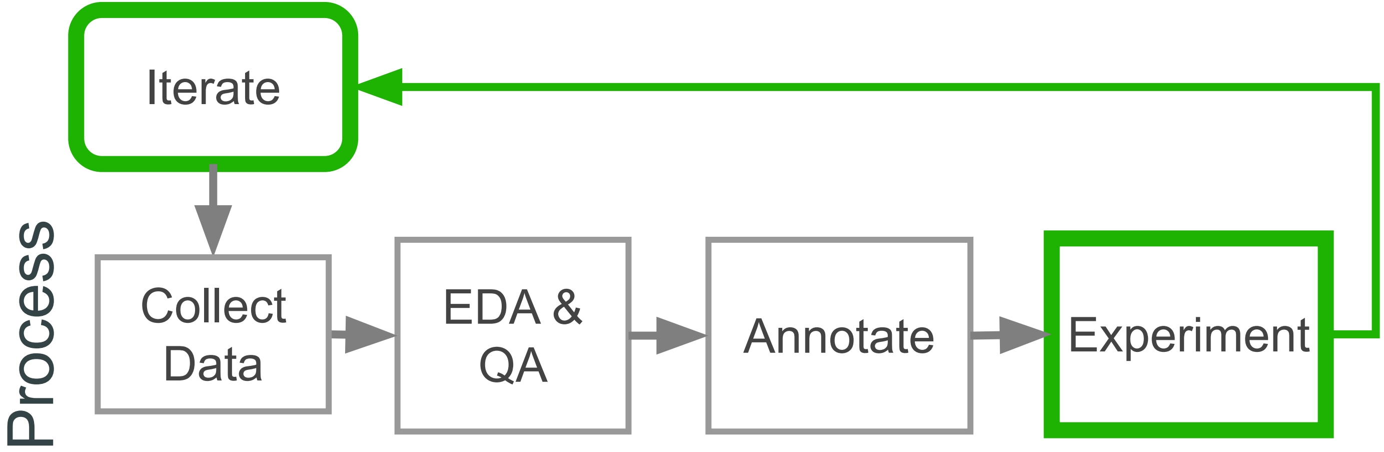


Image Segmentation Experiments

- Goal: Classify each pixel in an RGB image
- Architecture: ResNet50 encoder + U-Net decoder
- Metrics:
  - Intersection over Union (IoU): measures similarity between prediction and raster
  - Class metrics: Precision, Recall, NPV, Sensitivity, Specificity, Accuracy
- GEODOME Dataset:
  - 15,668 patches: RGB + raster
  - 59 classes (initially)

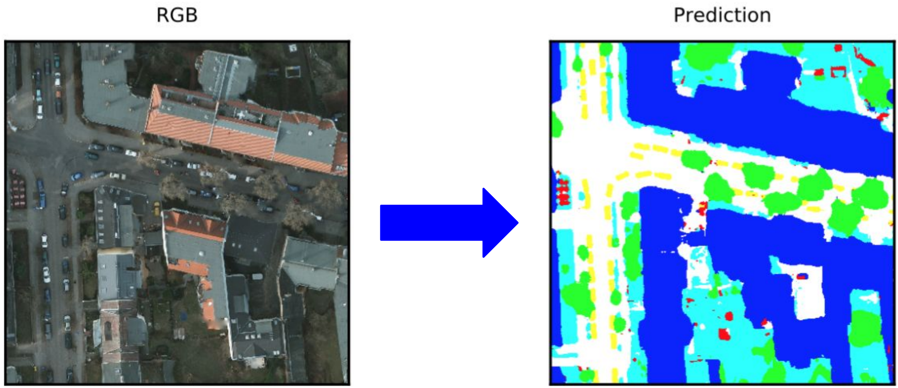
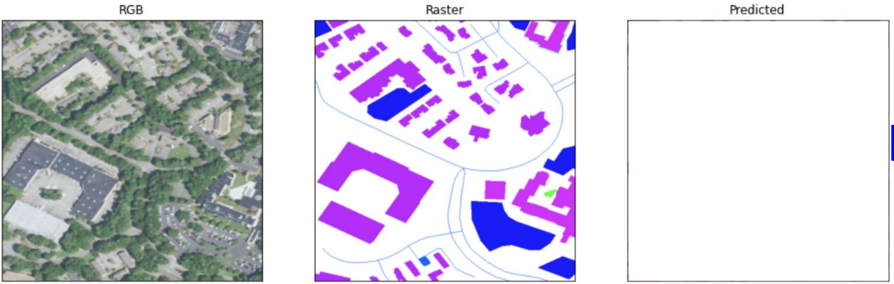


Image source: https://www.azavea.com/blog/2017/05/30/deep-learning-on-aerial-imagery/

Experiment Results

Experiment	Train IoU	Class 0 Precision	Class 0 Specificity	Roads Precision	Roads Specificity	Buildings Precision	Buildings Specificity
1	0.947	0.9108	0.0194	-	1.0000	0.2977	1.0000
2	0.676	0.9138 ↑	0.6847 ↑	-	1.0000	0.4117 ↑	0.8670
3	0.770	0.9439 ↑	0.8316 ↑	0.8442 ↑	0.9817	0.8514 ↑	0.9812

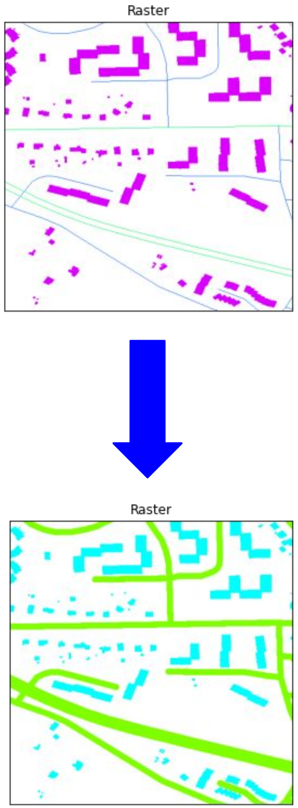


Experiment 1

Experiment 3

What Went Wrong?

