**Group Member**

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**Preliminary Results**

We use KITTI dataset (Fritsch, Kühnl, & Geiger, 2013) to conduct a traffic lane segmentation research. Some of our current results are shown in Figure 1.



Figure 1 Current Results

The loss for each epoch is shown in Figure 2.The results of the upper four images are much better than the bottom ones, which means our algorithm still needs large improvement.

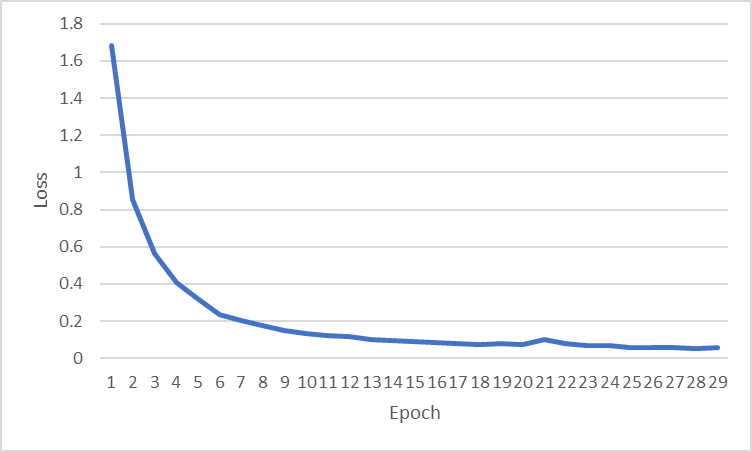


Figure Loss of Each Epoch

**Current Used Approach**

Encoder-decoder architercture is used to solve this problem, besides, we also use skip connections from encoder to decoder to help decoder recover the object details better. Specfically, pretarined VGG-16 model is used for encoder and decorder part is a FCN.

**Original/Final Goal**

The original goal of this project is the detection of traffic lane and road markers. However, since the lack of road markers’ ground truth and the limitation of data sources. The final goal of this project is to conduct a traffic lane segmentation, plus a detection of the driving lanes. As there are many previous works about road segmentation, the work is about do some improvement to exsiting studies.

**The list and the definitions of the base line algorithms to compare your results**

* StixelNet

(Levi, Garnett, Fetaya, & Herzlyia, 2015) proposed a convolutional neural network named StixelNet, which is a multi-layer CNN, the architecture is shown in Figure 3. It is a 5 layer network in which the first two layers are convolutional and the last three are fully connected. The ReLU non-linearity is applied to the output of all layers except the last one, and for the convolutional layers a Max-pooling layer follows the ReLU operation as well. Given a single RGB image vertical stripe Is of dimensions (w; h; 3), this network can find the pixel location y of the bottom point of the closest obstacle in the center column of Is.



Figure 3 StixelNet Architecture

The segmentation task is done in three step, which is shown in Figure 4. The first two, StixelNet (trained on the road segmentation task) followed by a Conditional Random Field (CRF). The final stage performs a graph-cut segmentation on the image to achieve higher accuracy by enforcing road boundaries to coincide with image contours.



Figure 4 Road Segmentation algorithm flowchart

* Convolutional Neural Network with Context Fusion

(Brust, Sickert, Simon, Rodner, & Denzler, 2015) proposed a Neural Network that combines a 3-layer CNN with context information in the last two layers, the architecture is shown in Figure 5. In total, the network is constrcuted with 2 convolutional layer, 1 max-polling layer and 3 fully connected layers. An important architectural choice is the incorporation of the absolute position of the patch as an input in one fully connected layer, which allows for learning a spatial prior of the road category.



Figure 5 Network Architecture

* Fully Convolutional Neural Network with Large Context

(Mendes, Frémont, & Wolf, 2016) applied a fully convolutional network for road detection problem, the network archtercture is shown in Figure 6. It consists of extracting patches around a pixel or region of the image and classifying those patches using a trained CNN. The output class it attributed to the pixel or region from which the patch was centered. The main advantage of this method is it classify the pixel or region using not only its information but also information about its surrounding, that is, contextual information.

