

Building Detection with the SpaceNet Dataset

6th semester project
Geospatial Big Data Analytics
National Technical University of Athens

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Part 1 Data Exploration

SpaceNet Challenges

- 8 SpaceNet mapping Challenges
- Each dataset focuses on a different aspect of ML to solve mapping challenges
 - Building detection
 - Road network detection
 - Road network extraction and travel time estimation
 - Multi sensor all-weather mapping
 - Multi temporal urban development
 - Flood detection
- This project: SpaceNet1 Dataset for <u>building detection</u>



SpaceNet1 Dataset for Building Detection

- Building detection is important in Urban Planning tasks
- Dataset with TorchGeo through Radiant MLHub (cloud based library)
- Dataset contains building footprints over the city of Rio de Janeiro
- 6940 8-band images 6940 RGB images
- 382,534 polygons (labels) in GeoJSON format
- 8-band image 1m² x 1m²
- RGB image used 50cm² x 50cm² 406x429 pixels (lower cost, effective)



The data

RGB Image



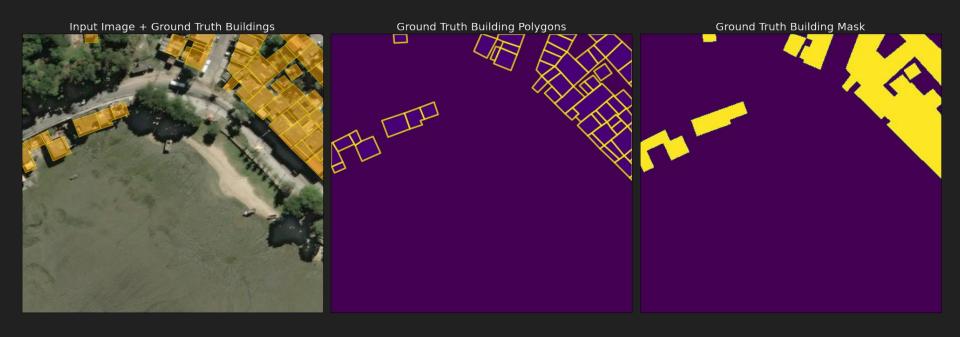
GeoJSON label

```
{'crs': {'properties': {'name': 'urn:ogc:def:crs:OGC:1.3:CRS84'},
         'type': 'name'},
'features': [{'geometry': {'coordinates': [[[-43.69487929999997,
                                              -22.984465499999942,
                                              0.0],
                                              [-43.69493559999995,
                                              -22.984406699999965,
                                              0.0],
                                              [-43.694879399999934,
                                              -22.984365499999967,
                                              0.0],
                                             [-43.694828,
                                              -22.98442369999998,
                                              0.0],
                                              [-43.69487929999997,
                                              -22.984465499999942.
                                              0.0]]],
                            'type': 'Polygon'},
               'properties': {'HGISOID': 946847.0,
                              'HGIS OID': '946847.0',
                              'QAStatus': 'Original_Building',
                              'Revision1': 'No',
                              'Shape Area': 0.0,
                              'Shape Leng': 0.000295,
                              'TaskArea': 'West',
                              'area': 'None',
                              'building': 'yes',
                              'changeset': '5404',
                              'id': 'way/70607',
                              'partialBuilding': 0.0,
                              'partialDec': 1.0,
                              'timestamp': '2016-06-22T21:22:31Z',
                              'type': 'None',
```

Semantic Segmentation needs masks as target!

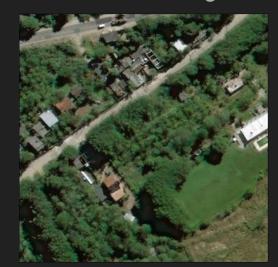
Ground Truth Transform

- Polygon vertices (latitude and longitude) to pixel coordinates -> Polygons
- Filled polygons -> Building masks



Build Torch Dataset

- Select subset of images for faster training
- 1000 images used, containing at least one building
- Crop 400x400 pixels of each image standard size for Unet
- 70-20-10 Train Validation Test split
- Normalize images with mean and standard deviation of training set







Part 2

Literature Review

Approaches for building detection

- Semantic Segmentation
 - Fully Convolutional Architecture SegNet
 - UNet Architecture
 - UNet with Residual blocks
 - UNet with Attention mechanism
- Object Detection
 - Faster RCNN
 - HOG Detector
 - YOLO YOLT YOLT2
- Conditional Random Fields

SpaceNet Challenge Metric

- Based on the Jaccard Index (IoU)
- Generated polygons to represent footprints
- Each <u>proposed</u> footprint is either a TP or FP
- TP if the proposal is closest to a labeled polygon and IoU>0.5
- After detection is defined, calculate precision, recall and F1 score (over ALL of the test imagery)
- Winning F1 score was 0.26!



