Semantic Segmentation Using Deep Learning

A basic example can be found in the following documentation page:

```
web(fullfile(docroot, 'vision/examples/_mw_c671533a-9d94-4d6a-bef0-2982e5d45318.html'))
```

Motivation

The motivation for this example is to use Semantic Segmentation to detect the free space on the road as well as lanes and pavements. This will provide the necessary information for an autonomous driving mediated perception approach. This involves the recognition of multiple objects within the scene (cars, road, lanes etc.) so that an AI-based engine can perform accurate path-planning. To demonstrate this, we will train a deep CNN using the CamVid dataset, and we will provide visual and quantitative results proving the accuracy Semantic Segmentation.

Setup

SegNet training is based on the VGG-16 network. `vgg16` returns a pretrained VGG-16 model. This model is trained on a subset of the ImageNet database [1], which is used in the ImageNet Large-Scale Visual Recognition Challenge (ILSVRC) [2]. VGG-16 is trained on more than a million images and can classify images into 1000 object categories. For example, keyboard, mouse, pencil, and many animals. As a result, the model has learned rich feature representations for a wide range of images.

This function requires Neural Network Toolbox Model *for VGG-16 Network* support package. If this support package is not installed, then the function provides a download link.

```
% Download and install Neural Network Toolbox Model for VGG-16 Network support package.
vgg16()
```

```
ans =
  SeriesNetwork with properties:

    Layers: [41×1 nnet.cnn.layer.Layer]
```

Download CamVid Dataset [3]

Download the CamVid (Cambridge-driving Labeled Video) Database from the following URLs:

```
imageURL = 'http://web4.cs.ucl.ac.uk/staff/g.brostow/MotionSegRecData/files/701_StillsRaw_ful
labelURL = 'http://web4.cs.ucl.ac.uk/staff/g.brostow/MotionSegRecData/data/LabeledApproved_fu

% Set the outputFolder to be on the current path
outputFolder = fullfile(pwd, 'CamVid');

if ~exist(outputFolder, 'dir')
    disp('Downloading 557 MB CamVid data set...');

    unzip(imageURL, fullfile(outputFolder,'images'));
```

```
    unzip(labelURL, fullfile(outputFolder,'labels'));
end
```

Note: Download time of the data depends on your internet connection. The commands used above will block MATLAB until the download is complete. Alternatively, you can use your web browser to first download the dataset to your local disk. To use the file you downloaded from the web, change the `outputFolder` variable above to the location of the downloaded file.

Resize the data

The images in the CamVid data set are 720 by 960. To reduce training time and memory usage, resize the images and pixel label images to 360 by 480. It takes approximately 104 seconds for all the images and labels.

```
imgDir = fullfile(outputFolder,'images','701_StillsRaw_full');
labelDir = fullfile(outputFolder,'labels');
HelperFunctions.prepareData(imgDir,labelDir);
```

```
Image data already resized
Label data already resized
```

References

[1] Badrinarayanan, Vijay, Alex Kendall, and Roberto Cipolla. "SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation." arXiv preprint arXiv:1511.00561, 2015.

[2] Brostow, Gabriel J., Julien Fauqueur, and Roberto Cipolla. "Semantic object classes in video: A high-definition ground truth database." Pattern Recognition Letters Vol 30, Issue 2, 2009, pp 88-97.

[3] G.J. Brostow, J. Fauqueur, R. Cipolla, "Semantic object classes in video: A high-definition ground truth database" , Pattern Recognition Letters 30(2): 88-97, 2009

Load CamVid Images

Use `imageDatastore` to load CamVid images. The `imageDatastore` enables you to efficiently load a large collection of images on disk. It creates a datastore from the collection of image data specified by `location`. A datastore is a repository for collections of data that are too large to fit in memory. After creating an `ImageDatastore` object, you can read and process the data in various ways.

```
% Get the full path for the folder containing all the raw images
imgDir = fullfile(outputFolder,'images','701_StillsRaw_full');

% Load the images located in the above path using imageDatstore - ML Function
imds = imageDatastore(imgDir);
```

Display one of the images.

```
% Suppress image display warnings
warning('off','images:initSize:adjustingMag')
```

```
pic_num = 30;
I_raw = readimage(imds, pic_num);

% Because images are dark histogram equalization is performed. - Image Processing toolbox
I = histeq(I_raw);

figure
imshow(I_raw)
title('Raw image')
```

Raw image

```
figure
imshow(I)
title('Image with equalized histogram')
```

Image with equalized histogram

Load CamVid Pixel Labeled Images

Use `pixelLabelDatastore` to load CamVid pixel label image data.
A `pixelLabelDatastore` encapsulates the pixel label data and the label ID to class name mapping.
Following the procedure used in original SegNet paper, the 32 original classes in CamVid will be reduced to the following 10:

```
classes = [
    "Environment"
    "Building"
    "Pole"
    "Road"
    "Lane"
    "Pavement"
    "SignSymbol"
    "Car"
    "Pedestrian"
    "Bicyclist"
    ];
```

To reduce 32 classes into 10, multiple classes from the orignal dataset are grouped together. For example, "Car" is a combination of "Car", "SUVPickupTruck", "Truck_Bus", "Train", and "OtherMoving". The grouped label IDs are returned by the supporting function `camvidPixelLabelIDs`, which is listed at the end of this example. In our labeled data, every pixel label ID is provided as an RGB color value.

To associate the labels with the corresponding classes, we have to associate the RGB values with the corresponding class.

```
labelIDs = HelperFunctions.camvidPixelLabelIDs();
```

