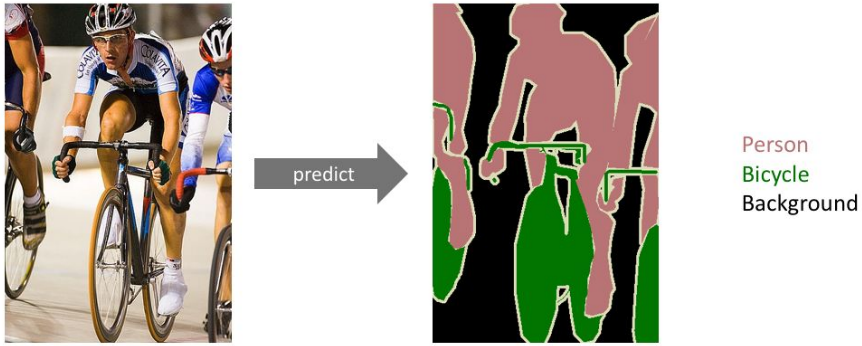
Reducing Class Confusion in Semantic Segmentation

Sharat Agarwal, PhD17005
Divyam Anshumaan, 2017147

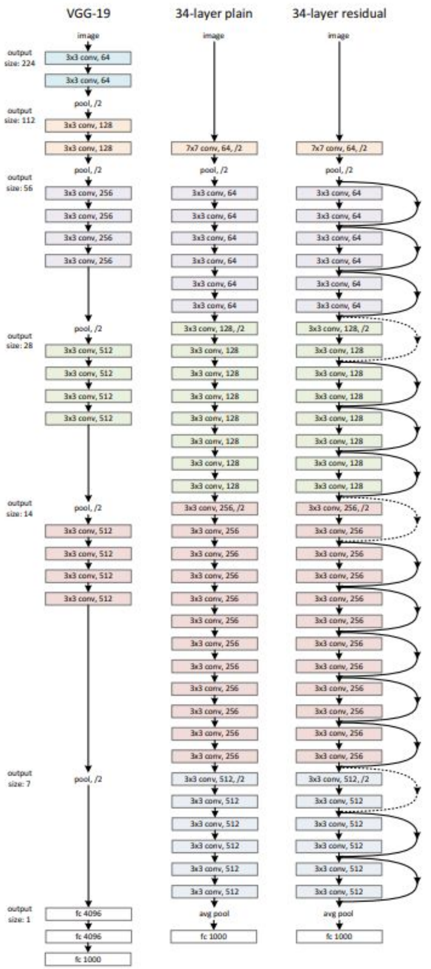
Introduction: Semantic Segmentation

- We aim to assign every pixel in the image a class label.
- The class label corresponds to the object the pixel is representing.
- For example, in the segmentation given below, each pixel is assigned to one of three categories; ‘Background’, ‘Cycle’, ‘Person’. (Source)



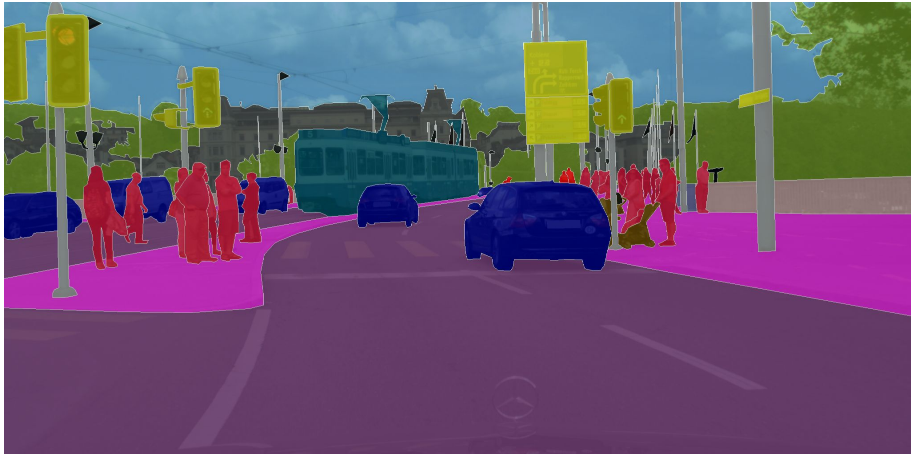
DNN: ResNet-101

- Neural networks have certain problems that made them very difficult to train as they got deeper.
- A major problem was that of exploding or vanishing gradients, where partial derivatives calculated between the error and weights of a particular layer became very large or small as the intermediate values got multiplied.
- ResNets solved this problem by using skip connections between layers. Since the network could now be very deep, a novel bottleneck design with 1x1 convolution filters was used to reduce time complexity while preserving accuracy.
- ResNet-101 has 101 layers, and is used for feature extraction in this project.



Dataset: Cityscapes

- Made for semantic understanding of urban street scenes. Contains pixel-level labeling for semantic segmentation.
- 30 classes, including; ‘road’, ‘sidewalk’, ‘person’, ‘rider’ etc.
- 5000 images with fine annotation, 20000 with coarse annotations.
- Diverse data. Images consist of a large number of dynamic objects. Collected from 50 European cities, over several months with varying backgrounds and scene layouts.



Example of a finely annotated segmentation from the dataset.

