Fully Convolutional Network (FCN)

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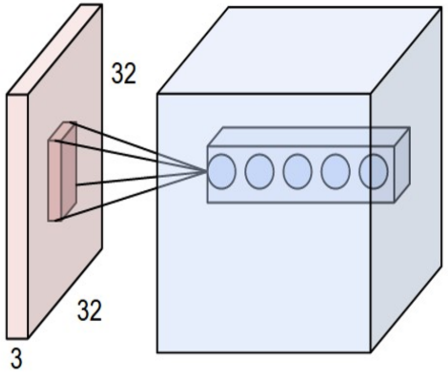
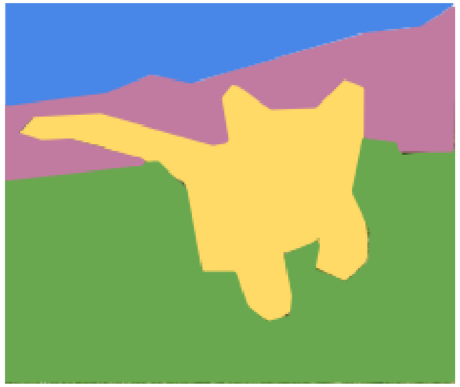
Deep Learning for Computer Vision: Review

Foundations	CNNs	Applications
• Why computer vision? • Representing images • Convolutions for feature extraction	• CNN architecture • Application to classification: ImageNet	• Segmentation, object detection, image captioning • Visualization





Source: 6.S191 Intro. to Deep Learning at MIT

Segmentation

- Segmentation task is different from classification task because it requires predicting a class for each pixel of the input image, instead of only 1 class for the whole input.
- Segment images into regions with different semantic categories. These semantic regions label and predict objects at the pixel level

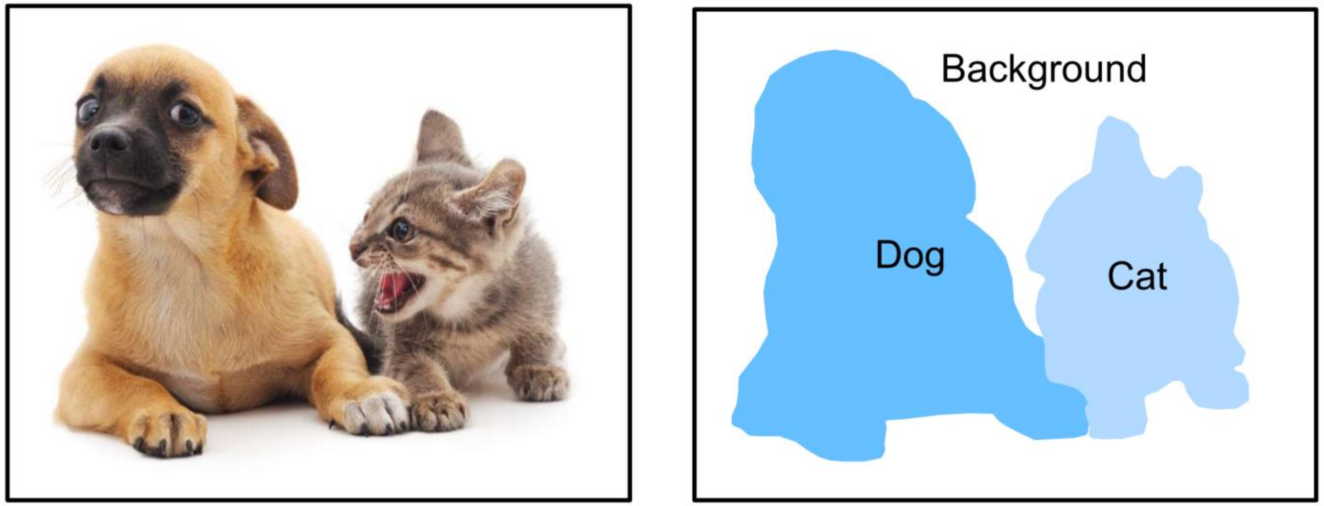


Image from http://d2l.ai/

Segmentation

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- Segment images into regions with different semantic categories. These semantic regions label and predict objects at the pixel level
- Classification needs to understand what is in the input (namely, the context).
- However, in order to predict what is in the input for each pixel, segmentation needs to recover not only what is in the input, but also where.

