Practical Deep Learning Examples with MATLAB

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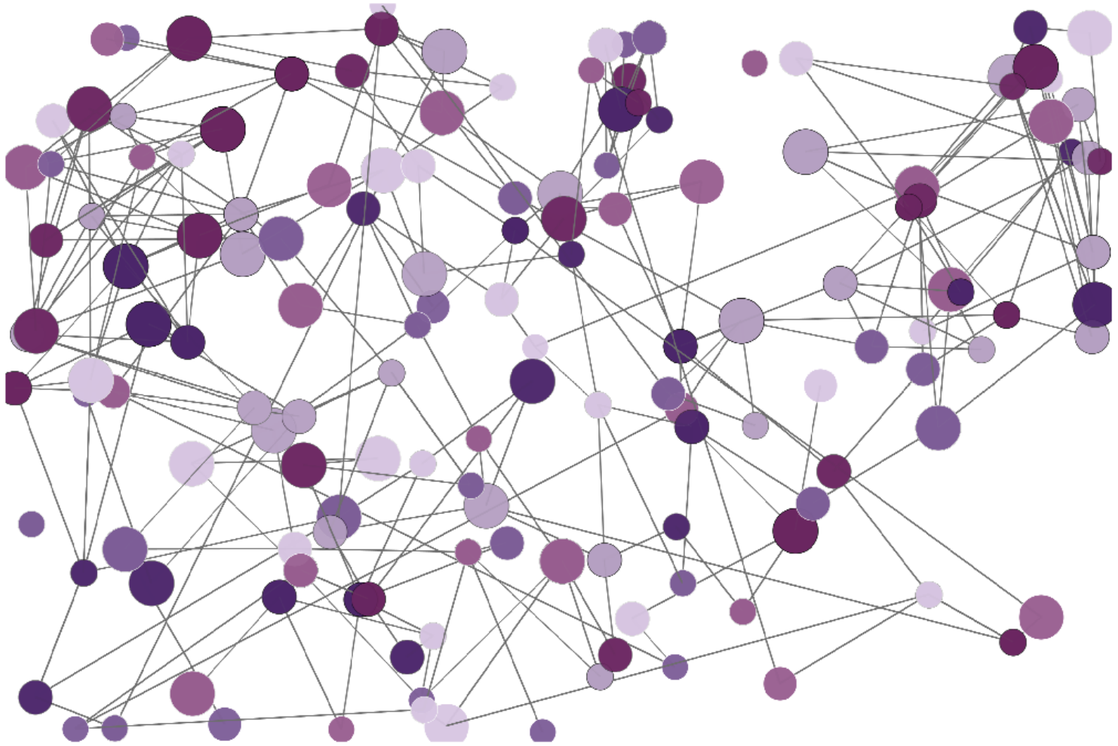
Introduction

This ebook builds on *Introducing Deep Learning with MATLAB*, which answered the question "What is deep learning?" Here, we show you how it's done. We'll demonstrate three approaches to training a deep learning network:

- Training a network from scratch
- Using transfer learning to train an existing network
- Training an existing network to perform semantic segmentation

These examples focus on image classification. But deep learning has become increasingly popular for other applications as well. In the second part of the ebook, we present two examples showing how many of the deep learning techniques used on images can also be applied to signal data.

All the examples and code are available for *download*.

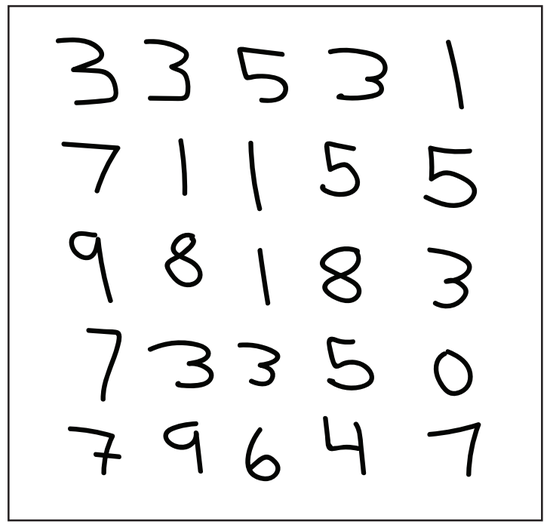


Review the Basics

- *What Is Deep Learning?* 3:33
- *Deep Learning vs. Machine Learning* 3:48

Practical Example #1: Training a Model from Scratch

In this example, we want to train a *convolutional neural network* (CNN) to identify handwritten digits. We will use data from the *MNIST dataset*, which contains 60,000 images of handwritten numbers 0–9. Here is a random sample of 25 handwritten numbers in the MNIST dataset:



By using a simple dataset, we'll be able to cover all the key steps in the deep learning workflow without dealing with challenges such as processing power or datasets that are too large to fit into memory. The workflow described here can be applied to more complex deep learning problems and larger datasets.

If you are just getting started with applying deep learning, another advantage to using this dataset is that you can train it without investing in an expensive GPU.

Even though the dataset is simple, with the right deep learning model and training options, it is possible to achieve over 99% accuracy. So how do we create a model that will get us to that point?

This will be an iterative process in which we build on previous training results to figure out how to approach the training problem. The steps are as follows:

1. Accessing the Data

We begin by downloading the *MNIST* images into MATLAB®. Datasets are stored in many different file types. This data is stored as binary files, which MATLAB can quickly use and reshape into images.

These lines of code will read an original binary file and create an array of all the training images:

```
rawImgDataTrain = uint8 (fread(fid, numImg * numRows * numCols,...
    'uint8'));

% Reshape the data part into a 4D array
rawImgDataTrain = reshape(rawImgDataTrain, [numRows, numCols,...
    numImgs]);
imgDataTrain(:,:,1,ii) = uint8(rawImgDataTrain(:,:,ii));
```

We can check the size and class of the data by typing **whos** in the command window.

```
>> whos imgDataTrain

Name            Size                      Bytes     Class

imgDataTrain    28x28x1x60000             47040000   uint8
```

The MNIST images are quite small—only 28 x 28 pixels—and there are 60,000 training images in total.

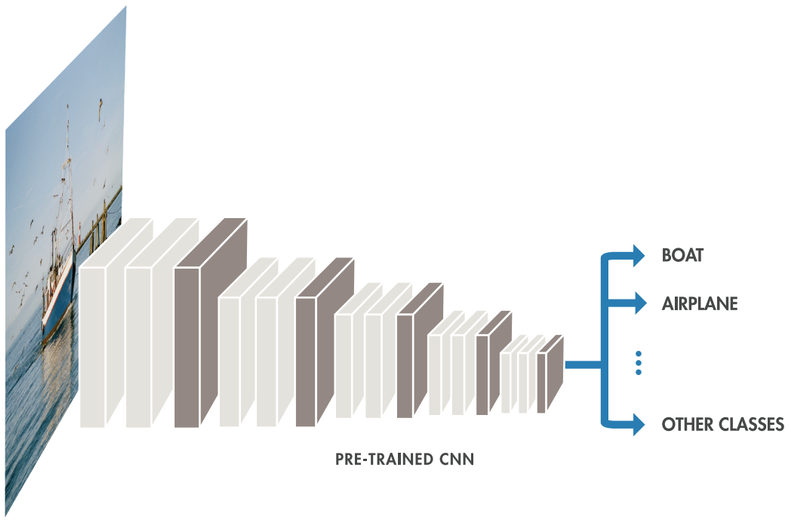
The next task would be image labeling, but since the MNIST images come with labels, we can skip that tedious step and quickly move on to building our neural network.

2. Creating and Configuring Network Layers

We'll be building a CNN, the most common kind of deep learning network.