Loss: Cross Entropy

- In information theory, cross-entropy between two distributions *p* and *q* over a set of common events measures the average number of bits required to identify an event drawn from the set if a coding scheme is used for the set is optimized for an estimated distribution *q* rather than the true distribution *p*.
- In terms of classification, the true distribution *p(x)* for an object *x* would be (y_1,y_2, … , y_k, … , y_n), where y_k = 1 for the true class k, and y_i = 0 for others. The distribution approximated by our model might predict y_k to be some value less than one, while some y_i's have a value greater than 0.
- Cross-entropy is minimized when the predicted distribution matches the true distribution.
- This is equivalent to minimizing the KL divergence between two distributions.
- Given by:

$$-\sum_{i=1}^{n} y_k log(p(x_k))$$

Dice Coefficient

- For determining the goodness of the predicted segmentation, we use the Dice coefficient.
- It is given by:

$$\frac{2|X \cap Y|}{|X| + |Y|}$$

- Where *X* and *Y* are the set of points belonging the predicted segmentation and the true segmentation respectively.

Proposed Pairwise Loss

- Inspired by the Dice coefficient and the limitation of cross entropy loss (not being able to penalize misclassified samples) we propose a pairwise confusion reward that can be used with cross entropy.
- Considering the classes ‘Road’ (R) and ‘Sidewalk’ (S) whose pairwise confusion we wish to maximize, the loss is given by:

$$PW_{R,S} = \frac{2\sum R_{gt}R_{pred}P_R}{\sum R_{gt}R_{pred}(1+P_r) + \sum R_{gt}S_{pred}P_S}$$

- We wish to maximize this term as it must reduce confusion between the ‘Road’ and ‘Sidewalk’ pixels. We expect that this in turn improves accuracy.

Smooth Cross Entropy

- The pairwise loss is weighted with cross entropy. This helps in reducing confusion between classes that are spatially nearby, while also improving performance.
- Given by:

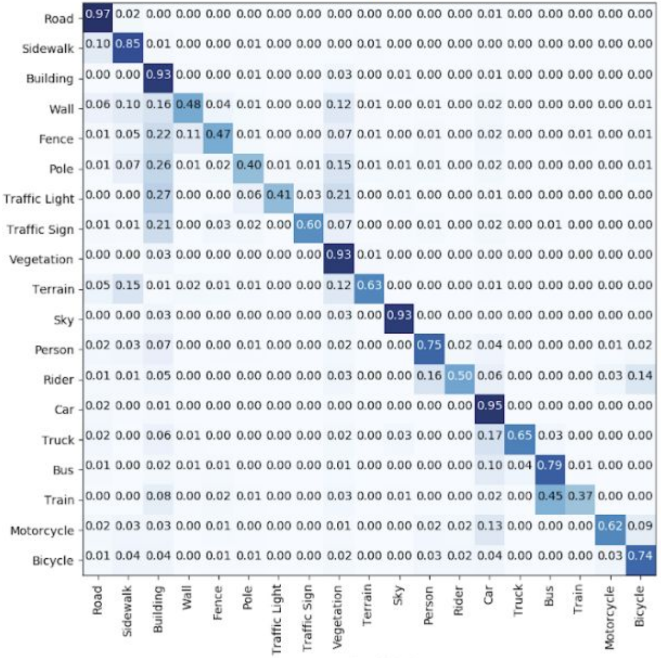
$$\lambda_1 H(p, q) + \lambda_2 PW_{R,S}$$

- Where λ_1 and λ_2 are set to 0.8 and 0.2 respectively.

Results

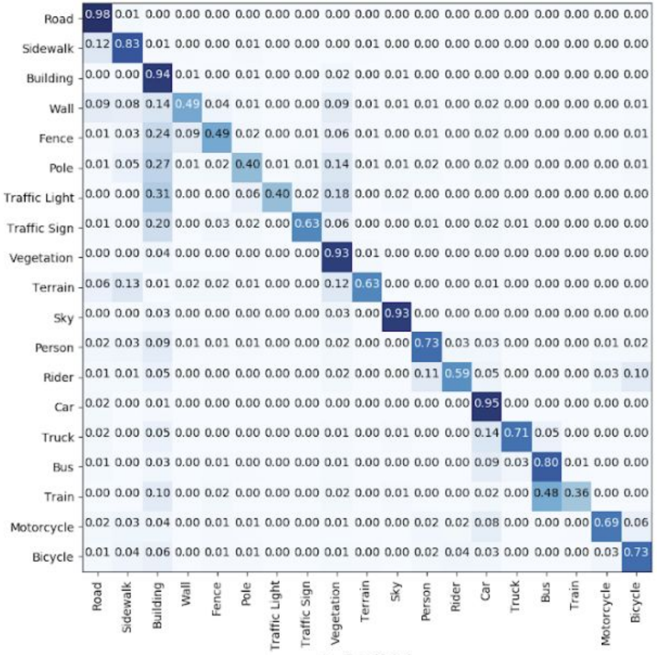
- The proposed loss is able to improve mIoU by at least 1% in all our experiments, as compared to traditional cross entropy loss.
- We reduce the confusion between classes selected for the pairwise confusion reward. For example, we were able to reduce confusion between the ‘Road’ and ‘Sidewalk’ classes from 0.21 to 0.09.
- We also managed to increase the separation between the feature vectors of classes. For example, the average distance between the feature vectors of the ‘Bus’ and ‘Train’ classes was 10.14 units while using cross entropy, but increased to 23.39 units with the proposed loss. This means that the confusion between the classes reduced.