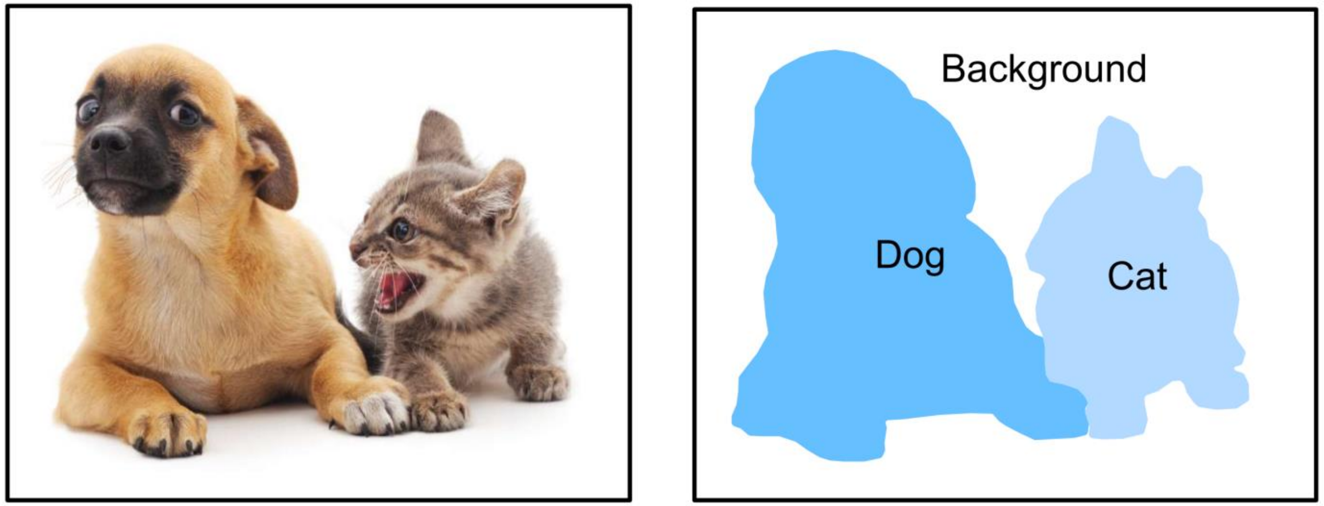


Image from http://d2l.ai/

Semantic Segmentation: FCNs

- FCN uses a convolutional neural network to transform image pixels to pixel categories.
- Network designed with all convolutional layers, with down-sampling and up-sampling operations
- Given a position on the spatial dimension, the output of the channel dimension will be a category prediction of the pixel corresponding to the location.

