Supplementary Material: Hierarchical Recurrent Attention Networks for Structured Online Maps

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1. Videos
We have attached a video that displays how for one example, our model attends to the initial regions of the lane boundaries and traces them sequentially until there are no more left. Furthermore, the video contains the results of our model applied to a couple of sequences from the test set.

2. Model Details
In this section, we present a detailed diagram of the architecture used in our experiments. The basic building blocks are defined below:

- $\text{Conv2D}(\text{kernel}_\text{size} \times \text{kernel}_\text{size} \times \text{out}\_\text{channels}, \text{stride}, \text{padding})$ corresponds to a 2D convolution kernel.
- $\text{BRC}(\text{kernel}_\text{size} \times \text{kernel}_\text{size} \times \text{out}\_\text{channels}, \text{stride}, \text{padding})$ corresponds to batch normalization followed by a ReLU and a $\text{Conv2D}(\text{kernel}_\text{size} \times \text{kernel}_\text{size} \times \text{out}\_\text{channels}, \text{stride}, \text{padding})$.
- $\text{BRUC}(\text{kernel}_\text{size} \times \text{kernel}_\text{size} \times \text{out}\_\text{channels}, \text{stride}, \text{padding})$ corresponds to batch normalization followed by a ReLU, followed by a nearest neighbour upsampling and finally a $\text{Conv2D}(\text{kernel}_\text{size} \times \text{kernel}_\text{size} \times \text{out}\_\text{channels}, \text{stride}, \text{padding})$.
- $\text{Residual}(\text{kernel}_\text{size} \times \text{kernel}_\text{size} \times \text{out}\_\text{channels}, \text{stride}, \text{padding})$ corresponds to consecutive $\text{BRC}(\text{kernel}_\text{size} \times \text{kernel}_\text{size} \times \text{out}\_\text{channels}, \text{stride}, \text{padding})$ followed by another $\text{BRC}(\text{kernel}_\text{size} \times \text{kernel}_\text{size} \times \text{out}\_\text{channels}, 1, 1)$.
- $\text{ConvRNN}$ is a vanilla RNN where matrix multiplications are replaced by convolutions. Moreover, we use a hardtanh instead of the usual tanh non-linearity.
- Similarly, the $\text{ConvLSTM}$ module has convolutions instead of matrix multiplications.
- $\text{Crop}(\text{height} \times \text{width} \times \text{channels})$ corresponds to cropping a height x width region.
Figure 1. Model Details