



Universidad Veracruzana

Convolutional Neural Networks in Matlab

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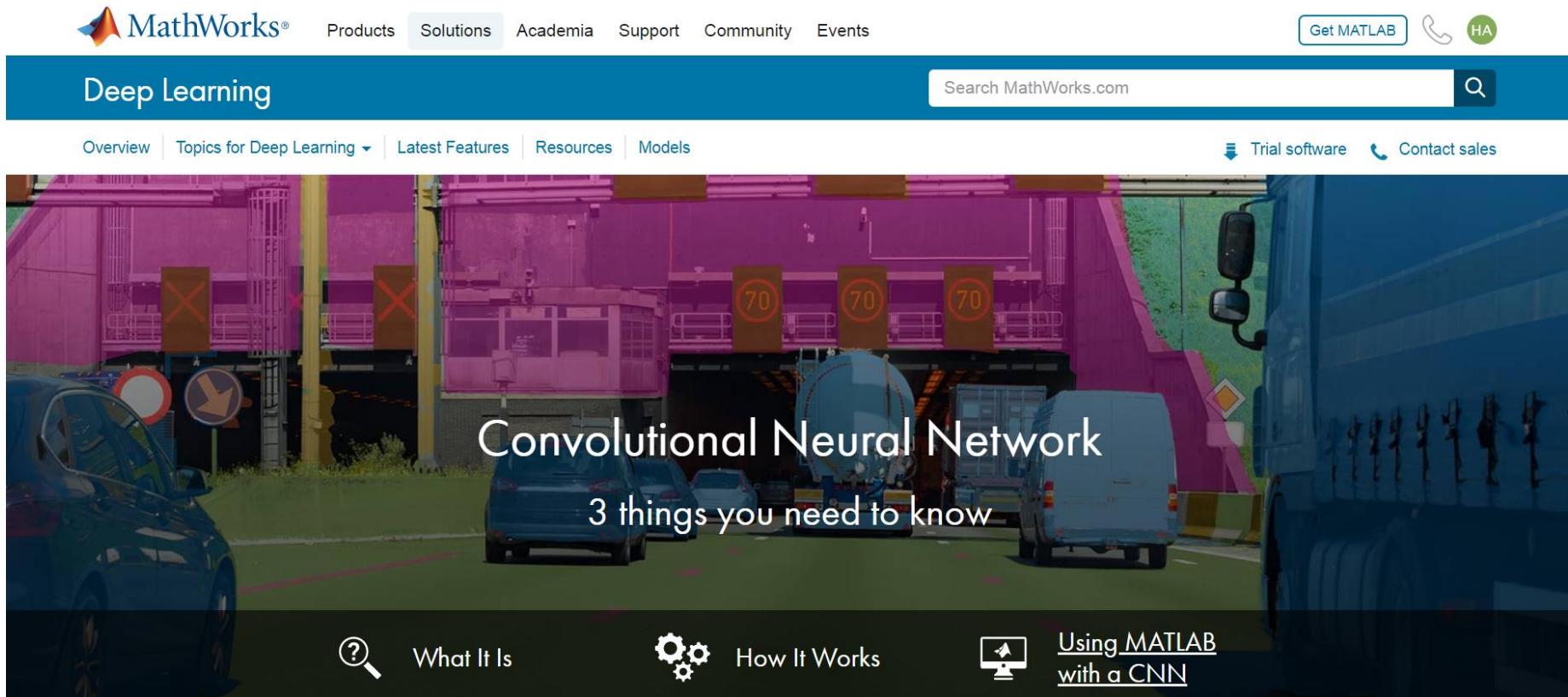
heacosta@uv.mx

www.uv.mx/personal/heacosta

Convolutional Neural Networks

Cuerpo Académico de Investigación y Aplicaciones de la Inteligencia Artificial

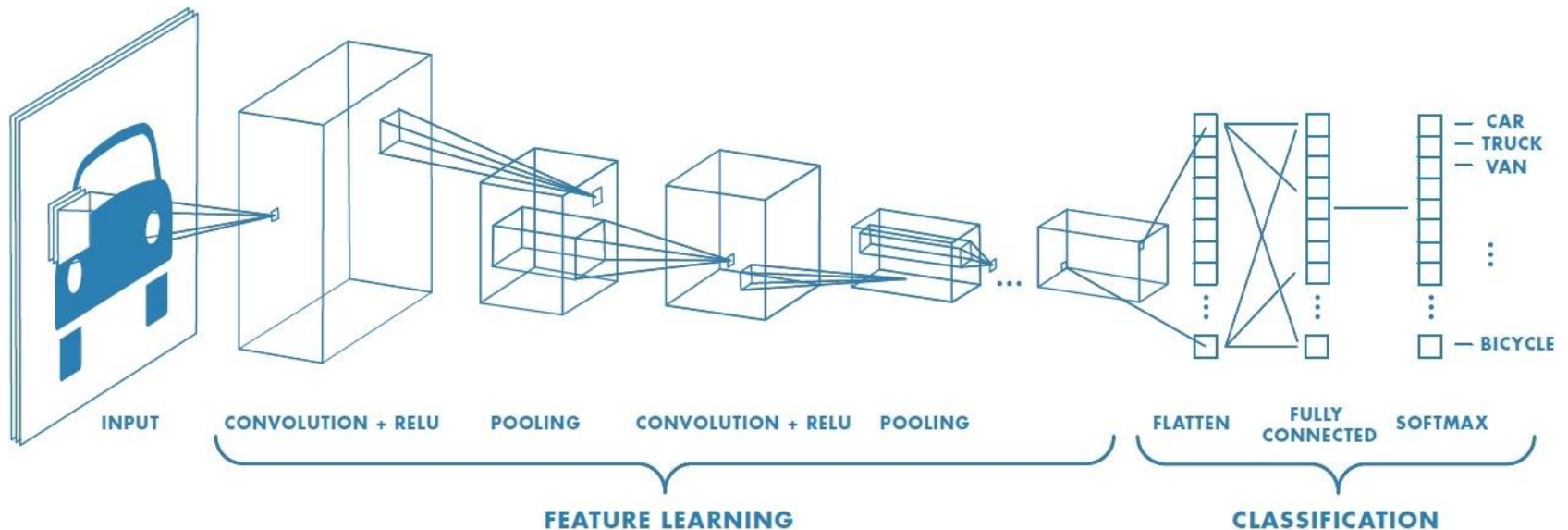
CNN in Matlab



Material taken from MathWorks

<https://www.mathworks.com/solutions/deep-learning/convolutional-neural-network.html>