Use the classes and labelIDs to create the `pixelLabelDatastore`. `pixelLabelDatastore` will associate the RGB values with the labels and so when an image is read, it will return a categorical array. It works in a similar way to an `imageDatastore` with the main difference that the labeling is not for a single object (i.e. a car in the image) but it is for each pixel individually. For this reason, the images containing the data and the images containing the labels need to have 1-1 correspondence in the order they are read. That is why the filenames are usually the same with the labels have a _L suffix.

```
% Create the full path to the directory that contains the ground truth pictures.
labelDir = fullfile(outputFolder,'labels');

% This function works similarly to imageDatastore. Instead it returns a datastore object that
pxds = pixelLabelDatastore(labelDir,classes,labelIDs);

% Create a custom colormap to color each label in a different way
cmap = HelperFunctions.camvidColorMap;

% Show a ground-truth image
HelperFunctions.showImageMapping(pxds,cmap)
```

```
ans = 26×26 categorical array
    Lane    Lane    Lane    Lane    Lane    Road    Road    Road    Road    Road    Road
    Road    Lane    Lane    Lane    Lane    Lane    Lane    Road    Road    Road    Road
    Road    Road    Lane    Lane    Lane    Lane    Lane    Lane    Road    Road    Road
    Road    Road    Road    Lane    Lane    Lane    Lane    Lane    Lane    Road    Road
    Road    Road    Road    Road    Lane    Lane    Lane    Lane    Lane    Lane    Road
    Road    Road    Road    Road    Road    Road    Lane    Lane    Lane    Lane    Lane
    Road    Road    Road    Road    Road    Road    Road    Lane    Lane    Lane    Lane
    Road    Road    Road    Road    Road    Road    Road    Road    Lane    Lane    Lane
    Road    Road    Road    Road    Road    Road    Road    Road    Road    Lane    Lane
    Road    Road    Road    Road    Road    Road    Road    Road    Road    Road    Lane
    Road    Road    Road    Road    Road    Road    Road    Road    Road    Road    Road
    Road    Road    Road    Road    Road    Road    Road    Road    Road    Road    Road
    Road    Road    Road    Road    Road    Road    Road    Road    Road    Road    Road
    Road    Road    Road    Road    Road    Road    Road    Road    Road    Road    Road
    Road    Road    Road    Road    Road    Road    Road    Road    Road    Road    Road
    Road    Road    Road    Road    Road    Road    Road    Road    Road    Road    Road
    Road    Road    Road    Road    Road    Road    Road    Road    Road    Road    Road
    Road    Road    Road    Road    Road    Road    Road    Road    Road    Road    Road
    Road    Road    Road    Road    Road    Road    Road    Road    Road    Road    Road
    Road    Road    Road    Road    Road    Road    Road    Road    Road    Road    Road
    Road    Road    Road    Road    Road    Road    Road    Road    Road    Road    Road
    Road    Road    Road    Road    Road    Road    Road    Road    Road    Road    Road
    Road    Road    Road    Road    Road    Road    Road    Road    Road    Road    Road
    Road    Road    Road    Road    Road    Road    Road    Road    Road    Road    Road
    Road    Road    Road    Road    Road    Road    Road    Road    Road    Road    Road
    Road    Road    Road    Road    Road    Road    Road    Road    Road    Road    Road
```

Read and display one of the pixel labeled images by overlaying it on top of an image.

```
C = readimage(pxds, pic_num);

% Overlay segmentation results onto original image. - Computer Vision System Toolbox
B = labeloverlay(I,C,'ColorMap',cmap);

figure
imshow(B)
HelperFunctions.pixelLabelColorbar(cmap,classes);
```

Dataset Statistics

To see the distribution of class labels in the CamVid dataset, use `countEachLabel[CVST]`. This counts the number of pixels by class label and returns a summary table of the labels in imds and the number of files associated with each. The reason that the total number of pixels differs from class to class, is because the function only counts images that contain the class in question.

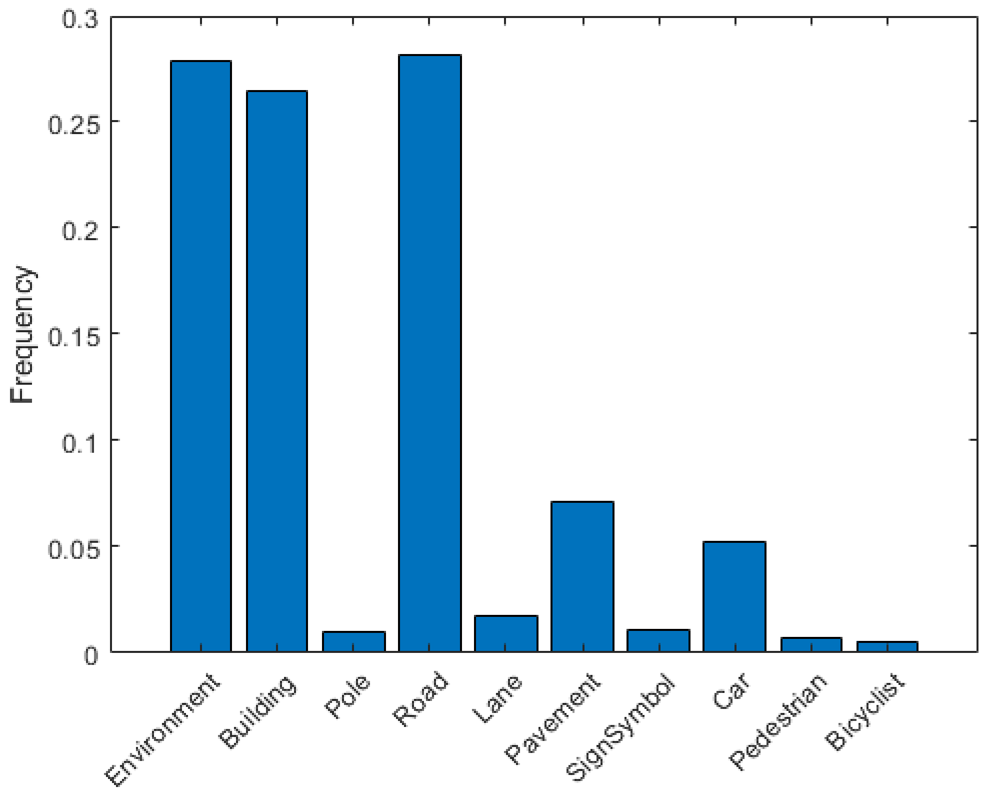
(The difference between the CVST `countEachLabel` and the one that basic ML has is the following: ML one counts files in ImageDatastore labels whereas the CVST one counts pixel labels for each class)

```
tbl = countEachLabel(pxds)
```

tbl = *10×3 table*

	Name	PixelCount	ImagePixelC...
1	'Environment'	32708328	120960000
2	'Building'	31050511	120960000
3	'Pole'	1197513	120787200
4	'Road'	33134466	121132800
5	'Lane'	2078016	120268800
6	'Pavement'	8400966	118022400
7	'SignSymbol'	1304945	117158400
8	'Car'	6108369	120787200
9	'Pedestrian'	850286	111110400
10	'Bicyclist'	647454	65491200

```
% We calculate the frequency in order to get a histogram of the data
frequency = tbl.PixelCount/sum(tbl.PixelCount);

figure
bar(1:numel(classes),frequency)
xticks(1:numel(classes))
xticklabels(tbl.Name)
xtickangle(45)
ylabel('Frequency')
```



Using this information we can see that the classes are not balanced and that some of the classes are rare. These classes can be difficult to learn and thus class balancing will be performed.