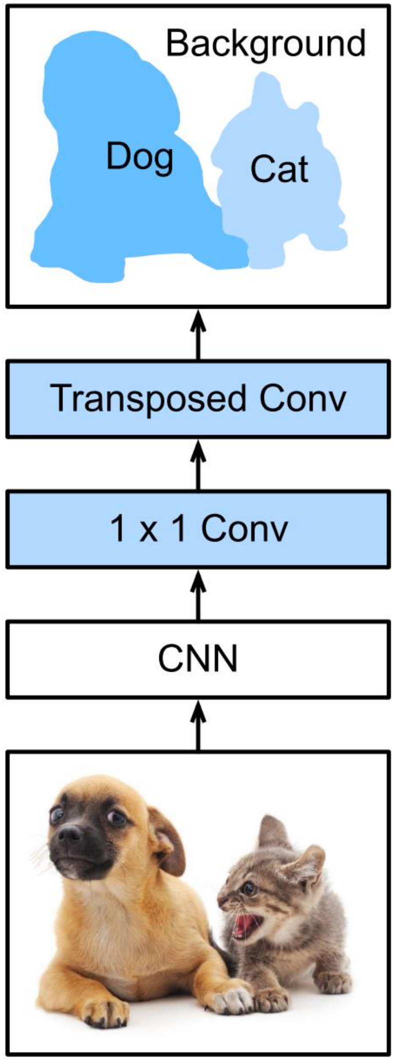
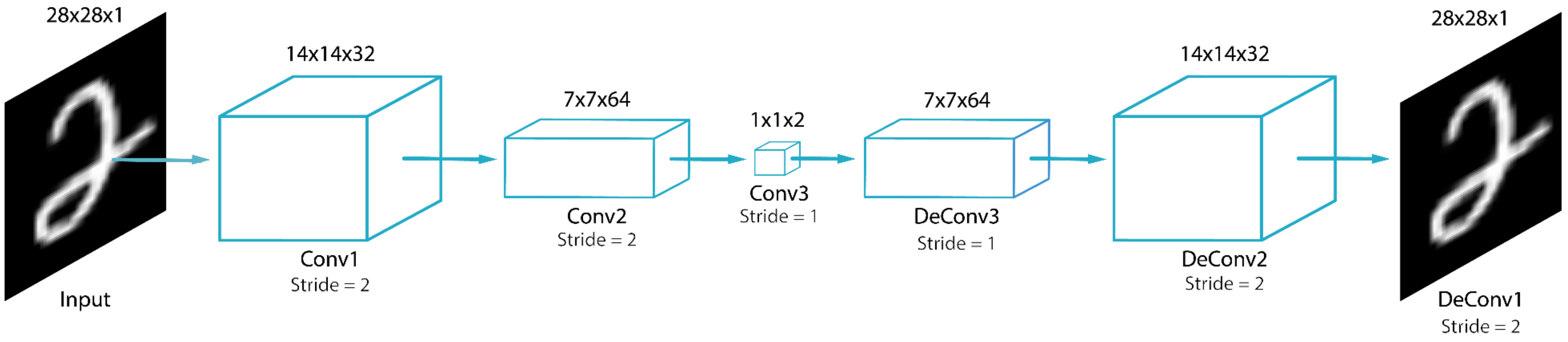
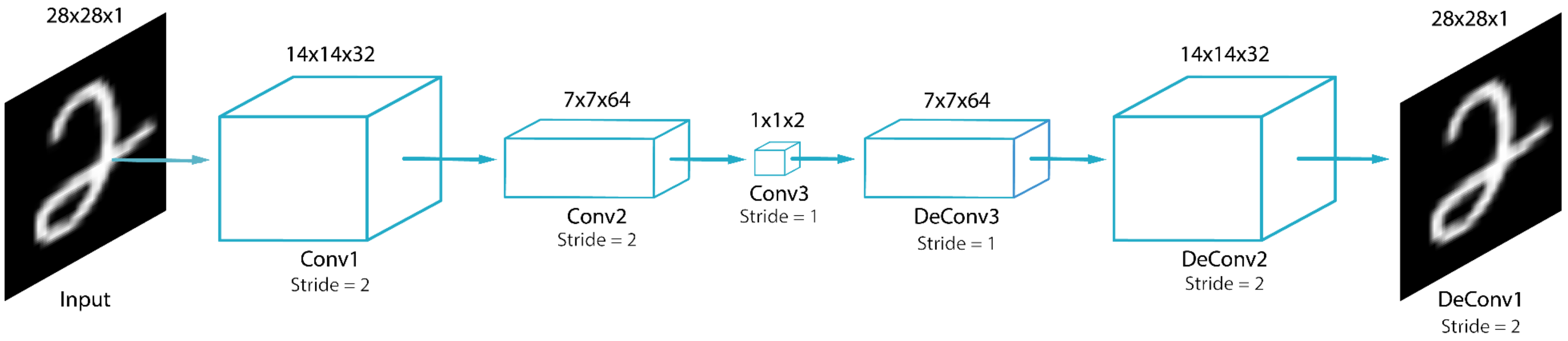


