Semantic segmentation using full convolutional network

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Abstract

In this report, we explore the full convolutional network (fcn) and use full convolutional network to perform semantic segmentation task on Indian driving dataset. Using our baseline dataset, we archive pixel accuracy of 0.79 and average IOU of 0.33.

1   Introduction

In the report we try to solve the sematic segmentation task using full convolutional network. The goal of semantic segmentation is to label each pixel of an image with a corresponding class of what is being represented [5]. To solve the task, we utilize full convolutional network. In full convolutional network, there is no fully connected layer, only convolutional layer. In the full convolutional network structure, we use Xavier weight initialization. Deep neural network suffers from weight vanishing problem. If we use normal weight initialization methods like uniform distribution, the weight will vanish quickly during matrix calculation. Therefore, we introduces Xavier weight initialization [3], which can help us eliminate the problem. To further improve the training speed and stability of the network, we introduce batch normalization layer [4]. The batch normalization layer solves that the distribution of each layer's inputs changes during training by normalizing layer inputs.

2   Related Work

3   Methods

3.1   Baseline

The baseline model is an encoder-decoder structure. It first encode the picture using convolution layers and then decode the segmentation map using deconvolution layers. In the baseline model, we use batch normalization and use ReLU as the activation function. For the last layer, we use softmax to get the classify results.

3.2   Improved baseline

3.2.1   Dataset Augmentation

From the baseline model, we tried to do some data augmentation on the training dataset to see whether the performance could be approved. Since training is quite time-consuming, in this report, we implemented and tested two different data augmentation algorithm and tried to compare the performance with each other.

The data augmentation methods used are:

- Mirror flip: for the training dataset, we mirror flipped the dataset and fed them into the model

- Image Rotating: rotate the images slightly (for a certain degree), in this report, we tried to rotate the images by 1 degree and then fed them into the model

3.2.2   Imbalanced class problem

For the imbalanced class problem, what we usually do is to pressuring the network to categorize the infrequently seen class. We proposed to use the weighted loss method to accommodate this issue, which will weight infrequent classes more.

For the weighted loss, the idea is to set the weight of the loss of each class inversely proportion to the frequency of each class in the training dataset. For the data pre-processing, we calculated the total pixel count of each class in all the training dataset and then use this information to help us set the weight of the loss.

Suppose, the number of samples for each class is stored in nSamples, then we use $\text{normedWeights} = [1 - (x / \sum \text{nSamples})$ for x in nSamples$]$ as the normalized weight of the loss for each class.

For this dataset, we calculated the number of samples for each class is:

$\text{nSamples} = [2198453584, 519609102, 28929892, 126362539, 58804972, 59032134,$

$94293190, 2569952, 101519794, 163659019, 105075839, 47400301, 30998126, 133835645,$

$135950687, 41339482, 15989829, 104795610, 8062798, 450973, 94820222, 341805135,$

$557016609, 71159311, 1465165566, 1823922767, 2775322]$

Then we could be able to set the weight of the loss for each class according to nSamples.

3.3   Custom model

Inspired by this paper[2], we replace the encoder part in FCN model with the RRCNN layer instead, the RRCNN represent better abstraction ability, thus we would expect better IoU and precision. However the RRCNN is really memory-intensive, we have to crop the image to only 256 *256 size and delete 3 layers from original model's encoding part, which severly influence the performance of our model. What's worse is the RRCNN encoding part contains maxpooling operation after each RRCNN block, which means the images size would shrinks even more, since we have already started from a relative small size, maxpool will almost ruin all the details in the feature map.

3.4 Transfer learning

In this part we employ the DEEPLABV3-RESNET101 model, which is a default pre-trained net work in PyTorch, from the website[1] we know that this model is constructed by a Deeplabv3 model with a ResNet-101 backbone. The pre-trained model has been trained on a subset of COCO train2017, on the 20 categories that are present in the Pascal VOC dataset. We modifier the classifier part so that it could match the number of our feature, and we freeze the parameters of the pretrained part to accelerate the whole procedure.

3.5 U-Net

Folowing the routine demostrated in the U-net paper [6], we build the U-net by our self. The obvious difference is the U-net convolution block contains 2 convolution of the same size, while the FCN model only contains 1 convolution operation. We notice that the U-net model is also memory intensive while the datahub only give us a GTX 1080 ti with 11GB memory, hence there's a trade-off of between batch size, image size and model's completeness. We decide to crop the image and shrink the batch size to run the whole model, though this might not be the best solution, but this could give us a flavor of how the complete network looks like.