Preparation and Training of the Neural Network

Prepare Training And Test Sets

SegNet is trained using 60% of the images from the dataset. The rest of the images are used for testing. The following code randomly (using randperm) splits the image and pixel label data into a training (imdsTrain, pxdsTrain) and test set (imdsTest, pxdsTest).

```
[imdsTrain, imdsTest, pxdsTrain, pxdsTest] = HelperFunctions.partitionCamVidData(imds,pxds,lab
```

The 60/40 splits results in the following number of training and test images:

```
numTrainingImages = numel(imdsTrain.Files)
```

```
numTrainingImages = 421
```

```
numTestingImages = numel(imdsTest.Files)
```

```
numTestingImages = 280
```

Create The Network

Use `segnetLayers` to create a SegNet network initialized using VGG-16 weights. `segnetLayers` automatically performs the network surgery needed to transfer the weights from VGG-16 and adds the additional layers required for semantic segmentation.

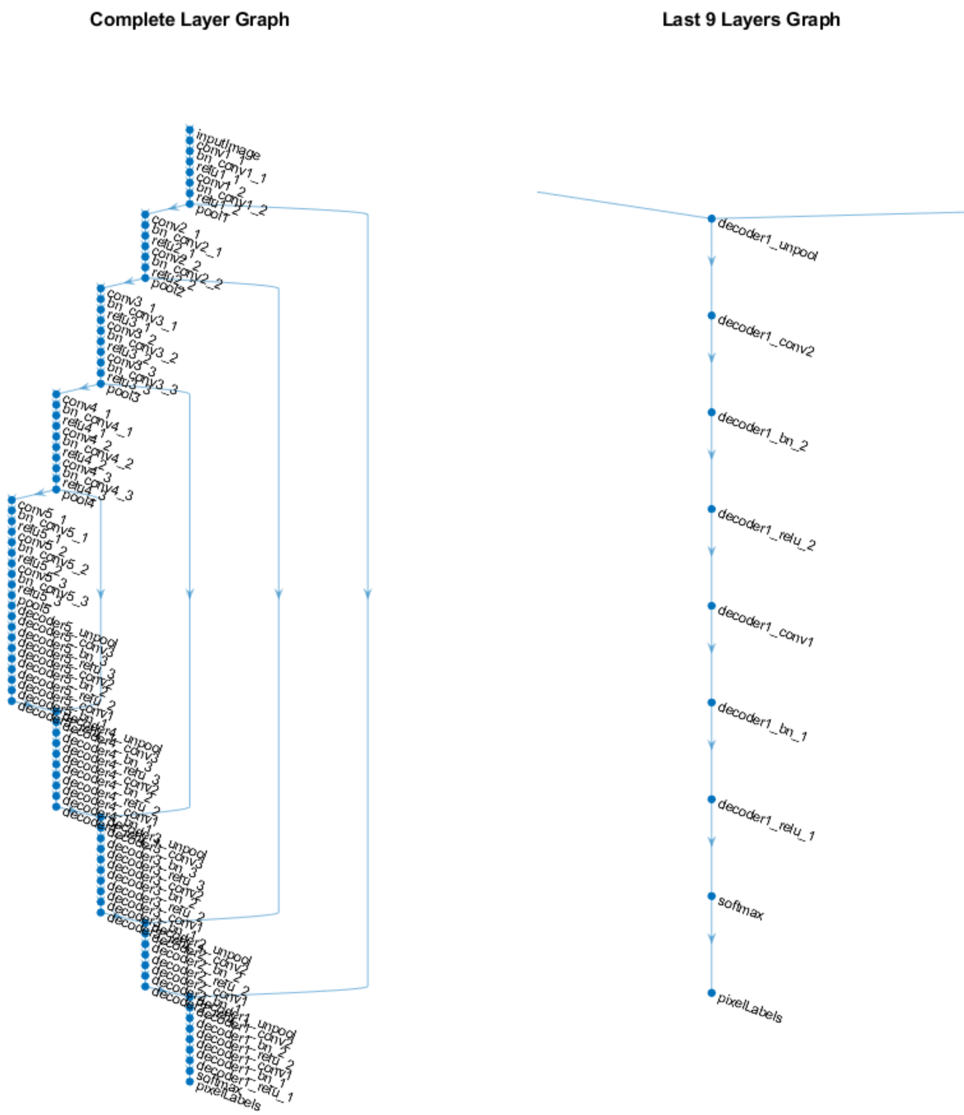
```
imageSize = [360 480 3];
numClasses = numel(classes);

% segnetLayers returns SegNet network layers, lgraph, that is preinitialized with layers and w
lgraph = segnetLayers(imageSize,numClasses,'vgg16');

% lgraph initially has 91 Layers.
lgraph.Layers
```

```
ans = 
  91x1 Layer array with layers:

     1   'inputImage'         Image Input                   360x480x3 images with 'zerocenter' normalization
     2   'conv1_1'            Convolution                   64 3x3x3 convolutions with stride [1  1] and padding [1
     3   'bn_conv1_1'         Batch Normalization           Batch normalization
     4   'relu1_1'            ReLU                          ReLU
     5   'conv1_2'            Convolution                   64 3x3x64 convolutions with stride [1  1] and padding [1
     6   'bn_conv1_2'         Batch Normalization           Batch normalization
     7   'relu1_2'            ReLU                          ReLU
     8   'pool1'              Max Pooling                   2x2 max pooling with stride [2  2] and padding [0  0  0
     9   'conv2_1'            Convolution                   128 3x3x64 convolutions with stride [1  1] and padding [
    10   'bn_conv2_1'         Batch Normalization           Batch normalization
    11   'relu2_1'            ReLU                          ReLU
    12   'conv2_2'            Convolution                   128 3x3x128 convolutions with stride [1  1] and padding
    13   'bn_conv2_2'         Batch Normalization           Batch normalization
    14   'relu2_2'            ReLU                          ReLU
    15   'pool2'              Max Pooling                   2x2 max pooling with stride [2  2] and padding [0  0  0
    16   'conv3_1'            Convolution                   256 3x3x128 convolutions with stride [1  1] and padding
    17   'bn_conv3_1'         Batch Normalization           Batch normalization
    18   'relu3_1'            ReLU                          ReLU
    19   'conv3_2'            Convolution                   256 3x3x256 convolutions with stride [1  1] and padding
    20   'bn_conv3_2'         Batch Normalization           Batch normalization
    21   'relu3_2'            ReLU                          ReLU
    22   'conv3_3'            Convolution                   256 3x3x256 convolutions with stride [1  1] and padding
    23   'bn_conv3_3'         Batch Normalization           Batch normalization
    24   'relu3_3'            ReLU                          ReLU
    25   'pool3'              Max Pooling                   2x2 max pooling with stride [2  2] and padding [0  0  0
    26   'conv4_1'            Convolution                   512 3x3x256 convolutions with stride [1  1] and padding
    27   'bn_conv4_1'         Batch Normalization           Batch normalization
    28   'relu4_1'            ReLU                          ReLU
    29   'conv4_2'            Convolution                   512 3x3x512 convolutions with stride [1  1] and padding
    30   'bn_conv4_2'         Batch Normalization           Batch normalization
    31   'relu4_2'            ReLU                          ReLU
    32   'conv4_3'            Convolution                   512 3x3x512 convolutions with stride [1  1] and padding
    33   'bn_conv4_3'         Batch Normalization           Batch normalization
    34   'relu4_3'            ReLU                          ReLU
    35   'pool4'              Max Pooling                   2x2 max pooling with stride [2  2] and padding [0  0  0
    36   'conv5_1'            Convolution                   512 3x3x512 convolutions with stride [1  1] and padding
    37   'bn_conv5_1'         Batch Normalization           Batch normalization