Convolutional Neural Networks



MATLAB Commands

```
>> newnet = trainNetwork(data, layers, options)
```

MATLAB Variables

 **layers**
 **data**
 **options**

Convolutional Neural Networks

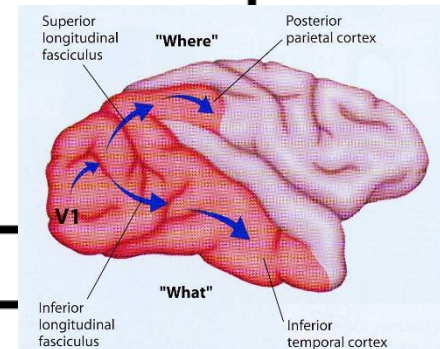
Classification

CNN - Deep Learning Toolbox™

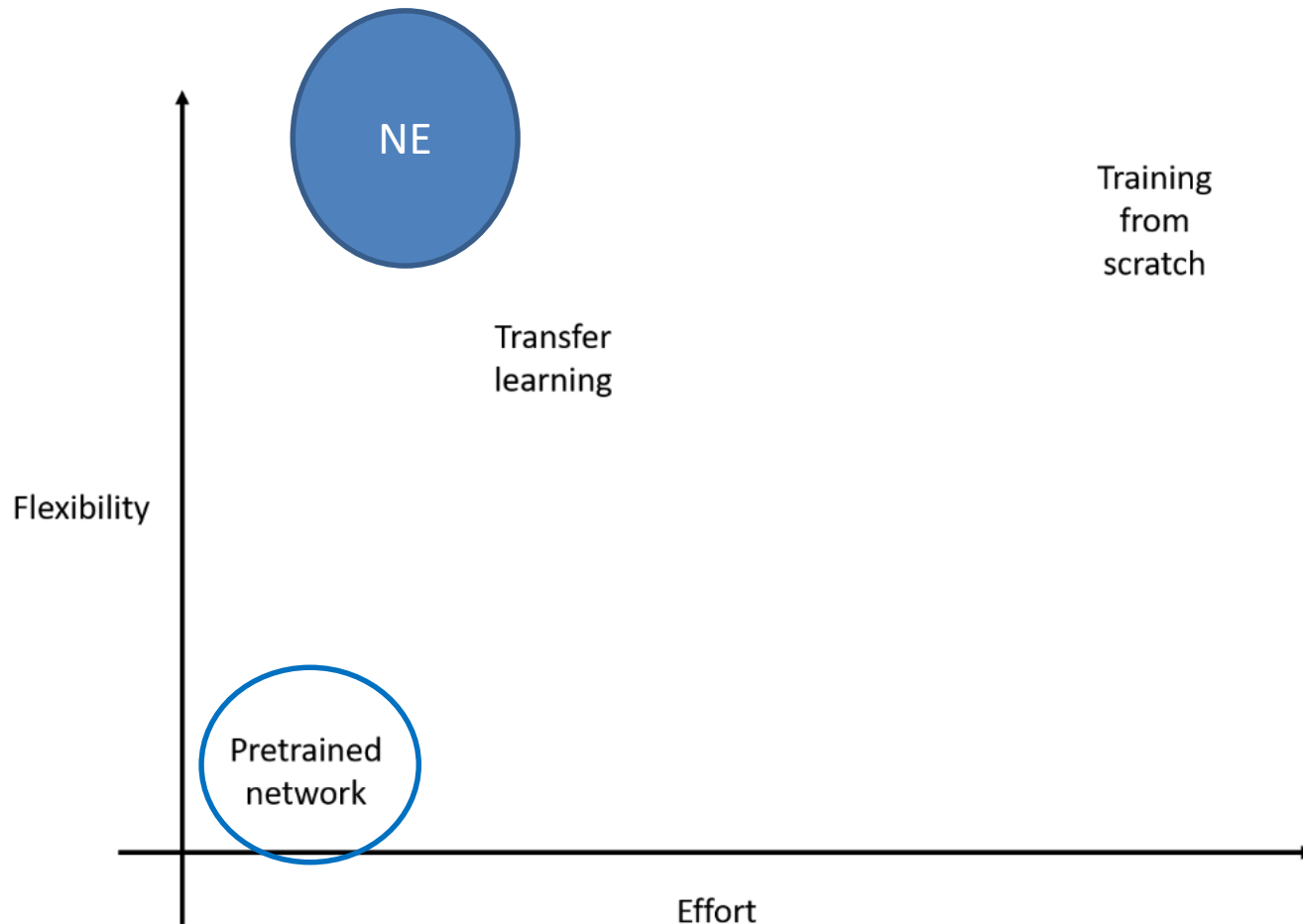
Regression

Object detection

R-CNN - Computer Vision Toolbox™

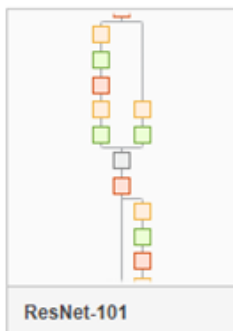
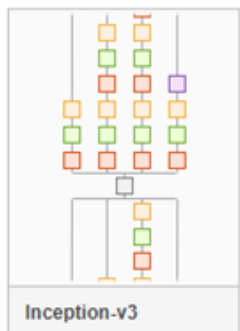
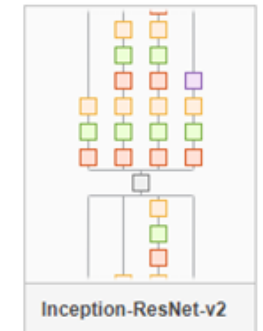
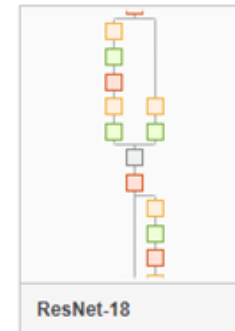
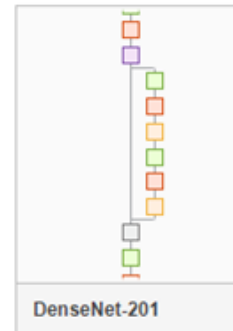
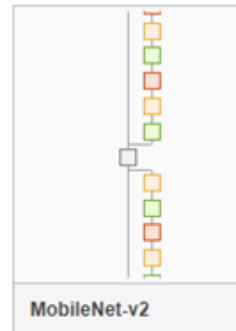
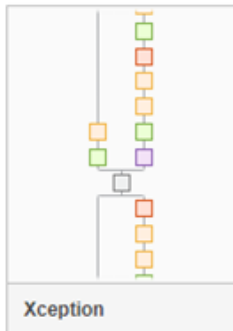
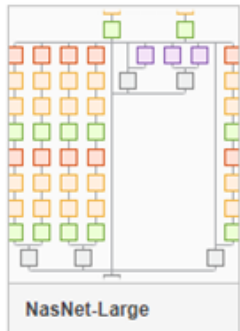
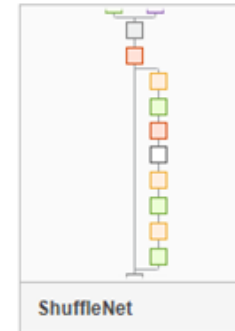
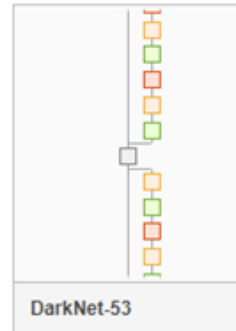
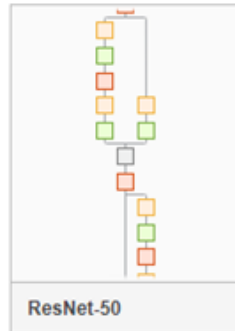
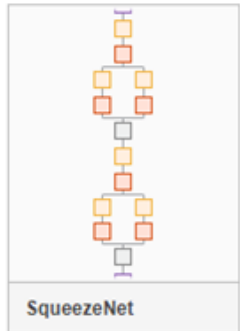


Convolutional Neural Networks



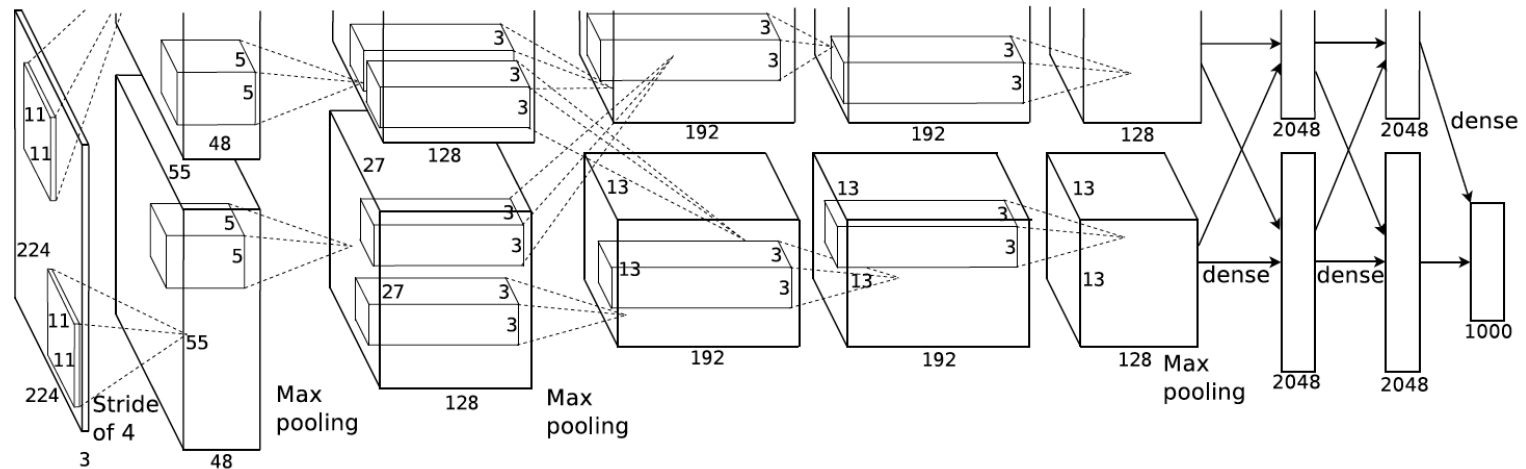
Networks

▼ Pretrained Networks



Alexnet

AlexNet is a pretrained Convolutional Neural Network (CNN) that has been trained on approximately 1.2 million images from the ImageNet Dataset (<http://image-net.org/index>). The model has 23 layers and can classify images into 1000 object categories (e.g. keyboard, mouse, coffee mug, pencil).



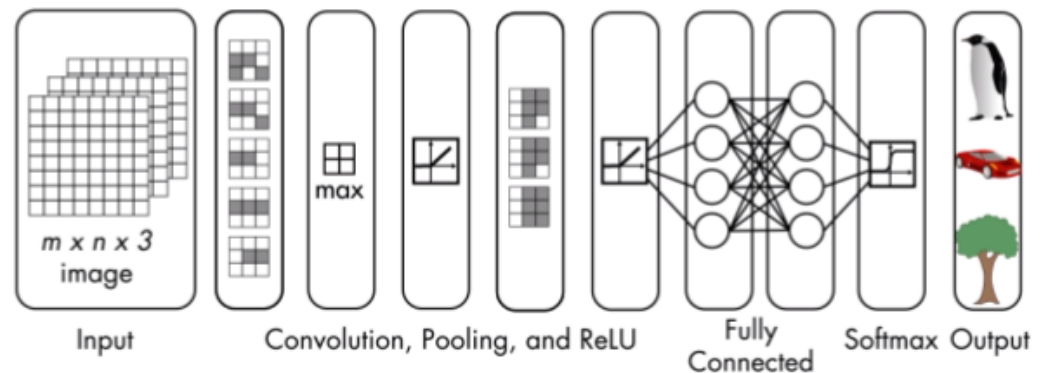
Alexnet in Matlab

Install: Deep Learning Toolbox Model for AlexNet
Network support package for the pretrained weights.

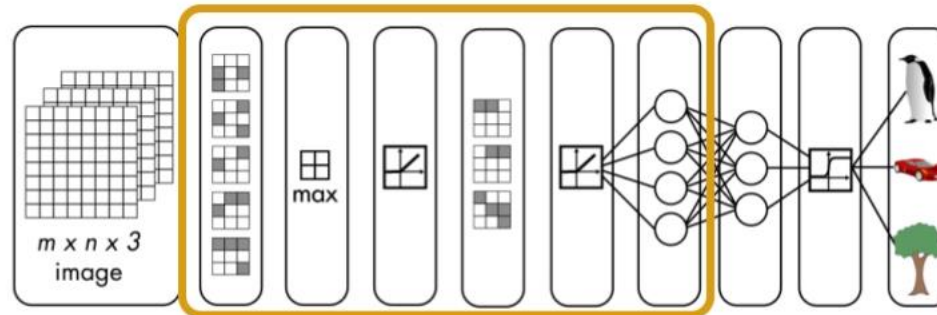
```
%Get AlexNet
```

```
net = alexnet;
```

```
layers = net.Layers:
```