About CNNs

A CNN passes an image through the network layers and outputs a final class. The network can have tens or hundreds of layers, with each layer learning to detect different features. Filters are applied to each training image at different resolutions, and the output of each convolved image is used as the input to the next layer. The filters can start as very simple features, such as brightness and edges, and increase in complexity to features that uniquely define the object as the layers progress.



Learn More

What Is a Convolutional Neural Network? 4:44

Commonly Used Network Layers

Convolution puts the input images through a set of convolutional filters, each of which activates certain features from the images.

Rectified linear unit (ReLU) allows for faster and more effective training by mapping negative values to zero and maintaining positive values.

Pooling simplifies the output by performing nonlinear downsampling, reducing the number of parameters that the network needs to learn about.

Fully connected layers "flatten" the network's 2D spatial features into a 1D vector that represents image-level features for classification purposes.

Softmax provides probabilities for each category in the dataset.

When building a network from scratch, it's a good idea to start with a simple combination of commonly used layers—the lack of complexity will make debugging much easier—but we'll probably need to add a few more layers to achieve the accuracy we're aiming for.

```
layers = [  imageInputLayer([28 28 1])
            convolution2dLayer(5,20)
            reluLayer
            maxPooling2dLayer(2, 'Stride', 2)
            fullyConnectedLayer(10)
            softmaxLayer
            classificationLayer()   ]
```

3. Training the Network

Before training, we select training options. There are many options available.

The table shows the most commonly used options.

Training Options	Definition	Hint
Plot of training progress	The plot shows the mini-batch loss and accuracy. It includes a stop button that lets you halt network training at any point.	('Plots','training-progress') Plot the progress of the network as it trains.
Max epochs	An epoch is the full pass of the training algorithm over the entire training set.	('MaxEpoch',20) The more epochs specified, the longer the network will train, but the accuracy may improve with each epoch.
Minibatch size	Minibatches are subsets of the training dataset that are processed on the GPU at the same time.	('MiniBatchSize',64) The larger the minibatch, the faster the training, but the maximum size will be determined by the GPU memory. If you get a memory error when training, reduce the minibatch size.
Learning rate	This is a major parameter that controls the speed of training.	A lower learning rate can give a more accurate result, but the network may take longer to train.

We specify two options: plot progress and minibatch size.

```
miniBatchSize = 8192;
options = trainingOptions( 'sgdm',...
    'MiniBatchSize', miniBatchSize,...
    'Plots', 'training-progress');
net = trainNetwork(imgDataTrain, labelsTrain, layers, options);
```

We then run the network and monitor its progress.

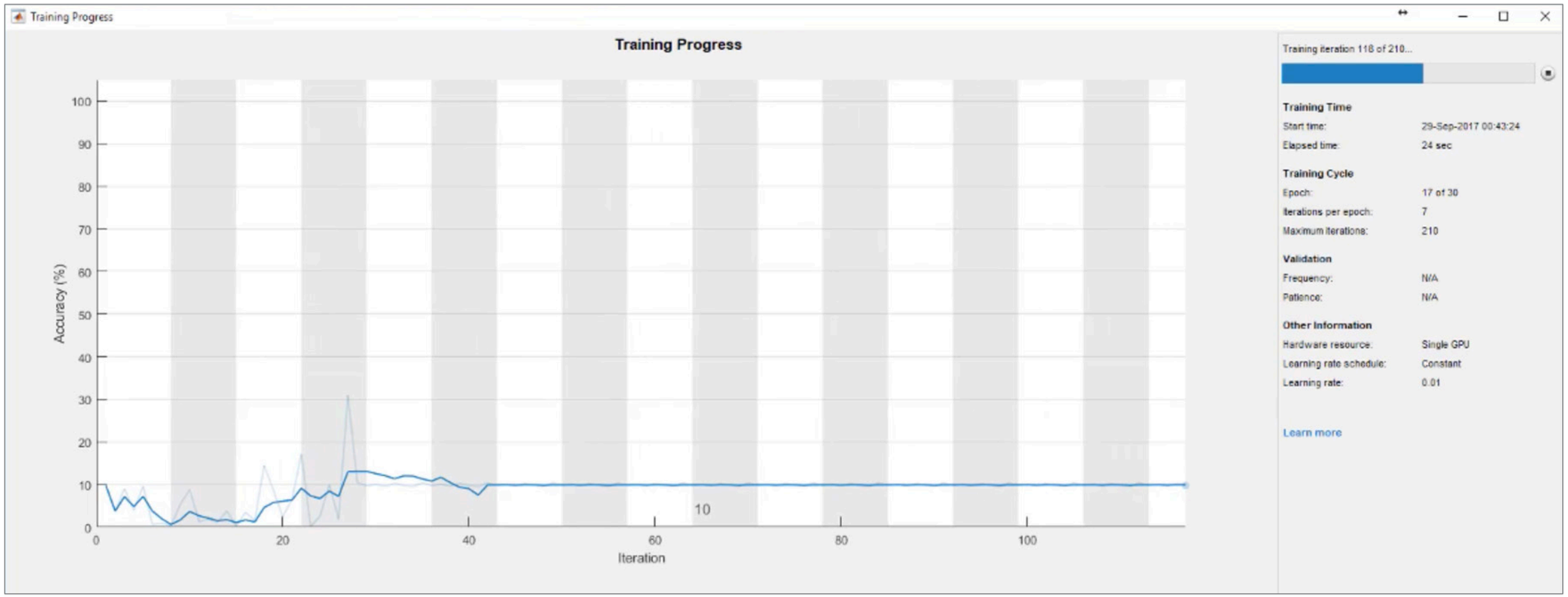
TIP

A large dataset can slow down processing time. But a deep learning network can take advantage of the massively parallelized architecture of a GPU. The exact speedup will vary depending on factors like hardware, dataset size, and network configuration, but you could see training time reduced from hours to minutes.

In the training options in MATLAB, you can quickly change the hardware resource to use for training a network. If this option is not specified, training will default to a single GPU if available.

4. Checking Network Accuracy

Our goal is to have the accuracy of the model increase over time. As the network trains, the progress plot appears.



Our model seems to have stopped improving after the 28th iteration and then dropped to approximately 10% accuracy. This is a common occurrence when training a network from scratch. It means the network is unable to converge on a solution. The accuracy has reached a plateau, and is no longer improving. There is no need to continue—we can stop the training and try some different approaches.

We can stop training and return the current state of the network by clicking the stop button in the top right corner of the screen. Once the execution stops, we need to restart the training from the beginning—we cannot resume from the point where it stopped.

There are many ways to adjust the accuracy of the network.
For example, we could:

- Increase the number of training images
- Increase the quality of the training images
- Alter the training options
- Alter the network configuration (for example, by adding, removing, or reorganizing layers)

We'll try altering the training options and the network configuration.

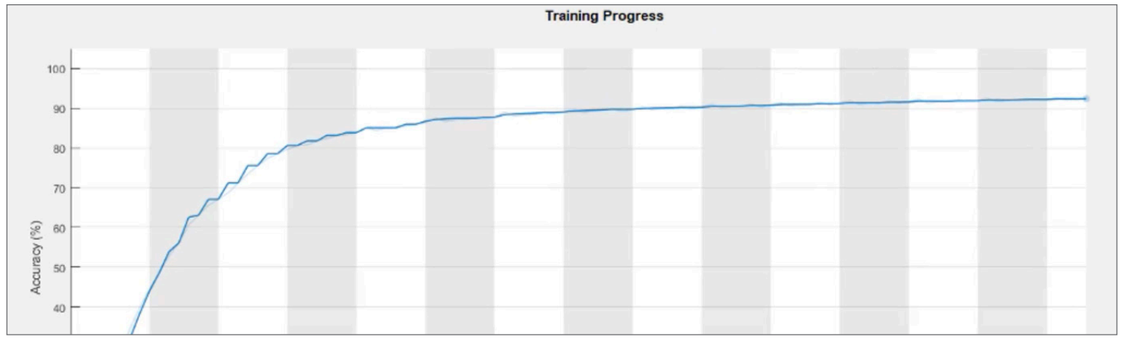
Changing Training Options

First, we'll adjust the learning rate. We set the initial learning rate to be much lower than the default rate of 0.01.

```
'InitialLearnRate', 0.0001
```

As a result of changing that one parameter, we get a much better result—nearly 90% accuracy!