    38   'relu5_1'            ReLU                          ReLU
    39   'conv5_2'            Convolution                   512 3x3x512 convolutions with stride [1  1] and padding
    40   'bn_conv5_2'         Batch Normalization           Batch normalization
    41   'relu5_2'            ReLU                          ReLU
    42   'conv5_3'            Convolution                   512 3x3x512 convolutions with stride [1  1] and padding
```

```
43   'bn_conv5_3'        Batch Normalization        Batch normalization
44   'relu5_3'           ReLU                       ReLU
45   'pool5'             Max Pooling                2x2 max pooling with stride [2  2] and padding [0  0  0
46   'decoder5_unpool'   Max Unpooling              Max Unpooling
47   'decoder5_conv3'    Convolution                512 3x3x512 convolutions with stride [1  1] and padding
48   'decoder5_bn_3'     Batch Normalization        Batch normalization
49   'decoder5_relu_3'   ReLU                       ReLU
50   'decoder5_conv2'    Convolution                512 3x3x512 convolutions with stride [1  1] and padding
51   'decoder5_bn_2'     Batch Normalization        Batch normalization
52   'decoder5_relu_2'   ReLU                       ReLU
53   'decoder5_conv1'    Convolution                512 3x3x512 convolutions with stride [1  1] and padding
54   'decoder5_bn_1'     Batch Normalization        Batch normalization
55   'decoder5_relu_1'   ReLU                       ReLU
56   'decoder4_unpool'   Max Unpooling              Max Unpooling
57   'decoder4_conv3'    Convolution                512 3x3x512 convolutions with stride [1  1] and padding
58   'decoder4_bn_3'     Batch Normalization        Batch normalization
59   'decoder4_relu_3'   ReLU                       ReLU
60   'decoder4_conv2'    Convolution                512 3x3x512 convolutions with stride [1  1] and padding
61   'decoder4_bn_2'     Batch Normalization        Batch normalization
62   'decoder4_relu_2'   ReLU                       ReLU
63   'decoder4_conv1'    Convolution                256 3x3x512 convolutions with stride [1  1] and padding
64   'decoder4_bn_1'     Batch Normalization        Batch normalization
65   'decoder4_relu_1'   ReLU                       ReLU
66   'decoder3_unpool'   Max Unpooling              Max Unpooling
67   'decoder3_conv3'    Convolution                256 3x3x256 convolutions with stride [1  1] and padding
68   'decoder3_bn_3'     Batch Normalization        Batch normalization
69   'decoder3_relu_3'   ReLU                       ReLU
70   'decoder3_conv2'    Convolution                256 3x3x256 convolutions with stride [1  1] and padding
71   'decoder3_bn_2'     Batch Normalization        Batch normalization
72   'decoder3_relu_2'   ReLU                       ReLU
73   'decoder3_conv1'    Convolution                128 3x3x256 convolutions with stride [1  1] and padding
74   'decoder3_bn_1'     Batch Normalization        Batch normalization
75   'decoder3_relu_1'   ReLU                       ReLU
76   'decoder2_unpool'   Max Unpooling              Max Unpooling
77   'decoder2_conv2'    Convolution                128 3x3x128 convolutions with stride [1  1] and padding
78   'decoder2_bn_2'     Batch Normalization        Batch normalization
79   'decoder2_relu_2'   ReLU                       ReLU
80   'decoder2_conv1'    Convolution                64 3x3x128 convolutions with stride [1  1] and padding [
81   'decoder2_bn_1'     Batch Normalization        Batch normalization
82   'decoder2_relu_1'   ReLU                       ReLU
83   'decoder1_unpool'   Max Unpooling              Max Unpooling
84   'decoder1_conv2'    Convolution                64 3x3x64 convolutions with stride [1  1] and padding [1
85   'decoder1_bn_2'     Batch Normalization        Batch normalization
86   'decoder1_relu_2'   ReLU                       ReLU
87   'decoder1_conv1'    Convolution                10 3x3x64 convolutions with stride [1  1] and padding [1
88   'decoder1_bn_1'     Batch Normalization        Batch normalization
89   'decoder1_relu_1'   ReLU                       ReLU
90   'softmax'           Softmax                    softmax
91   'pixelLabels'       Pixel Classification Layer Cross-entropy loss
```

```
% Plot the 91-Layer lgraph
fig1=figure('Position', [100, 100, 1000, 1100]);
subplot(1,2,1)
plot(lgraph);
axis off
axis tight
title('Complete Layer Graph')

subplot(1,2,2)
plot(lgraph);
xlim([2.862 3.200])
ylim([-0.9 10.9])
```

```
axis off
title('Last 9 Layers Graph')
```



The image size is selected based on the size of the images in the dataset, and the number of classes is selected based on the classes in CamVid.