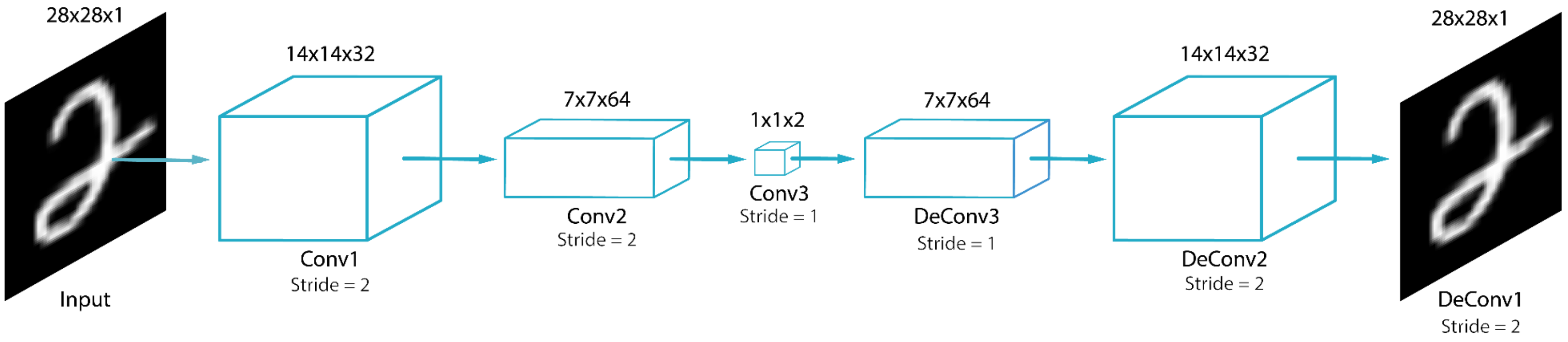
Image from http://d2l.ai/

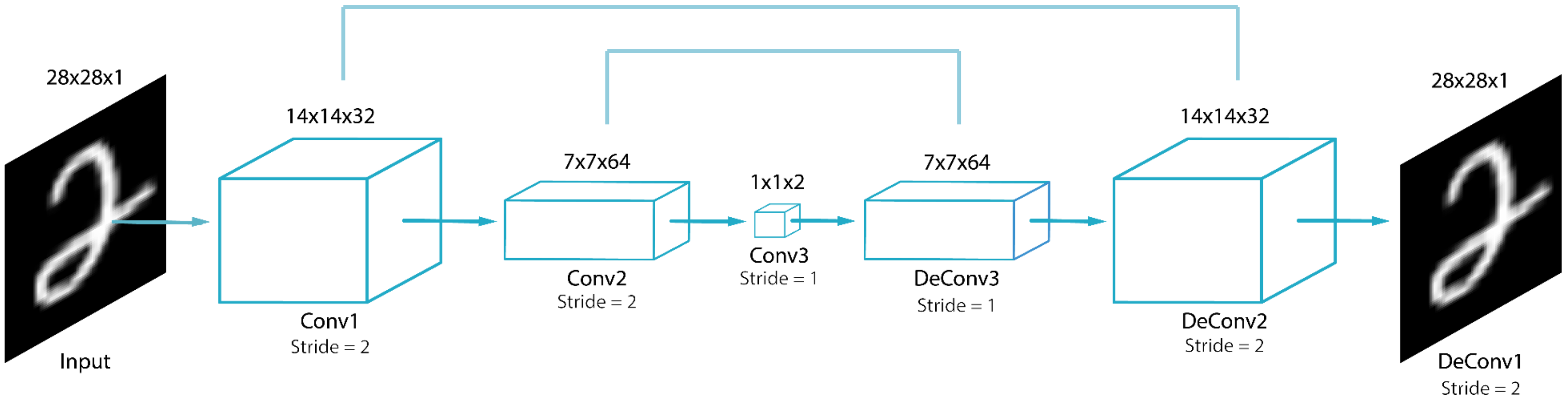
From CAE to FCN





From CAE to FCN

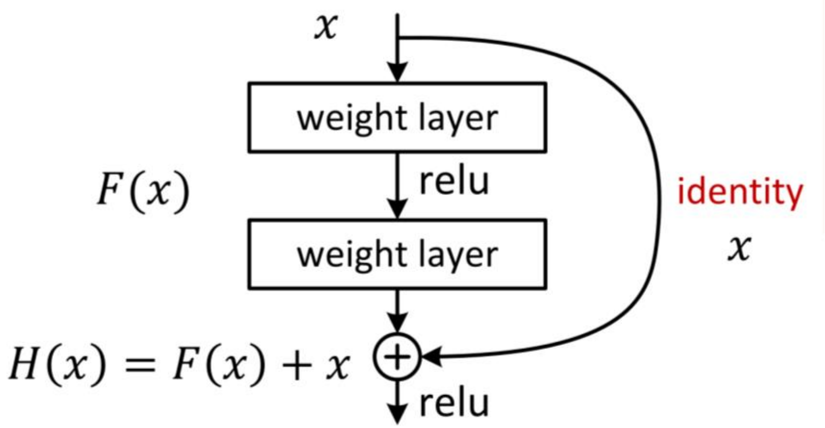




Skip Connection

- A skip connection is a connection that bypasses at least one layer.

- Here, it is often used to transfer local information by summing feature maps from the downsampling path with feature maps from the upsampling path.
  - Merging features from various resolution levels helps combining context information with spatial information.

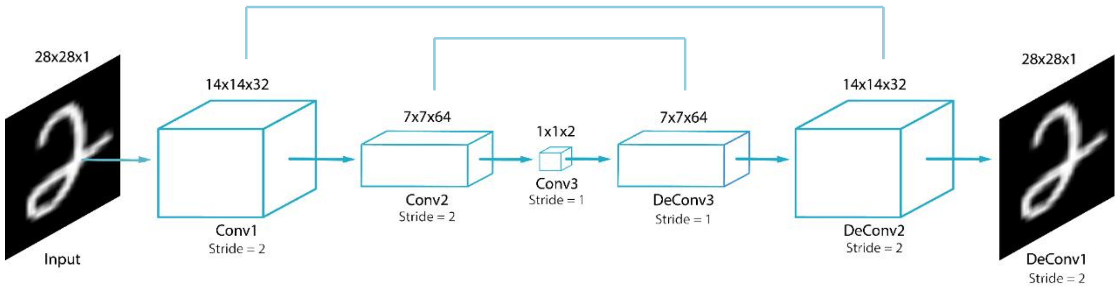


Fully Convolutional Networks (FCNs)

- To obtain a segmentation map (output), segmentation networks usually have 2 parts
  - Downsampling path: capture semantic/contextual information
  - Upsampling path: recover spatial information
- The downsampling path is used to extract and interpret the context (what), while the upsampling path is used to enable precise localization (where).

- Furthermore, to fully recover the fine-grained spatial information lost in the pooling or downsampling layers, we often use skip connections.

- Network can work regardless of the original image size, without requiring any fixed number of units at any stage.



