FOLLOW ME PROJECT

The following sections outline my implementation of the segmentation network used in the Follow Me project.

NEURAL NETWORK ARCHITECTURE

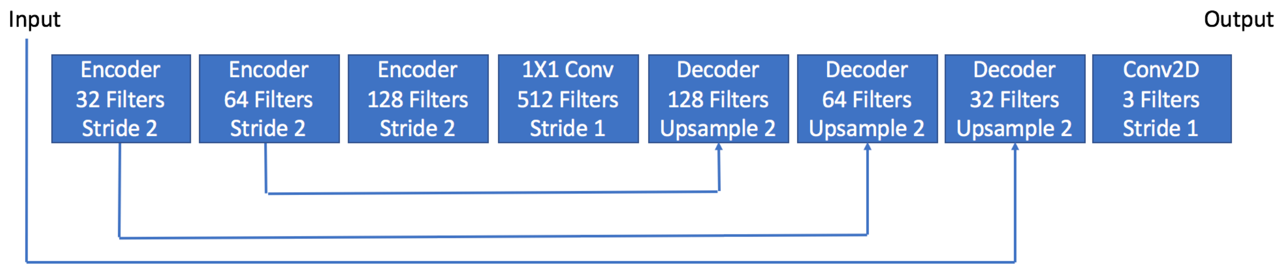
The diagram below illustrates the fully-convolutional neural network architecture with which I was able to obtain a final weighted IOU score of 0.42.

Overall the network is divided into an encoding stage and a decoding stage. The encoding stage is responsible for extracting image representations (feature maps) at different scales. The different feature maps are produced by the different filters and the variable scales arise from the fact that each encoder halves the spatial extent (height and width) of its input. The decoder stage uses both the final and intermediate feature maps generated by the encoder stage (through skip connections) to reconstruct an image (through upsampling and filtering) with the same size as the original image but with pixel-wise segmentation.

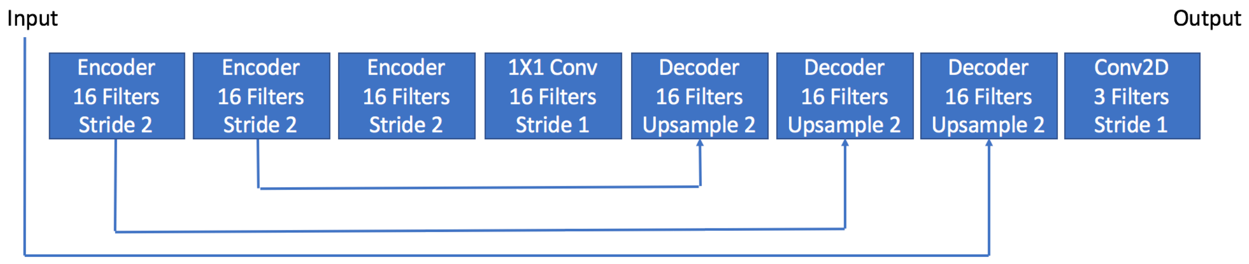
More specifically, the network takes as input a 160x160x3 input image and passes that image through 3 encoders. Each encoder applies a different number of 3x3 kernels with a stride of 2 followed by batch normalization. Since we use a stride of 2, the output of the final encoder is 20x20x128. At this point we've gone from a wide and shallow input (image with 3 channels) to a narrow and deep representation (128 channels).

To connect the encoding and decoding stages, the network uses a 1x1 convolution with 512 filters. This is necessary for preserving spatial information (something that would be lost if we used a fully-connected layer). The 1x1 convolution also allows our neural network to accept an input image of any size (again something not possible with a fully-connected layer). The output of the 1x1 convolution is then fed into the three decoders. Each decoder up-samples the input by a factor of 2; concatenates the result with an input from the encoder stage using a skip connection; and applies two convolution and batch normalization layers using a different number of 3x3 kernels with a stride of 1.

The output of the last decoder has dimensions 160x160x32. This tensor is passed into a final convolutional layer that is responsible for producing an image segmentation of dimension 160x160x3 (3 channels for each segmentation class).