For some applications, this result would be satisfactory, but you may recall that we're aiming for 99%.



ADVANCED TIP

You can use Bayesian optimization to identify the optimal values of the training parameters. Bayesian optimization will run the network multiple times (and you can parallelize the process).

Changing the Network Configuration

Getting to 99% from 90% requires a deeper network and many rounds of trial and error. We add more layers, including batch normalization layers, which will help speed up the network convergence (the point at which it responds correctly to new input).

```
layers = [
    imageInputLayer([28 28 1])
    convolution2dLayer(3,16,'Padding',1)
    batchNormalizationLayer
    reluLayer
    maxPooling2dLayer(2,'Stride',2)
    convolution2dLayer(3,32,'Padding',1)
    batchNormalizationLayer
    reluLayer
    maxPooling2dLayer(2,'Stride',2)
    convolution2dLayer(3,64,'Padding',1)
    batchNormalizationLayer
    reluLayer
    fullyConnectedLayer(10)
    softmaxLayer
    classificationLayer];
```

The network is now "deeper." This time, we'll change the network but leave the training options the same as they were before.

After the network has trained, we test it on 10,000 images.

```
predLabelsTest = net.classify(imgDataTest);
accuracy = sum(predLabelsTest == labelsTest) / numel(labelsTest)
```

```
accuracy = 0.9880
```

This network achieves the highest accuracy of all—around 99%. We can now use it to identify handwritten letters in online images, or even in a live video stream.

Learn More

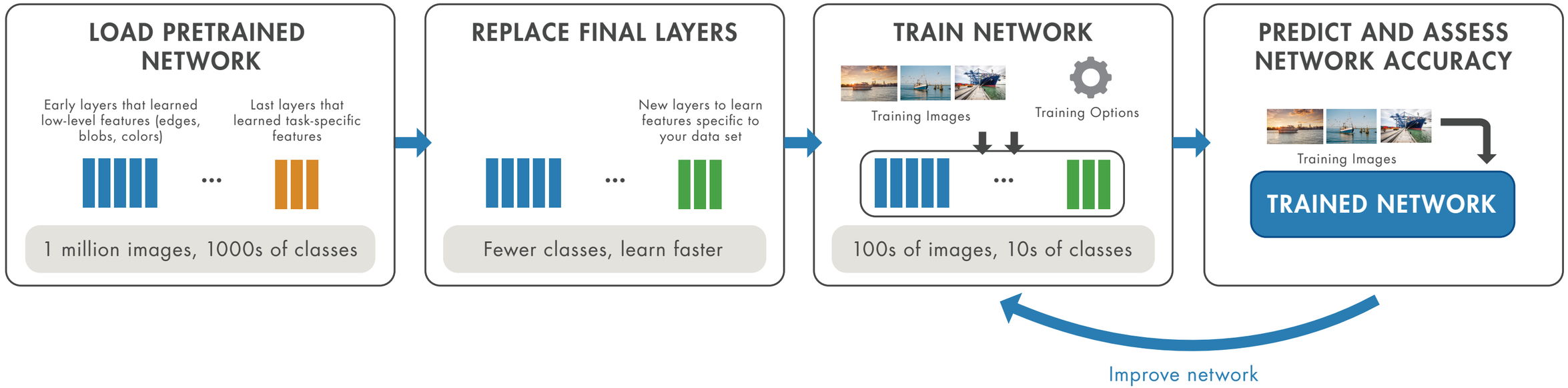
Training a Neural Network from Scratch with MATLAB 5:13
Deep Learning in 11 Lines of MATLAB Code 2:38

Practical Example #2: Transfer Learning

In this example, we'll modify a pretrained network and use transfer learning to train it to perform a new recognition task. Fine-tuning a pre-trained network is much faster and easier than constructing and training a new network: You can quickly transfer learning to a new task using a smaller number of training images. The advantage of transfer learning is that the pretrained network has already learned a rich set of features because of the large number of images it was trained on.

We'll use GoogLeNet, a network trained on 1000 categories of objects, including bicycles, cars, and dogs. We want to retrain this network to identify five categories of food. Here are the steps:

1. Import the pretrained network.
2. Configure the last three layers to perform a new recognition task.
3. Train the network on new data.
4. Test the results.



1. Importing a Pretrained Network

We can import GoogLeNet in one line of code:

```
% Load a pretrained network
net = googlenet;
```

With a pretrained network, most of the heavy lifting of setting up the network (selecting and organizing the layers) has already been done. This means we can test the network on images in the categories the network was original trained on without any reconfiguring:

```
%% Test it on an image
img = imread('peppers.png');
imgLabel = net.classify(imresize(img, [224 224]));
```

googlenet prediction: bell pepper

TIP

Use this line of code to see all 1000 categories that GoogLeNet is trained on:

```
class_names = net.Layers(end).ClassNames;
```

Transfer Learning Tips

- Start with a highly accurate network. If a network only performs at 50% on its original recognition task, it is unlikely to be accurate on a new recognition task.
- A model will probably be more accurate if the new recognition categories have similar features to the original ones. For example, a network trained on dogs will probably learn other animals relatively quickly.

2. Configuring the Network to Perform a New Task

To train GoogLeNet to classify new images, we simply reconfigure the last three layers of the network. These layers contain the information needed to combine the features that the network extracts into class probabilities and labels. GoogLeNet has 144 layers. Here we display the last 5 layers of the network.

```
>>net.Layers(end-4:end)
```

```
140        'pool5-7x7_s1'                  Average Pooling

141        'pool5-drop_7x7_s1'             Dropout

142        'loss3-classifier'              Fully Connected

143        'prob'                          Softmax

144        'output'                        Classification Output
```

We'll reset layers 143 and 144, a softmax layer and a classification output layer. These layers are responsible for assigning the correct categories to the input images. We want these layers to correspond to the new categories, not to the ones that the original network learned. We set the final fully connected layer to the same size as the number of classes in the new dataset—five in this example.

TIP

To make speed of learning in the new layers faster than in the original layers, increase the learning rate of the fully connected layer.

```
lgraph = removeLayers(lgraph, {'loss3-classifier', 'prob', ...
    'output'});
numClasses = numel(unique(categories(trainDS.Labels)));
newLayers = [
    fullyConnectedLayer(numClasses, 'Name','fc',...
    'WeightLearnRateFactor',20,'BiasLearnRateFactor',20)
    softmaxLayer('Name','softmax')
    classificationLayer('Name','classoutput')];
lgraph = addLayers(lgraph,newLayers);
```

3. Training the Network on New Data

As with training a network from scratch, to increase the network's accuracy we adjust some of the training options (in this example, batch size, learning rate, and validation data).

```
opts = trainingOptions('sgdm','InitialLearnRate',0.001,...
    'ValidationData',valDS,...
    'Plots','training-progress',...
    'MiniBatchSize',64,...
    'ValidationPatience',3);

% Training with the optimized set of hyperparameters
tic
disp('Initialization may take up to a minute before training
begins')
net = trainNetwork(trainDS, layers_train, opts);
toc
```

Training time for this model can vary significantly depending on the hardware used among other factors. A single Tesla P100 GPU can train this model in roughly 20 minutes.

