ENERGY GeoHackathon
Society of Petroleum Engineers

SPE International
SPE Europe Region

# 2022 SPE EUROPE ENERGY GEOHACKATHON

## 15. Computer Vision with MATLAB

17 October 2022

#DatafyingEnergy

ENERGY GeO Hackathon
Society of Petroleum Engineers

Italian Section | London Section | Netherlands Section | Romanian Section | Copenhagen Section | Geothermal Technical Section

# Ayon Kumar Dey, Ph.D.

## Senior Application Engineer, MathWorks

Geological Survey of Denmark and Greenland | accenture | CGG | MathWorks | Microsoft | NVIDIA | Oilfield International | SAMSUNG | TNO innovation for life | TRE ALTAMIRA

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ENERGY GeO Hackathon
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Italian Section | London Section | Netherlands Section | Romanian Section | Copenhagen Section | Geothermal Technical Section

# Q&A

## Please, type your Question in the Zoom Chat

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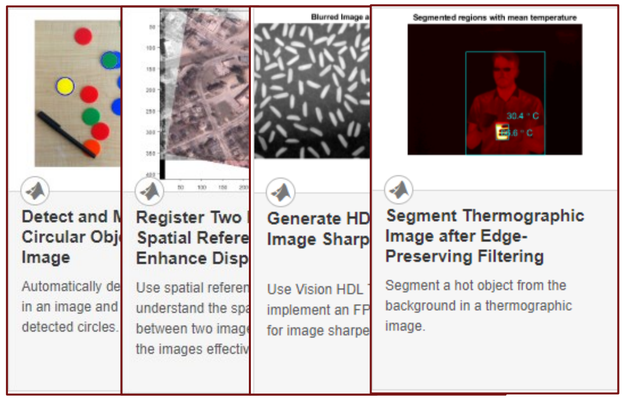
# Objective

To get started with solving computer vision problems through real-world examples

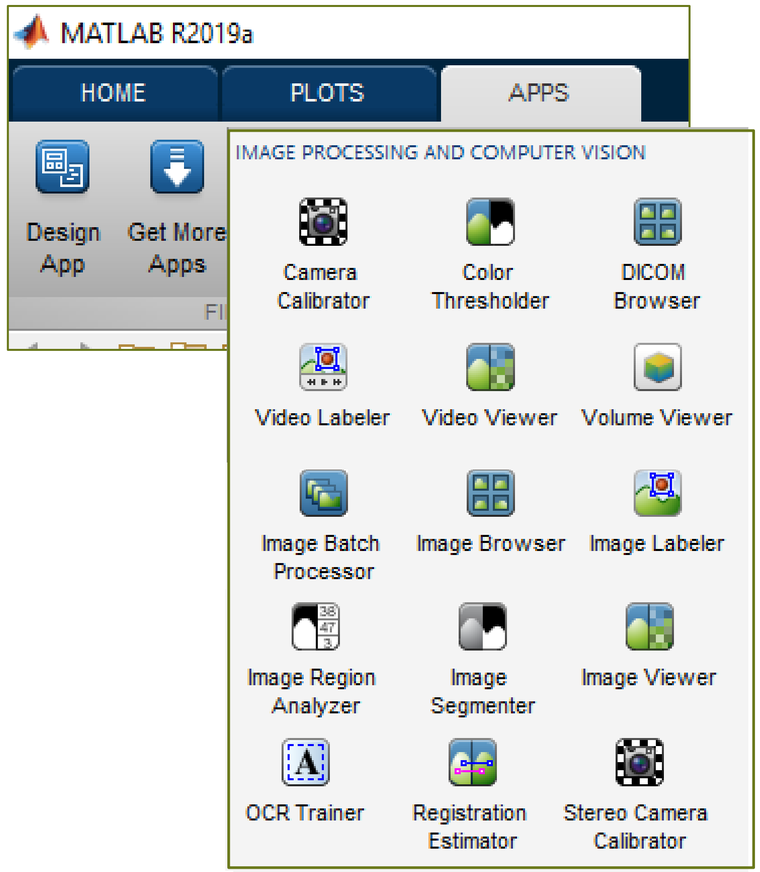
# Why Use MATLAB?