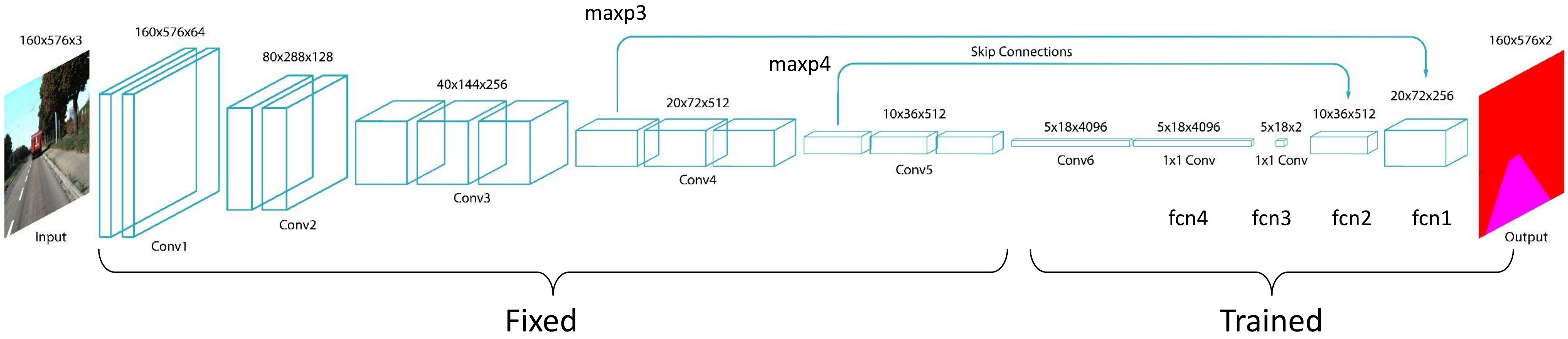
Segmented (Labeled) Images

input

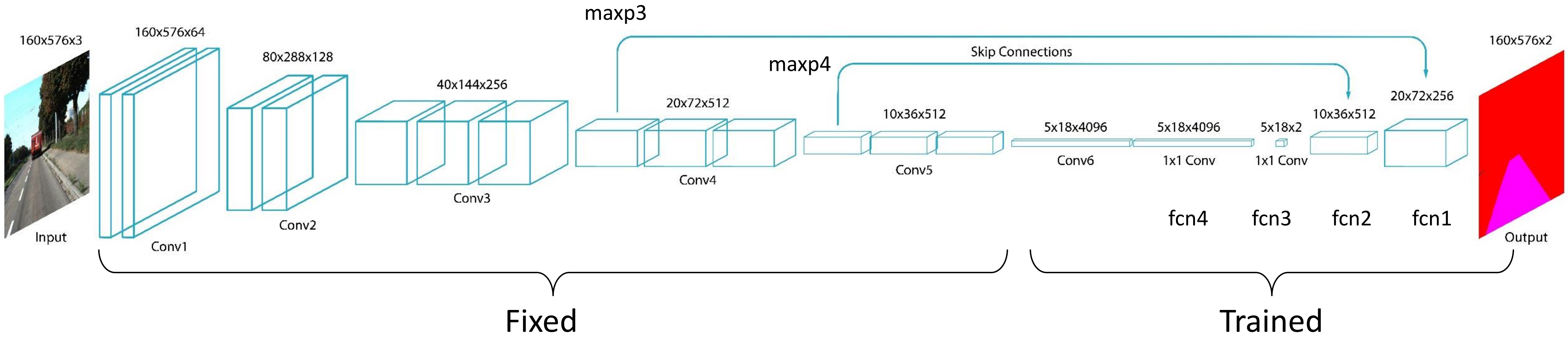
output

output

FCN Architecture



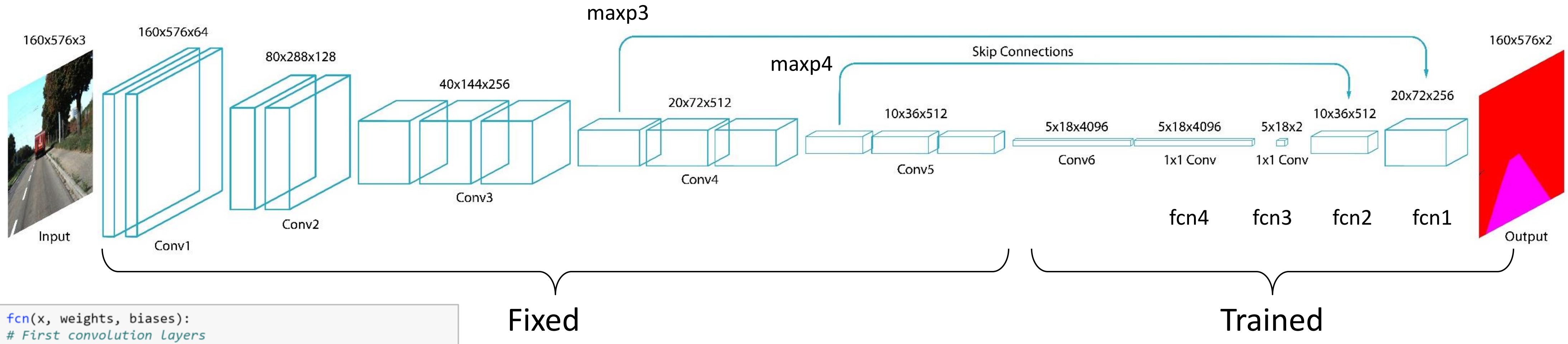
FCN Architecture




```
vgg16_weights = model.get_weights()

weights = {
    'conv1_1' : tf.constant(vgg16_weights[0]),
    'conv1_2' : tf.constant(vgg16_weights[2]),

    'conv2_1' : tf.constant(vgg16_weights[4]),
    'conv2_2' : tf.constant(vgg16_weights[6]),

    'conv3_1' : tf.constant(vgg16_weights[8]),
    'conv3_2' : tf.constant(vgg16_weights[10]),
    'conv3_3' : tf.constant(vgg16_weights[12]),

    'conv4_1' : tf.constant(vgg16_weights[14]),
    'conv4_2' : tf.constant(vgg16_weights[16]),
    'conv4_3' : tf.constant(vgg16_weights[18]),

    'conv5_1' : tf.constant(vgg16_weights[20]),