TIP

Use `tic` and `toc` to quickly see how long it takes the training to run. `tic` starts a stopwatch timer to measure performance. `toc` stops the timer and reads the elapsed time displayed in the command window.

TIP

If you get an out-of-memory error for the GPU, lower the `'MiniBatchSize'` value.

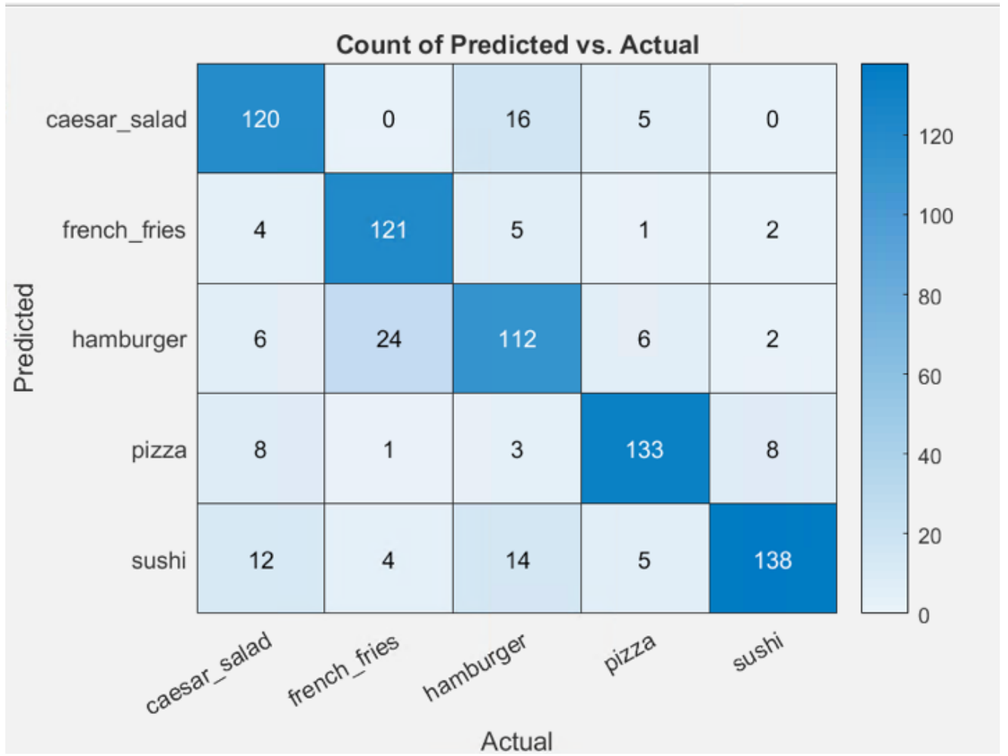
4. Evaluating the Network

Now that the network is trained, it is time to see how well it performs on the new data.

```
% Classify all images from test dataset
[labels,err_test] = classify(net, testDS);

accuracy_default = sum(labels == testDS.Labels)/numel(labels);
disp(['Test accuracy is ' num2str(accuracy_default)])
```

The confusion matrix shows the network's predictions for 150 images in each category. If all values on the diagonal were 150, this would indicate that each test image was correctly classified. Clearly, for our network, this is not the case. The values outside the diagonal give a sense of which category is getting misclassified. This can help direct us to where we should investigate our data.



The final accuracy after training the model is 83%. While this is sufficient for our example, it would not be acceptable for a real-world application. To increase the accuracy of the model for a real-world application, we'd continue to iterate, revisiting the training options, inspecting the data, and reconfiguring the network.

Finally, we visually verify the network's performance on new images.

```
[label,conf] = classify(net,im);
% classify a random image
imshow(im_display);
title(sprintf('%s %.2f, actual %s', ...
    char(label),max(conf),char(actualLabel))
```

Even if you ultimately opt to create your own network from scratch, transfer learning can be an excellent starting point for learning about deep learning: You can take advantage of networks developed by experts in the field, change a few layers, and begin training—and since the model has already learned many features from the original training dataset, it needs less training time and fewer training images than a model developed from scratch.

Learn More

Pretrained Convolutional Neural Networks
Transfer Learning Using GoogLeNet
Transfer Learning in 10 Lines of MATLAB Code 4:00
Transfer Learning with Neural Networks in MATLAB 4:06

Practical Example #3: Semantic Segmentation

Semantic segmentation, one of the newer advances in deep learning, provides a granular, pixel-level understanding of the characteristics of an image. Where a traditional CNN classifies features in an image, semantic segmentation associates each pixel with a certain category (such as flower, road, person, or car). The results look something like this:

Notice that with semantic segmentation, an irregularly shaped object such as a road is well-defined.

Semantic segmentation can be a useful alternative to object detection because it allows the object of interest to span multiple areas in the image. This technique cleanly detects objects that are irregularly shaped, in contrast to object detection, where objects must fit within a bounding box.

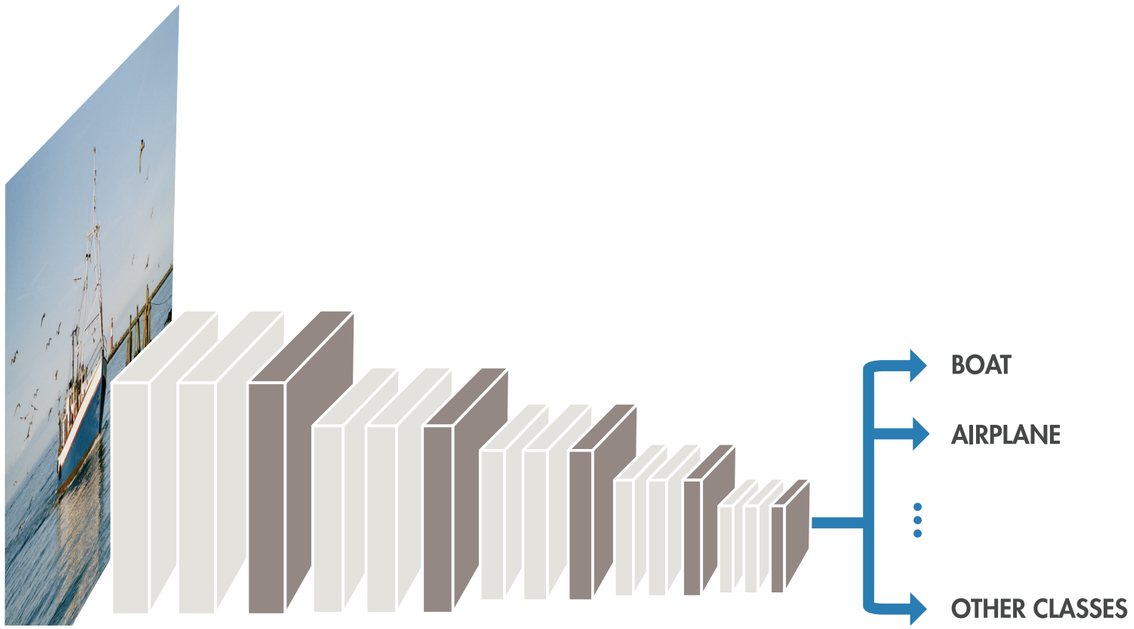
Common Semantic Segmentation Applications

- Autonomous driving: for identifying a drivable path for cars by separating the road from obstacles like pedestrians, sidewalk, poles, and other cars
- Industrial inspection: for detecting defects in materials, such as wafer inspection
- Satellite imagery: for identifying mountains, rivers, deserts, and other terrain
- Medical imaging: for analyzing and detecting cancerous anomalies in cells

Before we get into the example, let's take a quick look at the architecture of a semantic segmentation network.

