

Weakly-Supervised Semantic Segmentation by Learning Label Uncertainty

Robby Neven

Master of Electronics and ICT Engineering Technology

1. Introduction

Problem statement

Since the rise of deep learning, semantic segmentation tasks have been able to excel. However, the necessity of a highly-detailed annotated training set is very costly to produce.

Objective

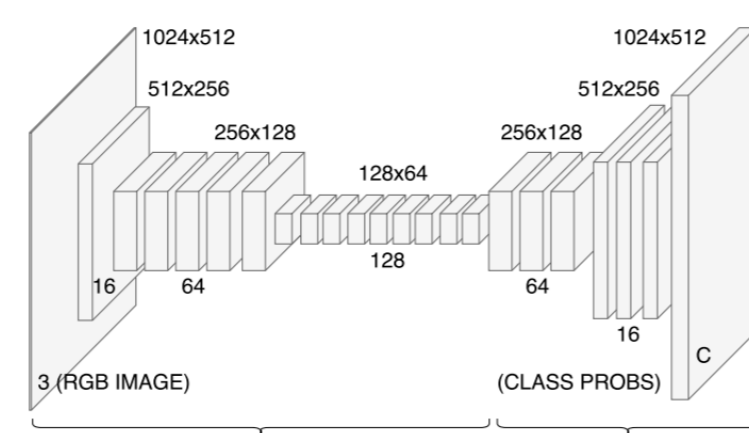
The objective of this thesis is to develop a weakly-supervised method to train a semantic segmentation network with bounding box labels, which are cheaper and faster to obtain.



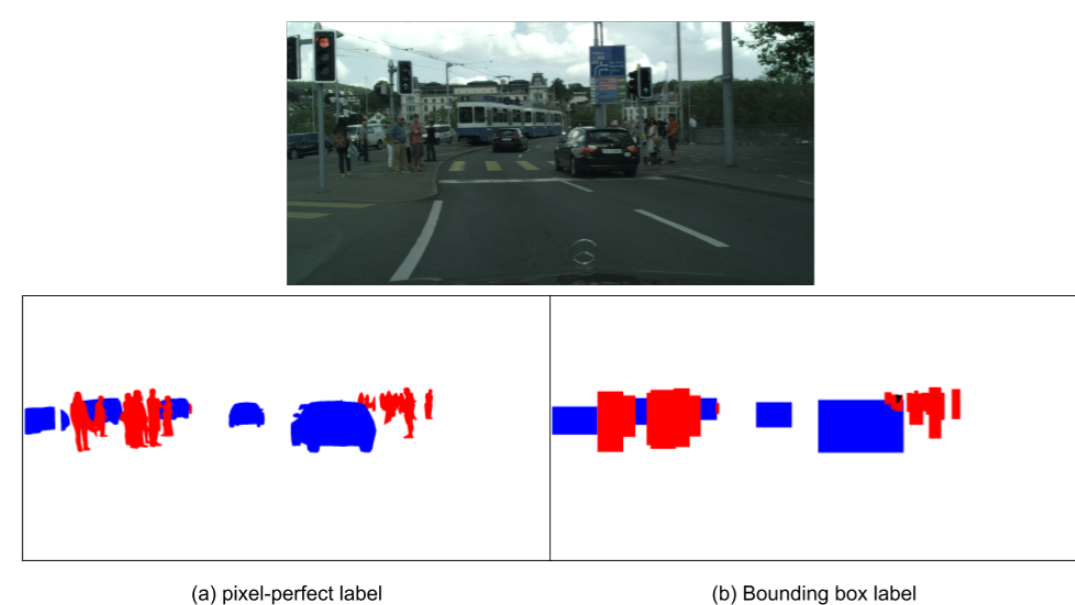
Pixel-perfect annotation from Cityscapes [1]

Method

A new loss function combining aleatory uncertainty and online bootstrapping is developed and implemented to train a deep CNN (ERFNet). The loss function is both implemented to perform binary segmentation as well as multi-class. The Cityscapes dataset is used to conduct the tests.