Results



Cross Entropy(CE) 57.03

	Road	Sidewalk	Building	Wall	Fence	Pole	Traffic Light	Traffic Sign	Vegetation	Terrain	Sky	Person	Rider	Car	Truck	Bus	Train	Motorcycle	Bicycle
Road	0.97	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
Sidewalk	0.10	0.85	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Building	0.00	0.00	0.93	0.00	0.00	0.01	0.00	0.00	0.03	0.00	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
Wall	0.06	0.10	0.16	0.48	0.04	0.01	0.00	0.00	0.12	0.01	0.00	0.01	0.00	0.02	0.00	0.00	0.00	0.00	0.01
Fence	0.01	0.05	0.22	0.11	0.47	0.01	0.00	0.00	0.07	0.01	0.00	0.01	0.00	0.02	0.00	0.00	0.01	0.00	0.01
Pole	0.01	0.07	0.26	0.01	0.02	0.40	0.01	0.01	0.15	0.01	0.01	0.01	0.00	0.02	0.00	0.00	0.00	0.00	0.01
Traffic Light	0.00	0.00	0.27	0.00	0.00	0.06	0.41	0.03	0.21	0.00	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
Traffic Sign	0.01	0.01	0.21	0.00	0.03	0.02	0.00	0.60	0.07	0.00	0.00	0.01	0.00	0.02	0.00	0.01	0.00	0.00	0.00
Vegetation	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.93	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Terrain	0.05	0.15	0.01	0.02	0.01	0.01	0.00	0.00	0.12	0.63	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
Sky	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.93	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Person	0.02	0.03	0.07	0.00	0.00	0.01	0.00	0.00	0.02	0.00	0.00	0.75	0.02	0.04	0.00	0.00	0.00	0.01	0.02
Rider	0.01	0.01	0.05	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.16	0.50	0.06	0.00	0.00	0.00	0.03	0.14
Car	0.02	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.95	0.00	0.00	0.00	0.00	0.00
Truck	0.02	0.00	0.06	0.01	0.00	0.00	0.00	0.00	0.02	0.00	0.03	0.00	0.00	0.17	0.65	0.03	0.00	0.00	0.00
Bus	0.01	0.00	0.02	0.01	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.10	0.04	0.79	0.01	0.00	0.00
Train	0.00	0.00	0.08	0.00	0.02	0.01	0.00	0.00	0.03	0.00	0.01	0.00	0.00	0.02	0.00	0.45	0.37	0.00	0.00
Motorcycle	0.02	0.03	0.03	0.00	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.02	0.02	0.13	0.00	0.00	0.00	0.62	0.09
Bicycle	0.01	0.04	0.04	0.00	0.01	0.01	0.00	0.00	0.02	0.00	0.00	0.03	0.02	0.04	0.00	0.00	0.00	0.03	0.74

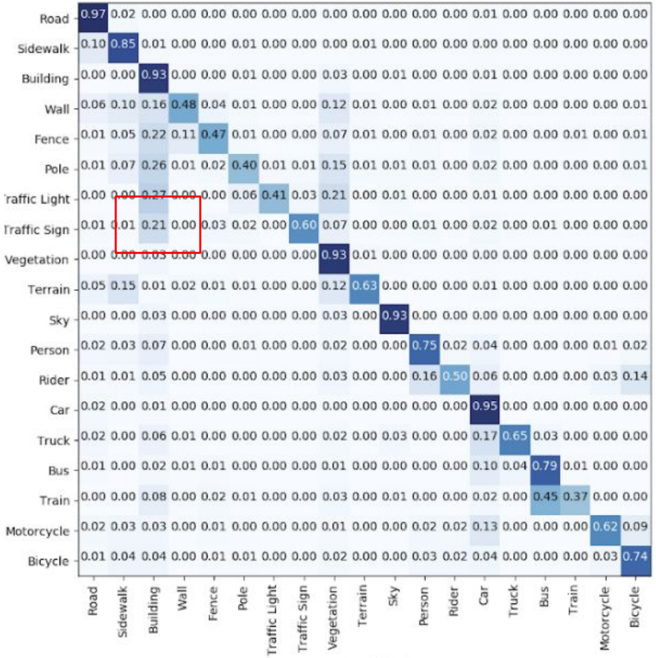


Cross Entropy(CE) + Dice (58.03)

	Road	Sidewalk	Building	Wall	Fence	Pole	Traffic Light	Traffic Sign	Vegetation	Terrain	Sky	Person	Rider	Car	Truck	Bus	Train	Motorcycle	Bicycle
Road	0.98	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sidewalk	0.12	0.83	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Building	0.00	0.00	0.94	0.01	0.00	0.01	0.00	0.00	0.02	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Wall	0.09	0.08	0.14	0.49	0.04	0.01	0.00	0.00	0.09	0.01	0.01	0.01	0.00	0.02	0.00	0.00	0.00	0.00	0.01
Fence	0.01	0.03	0.24	0.09	0.49	0.02	0.00	0.01	0.06	0.01	0.00	0.01	0.00	0.02	0.00	0.00	0.00	0.00	0.01
Pole	0.01	0.05	0.27	0.01	0.02	0.40	0.01	0.01	0.14	0.01	0.01	0.02	0.00	0.02	0.00	0.00	0.00	0.00	0.01
Traffic Light	0.00	0.00	0.31	0.00	0.00	0.06	0.40	0.02	0.18	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Traffic Sign	0.01	0.00	0.20	0.00	0.03	0.02	0.00	0.63	0.06	0.00	0.00	0.01	0.00	0.02	0.01	0.00	0.00	0.00	0.00
Vegetation	0.00	0.00	0.04	0.00	0.00	0.00	0.00	0.00	0.93	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Terrain	0.06	0.13	0.01	0.02	0.02	0.01	0.00	0.00	0.12	0.63	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
Sky	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.93	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Person	0.02	0.03	0.09	0.01	0.01	0.01	0.00	0.00	0.02	0.00	0.00	0.73	0.03	0.03	0.00	0.00	0.00	0.01	0.02
Rider	0.01	0.01	0.05	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.11	0.59	0.05	0.00	0.00	0.00	0.03	0.10
Car	0.02	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.95	0.00	0.00	0.00	0.00	0.00
Truck	0.02	0.00	0.05	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.01	0.00	0.00	0.14	0.71	0.05	0.00	0.00	0.00
Bus	0.01	0.00	0.03	0.00	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.09	0.03	0.80	0.01	0.00	0.00
Train	0.00	0.00	0.10	0.00	0.02	0.00	0.00	0.00	0.02	0.00	0.01	0.00	0.00	0.02	0.00	0.48	0.36	0.00	0.00
Motorcycle	0.02	0.03	0.04	0.00	0.01	0.01	0.00	0.00	0.01	0.00	0.00	0.02	0.02	0.08	0.00	0.00	0.00	0.69	0.06
Bicycle	0.01	0.04	0.06	0.00	0.01	0.01	0.00	0.00	0.01	0.00	0.00	0.02	0.04	0.03	0.00	0.00	0.00	0.03	0.73