## Ease of Use and Thorough Documentation

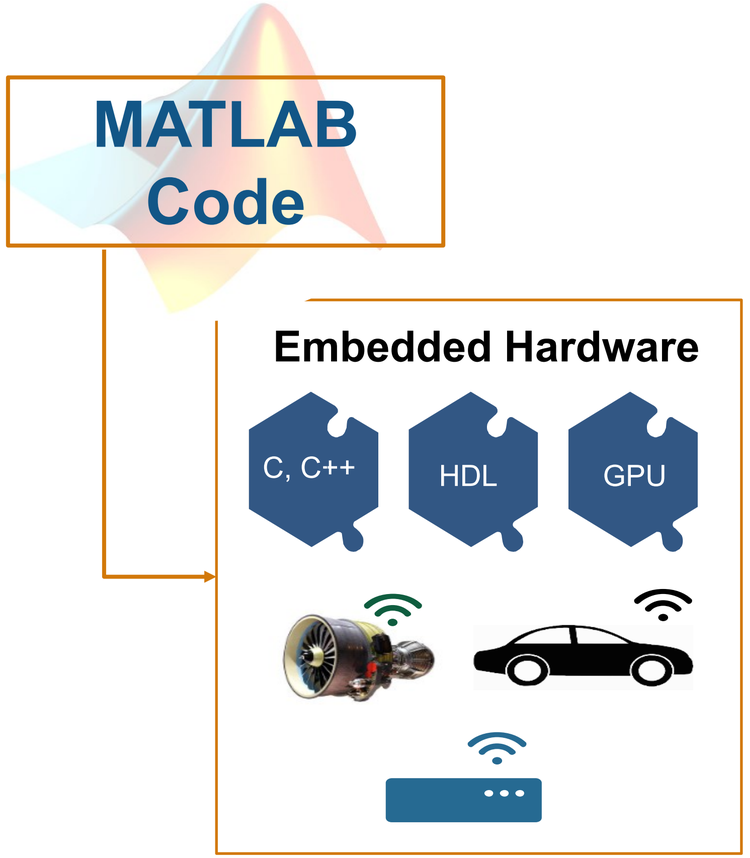



(…)

## Rapid Prototyping and Algorithm Development




## Code Generation for Embedded Deployment




## Need Technical Help?

- Technical Support
- Application Engineers

# Complete Set of Algorithms and Pre-built Models

## Algorithms

**Machine learning**
Trees, Naïve Bayes, SVM…

**Deep learning**
CNNs, GANs, LSTM, MIMO…

**Reinforcement learning**
DQN, A2C, DDPG…

**Regression**
Linear, nonlinear, trees…

**Unsupervised learning**
K-means, PCA, GMM…

**Predictive maintenance**
RUL models, condition indicators…

**Bayesian optimization**

## Pre-built models

**Image classification models**
AlexNet, GoogLeNet, VGG, SqueezeNet, ShuffleNet, ResNet, DenseNet, Inception…

## Reference examples

**Object detection**
Vehicles, pedestrians, faces…

**Semantic segmentation**
Roadway detection, land cover classification, tumor detection…

**Signal and speech processing**
Denoising, music genre recognition, keyword spotting, radar waveform classification…

**…and more…**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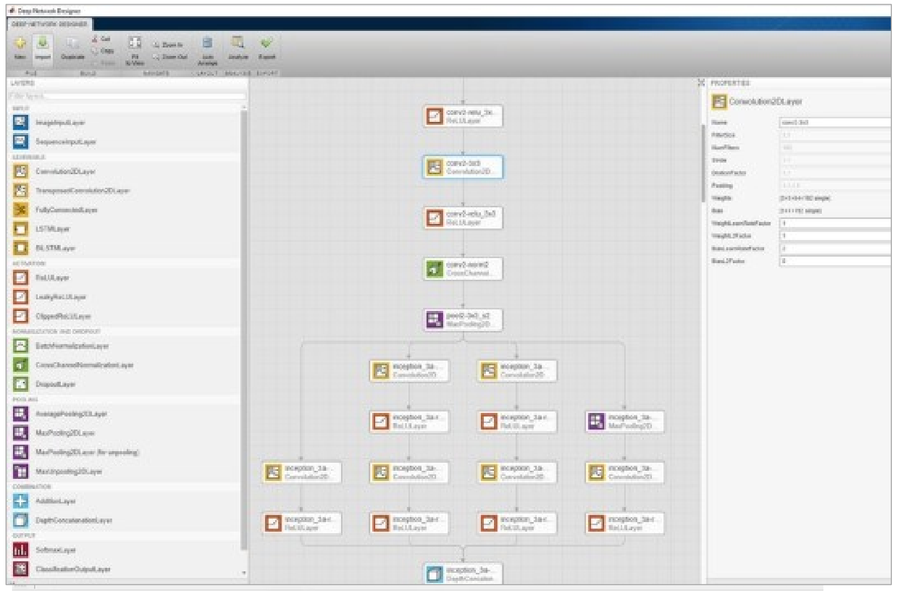
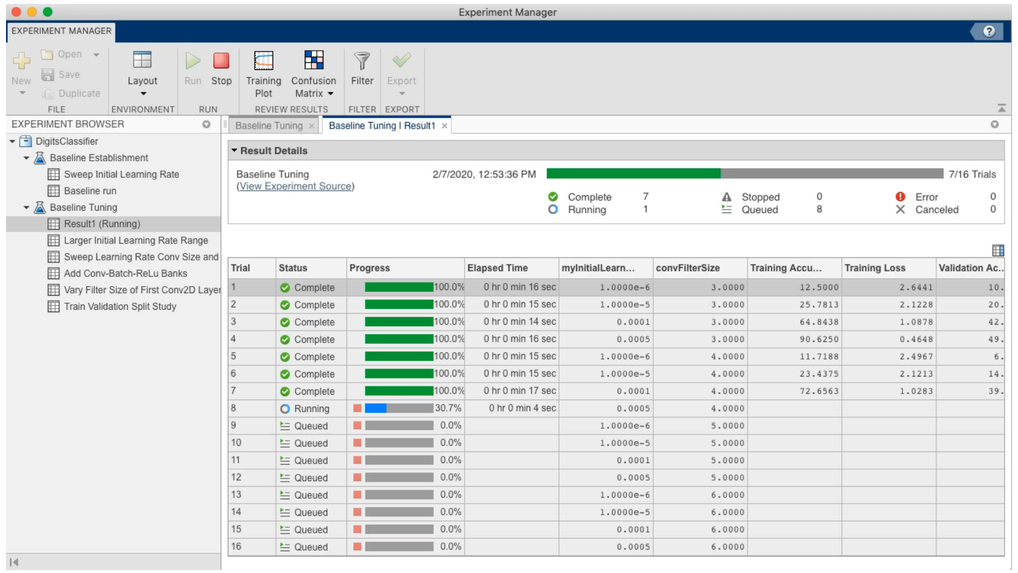
# Increase Productivity using Apps for Design and Analysis