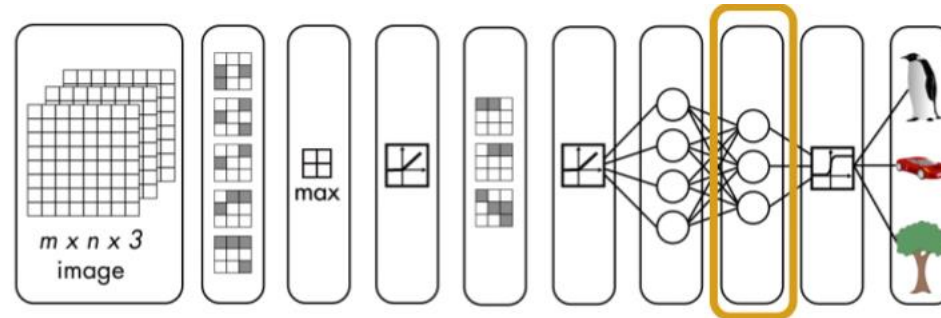


Structure



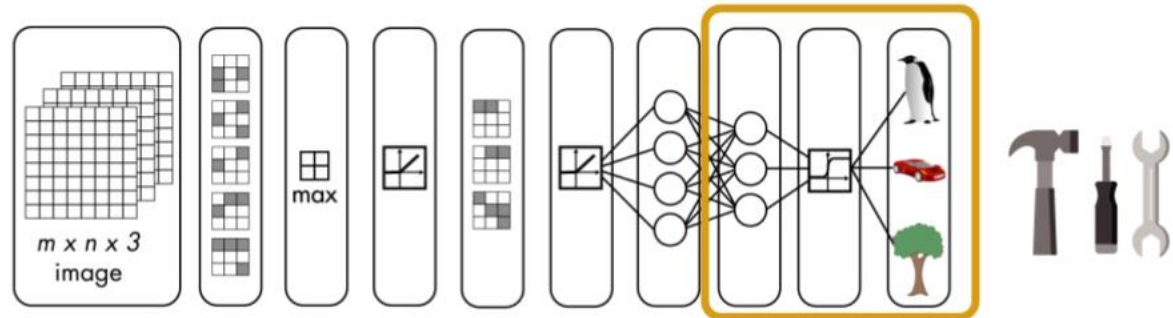
1	'data'	Image Input	227x227x3 images with 'zerocenter' normalization
2	'conv1'	Convolution	96 11x11x3 convolutions with stride [4 4] and padding [0 0 0 0]
3	'relu1'	ReLU	ReLU
4	'norm1'	Cross Channel Normalization	cross channel normalization with 5 channels per element
5	'pool1'	Max Pooling	3x3 max pooling with stride [2 2] and padding [0 0 0 0]
6	'conv2'	Convolution	256 5x5x48 convolutions with stride [1 1] and padding [2 2 2 2]
7	'relu2'	ReLU	ReLU
8	'norm2'	Cross Channel Normalization	cross channel normalization with 5 channels per element
9	'pool2'	Max Pooling	3x3 max pooling with stride [2 2] and padding [0 0 0 0]
10	'conv3'	Convolution	384 3x3x256 convolutions with stride [1 1] and padding [1 1 1 1]
11	'relu3'	ReLU	ReLU
12	'conv4'	Convolution	384 3x3x192 convolutions with stride [1 1] and padding [1 1 1 1]
13	'relu4'	ReLU	ReLU
14	'conv5'	Convolution	256 3x3x192 convolutions with stride [1 1] and padding [1 1 1 1]
15	'relu5'	ReLU	ReLU
16	'pool5'	Max Pooling	3x3 max pooling with stride [2 2] and padding [0 0 0 0]
17	'fc6'	Fully Connected	4096 fully connected layer
18	'relu6'	ReLU	ReLU
19	'drop6'	Dropout	50% dropout
20	'fc7'	Fully Connected	4096 fully connected layer
21	'relu7'	ReLU	ReLU
22	'drop7'	Dropout	50% dropout
23	'fc8'	Fully Connected	1000 fully connected layer
24	'prob'	Softmax	softmax
25	'output'	Classification Output	crossentropyex with 'tench', 'goldfish', and 998 other classes

Structure



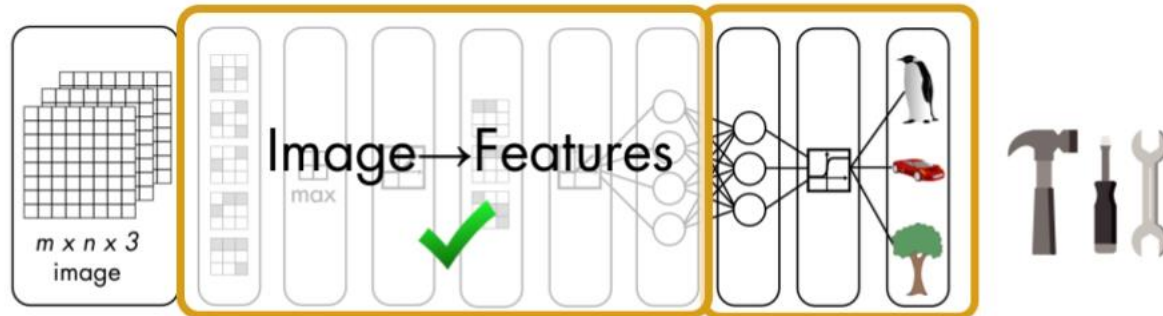
1	'data'	Image Input	227x227x3 images with 'zerocenter' normalization
2	'conv1'	Convolution	96 11x11x3 convolutions with stride [4 4] and padding [0 0 0 0]
3	'relu1'	ReLU	ReLU
4	'norm1'	Cross Channel Normalization	cross channel normalization with 5 channels per element
5	'pool1'	Max Pooling	3x3 max pooling with stride [2 2] and padding [0 0 0 0]
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22	'drop7'	Dropout	50% dropout
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Structure



1	'data'	Image Input	227x227x3 images with 'zerocenter' normalization
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4	'norm1'	Cross Channel Normalization	cross channel normalization with 5 channels per element
5	'pool1'	Max Pooling	3x3 max pooling with stride [2 2] and padding [0 0 0 0]
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Structure



1	'data'	Image Input	227x227x3 images with 'zerocenter' normalization
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22	'drop7'	Dropout	50% dropout
23	'fc8'	Fully Connected	1000 fully connected layer
24	'prob'	Softmax	softmax
25	'output'	Classification Output	crossentropyex with 'tench', 'goldfish', and 998 other classes

Pretrained Network

```
% CNN in 10 lines
camera=webcam;

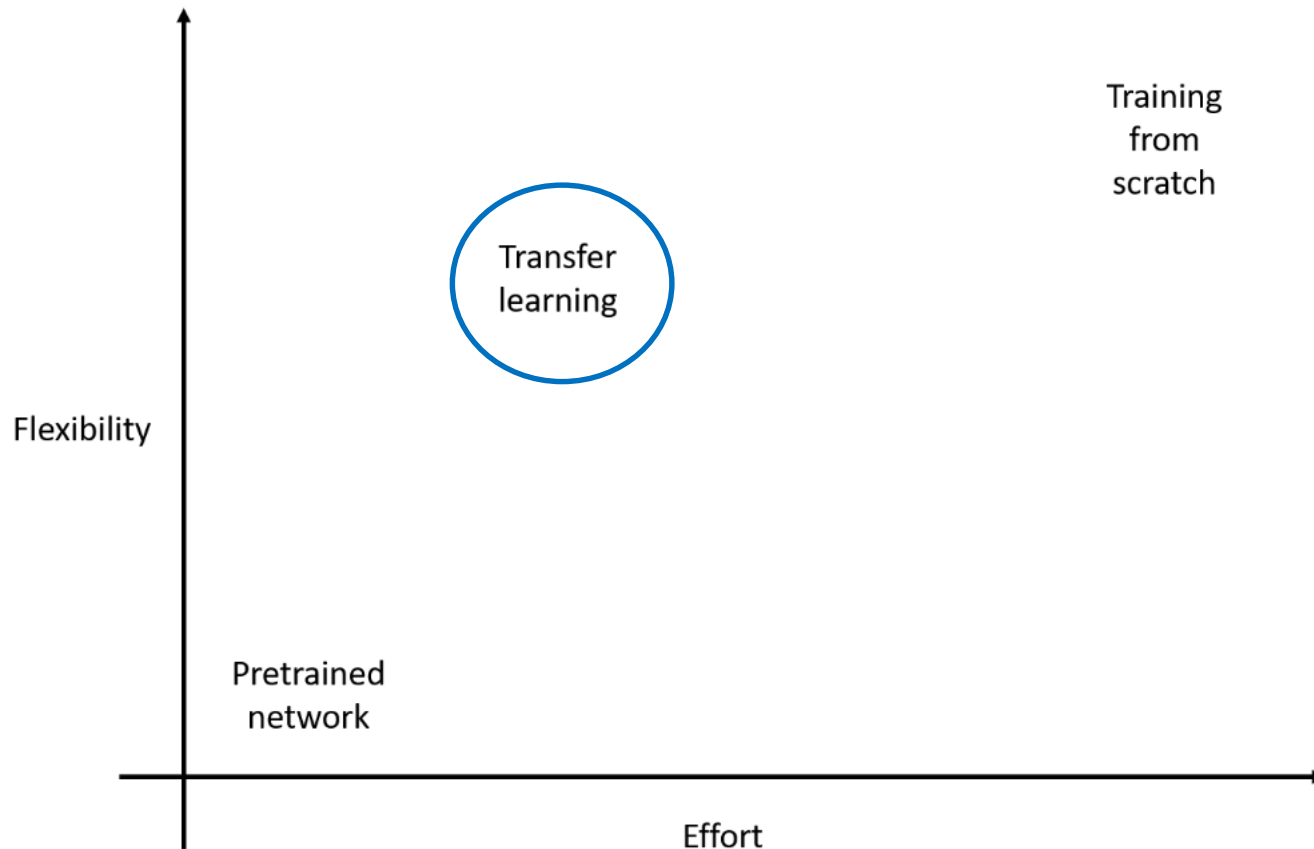
nnet=alexnet;

while true
    picture=camera.snapshot;
    picture=imresize(picture,[227,227]);

    label=classify(nnet,picture);

    image(picture)
    title(char(label))
    drawnow;
end
```

Transfer learning



Transfer learning

This example shows how to fine-tune a pretrained AlexNet convolutional neural network to perform classification on a new collection of images.

AlexNet has been trained on over a million images and can classify images into 1000 object categories (such as keyboard, coffee mug, pencil, and many animals). The network has learned rich feature representations for a wide range of images. The network takes an image as input and outputs a label for the object in the image together with the probabilities for each of the object categories.

Transfer learning is commonly used in deep learning applications. You can take a pretrained network and use it as a starting point to learn a new task. Fine-tuning a network with transfer learning is usually much faster and easier than training a network with randomly initialized weights from scratch. You can quickly transfer learned features to a new task using a smaller number of training images.

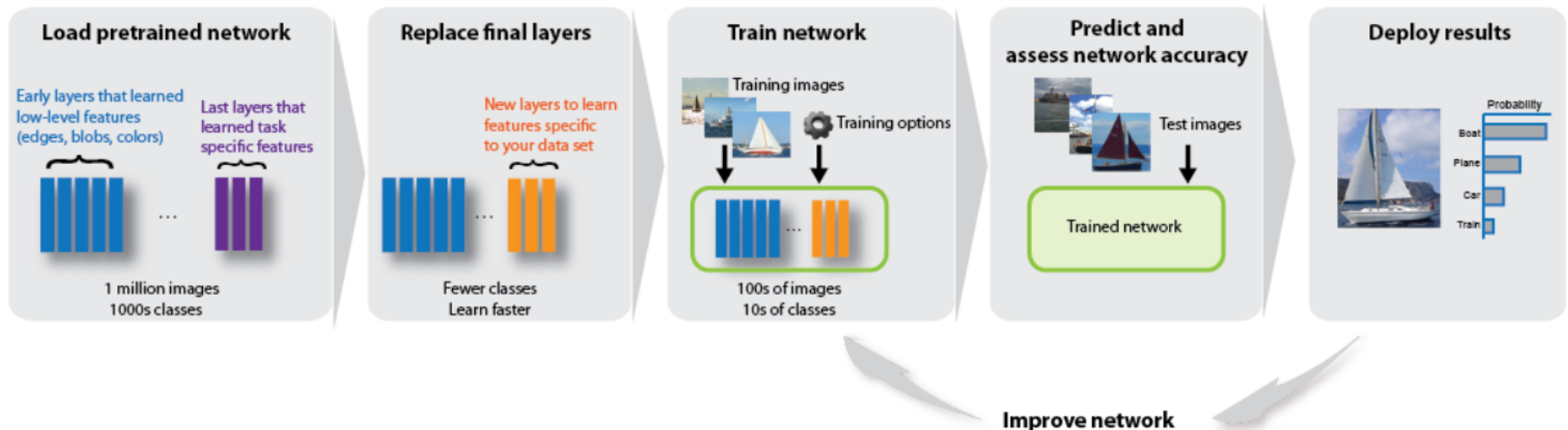
This example uses:

[Deep Learning Toolbox](#)

[Deep Learning Toolbox Model for AlexNet Network](#)

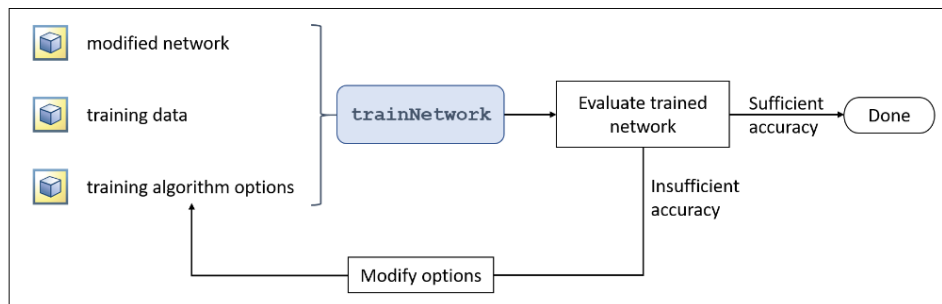
[View MATLAB Command](#)

Reuse Pretrained Network



Transfer learning

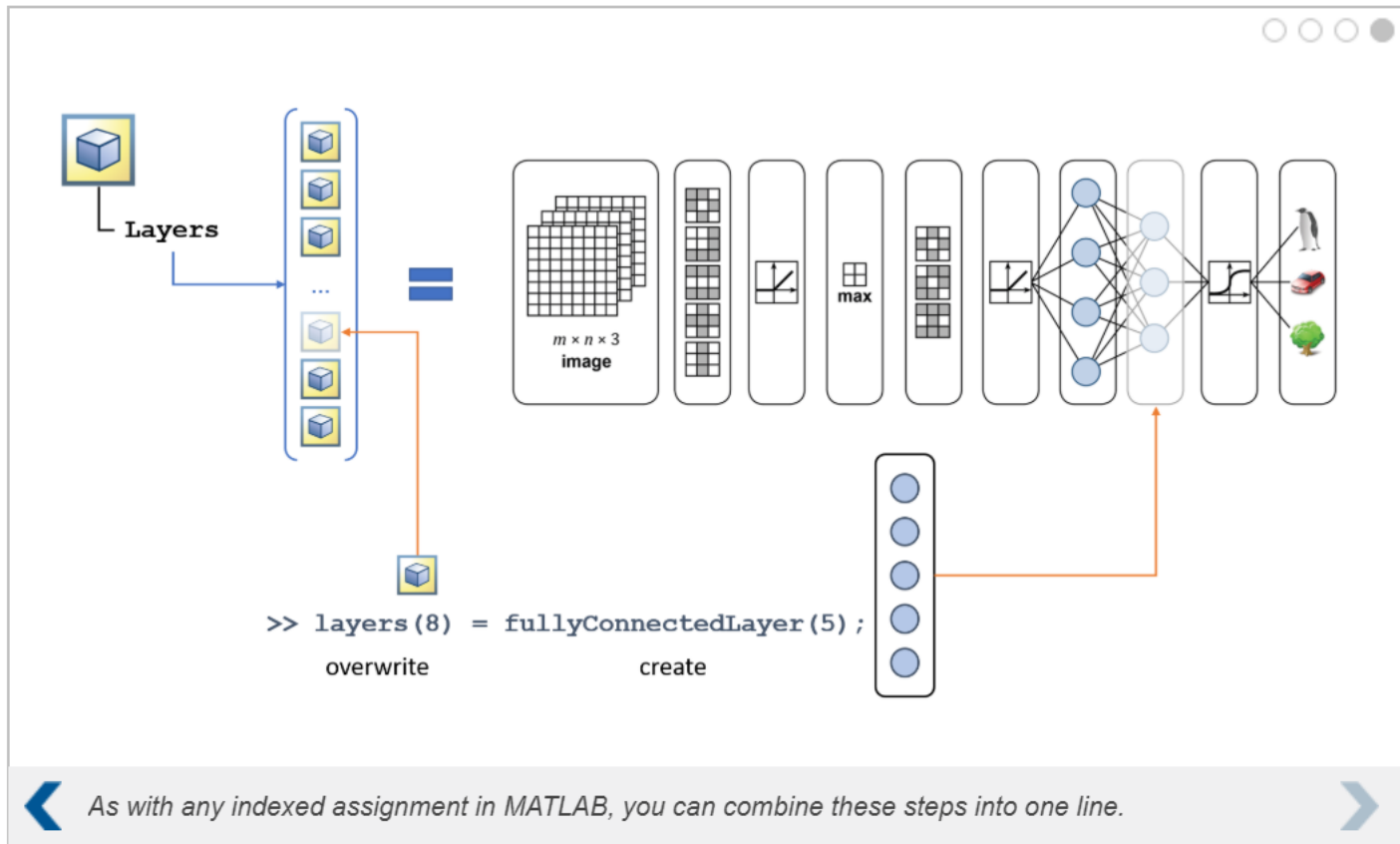
Typical workflow for transfer learning



To perform transfer learning, you need to create three components:

1. An array of layers representing the network architecture. For transfer learning, this is created by modifying a preexisting network such as AlexNet.
2. Images with known labels to be used as training data. This is typically provided as a datastore.