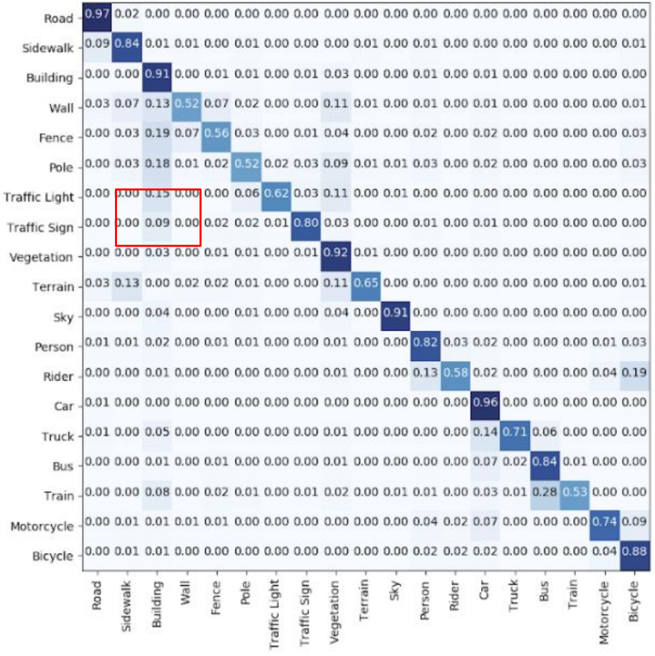
Results

Cross Entropy(CE) 57.03



	Road	Sidewalk	Building	Wall	Fence	Pole	Traffic Light	Traffic Sign	Vegetation	Terrain	Sky	Person	Rider	Car	Truck	Bus	Train	Motorcycle	Bicycle
Road	0.97	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
Sidewalk	0.10	0.85	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Building	0.00	0.00	0.93	0.00	0.00	0.01	0.00	0.00	0.03	0.00	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
Wall	0.06	0.10	0.16	0.48	0.04	0.01	0.00	0.00	0.12	0.01	0.00	0.01	0.00	0.02	0.00	0.00	0.00	0.00	0.01
Fence	0.01	0.05	0.22	0.11	0.47	0.01	0.00	0.00	0.07	0.01	0.00	0.01	0.00	0.02	0.00	0.00	0.01	0.00	0.01
Pole	0.01	0.07	0.26	0.01	0.02	0.40	0.01	0.01	0.15	0.01	0.01	0.01	0.00	0.02	0.00	0.00	0.00	0.00	0.01
raffic Light	0.00	0.00	0.27	0.00	0.00	0.06	0.41	0.03	0.21	0.00	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
Traffic Sign	0.01	0.01	0.21	0.00	0.03	0.02	0.00	0.60	0.07	0.00	0.00	0.01	0.00	0.02	0.00	0.01	0.00	0.00	0.00
Vegetation	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.93	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Terrain	0.05	0.15	0.01	0.02	0.01	0.01	0.00	0.00	0.12	0.63	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
Sky	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.93	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Person	0.02	0.03	0.07	0.00	0.00	0.01	0.00	0.00	0.02	0.00	0.00	0.75	0.02	0.04	0.00	0.00	0.00	0.01	0.02
Rider	0.01	0.01	0.05	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.16	0.50	0.06	0.00	0.00	0.00	0.03	0.14
Car	0.02	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.95	0.00	0.00	0.00	0.00	0.00
Truck	0.02	0.00	0.06	0.01	0.00	0.00	0.00	0.00	0.02	0.00	0.03	0.00	0.00	0.17	0.65	0.03	0.00	0.00	0.00
Bus	0.01	0.00	0.02	0.01	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.10	0.04	0.79	0.01	0.00	0.00
Train	0.00	0.00	0.08	0.00	0.02	0.01	0.00	0.00	0.03	0.00	0.01	0.00	0.00	0.02	0.00	0.45	0.37	0.00	0.00
Motorcycle	0.02	0.03	0.03	0.00	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.02	0.02	0.13	0.00	0.00	0.00	0.62	0.09
Bicycle	0.01	0.04	0.04	0.00	0.01	0.01	0.00	0.00	0.02	0.00	0.00	0.03	0.02	0.04	0.00	0.00	0.00	0.03	0.74