    'conv5_2' : tf.constant(vgg16_weights[22]),
    'conv5_3' : tf.constant(vgg16_weights[24]),
}
```

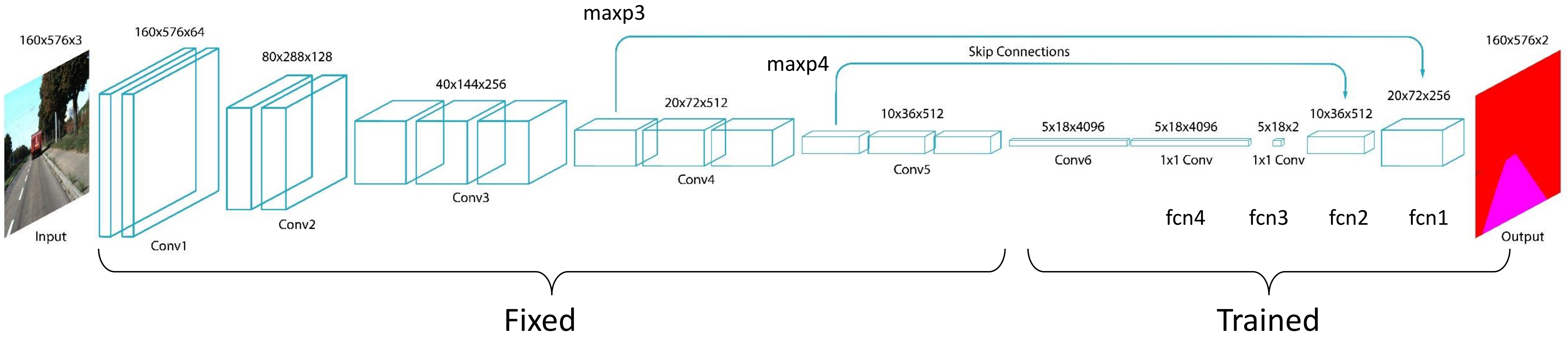
```
biases = {
    'conv1_1' : tf.constant(vgg16_weights[1]),
    'conv1_2' : tf.constant(vgg16_weights[3]),

    'conv2_1' : tf.constant(vgg16_weights[5]),
    'conv2_2' : tf.constant(vgg16_weights[7]),

    'conv3_1' : tf.constant(vgg16_weights[9]),
    'conv3_2' : tf.constant(vgg16_weights[11]),
    'conv3_3' : tf.constant(vgg16_weights[13]),

    'conv4_1' : tf.constant(vgg16_weights[15]),
    'conv4_2' : tf.constant(vgg16_weights[17]),
    'conv4_3' : tf.constant(vgg16_weights[19]),

    'conv5_1' : tf.constant(vgg16_weights[21]),
    'conv5_2' : tf.constant(vgg16_weights[23]),
    'conv5_3' : tf.constant(vgg16_weights[25]),
}
```

