Traffic Lane Detection with Fully Convolutional Networks

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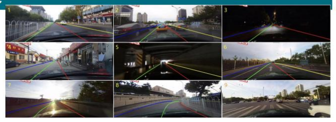
Presentation Video link: https://youtu.be/_7ZCXk3fXbA

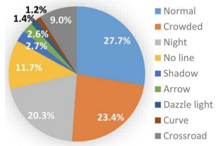
Predicting

Automatic lane detection enables self-driving cars to properly position themselves in a multi-lane urban driving environments. The lack of distinctive road markings can cause lane detection algorithms to be confused by other objects with similar appearance. In this project, we designed an Encoder-Decoder Fully Convolutional Network for lane detection and achieved an accuracy that outperformed the baseline model.

Dataset and Feature

CULane is a large dataset for lane detection which is comprised of 88,880 images for training, 9,675 images for validation and 34,680 images for test. Challenging driving conditions represent more than 72.3% of the whole dataset.

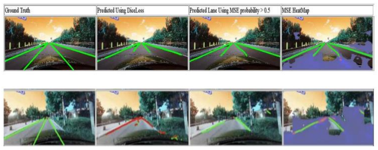




We developed a Python module that scans the dataset folders dynamically to collect the images and labels. We shuffled and divided the dataset into Train (90%) and Dev (10%). Furthermore, we developed a Python Generator script, which enabled us to load all images of the dataset without experiencing any performance issues.

Result

Dice-coefficient loss function provided a better prediction of lane markings. When there are cross lanes and object occlusions all models didn't perform very well which need to apply other techniques such as semantic segmentation or instance segmentation



References

[1] Qin Zou, Hanwen Jiang, Qiyu Dai, Yuanhao Yue, Long Chen, QianWang. Robust Lane Detection from Continuous Driving Scenes Using Deep Neural Networks. arxiv 2019. arXiv:1903.02193

[3] D. Neven, B. D. Brabandere, S. Georgoulis, M. Proesmans, and L. V.Gool, "Towards end-to-end lane detection: an instance segmentation approach," CoRR, vol. abs/1802.05591, 2018.

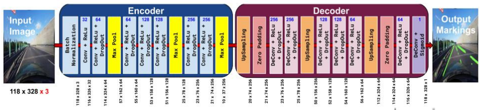
[4] Ze Wang,Weiqiang Ren, Qiang Qiu. LaneNet: Real-Time Lane Detection Networks for AutonomousDriving. arXiv:1807.01726v1 [cs.CV] 4 Jul 2018

[8] CULane: https://drive.google.com/drive/folders/1mSLgwVTiaUMAb4AVOWwlC D5JcWdrwpvu

[10] https://github.com/mvirgo/MLND-Capstone

Models

The Encoder component of our model consists of 7 Convolutional layers mixed with Maxpooling layers and Dropout regularization. Whereas, the decoder component consists of 6 Deconv layers.

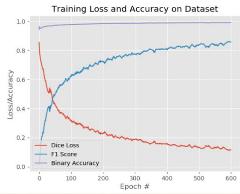


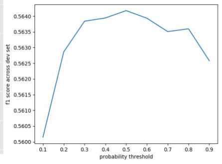
Dice Coefficient Loss Function, was applied to provide more importance to the accuracy of lane detection (label = 1)

$$DC = \frac{2TP}{2TP + FP + FN} = \frac{TP}{TP + FP + FN} = \frac{2|X \cap Y|}{|X| + |Y|}$$

$$DL(p, \hat{p}) = \frac{2\langle p, \hat{p} \rangle}{\|p\|_2^2 + \|\hat{p}\|_2^2}$$

Evaluation Metrics - We obtained an accuracy of 99% , and we calculated the average F1 score across all the 8 probability thresholds of our classifier.





Discussion

In this project we attempted to tackle the complex problem of lane detection using a large scale and challenging dataset. We extended a baseline model which was designed initially to handle small datasets. We developed customer Python modules to load the dataset efficiently. We tuned the hyper-parameters, extended the convolutional layers, added pooling layers and replaced the MSE cost function with the dice cost function.

Future work

Future work include multi-lane instance detection.

1) Use standard FCN (Alexnet, Resnet) as a backbone architecture)

2) Apply various Region-Based Convolutional Neural Networks (Mask R-CNN), designed for object detection and instance segmentation.

3) Apply a multi-task loss function including the loss of classification, localization and segmentation mask.

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