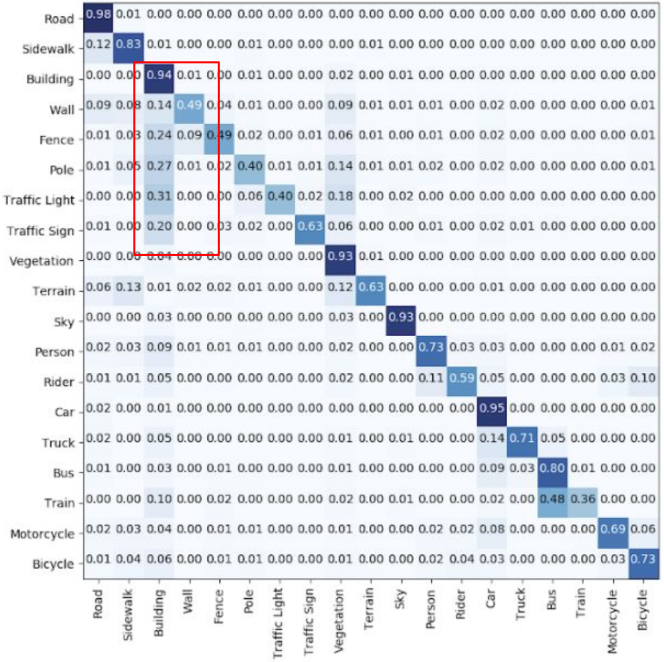
(WCE) + PW_(Building , traffic sign) 58.35



	Road	Sidewalk	Building	Wall	Fence	Pole	Traffic Light	Traffic Sign	Vegetation	Terrain	Sky	Person	Rider	Car	Truck	Bus	Train	Motorcycle	Bicycle
Road	0.97	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sidewalk	0.09	0.84	0.01	0.01	0.00	0.01	0.00	0.00	0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.01
Building	0.00	0.00	0.91	0.00	0.01	0.01	0.00	0.01	0.03	0.00	0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00
Wall	0.03	0.07	0.13	0.52	0.07	0.02	0.00	0.00	0.11	0.01	0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.01
Fence	0.00	0.03	0.19	0.07	0.56	0.03	0.00	0.01	0.04	0.00	0.00	0.02	0.00	0.02	0.00	0.00	0.00	0.00	0.03
Pole	0.00	0.03	0.18	0.01	0.02	0.52	0.02	0.03	0.09	0.01	0.01	0.03	0.00	0.02	0.00	0.00	0.00	0.00	0.03
Traffic Light	0.00	0.00	0.15	0.00	0.00	0.06	0.62	0.03	0.11	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Traffic Sign	0.00	0.00	0.09	0.00	0.02	0.02	0.01	0.80	0.03	0.00	0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00
Vegetation	0.00	0.00	0.03	0.00	0.01	0.01	0.00	0.01	0.92	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Terrain	0.03	0.13	0.00	0.02	0.02	0.01	0.00	0.00	0.11	0.65	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01
Sky	0.00	0.00	0.04	0.00	0.00	0.01	0.00	0.00	0.04	0.00	0.91	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Person	0.01	0.01	0.02	0.00	0.01	0.01	0.00	0.00	0.01	0.00	0.00	0.82	0.03	0.02	0.00	0.00	0.00	0.01	0.03
Rider	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.13	0.58	0.02	0.00	0.00	0.00	0.04	0.19
Car	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.96	0.00	0.00	0.00	0.00	0.00
Truck	0.01	0.00	0.05	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.14	0.71	0.06	0.00	0.00	0.00
Bus	0.00	0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.07	0.02	0.84	0.01	0.00	0.00
Train	0.00	0.00	0.08	0.00	0.02	0.01	0.00	0.01	0.02	0.00	0.01	0.01	0.00	0.03	0.01	0.28	0.53	0.00	0.00
Motorcycle	0.00	0.01	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.04	0.02	0.07	0.00	0.00	0.00	0.74	0.09
Bicycle	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.02	0.02	0.00	0.00	0.00	0.04	0.88

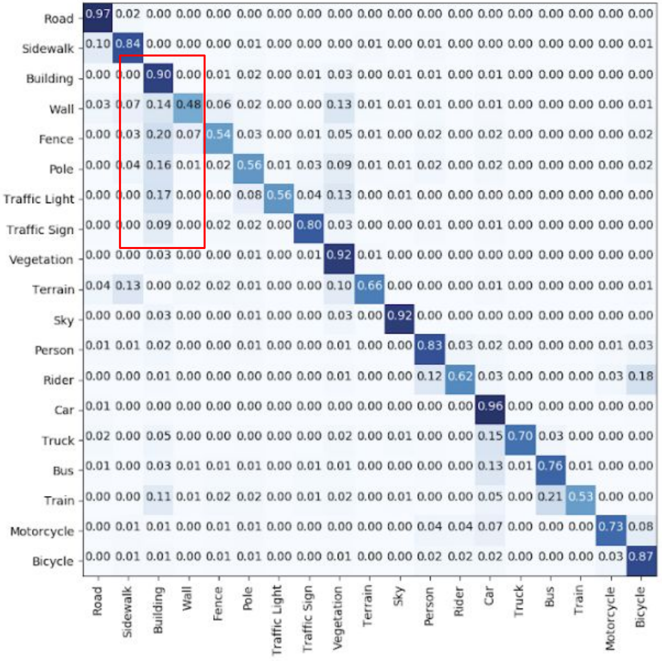
Results

Cross Entropy(CE) + Dice (58.03)