Semantic Segmentation Network Architecture

As we saw in examples 1 and 2, a traditional CNN takes an image, passes it through the layers of the network, and then outputs a final class.



A semantic segmentation network builds on this process with an up-sampling network, which has an architecture similar to a reversed CNN.

This series of new layers *upsamples* the result of the pretrained network back into the image. The result is an image with every pixel assigned a classification label.

1. Importing a Pretrained Network

In this example we want to build a network that an autonomous driving system can use to detect clear road space, driving lanes, and sidewalks.

The steps are as follows:

1. Import a pretrained network.
2. Load in the dataset.
3. Set up the network.
4. Train the network.
5. Evaluate the network's accuracy.

We could train a network from scratch, but for this example, we'll use a pretrained network—as we saw in the previous example, we can test a pretrained network on images in the categories that it was originally trained on without reconfiguring it.

Our pretrained network is the VGG-16. Used in the *ImageNet Large-Scale Visual Recognition Challenge* (ILSVRC), VGG-16 is trained on more than a million images and can classify images into 1000 object categories.

Importing the VGG-16 takes just one line of MATLAB code:

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

2. Loading in the Dataset

We're using the *CamVid Dataset*, a collection of images consisting of street-level views obtained while driving. The dataset provides pixel-level labels for 32 semantic classes, including car, pedestrian, and road.

Each image in the dataset has a color image and an image of labels for each pixel in that image.

It can be cumbersome to bring lots of images into memory. A datastore is a convenient way to import, access, and manage large data files. Any data store—image, pixel, or even spreadsheet—can act as a repository, as long as all the stored data has the same structure and formatting. For our semantic segmentation example, we've created two datastore objects:

- An **`ImageDatastore`**, which manages image files where each individual image fits into memory but the entire collection may not.
- A **`pixelLabelDatastore`**, for bringing in the directory of images containing the pixel labels.

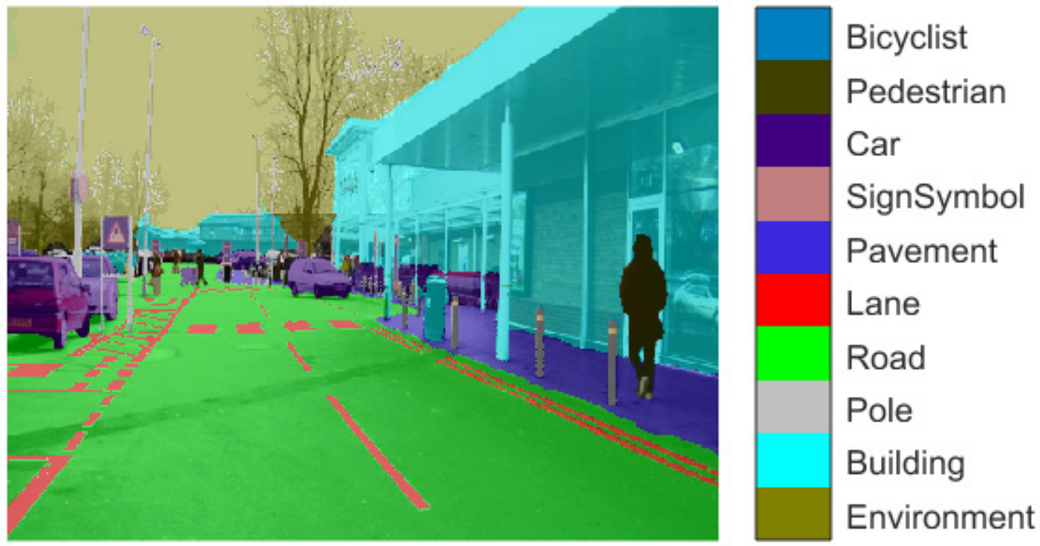
TIP

If you cannot find a pre-labeled dataset corresponding to the categories you wish to identify, you will need to create one yourself. This time-consuming task is easy to do with the Image Labeler: You simply select a group of pixels, and the app automatically labels it with a color and a corresponding category.

Once we've imported the image data and the pixel label data into MATLAB, we take a sample image and view a composite of the original image combined with the pixel labels.

Original Image

Composite Image



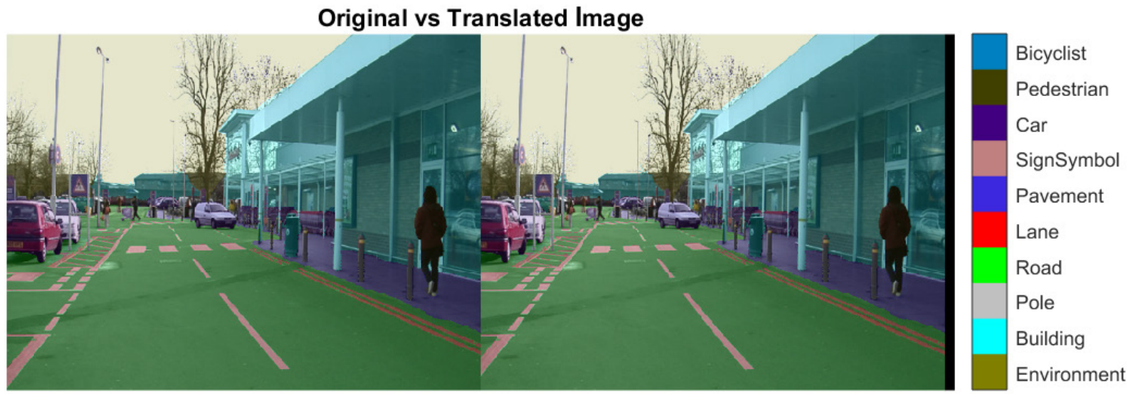

```
% Overlay segmentation results onto original image.
B = labeloverlay(I,C,'ColorMap',cmap);
```

Data augmentation is a useful technique for improving the accuracy of the trained model. In data augmentation, you increase the number of variations in the training images by adding altered versions of the original images. The most common types of data augmentation are image transformations: rotation, translation, and scale.

In this example, we incorporate a random translation.

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

Here's an example of a new image created by shifting the original image 10 pixels to the left.



While the effect of this translation is subtle, it can increase the robustness of the deep learning network by forcing it to learn and understand slight variations, which are very likely to occur in a real-world system.

3. Setting Up the Segmentation Network

Recall that a semantic segmentation network consists of an image classification network and an up-sampling portion that creates the final pixel classification.

We can create the upsampling portion of the network automatically with the MATLAB **`segnetLayers()`** function.

The result is a directed acyclic graph (DAG) network.

```
% segnetLayers returns SegNet network layers, lgraph, that is
preinitialized with layers and weights from a pretrained model.
lgraph = segnetLayers(imageSize,numClasses,'vgg16');
```

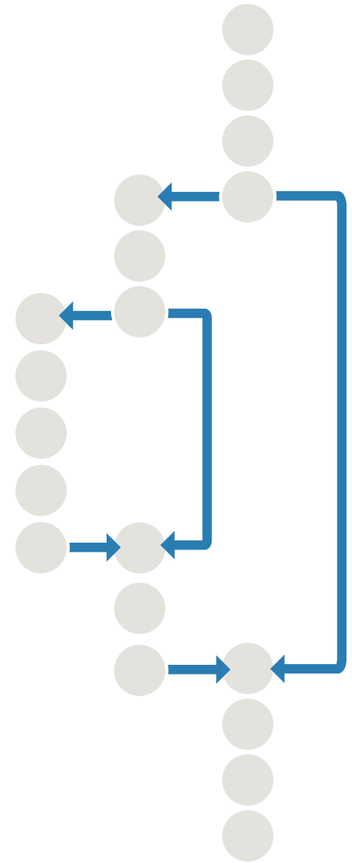
Unlike a series network, a DAG network can have inputs from, or outputs to, multiple layers. A DAG allows for more complex connections between layers, and can result in higher accuracy on difficult classification tasks.