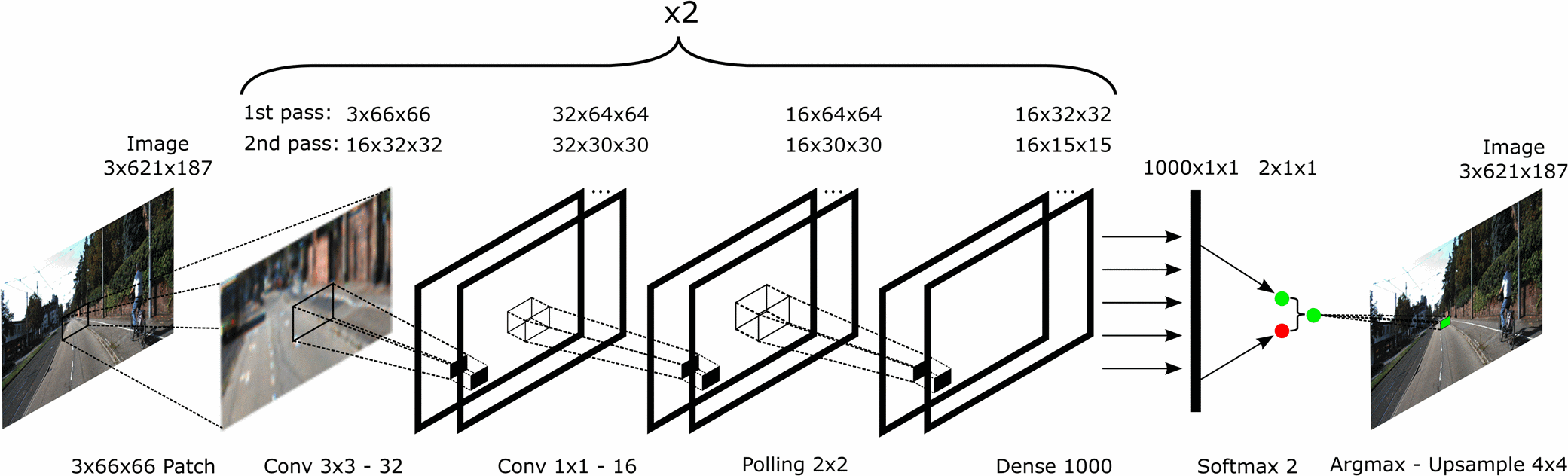


Figure 6 Network Architecture

* Up-Convolutional network

(Oliveira, Burgard, & Brox, 2016) proposed the Up-Convolutional network, the architecture is shown in Figure 7. Specifically, The contractive network layer parameters are initialized using the VGG classification network. The expansive network layers are consisted of successive convolution layers after a upsampling operation. One characteristic of the proposed expansive part is the inclusion of dropout after the first refinement layer to avoid overfitting. The output of the network are scores for each of the learned categories.

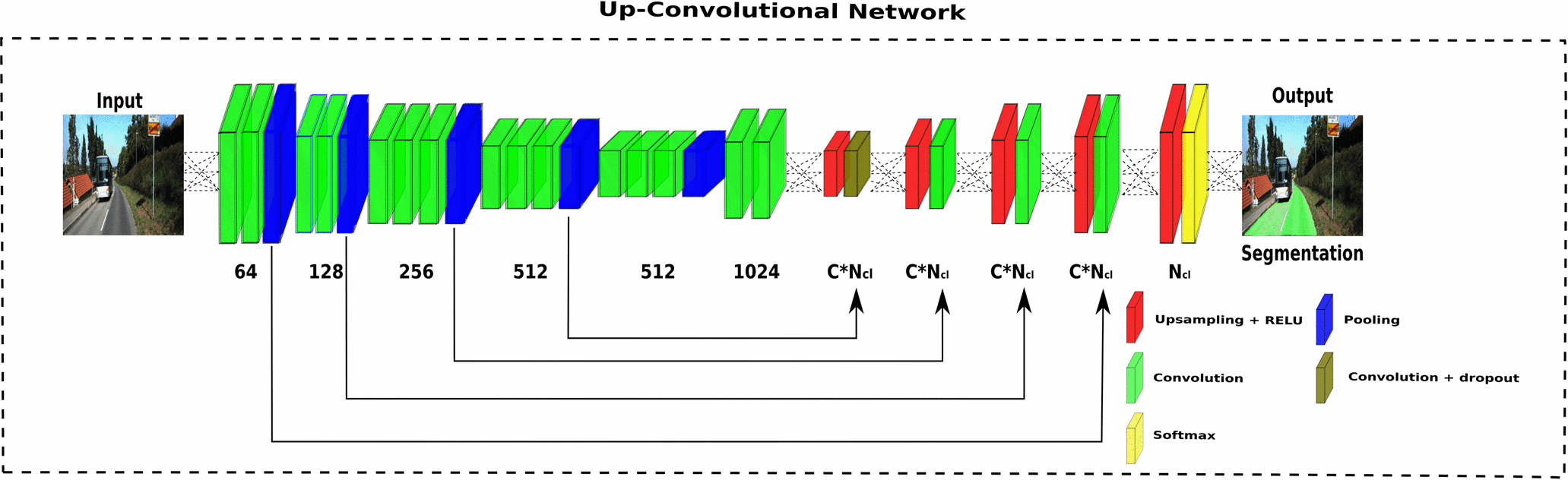


Figure 7 UP-Convolutional Network, where Ncl stands for number of classes and C for the scalar factor of filter augmentation.

At the same time, some studies (Alvarez, Gevers, LeCun, & Lopez, 2012; Fritsch et al., 2013; Kuhnl, Kummert, & Fritsch, 2012) can also be used to compare our methods.

**Project Plan**



**REFERENCE**

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