	Road	Sidewalk	Building	Wall	Fence	Pole	Traffic Light	Traffic Sign	Vegetation	Terrain	Sky	Person	Rider	Car	Truck	Bus	Train	Motorcycle	Bicycle
Road	0.98	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sidewalk	0.12	0.83	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Building	0.00	0.00	0.94	0.01	0.00	0.01	0.00	0.00	0.02	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Wall	0.09	0.08	0.14	0.49	0.04	0.01	0.00	0.00	0.09	0.01	0.01	0.01	0.00	0.02	0.00	0.00	0.00	0.00	0.01
Fence	0.01	0.03	0.24	0.09	0.49	0.02	0.00	0.01	0.06	0.01	0.00	0.01	0.00	0.02	0.00	0.00	0.00	0.00	0.01
Pole	0.01	0.05	0.27	0.01	0.02	0.40	0.01	0.01	0.14	0.01	0.01	0.02	0.00	0.02	0.00	0.00	0.00	0.00	0.01
Traffic Light	0.00	0.00	0.31	0.00	0.00	0.06	0.40	0.02	0.18	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Traffic Sign	0.01	0.00	0.20	0.00	0.03	0.02	0.00	0.63	0.06	0.00	0.00	0.01	0.00	0.02	0.01	0.00	0.00	0.00	0.00
Vegetation	0.00	0.00	0.04	0.00	0.00	0.00	0.00	0.00	0.93	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Terrain	0.06	0.13	0.01	0.02	0.02	0.01	0.00	0.00	0.12	0.63	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
Sky	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.93	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Person	0.02	0.03	0.09	0.01	0.01	0.01	0.00	0.00	0.02	0.00	0.00	0.73	0.03	0.03	0.00	0.00	0.00	0.01	0.02
Rider	0.01	0.01	0.05	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.11	0.59	0.05	0.00	0.00	0.00	0.03	0.10
Car	0.02	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.95	0.00	0.00	0.00	0.00	0.00
Truck	0.02	0.00	0.05	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.01	0.00	0.00	0.14	0.71	0.05	0.00	0.00	0.00
Bus	0.01	0.00	0.03	0.00	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.09	0.03	0.80	0.01	0.00	0.00
Train	0.00	0.00	0.10	0.00	0.02	0.00	0.00	0.00	0.02	0.00	0.01	0.00	0.00	0.02	0.00	0.48	0.36	0.00	0.00
Motorcycle	0.02	0.03	0.04	0.00	0.01	0.01	0.00	0.00	0.01	0.00	0.00	0.02	0.02	0.08	0.00	0.00	0.00	0.69	0.06
Bicycle	0.01	0.04	0.06	0.00	0.01	0.01	0.00	0.00	0.01	0.00	0.00	0.02	0.04	0.03	0.00	0.00	0.00	0.03	0.73

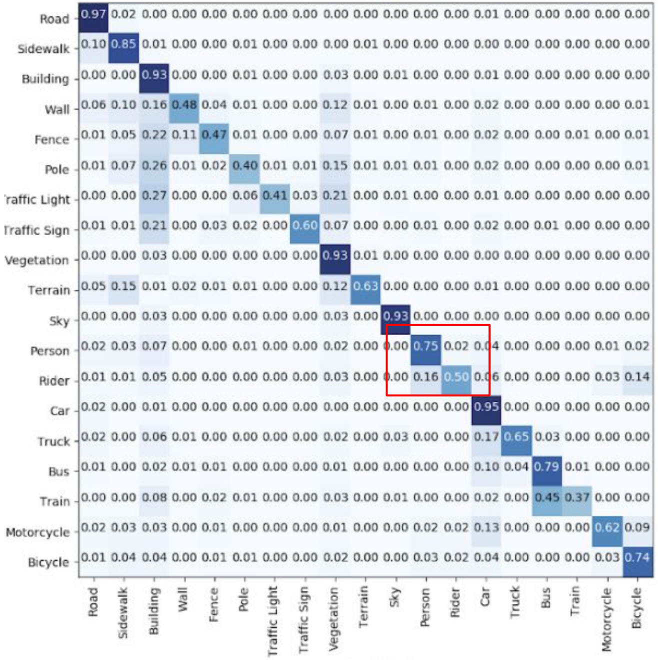
(WCE) + PW_(2-7) 59.29



	Road	Sidewalk	Building	Wall	Fence	Pole	Traffic Light	Traffic Sign	Vegetation	Terrain	Sky	Person	Rider	Car	Truck	Bus	Train	Motorcycle	Bicycle
Road	0.97	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sidewalk	0.10	0.84	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.01
Building	0.00	0.00	0.90	0.00	0.01	0.02	0.00	0.01	0.03	0.00	0.01	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00
Wall	0.03	0.07	0.14	0.48	0.06	0.02	0.00	0.00	0.13	0.01	0.01	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.01
Fence	0.00	0.03	0.20	0.07	0.54	0.03	0.00	0.01	0.05	0.01	0.00	0.02	0.00	0.02	0.00	0.00	0.00	0.00	0.02
Pole	0.00	0.04	0.16	0.01	0.02	0.56	0.01	0.03	0.09	0.01	0.01	0.02	0.00	0.02	0.00	0.00	0.00	0.00	0.02
Traffic Light	0.00	0.00	0.17	0.00	0.00	0.08	0.56	0.04	0.13	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Traffic Sign	0.00	0.00	0.09	0.00	0.02	0.02	0.00	0.80	0.03	0.00	0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00
Vegetation	0.00	0.00	0.03	0.00	0.00	0.01	0.00	0.01	0.92	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Terrain	0.04	0.13	0.00	0.02	0.02	0.01	0.00	0.00	0.10	0.66	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.01
Sky	0.00	0.00	0.03	0.00	0.00	0.01	0.00	0.00	0.03	0.00	0.92	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Person	0.01	0.01	0.02	0.00	0.00	0.01	0.00	0.00	0.01	0.00	0.00	0.83	0.03	0.02	0.00	0.00	0.00	0.01	0.03
Rider	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.12	0.62	0.03	0.00	0.00	0.00	0.03	0.18
Car	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.96	0.00	0.00	0.00	0.00	0.00
Truck	0.02	0.00	0.05	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.01	0.00	0.00	0.15	0.70	0.03	0.00	0.00	0.00
Bus	0.01	0.00	0.03	0.01	0.01	0.01	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.13	0.01	0.76	0.01	0.00	0.00
Train	0.00	0.00	0.11	0.01	0.02	0.02	0.00	0.01	0.02	0.00	0.01	0.00	0.00	0.05	0.00	0.21	0.53	0.00	0.00
Motorcycle	0.00	0.01	0.01	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.04	0.04	0.07	0.00	0.00	0.00	0.73	0.08
Bicycle	0.00	0.01	0.01	0.00	0.01	0.01	0.00	0.00	0.01	0.00	0.00	0.02	0.02	0.02	0.00	0.00	0.00	0.03	0.87