Notice the branching in this structure: A single input node can go to multiple outputs.

You can visualize the structure of any DAG network by calling this line of code:

```
plot(lgraph);
```

`lgraph` is a layer graph that describes the architecture of a DAG network, including all the layers and their interconnections.



4. Training the Network

As with the other examples, we have a wealth of training options. Options we specify include the following:

- Optimization algorithm. We're using a stochastic gradient descent with momentum (SGDM). This is a popular algorithm for CNN training.
- Batch size. We use a minibatch size of 4, to reduce memory usage while training. The batch size can be increased or reduced based on the amount of GPU memory available.
- Processor. This network was trained on an NVIDIA™ Tesla K40c. We could significantly reduce training time by specifying more advanced hardware—for example, we could use a multi-GPU cluster instead of a desktop with a single GPU.

TIP

There are many GPUs available to help speed training. Finding the right GPU depends on a variety of factors, including speed requirements and price. The minimum requirement to use GPUs in MATLAB is a 3.0 compute capable NVIDIA GPU.

```
options = trainingOptions('sgdm', ...
    'Momentum', 0.9, ...
    'InitialLearnRate', 1e-2, ...
    'L2Regularization', 0.0005, ...
    'MaxEpochs', 120,...
    'MiniBatchSize', 4, ...
    'Shuffle', 'every-epoch', ...
    'Verbose', false,...
    'Plots','training-progress');
```

Training the network with these options takes about 19 hours. To reduce training time, we can adjust some parameters. For example:

- Number of iterations. If we reduce the number of iterations by 20, the training takes approximately 10.5 hours.
- Minibatch size. Increasing the minibatch size will reduce the training time, since the GPU (or CPU) will process more data at the same time. An increase of 1 reduces training time from 19 hours to 12 hours.
- Learning rate. Every order-of-magnitude reduction in the learning rate (0.1 → 0.01) adds approximately half an hour to the total training time.

5. Evaluating the Network

We want to evaluate the accuracy of the network both quantitatively, by running it on test data and compiling metrics, and qualitatively, by visualizing the test data results.

We'll use test data that was set aside before training to calculate the global accuracy: the ratio of correctly classified pixels to total pixels, regardless of class.

```
metrics.DataSetMetrics
```

```
ans =  1×5 table
```

	GlobalAccuracy	MeanAccuracy	MeanIoU	WeightedIoU	MeanBFScore
1	0.9220	0.8976	0.6709	0.8511	0.7833

The global accuracy metric shows that 92% of the pixels will be labeled correctly—but what about the individual classes of images? If the network correctly identifies every street sign but misidentifies pedestrians, is that an acceptable result?

Network Accuracy Measures

- MeanAccuracy: Ratio of correctly classified pixels in each class to total pixels, averaged over all classes. The value is equal to the mean of **`ClassMetrics.Accuracy`**.
- MeanIoU: Average intersection over union (IoU) of all classes. The value is equal to the mean of **`ClassMetrics.IoU`**.
- WeightedIoU: Average IoU of all classes, weighted by the number of pixels in the class.
- MeanBFScore: Average boundary F1 (BF) score of all images. The value is equal to the mean of **`ImageMetrics.BFScore`**.

Learn More

Semantic Segmentation Metrics

To see how accurately the network identified individual classes of images, we can look at the class metrics.

```
metrics.ClassMetrics
```

```
ans =  10×3 table
```

	Accuracy	IoU	MeanBFScore
1 Environment	0.9485	0.9059	0.7871
2 Building	0.9055	0.8456	0.7828
3 Pole	0.8156	0.3104	0.7683
4 Road	0.9165	0.8912	0.8825
5 Lane	0.9310	0.4550	0.8242
6 Pavement	0.9288	0.8187	0.8673
7 SignSymbol	0.8274	0.4727	0.6441
8 Car	0.9403	0.8283	0.8212
9 Pedestrian	0.8895	0.4860	0.6717
10 Bicyclist	0.8729	0.6952	0.7875

The chart shows that the categories Cars, Environment, and Road are classified with an accuracy of 90% or more. Poles, Signs, and Bicyclists are classified with an accuracy under 90%.

Depending on the application, this may be an acceptable result, or the network may need to be retrained with a higher emphasis on the classes that were misclassified.

The cost of failure determines the level of accuracy required. For example, while it might be acceptable for the visual system of a small robot to occasionally misclassify a person, it certainly would not be acceptable for a self-driving car to misclassify pedestrians.

Finally, we display the original, hand-labeled image next to the output of the trained network.

```
pic_num = 200;
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')
```

We see some discrepancies—for example, the pole in the image on the right is misclassified as pavement.

Depending on the final application, this network may be accurate enough, or we may have to go back and train more images on the discrepancies we are interested in detecting more accurately.

Learn More

Demystifying Deep Learning: Semantic Segmentation and Deployment 47:10
Analyze Training Data for Semantic Segmentation

Beyond Images

The three examples we've explored so far have focused on image recognition. But deep learning is increasingly being used for other applications, such as speech recognition and text analytics, which use signal data rather than image data. In the following sections we'll briefly review two popular techniques for classifying signal data:

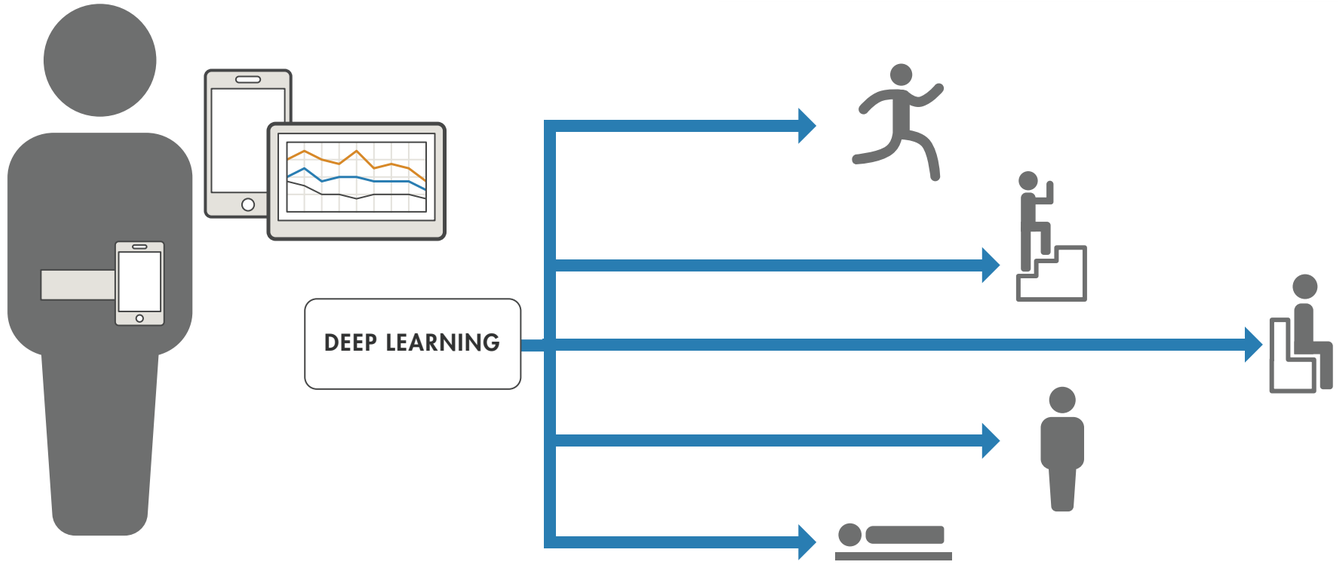
- Using long short-term memory (LSTM) to classify signal data captured on a smartphone
- Using a spectrogram to classify data from audio files