4 Results

Table 1: Pixel accuracy and IOUs for different models

Model	Pixel accuracy	Mean IOU	road IOU	sidewalk IOU	car IOU	billboard IOU	sky IOU
Baseline	0.7944	0.3371	0.8632	0.2323	0.5084	0.2419	0.9403
Mirror flip	0.6953	0.2313	0.7477	0.0874	0.2262	0.2542	0.8105
Rotation	0.7936	0.3393	0.8577	0.2483	0.4857	0.2755	0.9445
weighted loss	0.7991	0.3444	0.8648	0.2406	0.5104	0.2967	0.9472
Custom	TBA	TBA	TBA	TBA	TBA	TBA	TBA
Transfer learning	TBA	TBA	TBA	TBA	TBA	TBA	TBA
U-Net	TBA	TBA	TBA	TBA	TBA	TBA	TBA

4.1 Baseline model

Training and Validation loss for baseline model is in Figure 1. Training and Validation pixel accuracy and mean IOUs for baseline model is in Figure 2. Various IOUs for baseline model is in Figure 3.
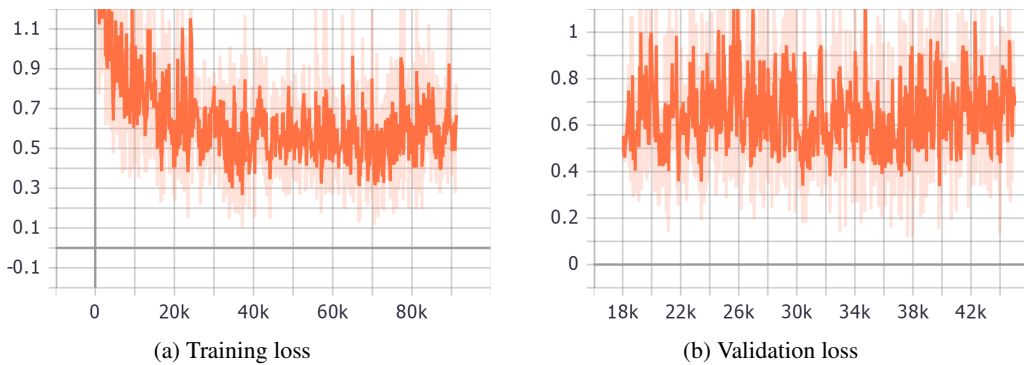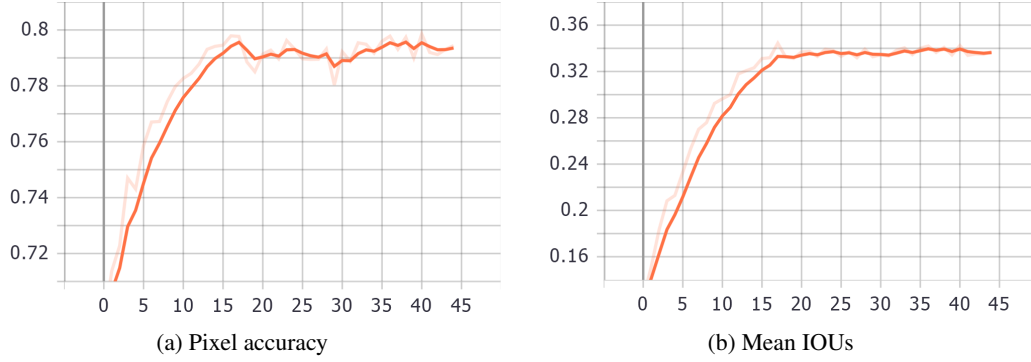

(a) Training loss

(b) Validation loss

Figure 1: Training and Validation loss for baseline model

(a) Pixel accuracy   (b) Mean IOUs

Figure 2: Training and Validation pixel accuracy and mean IOUs for baseline model

(a) Road IOU   (b) Sidewalk IOU   (c) Car IOU   (d) Billboard IOU   (e) Sky IOU
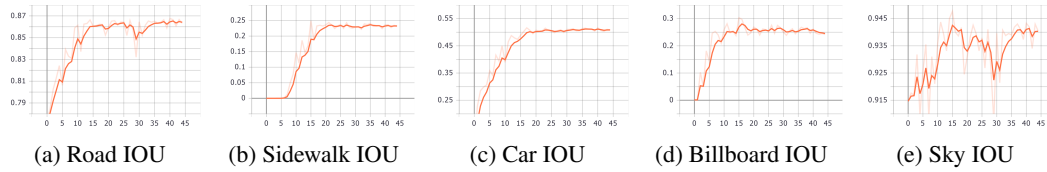
Figure 3: Various IOUs for baseline model

4.2 Improved baseline model

4.2.1 Dataset Augmentation

Table 1 shows the model performance of different augmentation method. From the table, we could see that the performance was improved by 10% simply by rotating the training dataset for a small angle.

The train and validation loss for mirror flip and rotation methods could be seen in Figure 5a and Figure 5b, respectively. The visualization of the segmented output for the first image in the test.csv overlaid on the image for mirror flip and rotation method could be seen in Figure 6a and Figure 6b, respectively.

4.2.2 Imbalanced class problem

The train and validation loss after introducing weighted loss method could be seen in Figure 7a. The performance of the model could be seen in Table 1 and the visualization of the segmented output for the first image in the testdataset overlaid on the image could be seen in Figure 7b

4.3 Custom model

4.4 Transfer learning

4.5 U-Net

5 Discussion

6 Individual contributions to the project

Fangzhou Ai   Custom model, Transfer learning and U-Net model.