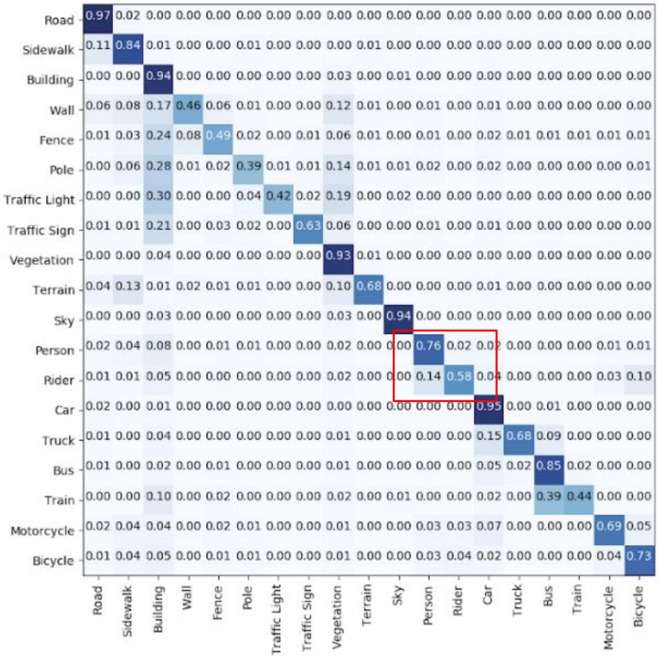
Results

Cross Entropy(CE) 57.03



	Road	Sidewalk	Building	Wall	Fence	Pole	Traffic Light	Traffic Sign	Vegetation	Terrain	Sky	Person	Rider	Car	Truck	Bus	Train	Motorcycle	Bicycle
Road	0.97	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
Sidewalk	0.10	0.85	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Building	0.00	0.00	0.93	0.00	0.00	0.01	0.00	0.00	0.03	0.00	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
Wall	0.06	0.10	0.16	0.48	0.04	0.01	0.00	0.00	0.12	0.01	0.00	0.01	0.00	0.02	0.00	0.00	0.00	0.00	0.01
Fence	0.01	0.05	0.22	0.11	0.47	0.01	0.00	0.00	0.07	0.01	0.00	0.01	0.00	0.02	0.00	0.00	0.01	0.00	0.01
Pole	0.01	0.07	0.26	0.01	0.02	0.40	0.01	0.01	0.15	0.01	0.01	0.01	0.00	0.02	0.00	0.00	0.00	0.00	0.01
raffic Light	0.00	0.00	0.27	0.00	0.00	0.06	0.41	0.03	0.21	0.00	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
Traffic Sign	0.01	0.01	0.21	0.00	0.03	0.02	0.00	0.60	0.07	0.00	0.00	0.01	0.00	0.02	0.00	0.01	0.00	0.00	0.00
Vegetation	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.93	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Terrain	0.05	0.15	0.01	0.02	0.01	0.01	0.00	0.00	0.12	0.63	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
Sky	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.93	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Person	0.02	0.03	0.07	0.00	0.00	0.01	0.00	0.00	0.02	0.00	0.00	0.75	0.02	0.04	0.00	0.00	0.00	0.01	0.02
Rider	0.01	0.01	0.05	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.16	0.50	0.06	0.00	0.00	0.00	0.03	0.14
Car	0.02	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.95	0.00	0.00	0.00	0.00	0.00
Truck	0.02	0.00	0.06	0.01	0.00	0.00	0.00	0.00	0.02	0.00	0.03	0.00	0.00	0.17	0.65	0.03	0.00	0.00	0.00
Bus	0.01	0.00	0.02	0.01	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.10	0.04	0.79	0.01	0.00	0.00
Train	0.00	0.00	0.08	0.00	0.02	0.01	0.00	0.00	0.03	0.00	0.01	0.00	0.00	0.02	0.00	0.45	0.37	0.00	0.00
Motorcycle	0.02	0.03	0.03	0.00	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.02	0.02	0.13	0.00	0.00	0.00	0.62	0.09
Bicycle	0.01	0.04	0.04	0.00	0.01	0.01	0.00	0.00	0.02	0.00	0.00	0.03	0.02	0.04	0.00	0.00	0.00	0.03	0.74