Using an LSTM Network to Classify Human Activities

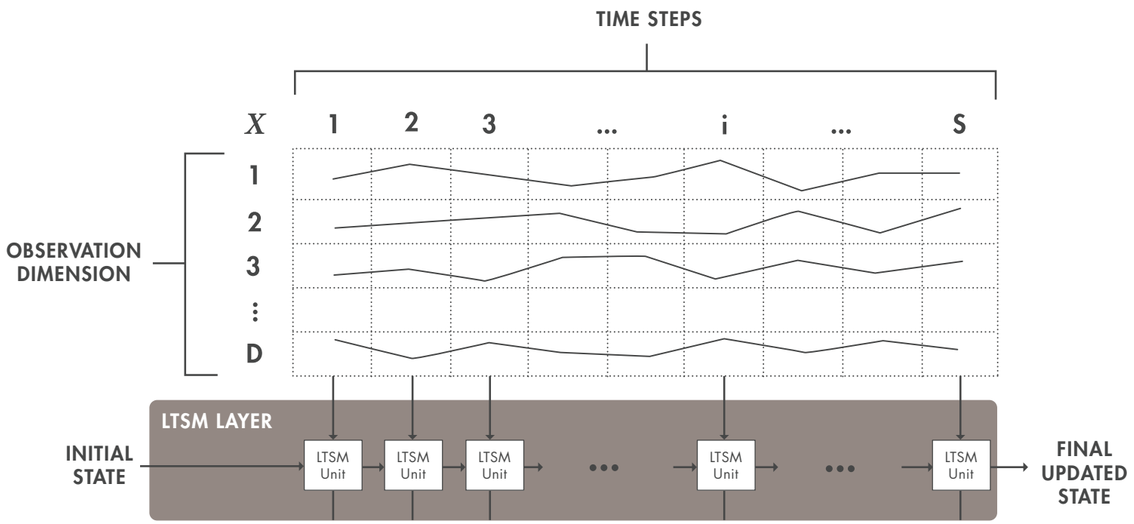
In this example, we want to use signal data captured from a smartphone to classify six activities: walking on flat ground, walking upstairs, walking downstairs, sitting, standing, and lying down.

An LSTM network is well suited to this type of classification task because the task involves sequence data: An LSTM lets you make predictions based on the individual time steps of the sequence data.

> An LSTM network is a type of recurrent neural network (RNN) that can learn long-term dependencies between time steps of sequence data. Unlike a conventional CNN, an LSTM can remember the state of the network between predictions.



LSTM Architecture



An LSTM network is defined by a sequence of input layers, one for each channel of data collected. The first LSTM unit takes the initial network state and the first time step of the sequence to make a prediction, and sends the updated network state to the next LSTM unit.

The core components of an LSTM network are a sequence input layer and an LSTM layer. A sequence input layer inputs sequence or time series data into the network. An LSTM layer learns long-term dependencies between time steps of sequence data.

This diagram illustrates the architecture of a simple LSTM network for classification.

The network starts with a sequence input layer followed by an LSTM layer. The remaining layers are identical to the image classification models created in the previous examples. (To predict class labels, the network ends with a fully connected layer, a softmax layer, and a classification output layer.)

With the incorporation of the two new layers (a sequence layer and an LSTM layer), our signal data can be used to train a model that can classify new activity signals.

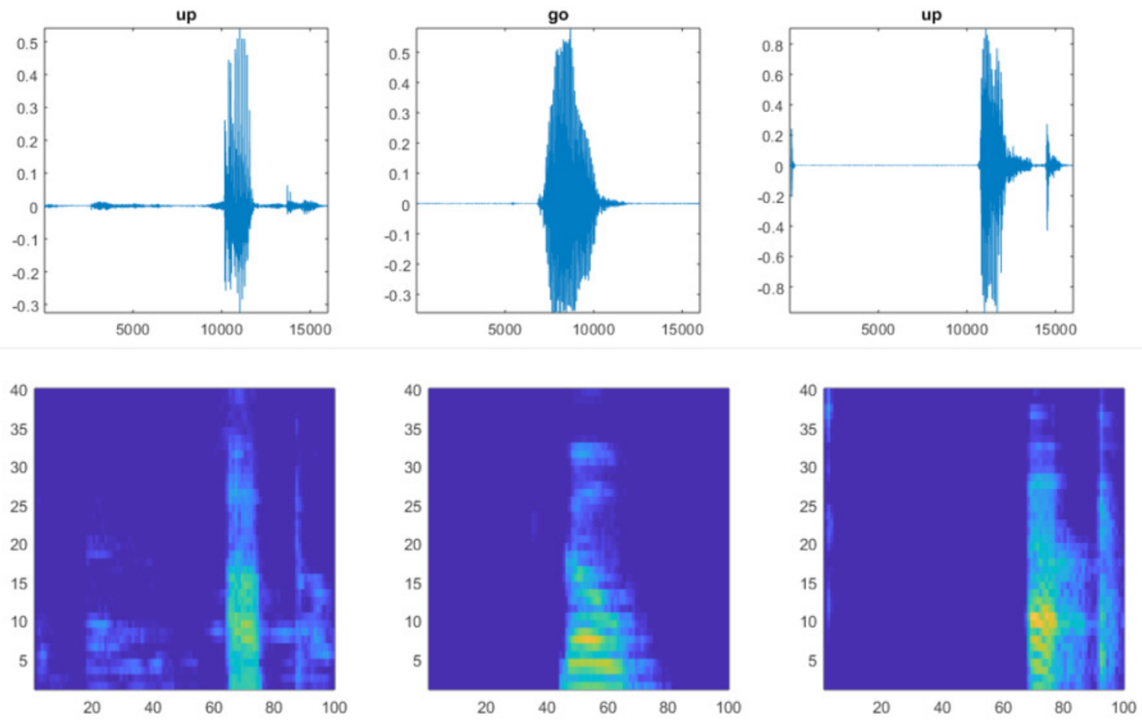
When the trained network is run on new data, it achieves 95% accuracy. This result is satisfactory for our activity tracking application.

Learn More

Long Short-Term Memory Networks
Classify Sequence Data Using LSTM Networks
Classify Text Data Using an LSTM Network