Balance Classes Using Class Weighting

As shown earlier, the classes in CamVid are not balanced. To improve training, class weighting can be used to balance the classes. Use the pixel label counts computed earlier with `countEachLabel` and calculate the median frequency class weights [3].

```
% Get the imageFreq using the data from the countEachLabel function
imageFreq = tbl.PixelCount ./ tbl.ImagePixelCount;

% The higher the frequency of a class the smaller the classWeight
classWeights = median(imageFreq) ./ imageFreq
```

```
classWeights =
   0.1255
   0.1322
   3.4218
   0.1240
   1.9635
   0.4766
   3.0458
   0.6708
   4.4331
   3.4315
```

Specify the class weights using a `pixelClassificationLayer`. We can use the pixel classification layer to provide a categorical label for each image pixel processed by a convolutional neural network (CNN). This layer will replace the last layer of our NN

```
pxLayer = pixelClassificationLayer('Name','labels','ClassNames', tbl.Name, 'ClassWeights', cla
```

```
pxLayer =
  PixelClassificationLayer with properties:

            Name: 'labels'
      ClassNames: {'Environment'  'Building'  'Pole'  'Road'  'Lane'  'Pavement'  'SignSymbol'  'Car'  'Pedestrian
    ClassWeights: [10×1 double]
      OutputSize: 'auto'

   Hyperparameters
    LossFunction: 'crossentropyex'
```

Update the SegNet network with the new `pixelClassificationLayer`. This requires removing and adding the new layer. The `pixelClassificationLayer` is located at index 91 in `lgraph.Layers`. Remove it using `removeLayers`, add the new one using `addLayers`, and reconnect it using `connectLayers`.

The reason that connectLayers needs to be used is because we are working with a DAG-Network.

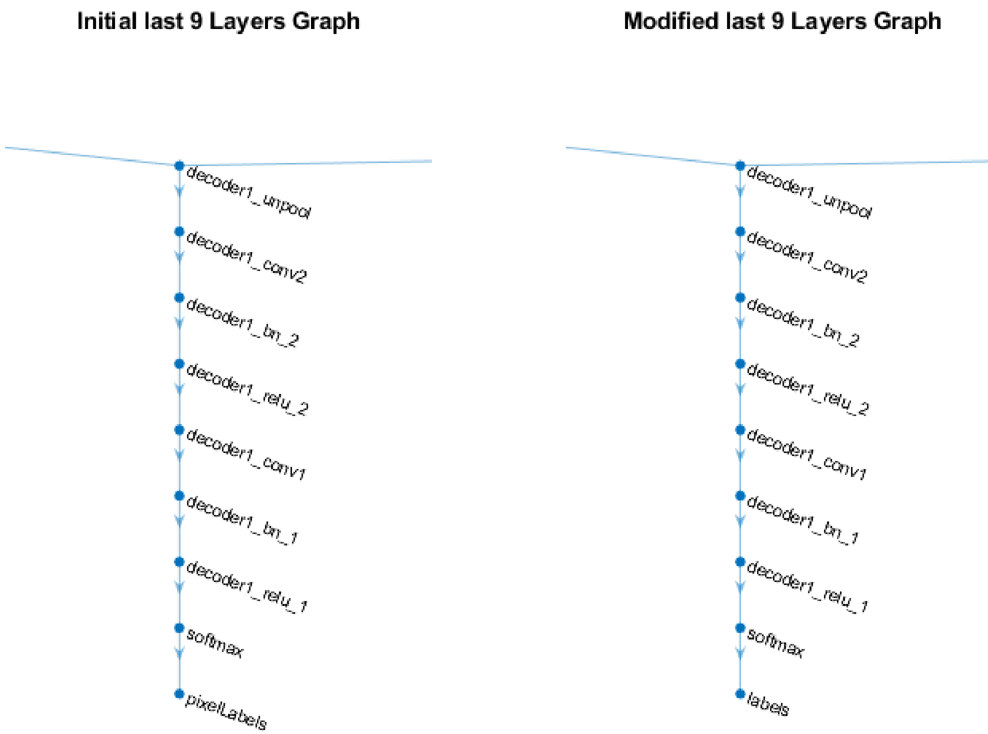
```
% Plot the 91-Layer lgraph
fig2=figure('Position', [100, 100, 800, 600]);
subplot(1,2,1)
plot(lgraph);
xlim([2.862 3.200])
ylim([-0.9 10.9])
axis off
```

```
title('Initial last 9 Layers Graph')

% Remove last layer of and add the new one we created.
lgraph = removeLayers(lgraph, {'pixelLabels'});
lgraph = addLayers(lgraph, pxLayer);

% Connect the newly created layer with the graph.
lgraph = connectLayers(lgraph, 'softmax','labels');
lgraph.Layers
```

```
ans =
  91x1 Layer array with layers:

     1   'inputImage'        Image Input             360x480x3 images with 'zerocenter' normalization
     2   'conv1_1'           Convolution             64 3x3x3 convolutions with stride [1  1] and padding [1
     3   'bn_conv1_1'        Batch Normalization     Batch normalization
     4   'relu1_1'           ReLU                    ReLU
     5   'conv1_2'           Convolution             64 3x3x64 convolutions with stride [1  1] and padding [1
     6   'bn_conv1_2'        Batch Normalization     Batch normalization
     7   'relu1_2'           ReLU                    ReLU
     8   'pool1'             Max Pooling             2x2 max pooling with stride [2  2] and padding [0  0  0
     9   'conv2_1'           Convolution             128 3x3x64 convolutions with stride [1  1] and padding [
    10   'bn_conv2_1'        Batch Normalization     Batch normalization
    11   'relu2_1'           ReLU                    ReLU
    12   'conv2_2'           Convolution             128 3x3x128 convolutions with stride [1  1] and padding
    13   'bn_conv2_2'        Batch Normalization     Batch normalization
    14   'relu2_2'           ReLU                    ReLU
    15   'pool2'             Max Pooling             2x2 max pooling with stride [2  2] and padding [0  0  0
    16   'conv3_1'           Convolution             256 3x3x128 convolutions with stride [1  1] and padding
    17   'bn_conv3_1'        Batch Normalization     Batch normalization
    18   'relu3_1'           ReLU                    ReLU
    19   'conv3_2'           Convolution             256 3x3x256 convolutions with stride [1  1] and padding
    20   'bn_conv3_2'        Batch Normalization     Batch normalization
    21   'relu3_2'           ReLU                    ReLU
    22   'conv3_3'           Convolution             256 3x3x256 convolutions with stride [1  1] and padding
    23   'bn_conv3_3'        Batch Normalization     Batch normalization
    24   'relu3_3'           ReLU                    ReLU
    25   'pool3'             Max Pooling             2x2 max pooling with stride [2  2] and padding [0  0  0
    26   'conv4_1'           Convolution             512 3x3x256 convolutions with stride [1  1] and padding
    27   'bn_conv4_1'        Batch Normalization     Batch normalization
    28   'relu4_1'           ReLU                    ReLU
    29   'conv4_2'           Convolution             512 3x3x512 convolutions with stride [1  1] and padding
    30   'bn_conv4_2'        Batch Normalization     Batch normalization
    31   'relu4_2'           ReLU                    ReLU
    32   'conv4_3'           Convolution             512 3x3x512 convolutions with stride [1  1] and padding
    33   'bn_conv4_3'        Batch Normalization     Batch normalization
    34   'relu4_3'           ReLU                    ReLU
    35   'pool4'             Max Pooling             2x2 max pooling with stride [2  2] and padding [0  0  0
    36   'conv5_1'           Convolution             512 3x3x512 convolutions with stride [1  1] and padding
    37   'bn_conv5_1'        Batch Normalization     Batch normalization
    38   'relu5_1'           ReLU                    ReLU
    39   'conv5_2'           Convolution             512 3x3x512 convolutions with stride [1  1] and padding
    40   'bn_conv5_2'        Batch Normalization     Batch normalization
    41   'relu5_2'           ReLU                    ReLU
    42   'conv5_3'           Convolution             512 3x3x512 convolutions with stride [1  1] and padding
    43   'bn_conv5_3'        Batch Normalization     Batch normalization
    44   'relu5_3'           ReLU                    ReLU
    45   'pool5'             Max Pooling             2x2 max pooling with stride [2  2] and padding [0  0  0
    46   'decoder5_unpool'   Max Unpooling           Max Unpooling
    47   'decoder5_conv3'    Convolution             512 3x3x512 convolutions with stride [1  1] and padding
    48   'decoder5_bn_3'     Batch Normalization     Batch normalization
    49   'decoder5_relu_3'   ReLU                    ReLU
```

```
50   'decoder5_conv2'    Convolution               512 3x3x512 convolutions with stride [1  1] and padding
51   'decoder5_bn_2'     Batch Normalization       Batch normalization
52   'decoder5_relu_2'   ReLU                      ReLU
53   'decoder5_conv1'    Convolution               512 3x3x512 convolutions with stride [1  1] and padding
54   'decoder5_bn_1'     Batch Normalization       Batch normalization
55   'decoder5_relu_1'   ReLU                      ReLU
56   'decoder4_unpool'   Max Unpooling             Max Unpooling
57   'decoder4_conv3'    Convolution               512 3x3x512 convolutions with stride [1  1] and padding
58   'decoder4_bn_3'     Batch Normalization       Batch normalization
59   'decoder4_relu_3'   ReLU                      ReLU
60   'decoder4_conv2'    Convolution               512 3x3x512 convolutions with stride [1  1] and padding
61   'decoder4_bn_2'     Batch Normalization       Batch normalization
62   'decoder4_relu_2'   ReLU                      ReLU
63   'decoder4_conv1'    Convolution               256 3x3x512 convolutions with stride [1  1] and padding
64   'decoder4_bn_1'     Batch Normalization       Batch normalization
65   'decoder4_relu_1'   ReLU                      ReLU
66   'decoder3_unpool'   Max Unpooling             Max Unpooling
67   'decoder3_conv3'    Convolution               256 3x3x256 convolutions with stride [1  1] and padding
68   'decoder3_bn_3'     Batch Normalization       Batch normalization
69   'decoder3_relu_3'   ReLU                      ReLU
70   'decoder3_conv2'    Convolution               256 3x3x256 convolutions with stride [1  1] and padding
71   'decoder3_bn_2'     Batch Normalization       Batch normalization
72   'decoder3_relu_2'   ReLU                      ReLU
73   'decoder3_conv1'    Convolution               128 3x3x256 convolutions with stride [1  1] and padding
74   'decoder3_bn_1'     Batch Normalization       Batch normalization
75   'decoder3_relu_1'   ReLU                      ReLU
76   'decoder2_unpool'   Max Unpooling             Max Unpooling
77   'decoder2_conv2'    Convolution               128 3x3x128 convolutions with stride [1  1] and padding
78   'decoder2_bn_2'     Batch Normalization       Batch normalization
79   'decoder2_relu_2'   ReLU                      ReLU
80   'decoder2_conv1'    Convolution               64 3x3x128 convolutions with stride [1  1] and padding [
81   'decoder2_bn_1'     Batch Normalization       Batch normalization
82   'decoder2_relu_1'   ReLU                      ReLU
83   'decoder1_unpool'   Max Unpooling             Max Unpooling
84   'decoder1_conv2'    Convolution               64 3x3x64 convolutions with stride [1  1] and padding [1
85   'decoder1_bn_2'     Batch Normalization       Batch normalization
86   'decoder1_relu_2'   ReLU                      ReLU
87   'decoder1_conv1'    Convolution               10 3x3x64 convolutions with stride [1  1] and padding [1
88   'decoder1_bn_1'     Batch Normalization       Batch normalization
89   'decoder1_relu_1'   ReLU                      ReLU
90   'softmax'           Softmax                   softmax
91   'labels'            Pixel Classification Layer   Class weighted cross-entropy loss with 'Environment', 'E
```

```
subplot(1,2,2)
plot(lgraph);
xlim([2.862 3.200])
ylim([-0.9 10.9])
axis off
title(' Modified last 9 Layers Graph')
```