Image Segmentation Metrics - pixelwise (simplified)

- Accuracy
- Precision
- Recall
- F1-Score
- loU (Jaccard)

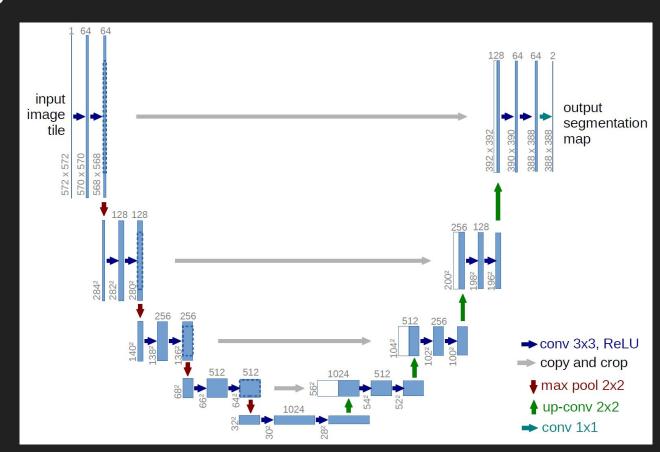
Architecture	Evaluation Metrics						
	Accuracy	Precision	Recall	F1	Jaccard		
SegNet [27]	0.919	0.569	0.813	0.662	(7.)		
SegNet with Sobel filters [10]	0.923	0.596	0.722	0.667	-		
CRF with Sobel filters [10]	0.931	0.632	0.763	0.675	-		
CRF with CNN boundaries [10]	0.924	0.624	0.764	0.674	-		
U-Net [29]	0.923	0.808	0.808	0.798	0.700		
ResU-Net	0.936	0.864	0.770	0.811	0.703		
Attention U-Net	0.940	0.851	0.809	0.826	0.726		

UNet Architecture for Semantic Segmentation

Part 3

UNet Architecture

- Skip connections
- Symmetric
- 400x400 input



Part 4

Model Training and Metrics

Model Training Notes

- Complex loss function (dice loss + binary cross entropy)
- Early stopping on pixel accuracy
- Model trained for 18 epochs on Google Colab's GPUs

(Binary) Cross Entropy (BCE):
$$BCE = -\frac{1}{N} \sum_{i=0}^{N} y_i \cdot log(\hat{y}_i) + (1 - y_i) \cdot log(1 - \hat{y}_i)$$

$$sof \ t \ Dice \ loss = 1 - \frac{2\sum_{pixels} y_{true} y_{pred}}{\sum_{pixels} y_{true}^2 + \sum_{pixels} y_{pred}^2}$$

Model Evaluation

Results on test set (100 images of 400x400 pixels each)

Model Results

Accuracy: 0.9235985

Precision: 0.7395110456998663 Recall: 0.700275604734716 F1-score: 0.7193587252377506

IoU: 0.7385114431381226

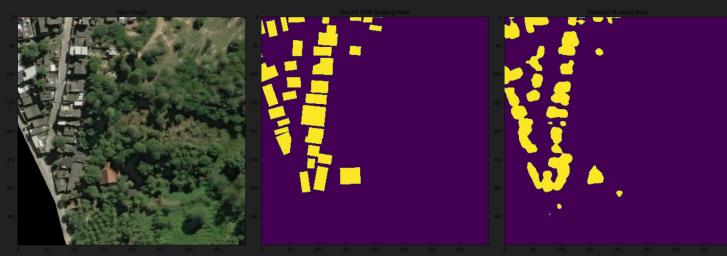
Literature Results

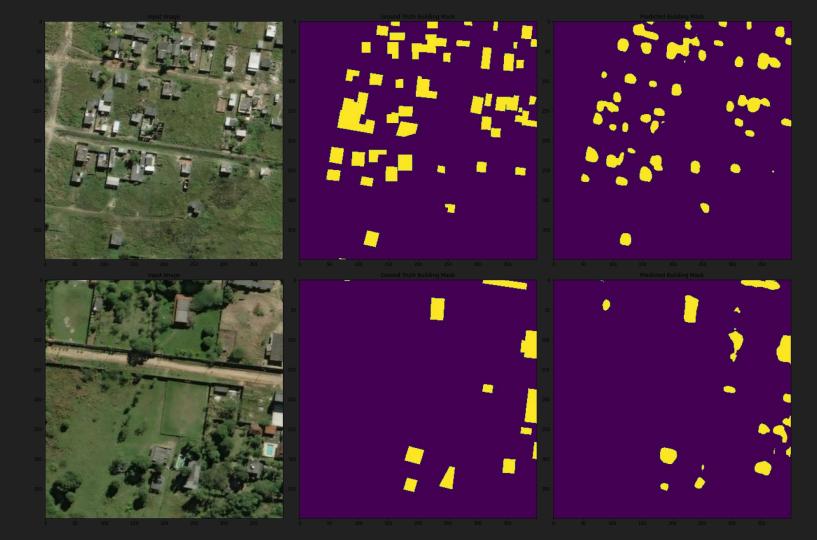
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Visualize Results

Part 5







References

- https://spacenet.ai/spacenet-buildings-dataset-v1/
- https://www.mdpi.com/2227-7080/10/1/19
- https://medium.com/the-downling/getting-started-with-spacenet-data-827fd2e
 c9f53
- https://arxiv.org/pdf/1807.01232.pdf
- https://medium.com/the-downling/building-extraction-with-yolt2-and-spacenetdata-a926f9ffac4f
- https://arxiv.org/pdf/1505.04597.pdf