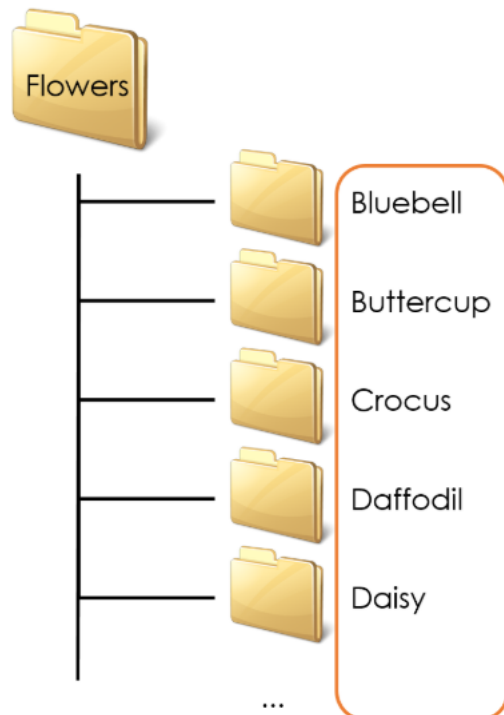
Transfer learning



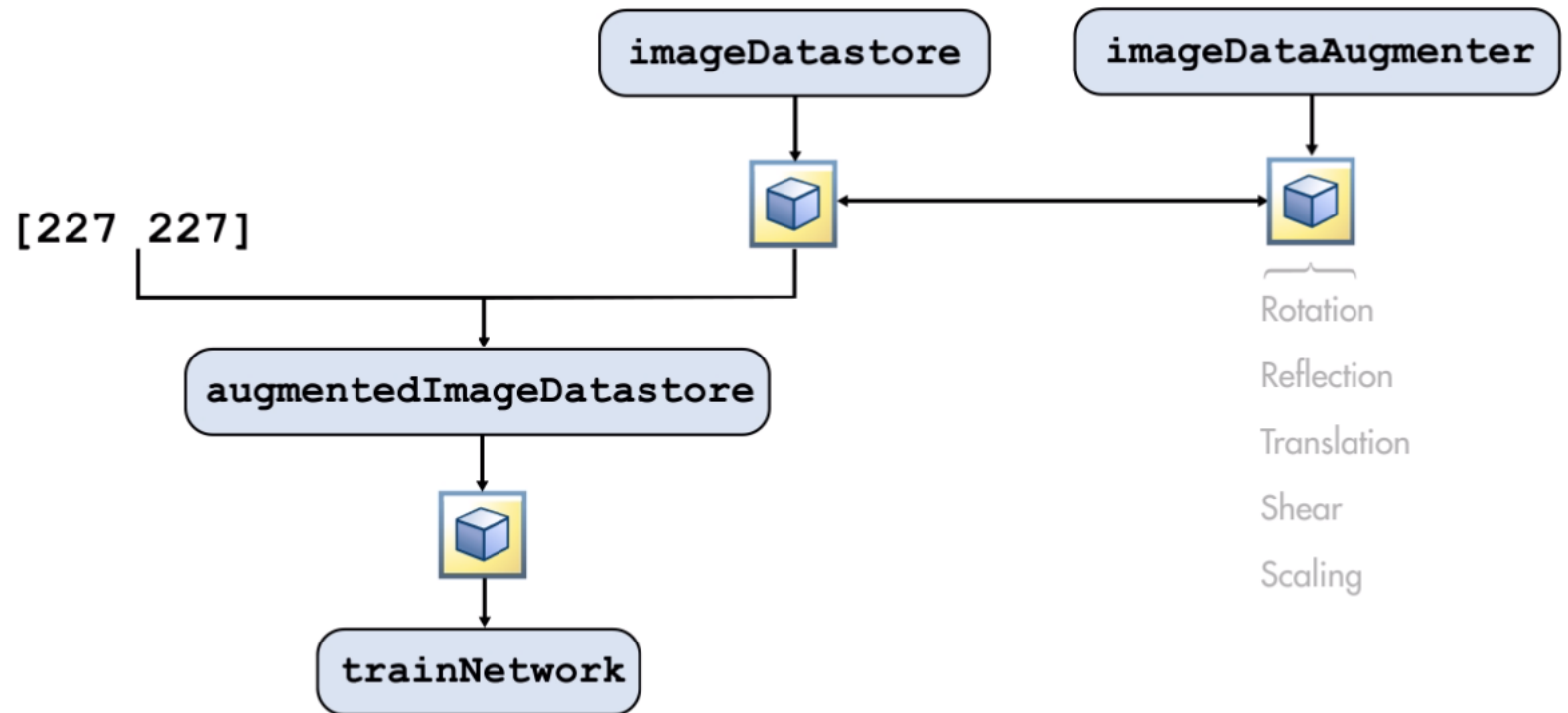
Data

Labeling training images

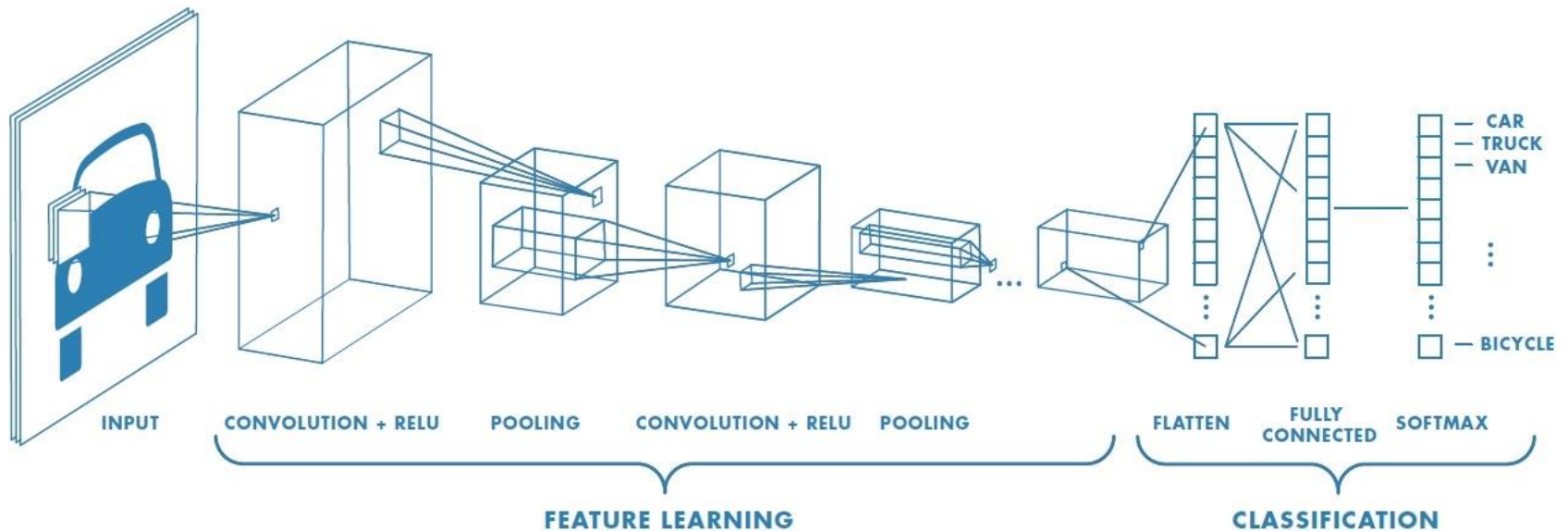
When training a network, you need to provide known labels for the training images. The `Flowers` folder contains 12 subfolders, each of which contains 80 images of one type of flower. The name of the folder can therefore be used to provide the labels needed for training.



Data

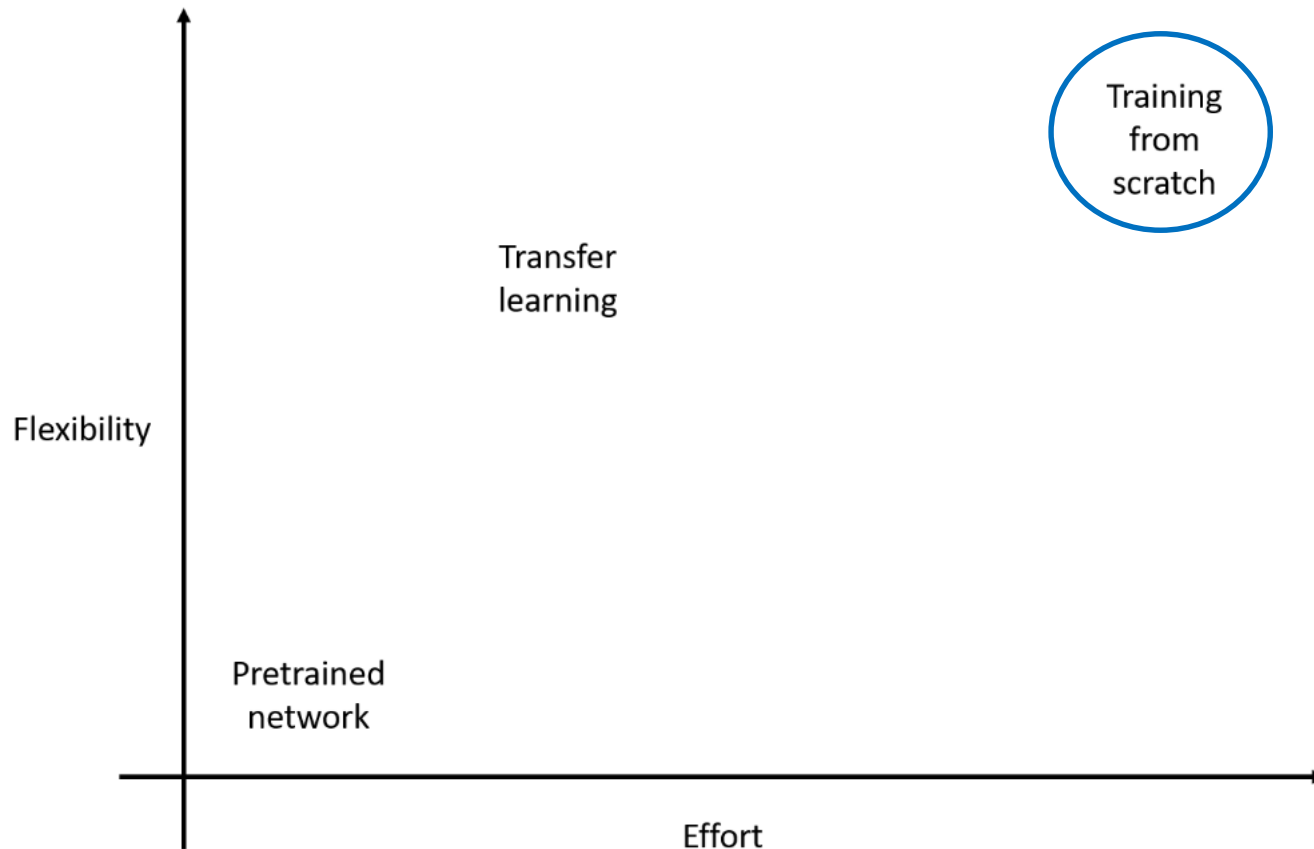


Transfer learning



See code: [TransfL_Alexnet1.m](#) (Flowers)

Training from scratch

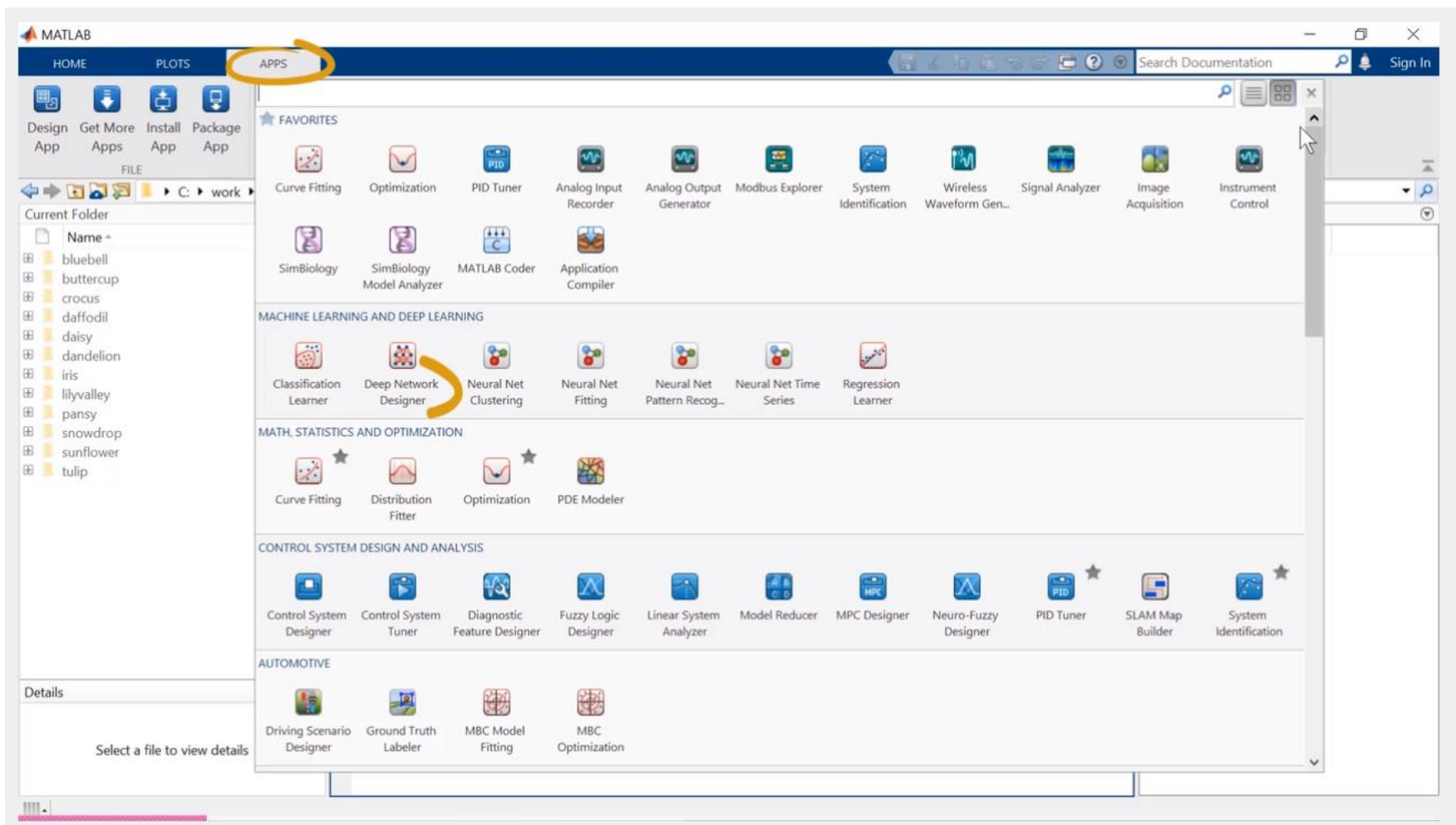


Training from scratch (Layers)