Select Training Options

The optimization algorithm used for training is Stochastic Gradient Decent with Momentum (SGDM). Use `trainingOptions` to specify the hyper-parameters used for SGDM.

During training, you can stop training and return the current state of the network by clicking the stop button in the top right corner. For example, you might want to stop training when the accuracy of the network reaches a plateau and it is clear that the accuracy is no longer improving. Once the execution is stopped, the script will continue executing. You cannot resume the training from where it stopped.

A mini-batch size of 4 is used to reduce memory usage while training. This can be increased or decreased based on the amount of GPU memory you have on your system.

```
options = trainingOptions('sgdm', ... % This is the solver's name; sgdm: stochastic gradient d
    'Momentum', 0.9, ...              % Contribution of the gradient step from the previous it
    'InitialLearnRate', 1e-2, ...     % low rate will give long training times and quick rate
    'L2Regularization', 0.0005, ...   % Weight decay - This term helps in avoiding overfitting
    'MaxEpochs', 120,...              % An iteration is one step taken in the gradient descent
    'MiniBatchSize', 4, ...           % A mini-batch is a subset of the training set that is u
    'Shuffle', 'every-epoch', ...     % Shuffle the training data before each training epoch a
    'Verbose', false,...
    'Plots','training-progress');
```

Data Augmentation

Data augmentation is used during training to provide more examples to the network because it helps improve the accuracy of network. Here, random left/right reflection and random X/Y translation of +/- 10 pixels is used for data augmentation. By performing data augmentation the training set is increased by creating and using synthetic data. A simple example would be the training of handwriting. Every letter \number can be skewed or wrapped so the training set can be increased and thus capture the hand-writing variability of different people.