Using Spectrograms for Speech Recognition

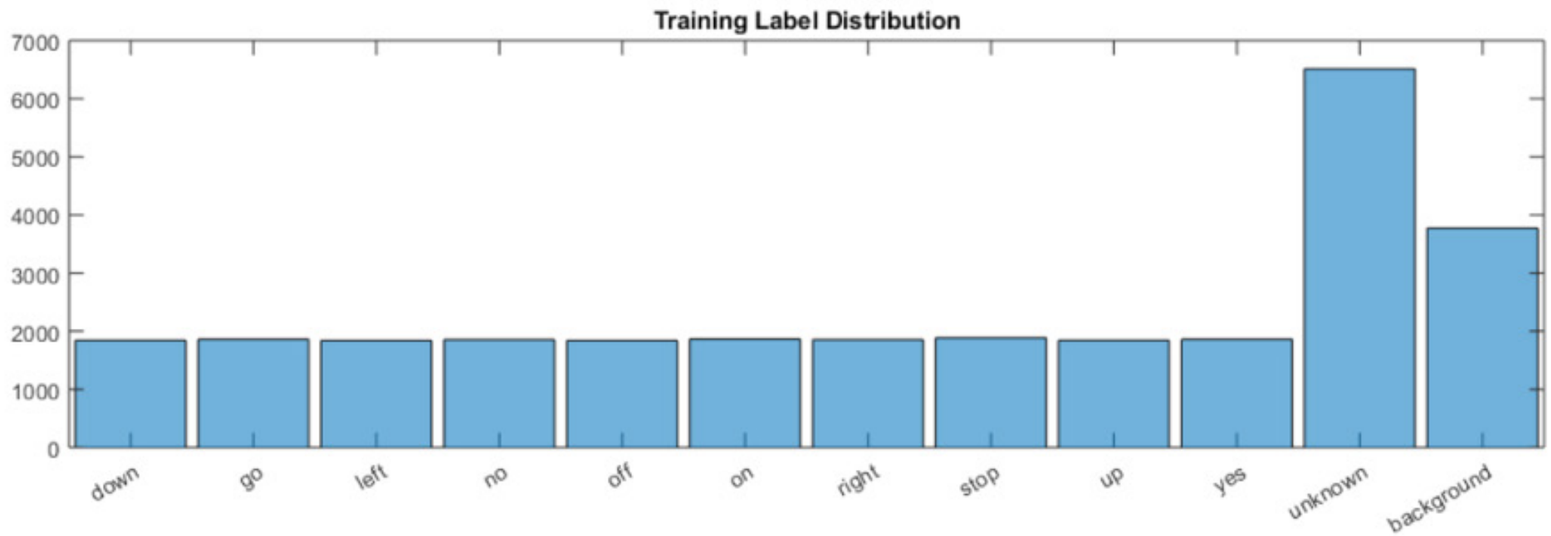
In this example, we want to classify speech audio files into their corresponding classes of words. We'll use spectrograms to convert the 1D audio files into 2D images that can be used as input to a conventional CNN.



Top: original audio signals. Bottom: corresponding spectrograms.

The **`spectrogram()`** command is a simple way of converting an audio file into its corresponding time-localized frequency. However, speech is a specialized form of audio processing, with important features localized in specific frequencies. Because we want the CNN to focus on these locations, we will use mel-frequency cepstral coefficients, which have been designed specifically to target the areas in frequency in which speech is most relevant.

We distribute the training data evenly between the classes of words we want to classify.



To reduce false positives, we include a category for words likely to be confused with the intended categories. For example, if the intended word is “on,” then words that sound similar or are easily confused with “on,”, such as “mom”, “dawn”, and “won” are placed in the “unknown” category.

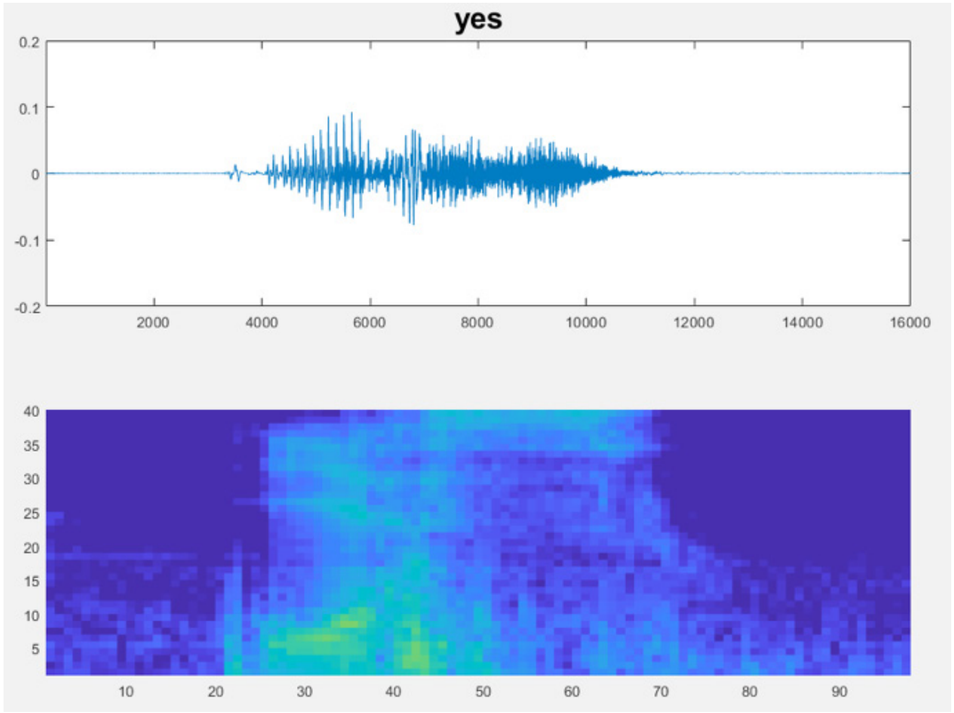
The network does not need to know these words, just that they are NOT the words to recognize.

We then define a CNN. Because we are using the spectrogram as an input, which is essentially a 2D representation of the 1D signal, the structure of our CNN can be very similar to the one we used for image processing.

TIP

Transfer learning does not work well if the features are different from the original training set. This means that pretrained networks like AlexNet or GoogLeNet, which were trained on images, will not transfer well to spectrograms.

After the model has been trained, it will take the input image (the spectrogram) and classify it into the appropriate categories. The accuracy of the validation set is about 96%.



The final model can be run on continuous live signals from a microphone using **`audioDeviceReader`** in Audio System Toolbox™.

Learn More

Train a Deep Learning Speech Recognition Model
Deep Learning with Time Series and Sequence Data Examples

Deploying a Deep Learning Network

Now that you have trained a network to meet your accuracy goals, you are ready to deploy it as an application. Deep learning models can be deployed into production systems (onsite or in the cloud), on desktops, and on an embedded device, such as an NVIDIA Tegra GPU or an Intel® or ARM® processor.

The deployment option you choose will, of course, depend on the kind of application you're developing. Here are the four most common ways engineers choose to deploy deep learning models:

Deploy the model as a desktop application

Use MATLAB Compiler™ to package the model as a standalone application that end users can run on a local machine.

Deploy to a server or cloud

Use MATLAB Production Server™ to deploy the model as an API that can be called from C, C++, Java®, .NET, or Python®.

Target desktop-based GPUs, for increased performance speed

Use GPU Coder™ to generate CUDA code for training and prediction.

Deploy to an embedded device

Use GPU Coder to generate optimized CUDA code that can run outside MATLAB.

Learn More

Sharing and Deploying MATLAB Applications 26:15

Handy Tools for Deep Learning

As the examples in this ebook have shown, with MATLAB you can build deep learning models without having to be an expert—and MATLAB makes light work of the more time-consuming or irksome tasks in deep learning, with tools and functions for managing and labeling data, monitoring training progress, and visualizing results. Here's a quick guide to tools we've used in working through the examples.

Tool or Function	Description
`ImageDataStore`	Manage large sets of training and test images for deep learning models. Create a custom read function to automate preprocessing of multiple images
`ImageLabeler`	Draw boundary boxes around objects of interest. Quickly label images at the pixel level for semantic segmentation.
`imageDataAugmenter`	Extend the training dataset by creating more test images through automatic translations, rotations, and scaling of existing images.
`heatmap`	Use this simple confusion matrix to visualize the accuracy of each category in a trained model.
`deepDreamImage` / `activations`	Visualize the layers of a model, and visualize the output of images passed through layers.
`spectrogram`	When working with signal data, easily convert an audio file into its corresponding time-localized frequency.

Learn More

A Guide to Tools and Resources for Deep Learning in MATLAB