ERFNet architecture [2]



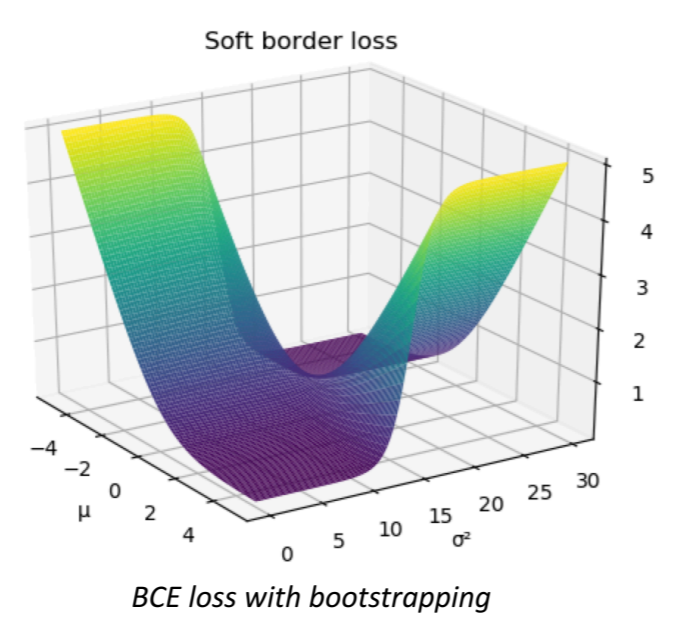
2. The loss function

The standard cross-entropy function cannot cope with bounding box labels right out of the box. Therefore, we introduce two new concepts to the loss:

- Aleatory uncertainty
- Online bootstrapping

Online bootstrapping

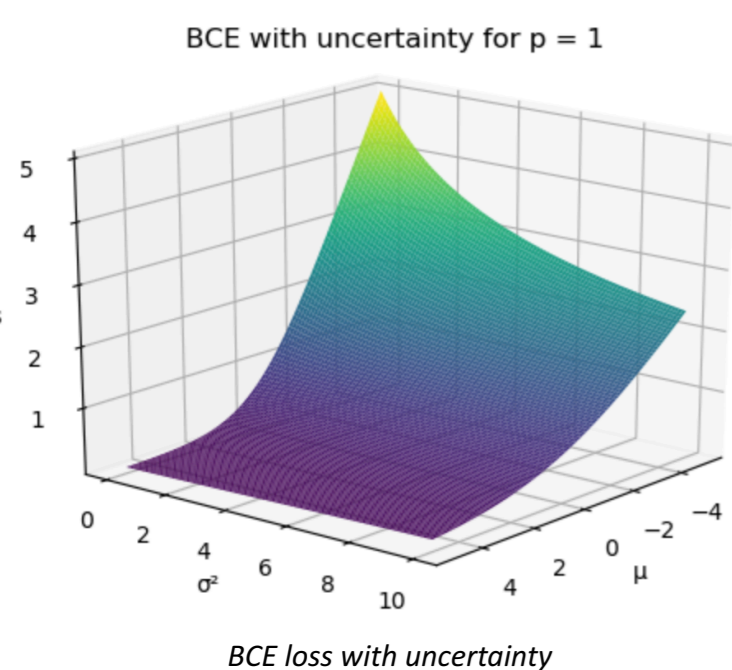
Online bootstrapping is a way to train on coarsely annotated data. The training targets get iteratively updated by the current state of the model. More specifically, the target is a weighted sum of the model's prediction and the training target. This allows the model to adapt the erroneous target to a more correct target which improves training. At a certain uncertainty threshold, the training target gets flipped.



BCE loss with bootstrapping

Aleatory uncertainty

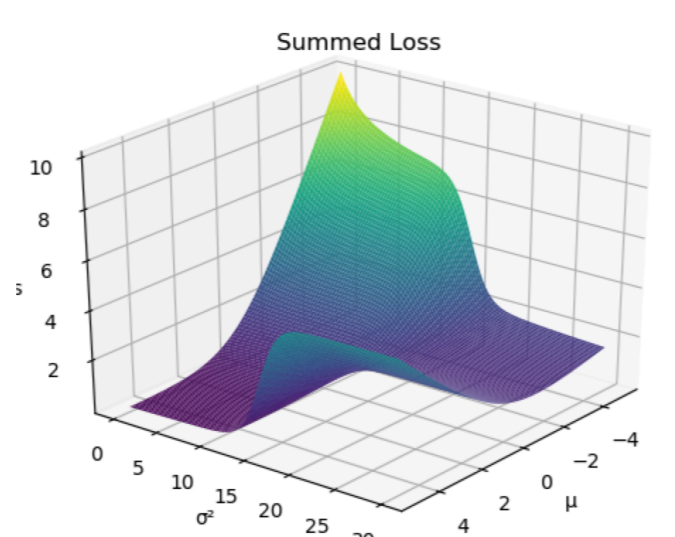
By introducing aleatory uncertainty to the BCE loss, the network can learn to increase its uncertainty for pixels which target is highly unlikely e.g. bounding box labels. This extra input parameter σ allows the loss to decrease, while the network outputs a label opposite to the target.



