

Project proposal: Semantic Segmentation of buildings in satellite imagery

Problem Statement

Satellite imagery is becoming commonplace as the costs of satellites have come down. Automatic extraction of features such as buildings and roads using machine learning techniques such as neural networks can have an important role to play in disaster response, and improve map data for poorer areas of the world where there might be less incentive for commercial companies to spend mapping efforts. The aim of this project is to build a model and inference pipeline that can detect buildings from satellite imagery that is both accurate and efficient (both in terms of training and inference time, and model size).

Domain background

This project is based on the computer vision task of [semantic segmentation](#) applied to satellite imagery.

There are many model architectures for image segmentation. According to [paperswithcode](#), some of the current top models (ranked on Mean IoU on the cityscapes dataset) are:

RANK	MODEL	MEAN IOU (CLASS)	EXTRA TRAINING DATA	PAPER	CODE	RESULT	YEAR
1	HRNet-OCR (Hierarchical Multi-Scale Attention)	85.1%		Hierarchical Multi-Scale Attention for Semantic Segmentation			2020
2	HRNetV2 + OCR +	84.5%		Object-Contextual Representations for Semantic Segmentation			2019
3	EfficientPS	84.21%		EfficientPS: Efficient Panoptic Segmentation			2020
4	Panoptic-DeepLab	84.2%		Panoptic-DeepLab: A Simple, Strong, and Fast Baseline for Bottom-Up Panoptic Segmentation			2019
5	HRNetV2 + OCR (w/ ASP)	83.7%		Object-Contextual Representations for Semantic Segmentation			2019

RANK	MODEL	MEAN IOU (CLASS)	EXTRA TRAINING DATA	PAPER	CODE	RESULT	YEAR
6	DCNAS	83.6%		DCNAS: Densely Connected Neural Architecture Search for Semantic Image Segmentation			2020
7	DeepLabV3Plus + SDCNetAug	83.5%		Improving Semantic Segmentation via Video Propagation and Label Relaxation			2018
8	GALDNet(+Mapillary)	83.3%		Global Aggregation then Local Distribution in Fully Convolutional Networks			2019
9	ResNeSt200	83.3%		ResNeSt: Split-Attention Networks			2020
10	HANet (Height-driven Attention Networks by LGE A&B)	83.2%		Cars Can't Fly up in the Sky: Improving Urban-Scene Segmentation via Height-driven Attention Networks			2020

In terms of building segmentation, a review of current models from [this paper](#) shows the performance of top models as of 2019:

Models	Precision	Recall	F1	Kappa	Overall Accuracy
FCN-8s	0.9163	0.9102	0.9132	0.8875	0.9602
SegNet	0.9338	0.8098	0.8674	0.8314	0.9431
DeconvNet	0.8529	0.9001	0.8758	0.8375	0.9413
U-Net	0.8840	0.9190	0.9012	0.8709	0.9537
ResUNet	0.9074	0.9315	0.9193	0.8948	0.9624
DeepUNet	0.9269	0.9245	0.9257	0.9035	0.9659

Models	Precision	Recall	F1	Kappa	Overall Accuracy
DeepResUnet	0.9401	0.9328	0.9364	0.9176	0.9709

Interesting, we can see that some of the more 'traditional' segmentation models such as SegNet still comes up top whereas for more diverse scene understanding there are a lot more models coming out of research papers. Perhaps this is just a case of newer models not being tested on the task of building segmentation, or that the nature of the problem mean that it's not so efficient to do so.

Datasets

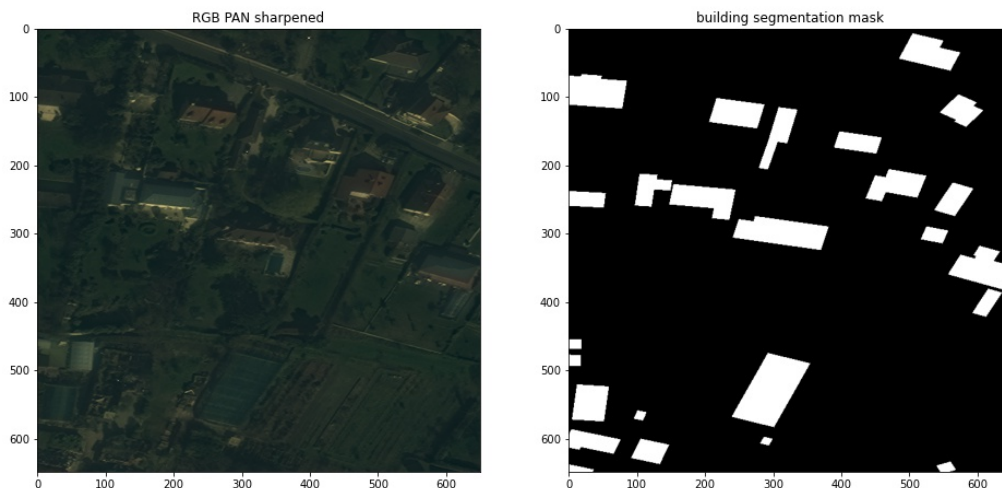
[Spacenet](#) has provided a comprehensive dataset of labelled satellite imagery data that can be used for this project. I will be using the [SpaceNet AOI 3 – Paris](#) dataset for training. Other cities are also available on spacenet and as an extension, time permitting, I will try to see how well a model trained on one city performs on another.

The dataset is organised as follows:

```
AOI_3_Paris
├─ MUL/                # geotiffs of 8-Band Multi-Spectral raster data from WorldView-3
├─ MUL-PanSharpen/    # 8-Band Multi-Spectral raster data pansharpened to 0.3m
├─ PAN/               # Panchromatic raster data from Worldview-3
├─ RGB-PanSharpen/    # geotiffs of RGB raster data from Worldview-3 pansharpened to 0.3m
├─ summaryData/       # building segmentation masks in csv format
└─ geojson/           # building segmentation masks
```

For this project, I will be using the `RGB-PanSharpen` images. In the Paris dataset, there are 1148 RGB pansharpened satellite imagery that is 650 x 650 pixels wide. They are saved as tiff files which can be read into numpy arrays by scikit-image using the `tifffile` plugin. The segmentation masks are in the form of geojson files. An example of an image-segmentation pair is shown below:

example of training data



Solution

My solution will be based on a pytorch model uses pretrained semantic segmentation networks, and fine tuned on labelled satellite data from the Spacenet dataset. The model is likely to be a variation on one of the well known semantic segmentation models such as [UNet](#) or [FastFCN](#). Some other options to explore include [PointRend](#) and [graph convolution networks](#)

Benchmark models

Spacenet has released winning models from the spacenet challenges at https://solaris.readthedocs.io/en/latest/pretrained_models.html Any of these can serve as a benchmark model. Quite a few of them are UNet based so it would be interesting to compare the performance of these with different architectures such as PointRend.

Evaluation metrics

I will be using the [Intersection over Union](#) score for measuring how well the model is performing. This metric is very common in semantic segmentation tasks and is also used as the judging criteria in the SpaceNet building segmentation challenges.

Project design

1. Data preprocessing
 - splitting satellite imagery into smaller chips for training
 - data augmentation (can also be done as a step in the dataloader)
2. Initial model training
 - train simple model (e.g. UNet with Resnet34 backbone) for baseline
3. Model tuning
 - error analysis: which images is the model most likely to make a mistake?
 - hyperparameter tuning
 - experimenting with other architectures e.g. EfficientNet
4. Test on data from another city from spacenet datasets
5. Further model refinement and analysis for better generalisation
6. Deploy model as web app that people can upload satellite imagery to and get building locations