Input
Output
Encoder 32 Filters Stride 2
Encoder 64 Filters Stride 2
Encoder 128 Filters Stride 2
1X1 Conv 512 Filters Stride 1
Decoder 128 Filters Upsample 2
Decoder 64 Filters Upsample 2
Decoder 32 Filters Upsample 2
Conv2D 3 Filters Stride 1

An architecture that I explored that did not meet the performance requirement (reached a score < 0.40) is illustrated below. The difference between this architecture and that shown above is the constant number of filters (16) used at each stage of the network. This results in a shallow representation at the output of the third encoder (20x20x16 vs 20x20x128 above) which does not allow the network to effectively perform the segmentation tas


Input
Output
Encoder 16 Filters Stride 2
Encoder 16 Filters Stride 2
Encoder 16 Filters Stride 2
1X1 Conv 16 Filters Stride 1
Decoder 16 Filters Upsample 2
Decoder 16 Filters Upsample 2
Decoder 16 Filters Upsample 2
Conv2D 3 Filters Stride 1

TRAINING HYPERPARAMETERS

Learning Rate: I chose a learning rate of 0.001 to ensure that network learning could progress at a reasonable rate without the risk of failing to converge.

Batch Size: I chose a batch size of 32 so as to avoid having very noisy gradient estimates as well as to well utilize the GPU (and avoid excessive copying of data from host CPU to GPU).

Steps per Epoch: I had approximately 4000 training images, and I wanted each epoch to pass all the data through the network. With a batch size of 32, this constrained my choice for steps per epoch to be 130.

Number of Epochs: I initially trained the network for 30-40 epochs and found that my score hovered between 0.36-0.38. Training the network for 130-140 steps (an additional 100 steps) pushed my score upt to 0.42.

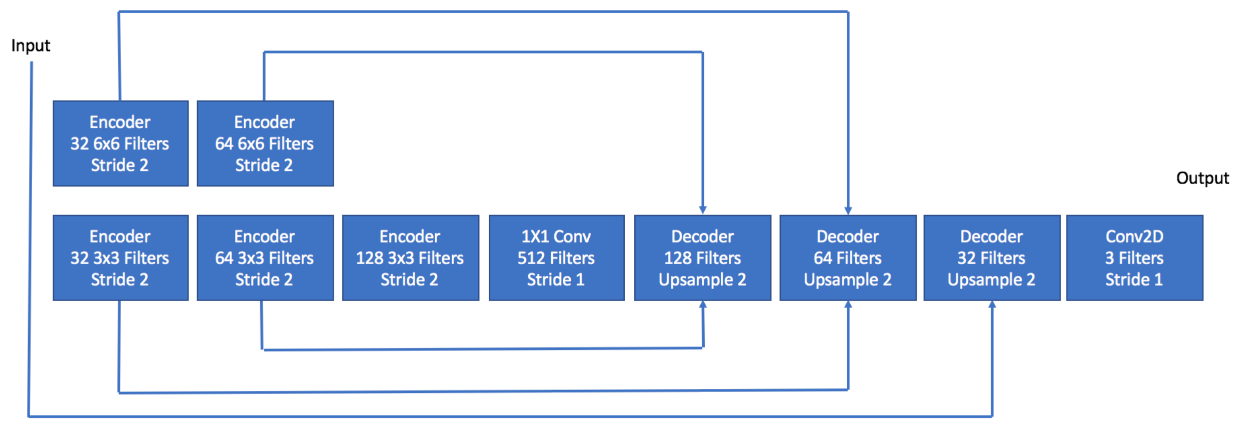
Validation Steps: I had approximately 1000 validation images, and I the validation score to encompass all of them. With a batch size of 32, this constrained my choice for validation steps to 30.

OTHER APPLICATIONS

The architecture presented here is general enough to be used for segmentation of other objects (e.g. roads, trees, pets). In order to do so, one must however provide additional input images and masks as training data. Once that is done the network can output a channel for each target class (e.g. one channel for the hero, another for roads, a third for tree etc).

FUTURE ENHANCEMENTS

The current network's worst performance metric is false negatives (missed hero detections) in images where the hero is far away. To remedy this deficiency, one should enrich the training dataset with such images and hopefully decrease this type of error. The second enhancement is architectural and involves performing encoding with *different size kernels. The current architecture uses 3x3 kernels in the encoding stage. Why not use multiple encoders with different size kernels (e.g. 3x3, 6x6, etc.) to capture different spatial relationships in each input? The output of these encoders would then be concatenated in the appropriate decoders as illustrated in the image below. Such encoding could enhance the neural network's performance.*


Input
Encoder 32 6x6 Filters Stride 2
Encoder 64 6x6 Filters Stride 2
Output
Encoder 32 3x3 Filters Stride 2
Encoder 64 3x3 Filters Stride 2
Encoder 128 3x3 Filters Stride 2
1X1 Conv 512 Filters Stride 1
Decoder 128 Filters Upsample 2
Decoder 64 Filters Upsample 2
Decoder 32 Filters Upsample 2
Conv2D 3 Filters Stride 1