BCE loss with uncertainty

Combined

The two parts of online bootstrapping and aleatory uncertainty are summed to become the new loss function.



Combined loss

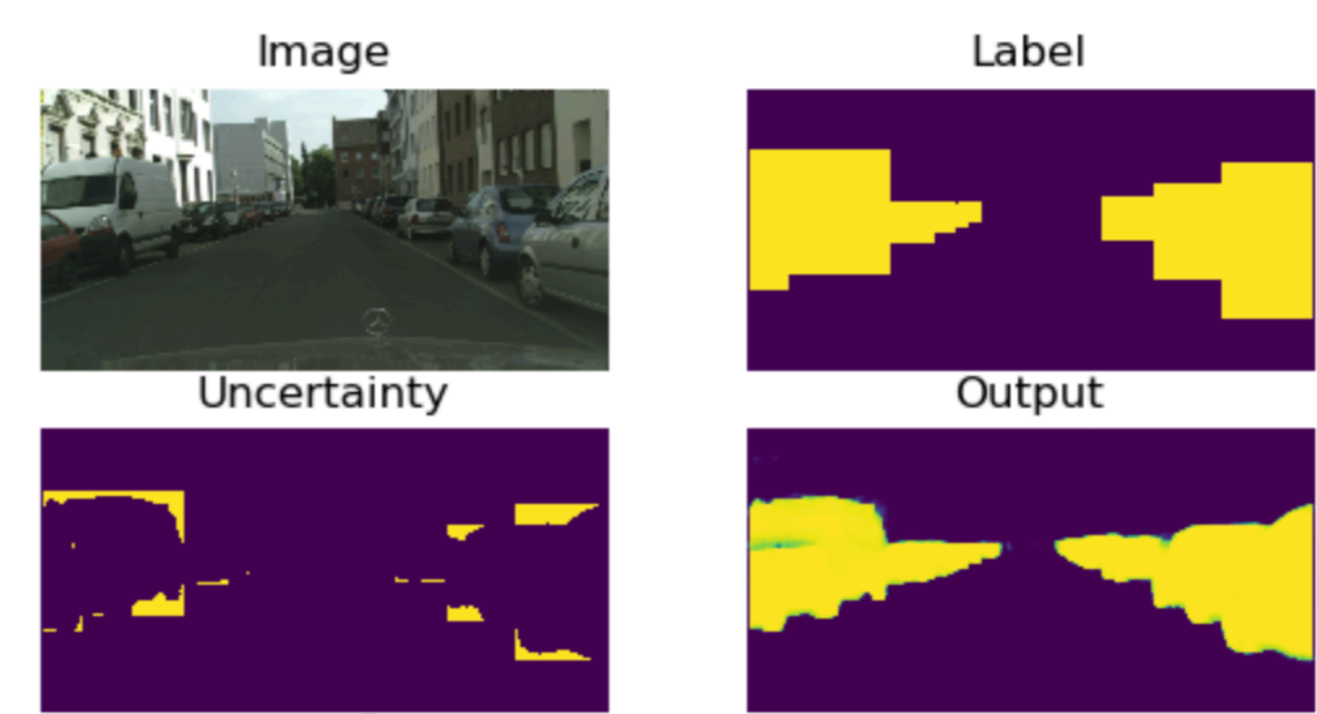
3. Results

Binary semantic segmentation

The loss was first tested to perform binary segmentation on cars. Trained with a small portion of ground truth labels and the rest bounding box labels, the network performs nearly as good as the standard approach.