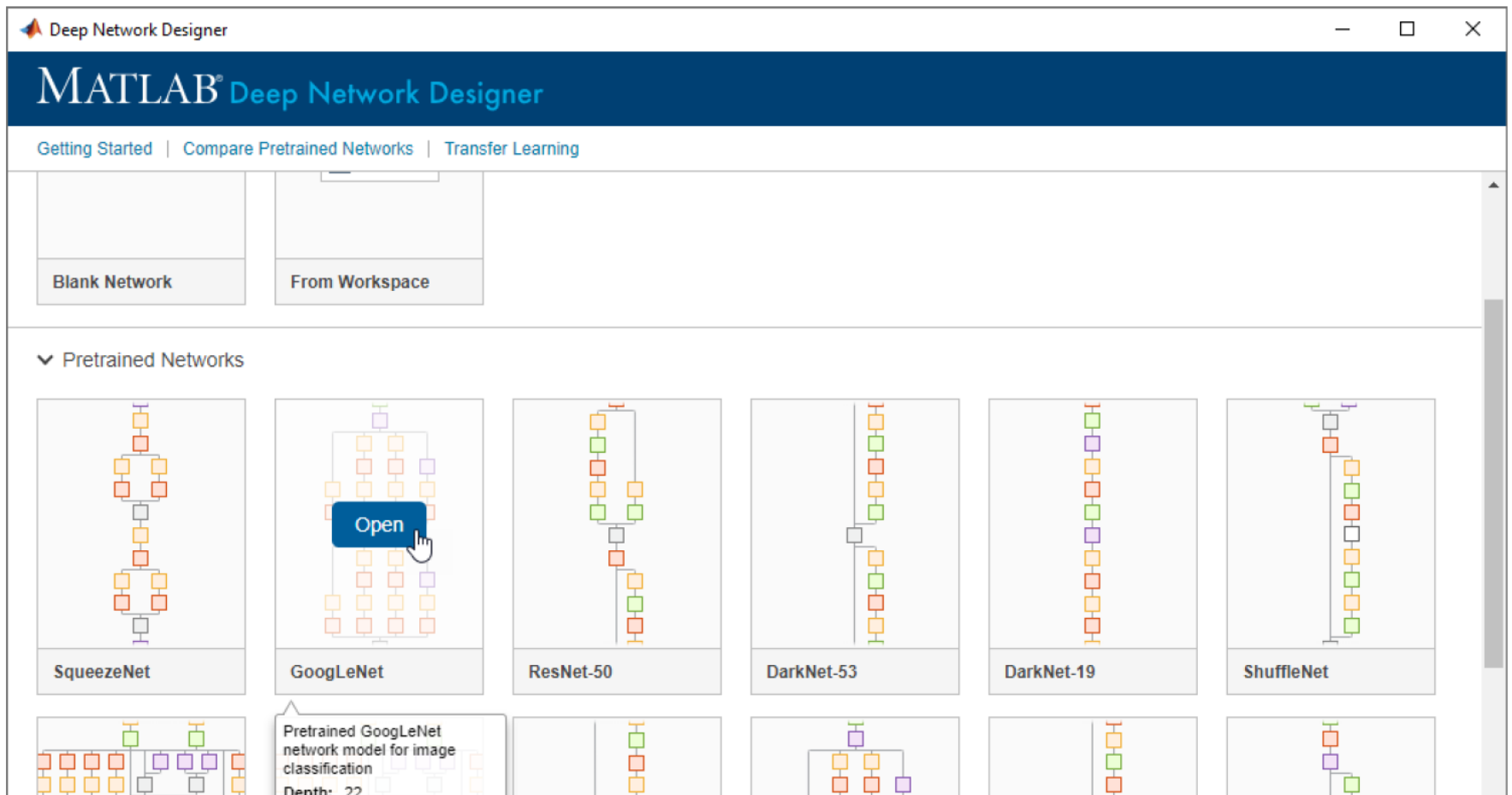
Example 1: **Scratch_Digits.m**

`analyzeNetwork(net)`

Deep Network Designer



Deep Network Designer



Deep Network Designer

The screenshot displays the Deep Network Designer software interface. The top menu bar includes options for New, Import, Duplicate, Cut, Copy, Paste, Fit to View, Zoom In, Zoom Out, Auto Arrange, Analyze, and Export. Below the menu is a toolbar with icons for these actions. The left sidebar contains a 'LAYER LIBRARY' with a search bar and two categories: 'INPUT' and 'CONVOLUTION AND FULLY CONNECTED'. The 'INPUT' category lists imageInputLayer, image3dInputLayer, sequenceInputLayer, and roiInputLayer. The 'CONVOLUTION AND FULLY CONNECTED' category lists convolution2dLayer, convolution3dLayer, groupedConvolution2dLayer, transposedConv2dLayer, transposedConv3dLayer, and fullyConnectedLayer. The central workspace shows a neural network diagram with five layers: 'data imageInputLayer', 'conv1 convolution2d...', 'bn_conv1 batchNormaliza...', 'conv1_relu reluLayer', and 'pool1 maxPooling2d...'. A tooltip points to the 'conv1' layer with the text 'Size of the input row vector of integers'. The right sidebar shows the 'PROPERTIES' panel for the selected 'imageInputLayer' layer. It includes fields for Name, InputSize, Normalization, NormalizationDimension, Mean, StandardDeviation, Min, and Max. The 'OVERVIEW' section at the bottom right shows a small thumbnail of the network diagram.

DESIGNER

FILE BUILD NAVIGATE LAYOUT ANALYSIS EXPORT

Layer Library

Filter layers...

INPUT

- imageInputLayer
- image3dInputLayer
- sequenceInputLayer
- roiInputLayer

CONVOLUTION AND FULLY CONNECTED

- convolution2dLayer
- convolution3dLayer
- groupedConvolution2dLayer
- transposedConv2dLayer
- transposedConv3dLayer
- fullyConnectedLayer

Size of the input row vector of integers

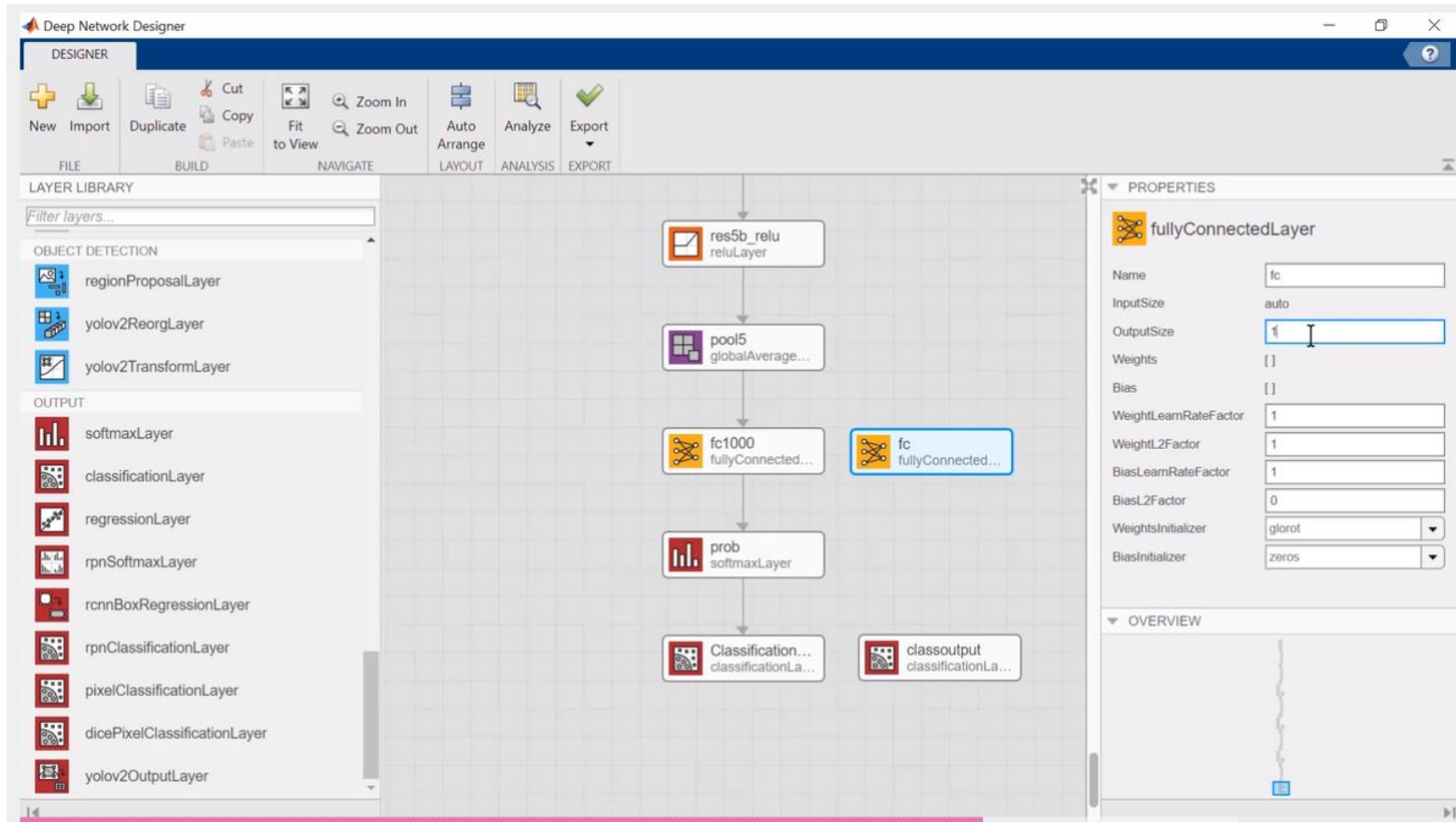
PROPERTIES

imageInputLayer

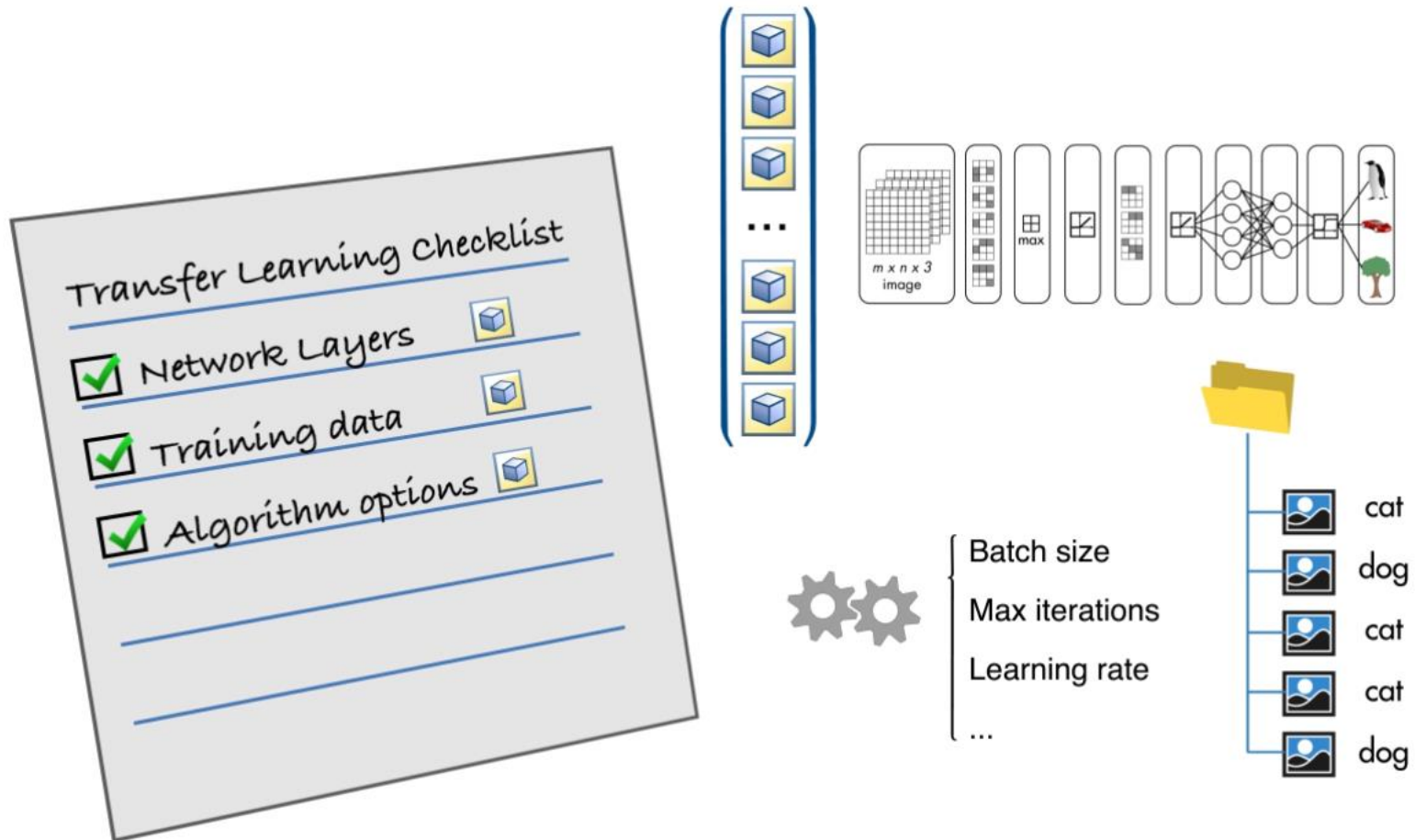
Name	data
InputSize	224,224,3
Normalization	zscore
NormalizationDimension	auto
Mean	[1×1×3 single]
StandardDeviation	[1×1×3 single]
Min	[]
Max	[]