Yue Qiao   Evaluation metrics, Dataset loading and Baseline Model.

Zunming Zhang   Improved baseline model with mirror flip, rotate and weighted loss for imbalanced classes.

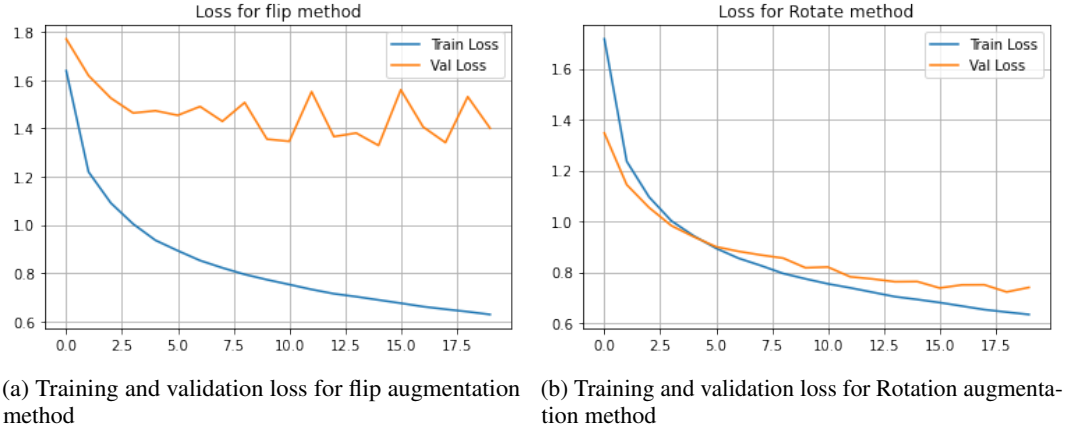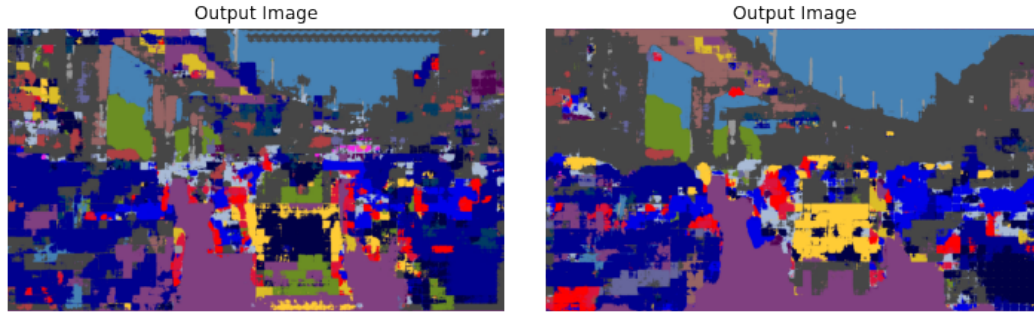Figure 4: Visualization of segmented output for baseline model

(a) Training and validation loss for flip augmentation method

(b) Training and validation loss for Rotation augmentation method

Figure 5: Training and validation loss for different augmentation methods

References

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[6] Olaf Ronneberger, Philipp Fischer, and Thomas Brox. U-net: Convolutional networks for biomedical image segmentation, 2015.

Output Image   Output Image

(a) Visualization of segmented output for Mirror flip augmentation method

(b) Visualization of segmented output for Rotation augmentation method

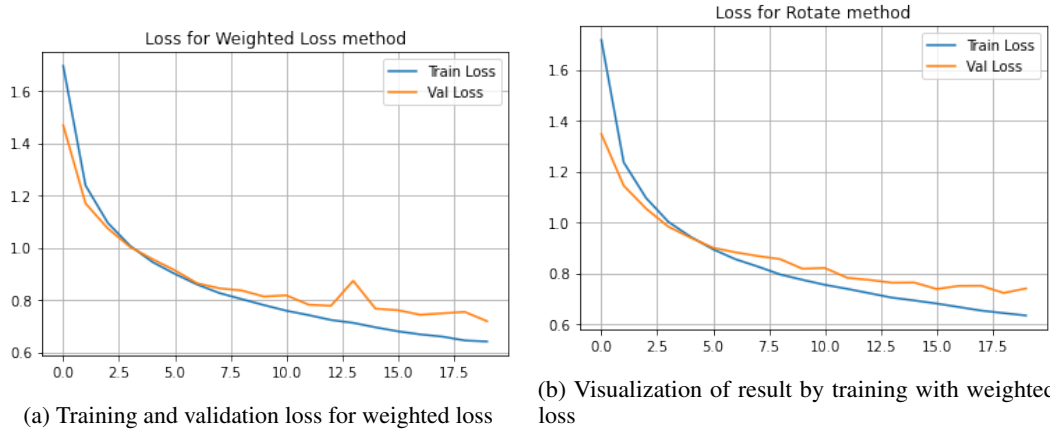Figure 6: Visualization of segmented output for different augmentation methods

(a) Training and validation loss for weighted loss

(b) Visualization of result by training with weighted loss

Figure 7: Weighted loss