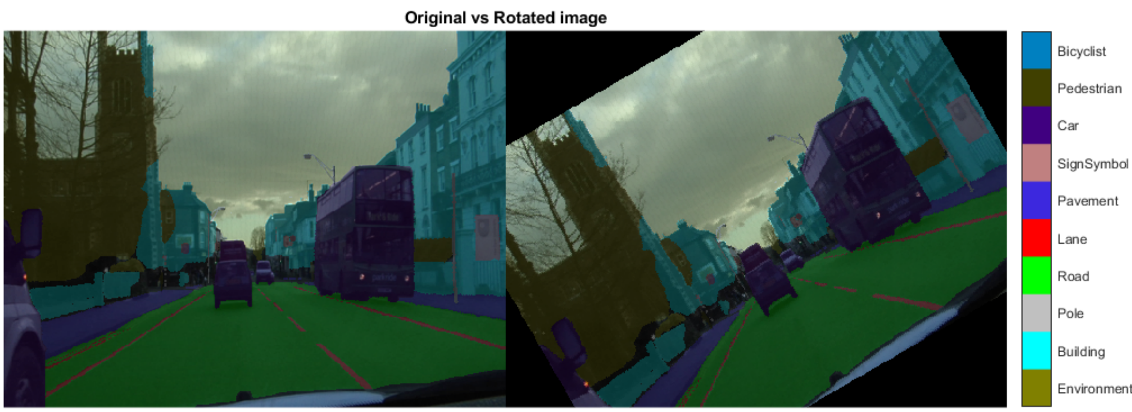
Use the `imageDataAugmenter` to specify these data augmentation parameters:

```
augmenter = imageDataAugmenter('RandXReflection',true,...
    'RandXTranslation', [-10 10], 'RandYTranslation',[-10 10]);
```

There are several other types of data augmentation supported by `imageDataAugmenter`. Choosing amongst them requires empirical analysis and is another level of hyper-parameter tuning.

The data augmentation process can also include the rotation of the image. While rotating, a portion of the image is going to be cropped and the values of the Data\Label images are going to be interpolated. An example of that can be seen in the following figure:

```
HelperFunctions.showRotationEffect(imds,pxds,pic_num,30);
```



Even though the images is rotated and the values of the images interpolated, the pixel labeling remains the same.

Start Training

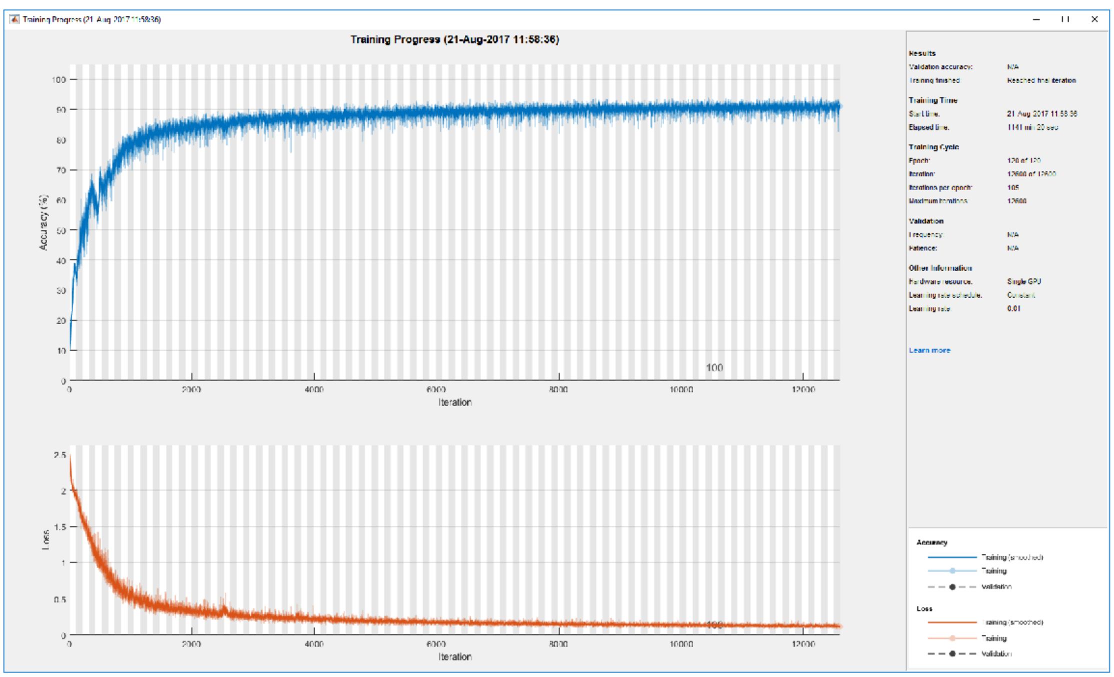
The training data and data augmentation selections are combined using `pixelLabelImageDatasource`. The pixelLabelDataImageDatasource reads batchs of training data, applies data augmentation, and sends the augmented data to the training algorithm.

```
datasource = pixelLabelImageSource(imdsTrain,pxdsTrain,...
    'DataAugmentation',augmenter);
```

Start training using `trainNetwork` if the doTraining flag is true. Otherwise, load a pretrained network. This networks was trained on an NVIDIA(TM) Tesla K40c.The training times may be longer depending on your GPU hardware.

To train the network with the options set above, the training process will take approximately 19 hours. The number of iterations and the mini batch size are the two most contributing factors to that time. If we decrease the number of iterations by 20, the training takes approximately 10.5 hours. When the mini-batch size is increased, the training time will go down since the GPU (or CPU) will process more data at the same time. By increasing it by 1, the 19 hours become 12 hours. Finally, the learning rate can affect the training time. Approximately, for every order of magnitude we decrease the learning rate (0.1 -> 0.01) half an hour will be added to the total training time.

```
doTraining = false;
if doTraining
    % Trains a network for image classification problems
    tic
    [net, info] = trainNetwork(datasource,lgraph,options);
    toc
    save('PreTrainedCnn.mat','net','info','options');
    disp('NN trained');
else
    % Load the pre-trained network.
    data = load('PreTrainedCnn.mat');
    net = data.net;
end

imshow(imread([pwd '\TrainingProgress90.png']))
```



The above network will have 90% accuracy on the training set. The metric for that accuracy is: how many pixel labels were predicted right divided by total number of pixels. To do that we sum over height and width for all images in the batch and we divide by the total number of images in that batch.

Show the image used on the beginning of the example

In the following example, we can see that the predicted image does a pretty good job in detecting the left most lane versus the ground truth. This is because the data was labeled by users and due to that, we can have intra and inter-observer variability. This means that even if I put the same user to tag the same data twice, the labeling will not be the same. In this case, we can see that the semantic segmentation outperforms the ground truth.