OVERVIEW

Deep Network Designer

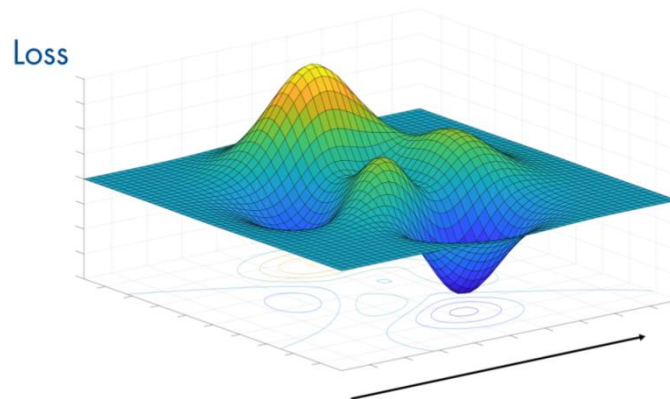


Training



Optimization parameters

See options code.



Training

```
>> newnet = trainNetwork(data, layers, options)
```

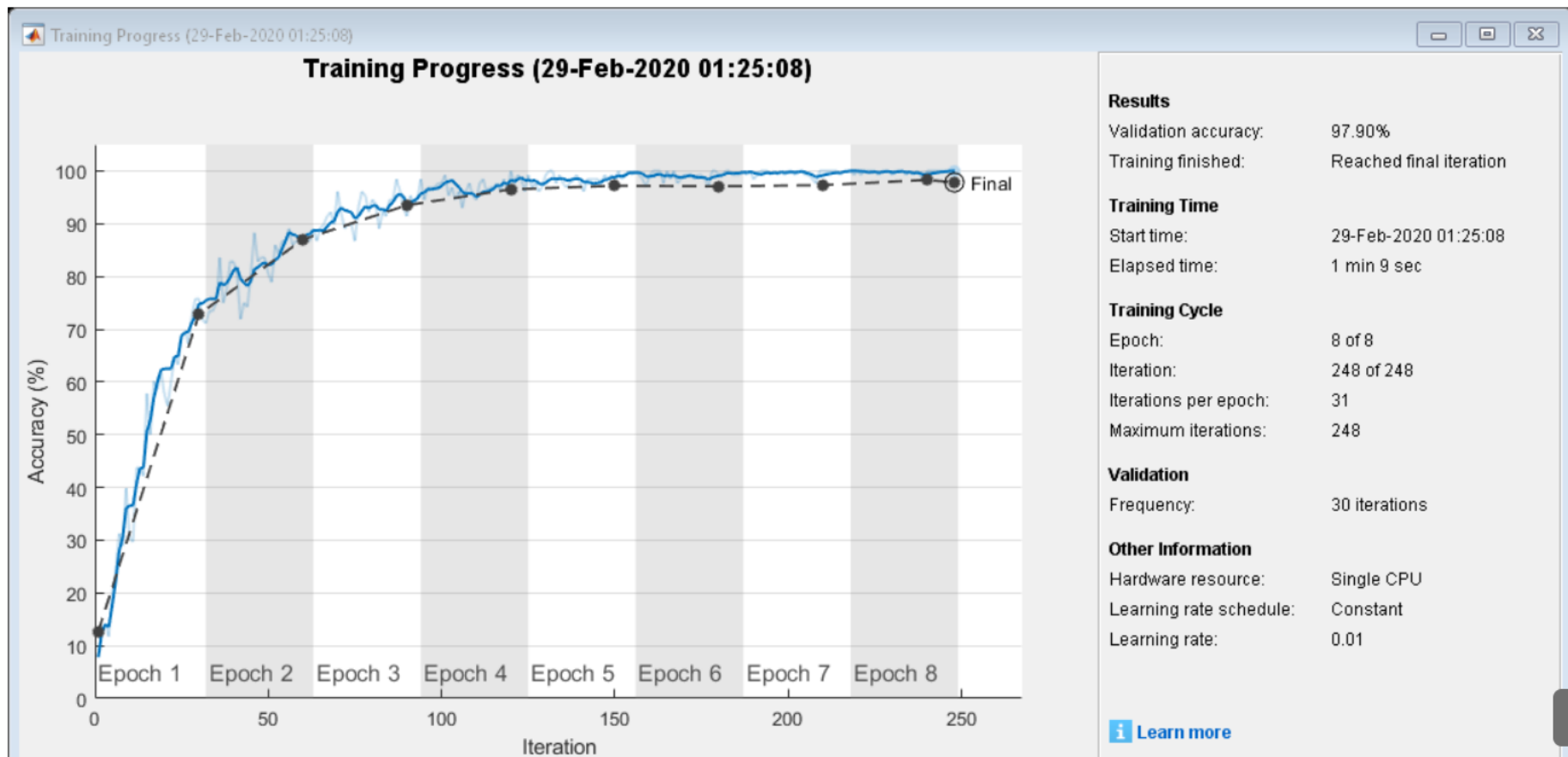


Training on single GPU.

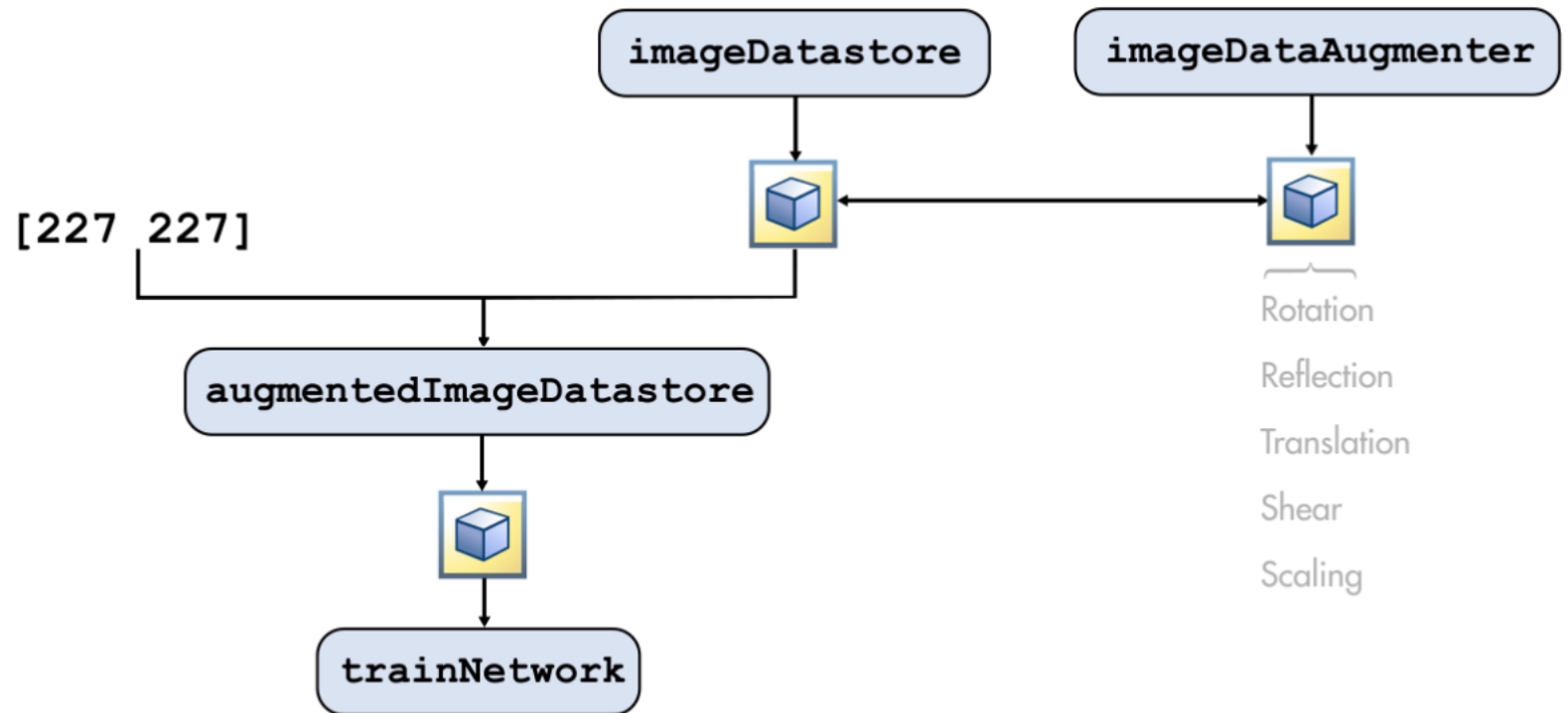
Initializing image normalization.

Epoch	Iteration	Time Elapsed (seconds)	Mini-batch Loss	Mini-batch Accuracy	Base Learning Rate
1	1	0.47	3.5061	7.81%	0.0010
3	10	10.31	0.7686	75.00%	0.0010
5	20	18.96	0.2371	92.19%	0.0010
8	30	27.43	0.0770	97.66%	0.0010
10	40	35.31	0.0336	99.22%	0.0010
13	50	43.17	0.0289	99.22%	0.0010
15	60	50.15	0.0104	100.00%	0.0010
18	70	56.84	0.0072	100.00%	0.0010
20	80	63.00	0.0210	99.22%	0.0010
23	90	69.37	0.0035	100.00%	0.0010

Training



Data



Data augmentation in Matlab

imageDataAugmenter

Description

An image data augmenter configures a set of preprocessing options for image augmentation, such as resizing, rotation, and reflection. The imageDataAugmenter is used by an [augmentedImageDatastore](#) to generate batches of augmented images. For more information, see [Augment Images for Training](#).