FCN Architecture




```python
def fcn(x, weights, biases):
    # First convolution layers
    conv1_1 = tf.nn.conv2d(x,
                     weights['conv1_1'],
                     strides = [1, 1, 1, 1],
                     padding = 'SAME')
    conv1_1 = tf.nn.relu(tf.add(conv1_1, biases['conv1_1']))
    conv1_2 = tf.nn.conv2d(conv1_1,
                     weights['conv1_2'],
                     strides = [1, 1, 1, 1],
                     padding = 'SAME')
    conv1_2 = tf.nn.relu(tf.add(conv1_2, biases['conv1_2']))
    maxp1 = tf.nn.max_pool(conv1_2,
                      ksize = [1, 2, 2, 1],
                      strides = [1, 2, 2, 1],
                      padding = 'VALID')

    # Second convolution layers
    conv2_1 = tf.nn.conv2d(maxp1,
                     weights['conv2_1'],
                     strides = [1, 1, 1, 1],
                     padding = 'SAME')
    conv2_1 = tf.nn.relu(tf.add(conv2_1, biases['conv2_1']))
    conv2_2 = tf.nn.conv2d(conv2_1,
                     weights['conv2_2'],
                     strides = [1, 1, 1, 1],
                     padding = 'SAME')
    conv2_2= tf.nn.relu(tf.add(conv2_2, biases['conv2_2']))
    maxp2 = tf.nn.max_pool(conv2_2,
                      ksize = [1, 2, 2, 1],
                      strides = [1, 2, 2, 1],
                      padding = 'VALID')
```

FCN Architecture




```
# sixth convolution layer
conv6 = tf.layers.conv2d(maxp5,
                         filters = 4096,
                         kernel_size = 7,
                         padding = 'SAME',
                         activation = tf.nn.relu)

# 1x1 convolution layers
fcn4 = tf.layers.conv2d(conv6,
                         filters = 4096,
                         kernel_size = 1,
                         padding = 'SAME',
                         activation = tf.nn.relu)
fcn3 = tf.layers.conv2d(fcn4,
                         filters = 2,
                         kernel_size = 1,
                         padding = 'SAME')
```

```
# Upsampling layers
fcn2 = tf.layers.conv2d_transpose(fcn3,
                                  filters = 512,
                                  kernel_size = 4,
                                  strides = (2, 2),
                                  padding = 'SAME')

fcn1 = tf.layers.conv2d_transpose(fcn2 + maxp4,
                                  filters = 256,
                                  kernel_size = 4,
                                  strides = (2, 2),
                                  padding = 'SAME')

output = tf.layers.conv2d_transpose(fcn1 + maxp3,
                                  filters = 2,
                                  kernel_size = 16,
                                  strides = (8, 8),
                                  padding = 'SAME')
```

Segmentation Result