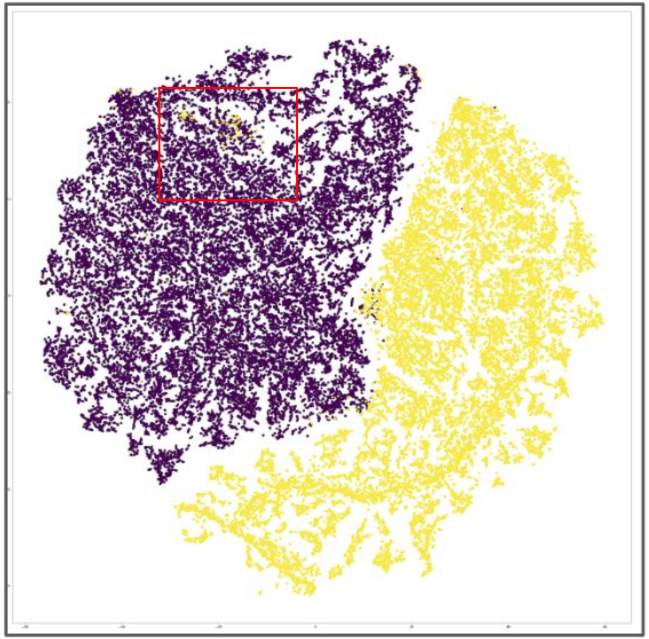
(WCE) + PW_(person , rider) 58.45



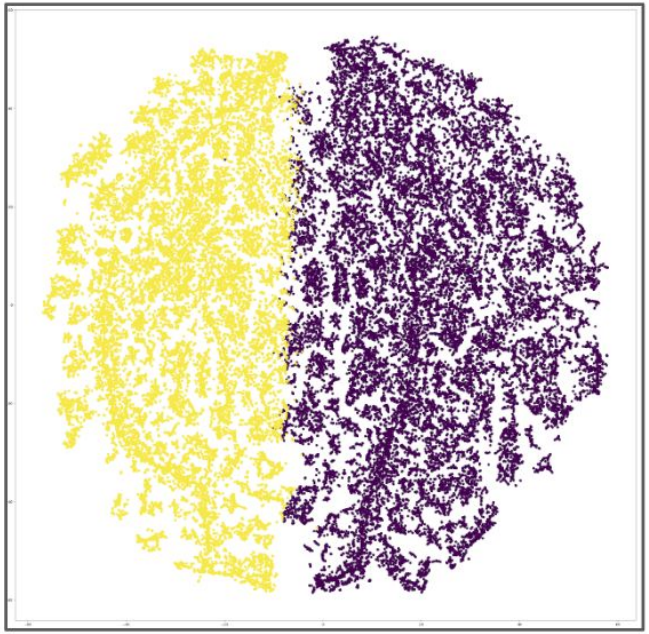
	Road	Sidewalk	Building	Wall	Fence	Pole	Traffic Light	Traffic Sign	Vegetation	Terrain	Sky	Person	Rider	Car	Truck	Bus	Train	Motorcycle	Bicycle
Road	0.97	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sidewalk	0.11	0.84	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Building	0.00	0.00	0.94	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Wall	0.06	0.08	0.17	0.46	0.06	0.01	0.00	0.00	0.12	0.01	0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00
Fence	0.01	0.03	0.24	0.08	0.49	0.02	0.00	0.01	0.06	0.01	0.00	0.01	0.00	0.02	0.01	0.01	0.01	0.01	0.01
Pole	0.00	0.06	0.28	0.01	0.02	0.39	0.01	0.01	0.14	0.01	0.01	0.02	0.00	0.02	0.00	0.00	0.00	0.00	0.01
Traffic Light	0.00	0.00	0.30	0.00	0.00	0.04	0.42	0.02	0.19	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Traffic Sign	0.01	0.01	0.21	0.00	0.03	0.02	0.00	0.63	0.06	0.00	0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00
Vegetation	0.00	0.00	0.04	0.00	0.00	0.00	0.00	0.00	0.93	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Terrain	0.04	0.13	0.01	0.02	0.01	0.01	0.00	0.00	0.10	0.68	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
Sky	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.94	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Person	0.02	0.04	0.08	0.00	0.01	0.01	0.00	0.00	0.02	0.00	0.00	0.76	0.02	0.02	0.00	0.00	0.00	0.01	0.01
Rider	0.01	0.01	0.05	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.14	0.58	0.04	0.00	0.00	0.00	0.03	0.10
Car	0.02	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.95	0.00	0.01	0.00	0.00	0.00
Truck	0.01	0.00	0.04	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.15	0.68	0.09	0.00	0.00	0.00
Bus	0.01	0.00	0.02	0.00	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.05	0.02	0.85	0.02	0.00	0.00
Train	0.00	0.00	0.10	0.00	0.02	0.00	0.00	0.00	0.02	0.00	0.01	0.00	0.00	0.02	0.00	0.39	0.44	0.00	0.00
Motorcycle	0.02	0.04	0.04	0.00	0.02	0.01	0.00	0.00	0.01	0.00	0.00	0.03	0.03	0.07	0.00	0.00	0.00	0.69	0.05
Bicycle	0.01	0.04	0.05	0.00	0.01	0.01	0.00	0.00	0.01	0.00	0.00	0.03	0.04	0.02	0.00	0.00	0.00	0.04	0.73

Results

CE Bus_Train 10.14



CE PW Bus_Train 23.39



Conclusion

- We analyse the shortcomings of traditional cross entropy wherein it does not penalize misclassification made by the network.
- We also note that the loss does not consider the confusion caused by neighboring pixels during classification.
- The proposed loss attempts to incorporate these and shows that it is capable of reducing inter-class confusion and improving performance.
- However it was seen that reducing the confusion between two classes caused confusion to increase elsewhere. More research can be done regarding this in the future.