Syntax

```
aug = imageDataAugmenter  
aug = imageDataAugmenter(Name,Value)
```


Data augmentation

% Create an imageDataAugmenter object that specifies preprocessing options for image augmentation

```
[XTrain,YTrain] = digitTrain4DArrayData;
```

```
imageAugmenter = imageDataAugmenter( ...  
    'RandRotation',[-20,20], ...  
    'RandXTranslation',[-3 3], ...  
    'RandYTranslation',[-3 3])
```

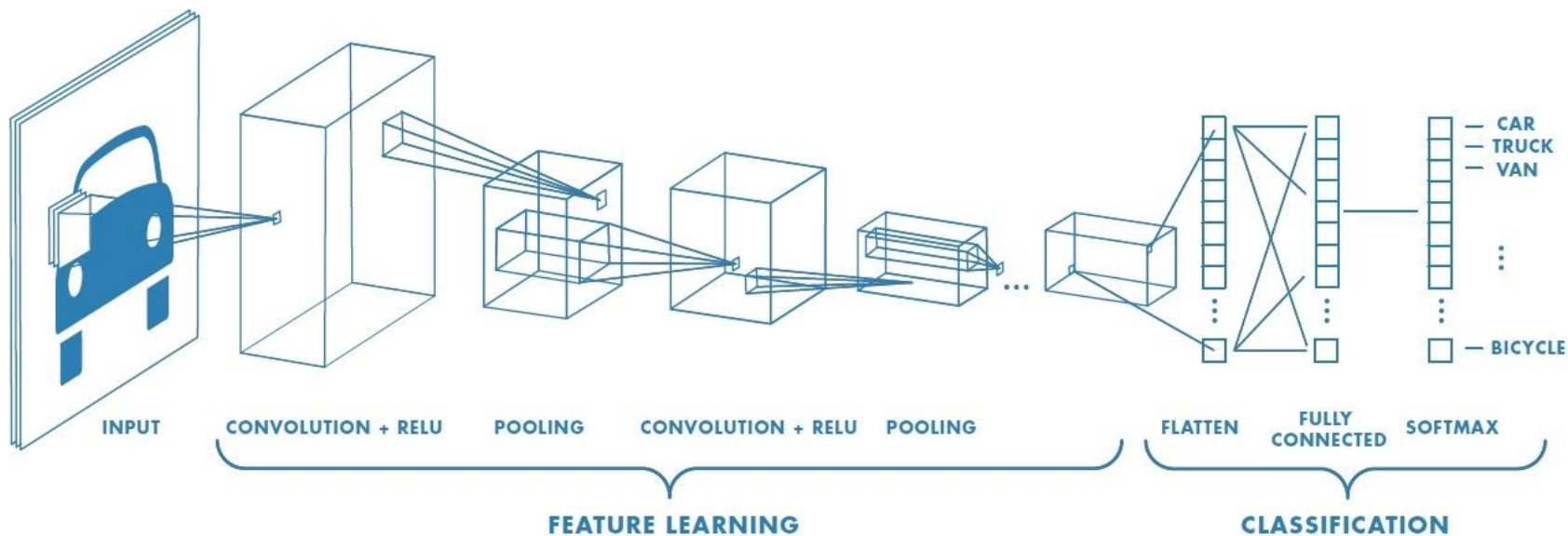
```
imageSize = [28 28 1];
```

```
augimds =  
augmentedImageDatastore(imageSize,XTrain,YTrain,'DataAug  
mentation',imageAugmenter);
```

Training from scratch (Layers)

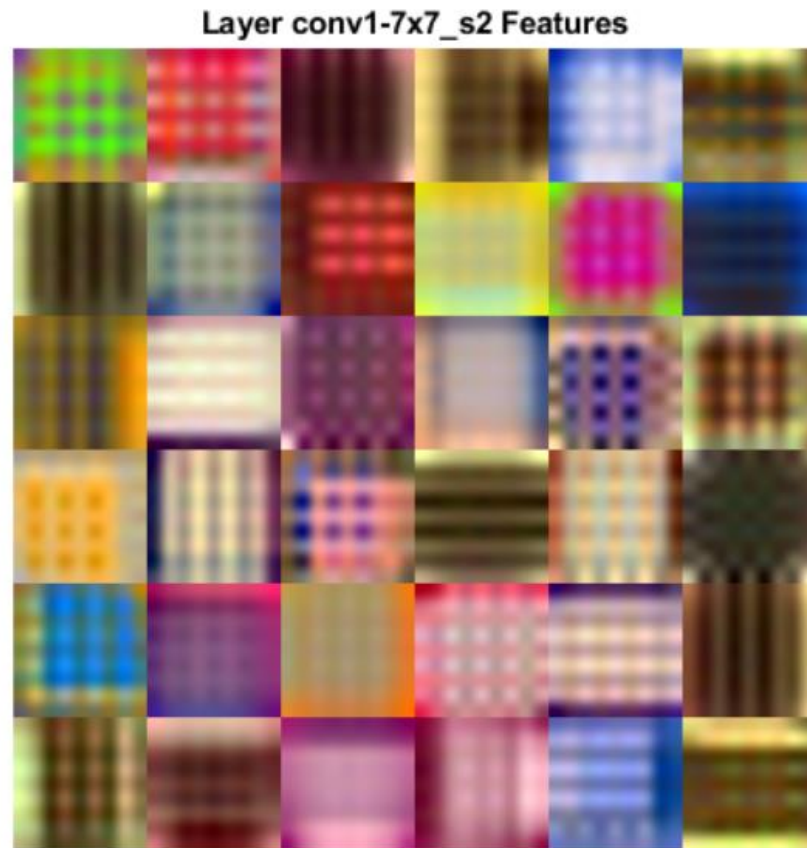
Example 2: `Scratch_Digits_Augment.m`

Feature extraction



See: [Demo_FeatureExtraction.m](#) (cfar10)

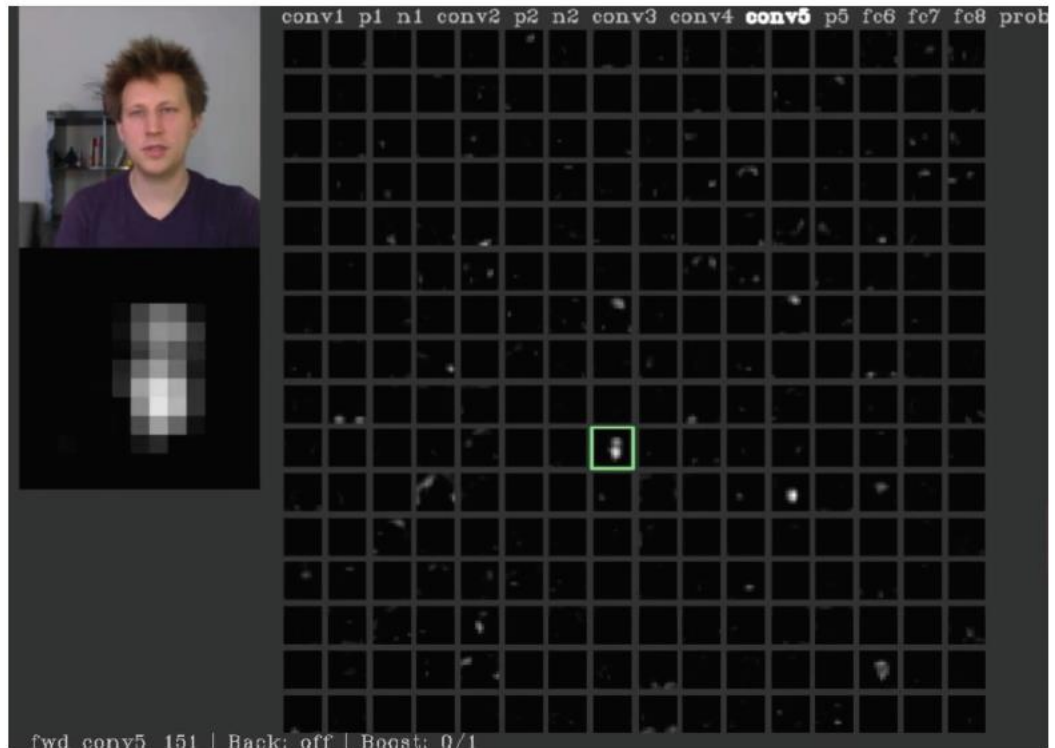
Visualize Features of a CNN



<https://www.mathworks.com/help/deeplearning/ug/visualize-features-of-a-convolutional-neural-network.html>

Visualize Features of a CNN

conv5 feature map is
128x13x13; visualize
as 128 13x13
grayscale images



Yosinski et al, "Understanding Neural Networks Through Deep Visualization", ICML DL Workshop 2014.
Figure copyright Jason Yosinski, 2014. Reproduced with permission.

<https://microscope.openai.com/models>

Convolutional Neural Networks

Classification

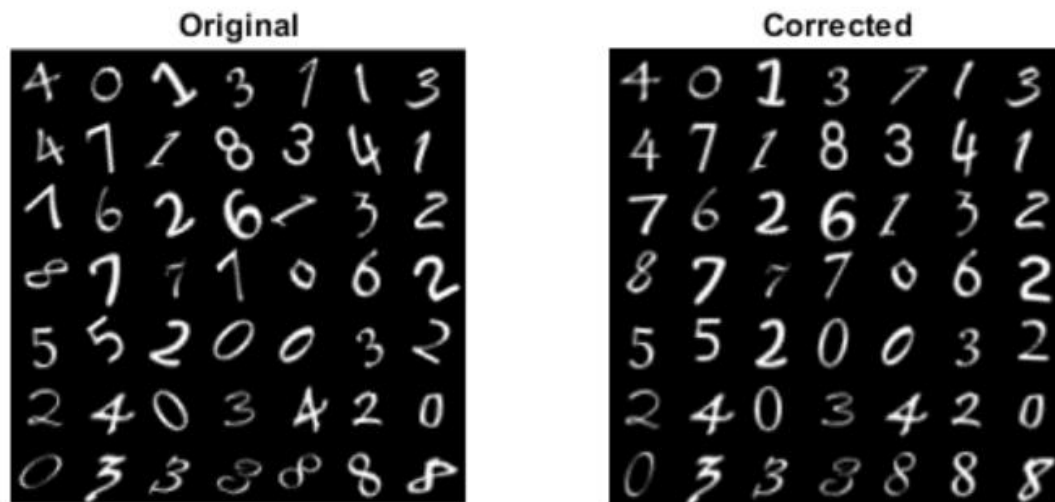
CNN - Deep Learning Toolbox™

Regression

Object detection

R-CNN - Computer Vision Toolbox™

CNN for regression



See: [Scratch_Digits_Regress.m](#)

Homework II: Worm classification

- Propose and implement a methodology using CNN to perform a binary classification of the worm database.
- A minimum accuracy of 90% is expected.