The issue with this lies in the metrics. When we calculate the metrics for the accuracy of the prediction, the correctly predicted lane will count as a false positive thus leading to low IOU. By observing the results visually, we can see that this is not the case and that we can have confidence on the results of the semantic segmentation. This phenomenon is observed when the overall acuracy of our Neural Network is above 80%.

```
pic_num = 30;
I = readimage(imds, pic_num);
Ib = readimage(pxds, pic_num);

IB = labeloverlay(I, Ib, 'Colormap', cmap, 'Transparency',0.8);
figure
% Show the results of the semantic segmentation
C = semanticseg(I, net);
CB = labeloverlay(I, C, 'Colormap', cmap, 'Transparency',0.8);
figure
imshowpair(IB,CB,'montage')
HelperFunctions.pixelLabelColorbar(cmap, classes);
title('Ground Truth vs Predicted')
```

Test Network On One Image

As a quick sanity check, run the trained network on one test image (1.74 seconds) using `semanticseg` [CVST].

```
I = read(imdsTest);

C = semanticseg(I, net);
```

Display the results.

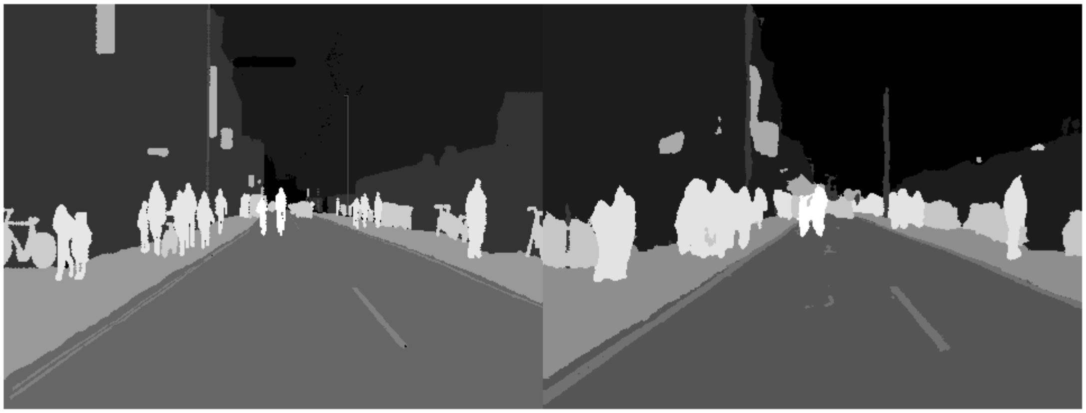
```
B = labeloverlay(I, C, 'Colormap', cmap, 'Transparency',0.8);
figure
imshow(B)
HelperFunctions.pixelLabelColorbar(cmap, classes);
```

Compare the results in `C` with the expected ground truth stored in `pxdsTest`. The important thing to note here is that although the semantic segmentation results do not have the granularity of the ground truth (ex. the persons in the image; They look like blobs instead of people), it is able to detect the objects in the correct position and label them accordingly. Due to that, the predicted labels contain a lot of False Positives. But, in a safety critical system such as Automated Driving, the ability to detect pedestrians, bicycles etc, makes the False Positives acceptable.

```
expectedResult = read(pxdsTest);
expected = uint8(expectedResult);
predicted = uint8(C);
```

```
% Compare differences between images - Image Processing toolbox
imshowpair(expected, predicted, 'montage')
title('Ground Truth labels vs Predicted labels')
```

Ground Truth labels vs Predicted labels



Visually, the semantic segmentation results overlap well for classes such as road, sky, and building. However, smaller objects like pedestrians and cars are not as accurate.The amount of overlap per class can be measured using the intersection-over-union (IoU) metric, also known as the Jaccard index. Use the jaccard function to measure IoU.

```
% Jaccard similarity coefficient for image segmentation - Image Processing Toolbox
iou = jaccard(C, expectedResult);

table(classes,iou)
```

```
ans = 10×2 table
```

	classes	iou
1	"Environment"	0.9192
2	"Building"	0.8274
3	"Pole"	0.2532
4	"Road"	0.9564
5	"Lane"	0.4590
6	"Pavement"	0.8926
7	"SignSymbol"	0.2020
8	"Car"	0.5261
9	"Pedestrian"	0.6157
10	"Bicyclist"	0.5560

Other common segmentation metrics include the Dice index and the Boundary-F1 contour matching score.

Evaluate Trained Network

To measure accuracy for multiple test images, run `semanticseg` on the entire test set.

If CPU is used it takes 1h 49 mins.

If GPU is used it takes 7.2 minutes.

```
pxdsResults = semanticseg(imdsTest,net,'WriteLocation',tempdir,'Verbose',false);
```

`semanticseg` returns the results for the test set as a `pixelLabelDatastore` object. The actual pixel label data for each test image in `imdsTest` is written to disk in the location specified by the 'WriteLocation' parameter. Use `evaluateSemanticSegmentation` measure semantic segmentation metrics on the test set results. It takes 32 seconds to run this command.

```
% Evaluate semantic segmentation data set against ground truth
metrics = evaluateSemanticSegmentation(pxdsResults,pxdsTest,'Verbose',false);
```

`evaluateSemanticSegmentation` returns various metrics for the entire dataset, for individual classes, and for each test image. To see the dataset level metrics inspect metrics.DataSetMetrics.

```
metrics.DataSetMetrics
```

ans = *1×5 table*

	GlobalAccuracy	MeanAccuracy	MeanIoU	WeightedIoU	MeanBFScore
1	0.9262	0.9020	0.6791	0.8548	0.7847

The dataset metrics provide a high-level overview of the network performance. To see the impact each class has on the overall performance, inspect the per-class metrics using `metrics.ClassMetrics`.

```
metrics.ClassMetrics
```

ans = *10×3 table*

	Accuracy	IoU	MeanBFScore
1	0.9636	0.9059	0.7759
2	0.8970	0.8526	0.7837
3	0.7997	0.3374	0.7940
4	0.9208	0.8948	0.8859
5	0.9202	0.4747	0.8387
6	0.9355	0.8232	0.8709
7	0.8189	0.5022	0.6881
8	0.9559	0.8188	0.7883
9	0.8999	0.4854	0.6619
10	0.9088	0.6956	0.7322

Although the overall dataset performance is quite high, the class metrics shows that underrepresented classes such as pedestrians, bicycles, and cars are not segmented as well as the larger classes such as road, and building. Additional data that includes more samples of the underrepresented classes may help improve the results.