

# Deep Learning for Road Segmentation

Stanford University, CS230: Deep Learning



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## Predicting:

Road segmentation for autonomous vehicle applications is difficult, as images can include partial occlusions, shadows, etc. Worse, such applications typically require **real-time performance**. Our team modified Marvin Teichmann's KittiSeg framework to, using a genetic algorithm, **optimally drop components** of a FCN8-VGG16 model to optimize for MaxF1 while running in less time than the original model.

## Data:

All models were patch-trained on the **KITTI Road Detection** dataset with a 241/48 (289 total) image train/validation split. Inputs are color road images in various locations/lighting conditions with ground truth color maps (Figure 1).

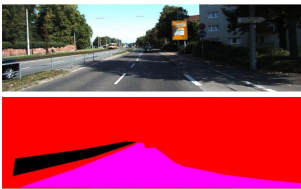


Figure 1: Training Example with Ground Truth from the KITTI Road Detection dataset

## Features:

During training, the FCN8 model accepts a single random 256x256 image patch, encodes it, then upsamples it into a block with one softmax output per original pixel. **No other features** (i.e. LIDAR, stereo imaging, etc.) are used.

## Model:

The standard KittiSeg model uses an FCN8-VGG16 model as an encoder, consisting of five pooling layers and thirteen standard convolutional layers:

$$y_{ij} = f_{ks}(\{x_{si+\delta i, sj+\delta j}\}_{0 \leq \delta i, \delta j \leq k})$$

It then uses a series of transpose convolutions for upsampling, following the definition below:

$$C_i(y^i) = \frac{\lambda}{2} \sum_{c=1}^{K_i} \sum_{k=1}^{K_i} z_k^i \oplus f_{k,c} - y_c^i \parallel_2^2 + \sum_{k=1}^{K_i} |z_k^i|^p$$

We optimized runtime using a **genetic algorithm** with mutation (random bit toggling) and crossover (random selection with union) on binary vectors representing layers to drop, splicing in `tf.Tile` ops wherever shape changes occur. Evaluation was performed after 250 steps as a benchmark.

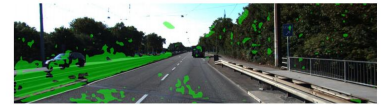
## Results:

Despite the simplicity of tiling relative to convolution, runtime was **not strongly affected** by any layer drops. As a follow up, a FCN8 with `conv2_2`, `conv3_2`, and `conv4_2` bypassed was trained for 1.5k steps alongside a vanilla FCN8. All results are in Figure 2.

	Max F1	Avg. Precision	Runtime (ms)
FCN8	<b>90.2379</b>	<b>90.6890</b>	358.1518
Learned FCN8	17.6806	30.0485	<b>356.5779</b>
FCN8 (1.5k steps)	<b>93.1652</b>	<b>91.5854</b>	<b>361.4553</b>
Trimmed FCN8, (1.5k steps)	33.3214	21.6512	372.0243

Figure 2: Summary of Performance Metrics for All Models

Trimmed FCN8



FCN8

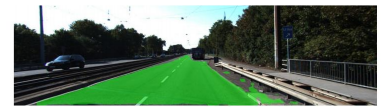


Figure 3a and 3b: Visualization of Predictions of FCN8 and Trimmed FCN8 after 1.5k steps

## Discussion:

Although layer splicing appears to hurt FCN8's ability to classify images, trimmed FCN8 sometimes finds road-like features (Figure 3). Loss **appears to stagnate** when training with several learning rates (w/ Adam), indicating the new loss function may be stuck in a local minimum. It was later found that statistics were recorded on dropped layers, suggesting further inspection of the TF graph **could lead to decreased run times**.

## Future:

Future work could include a second attempt with longer training and extensive hyperparameter tuning, as well as **exploring alternatives** to our method: optimizing the network for parallelization, following Molchanov et al. on **network pruning**, or performing **full image training** like Oliveira et al. Alternatives to the genetic algorithm (i.e. cross-entropy method) could also be explored.

## References:

- M. Teichmann. "KittiSeg." Internet: <https://github.com/MarvinTeichmann/KittiSeg>. Oct 16, 2017 [Mar 1, 2018].
- G. Oliveira et al. "Efficient and robust deep networks for semantic segmentation." *The International Journal of Robotics Research*. Jun 2017.
- P. Molchanov et al. "Pruning Convolutional Neural Networks for Resource Efficient Inference." <https://arxiv.org/abs/1611.05444>. Jun 8, 2017 [Mar 1, 2018].
- J. Fritsch, T. Kuhn, and A. Geiger. "A new performance measure and evaluation benchmark for road detection algorithms." in ITSC. 2013.