- Problems:
  - 96.75% of pixels of class 0
  - Unlabeled objects
  - Too many classes
  - Roads 1 pixel thick
- Solutions:
  - Handpicked dataset
  - Made roads thicker
  - Reduced to 4 classes
    - (class 0, buildings, parking, roads)



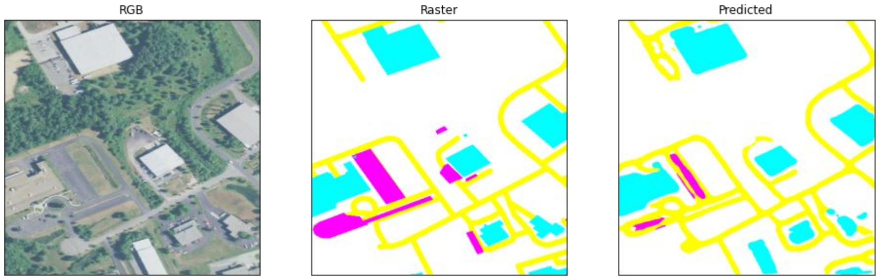
Fixing Our Dataset

- Automated filtering of RGB-raster pairs
  - **Method 1** [*30.55% kept*]: ≥2 classes and raster mean >0.08
  - **Method 2** [*7.47% kept*]: ≥3 classes and raster mean >0.08
  - **Method 3** [*13.72% kept*]: KNN classifier
  - **Method 4** [*2.34% kept*]: Logistic regression

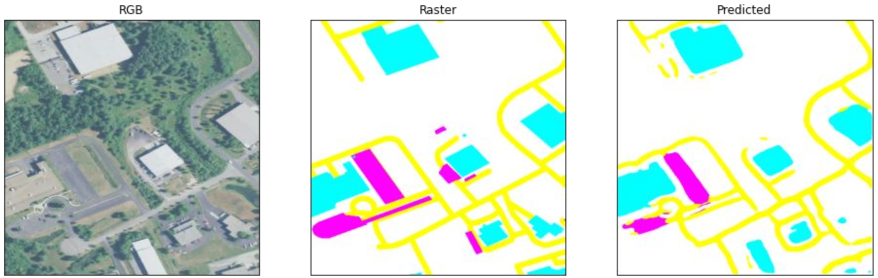
Method	Train Accuracy	Valid Accuracy
1 (2 classes)	47.2%	46.7%
2 (3 classes)	81.6%	83.3%
3 (knn)	88.4%	56.0%
4 (lr)	81.6%	66.0%

Experiment Results

Dataset Filter	Train IoU	Train IoU with Inria	Valid IoU	Valid IoU with Inria
1 (2 classes)	0.7079	0.9179 ↑	0.7200	0.7646 ↑
2 (3 classes)	0.7262	0.8583 ↑	0.7077	0.7415 ↑
3 (knn)	0.9059	0.9253 ↑	0.7252	0.7378 ↑
4 (lr)	0.7262	0.7451 ↑	0.7077	0.7321 ↑



Filter 1



Filter 4

Key Takeaways

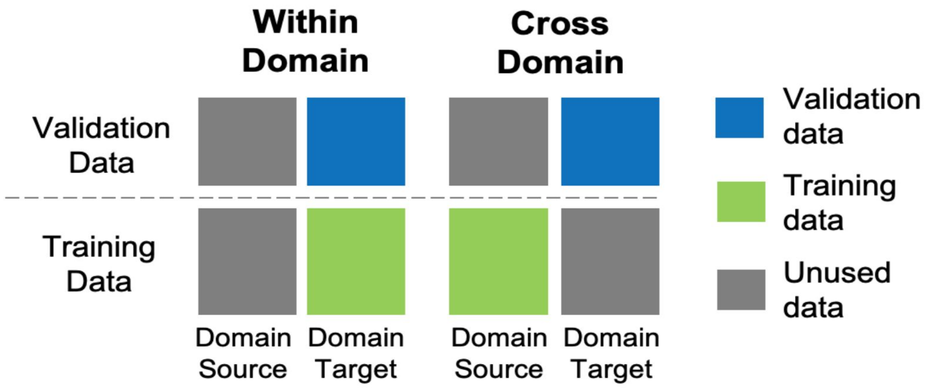
- Developing a systematic approach to improve data quality is better than chasing the state-of-the-art models with low-quality data.
- OSM labels are of better quality when the data source is supported by a large scale organization (government agencies) or the tags are high profile.

"If 80 percent of our work is data preparation, then ensuring data quality is the important work of a machine learning team."

Andrew Ng

Future Work

- Automate filtering of quality RGB-raster pairs
- Train baseline “within domain” model with training and validation data of the same domain
- Compare performance vs. “cross domain” models with training data of increasing domains to assess how adding domain diversity can help overcome the domain adaptation challenge
- Alternate use cases: partially labeled datasets



Acknowledgments

- Project Manager: Wei (Wayne) Hu
- Project Partner: Kyle Bradbury, PhD