	Dataset		IoU (%)
	GT	BBox	
Standard BCE	2780	/	86.9
	500	/	78.6
	/	2780	69.18
	500	2280	69.43
Loss With Uncertainty	500	2280	85.45
	400	2380	85.32
	300	2480	85.42
	200	2580	84.37
	100	2680	81*

Binary segmentation results



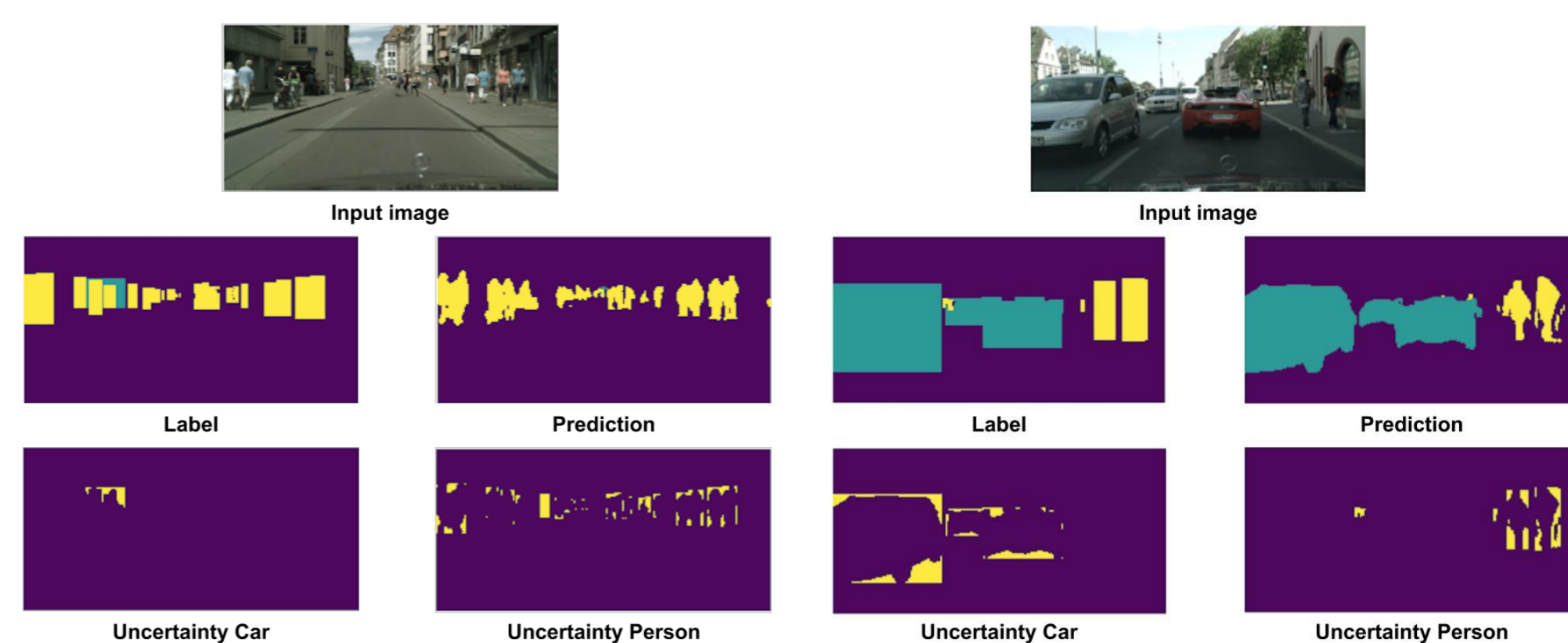
Binary segmentation output

Multi-class semantic segmentation

In a last stage, the loss was extended to multi-class and tested on persons and cars. The figures below show the prediction and uncertainty maps. The uncertainty maps indicate which pixels are being flipped due to the bootstrapping in function of the aleatory uncertainty.

	Dataset		IoU (%)			
	GT	BBox	Mean	Background	Car	Person
Cross-entropy	2780	/	79.80	98.21	85.82	55.68
	500	/	73.36	97.55	79.94	42.58
Our Loss	500	2280	77.75	98.01	82.05	53.2

Multi-class segmentation results



Multi-class segmentation output

4. Conclusion

The weakly-supervised loss function combining aleatory uncertainty and online bootstrapping performs well on binary and multiclass segmentation. The IoU score of a model trained with 18% ground-truth and 82% bounding box labels is nearly as high as the baseline of a network training with 100% ground-truth labels.

[1] Marius Cordts et al. "The Cityscapes Dataset for Semantic Urban Scene Understanding". In: Proc. of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2016.
 [2] Eduardo Romera et al. "Efficient ConvNet for real-time semantic segmentation". In: June 2017, pp. 1789-1794. doi:10.1109/IVS.2017.7995966.

Supervisors / Cosupervisors: dr. ir. Marc Proesmans
 dr. ir. Bert De Brabandere
 Prof. dr. ir. Bart Vanrumste (internal)