**Deep Network Designer** app to build, visualize, and edit deep learning networks




**Experiment Manager** app to manage multiple deep learning experiments, analyze and compare results and code

Use MATLAB Apps to design deep learning networks, explore a wide range of classifiers, train regression models, train an optical character recognition model, and more.



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# Today's Focus Toolboxes

Image Processing Toolbox

Search MathWorks.com

## Image Processing Toolbox

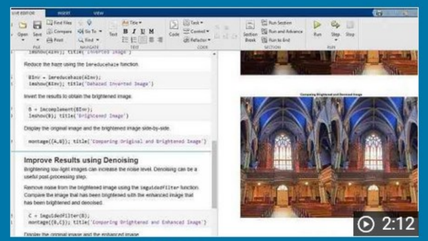
Perform image processing, visualization, and analysis

Get a free trial | View pricing

Image Processing Toolbox™ provides a comprehensive set of reference-standard algorithms and workflow apps for image processing, analysis, visualization, and algorithm development. You can perform image segmentation, image enhancement, noise reduction, geometric transformations, and image registration using deep learning and traditional image processing techniques. The toolbox supports processing of 2D, 3D, and arbitrarily large images.

Image Processing Toolbox apps let you automate common image processing workflows. You can interactively segment image data, compare image registration techniques, and batch-process large data sets. Visualization functions and apps let you explore images, 3D volumes, and videos; adjust contrast; create histograms; and manipulate

Show more

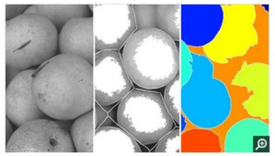



What Is Image Processing Toolbox?

### Image Analysis

Extract meaningful information from images, such as finding shapes, counting objects, identifying colors, or measuring object properties.

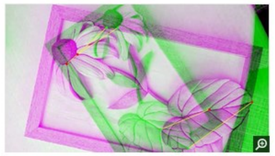
Documentation | Examples



### Image Segmentation

Determine region boundaries in an image using different approaches including automatic thresholding, edge-based methods, and morphology-based methods.

Documentation | Examples



### Image Registration

Align images to enable quantitative analysis or qualitative comparison using intensity-based, multimodal, and non-rigid registration techniques.

Documentation | Examples

Computer Vision Toolbox

Search MathWorks.com

## Computer Vision Toolbox

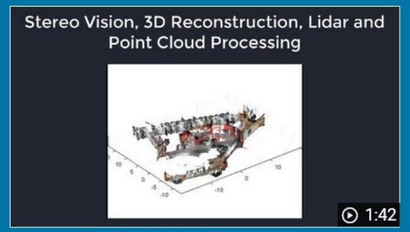
Design and test computer vision, 3D vision, and video processing systems

Get a free trial | View pricing


Computer Vision Toolbox™ provides algorithms, functions, and apps for designing and testing computer vision, 3D vision, and video processing systems. You can perform object detection and tracking, as well as feature detection, extraction, and matching. You can automate calibration workflows for single, stereo, and fisheye cameras. For 3D vision, the toolbox supports visual and point cloud SLAM, stereo vision, structure from motion, and point cloud processing. Computer vision apps automate ground truth labeling and camera calibration workflows.

You can train custom object detectors using deep learning and machine learning algorithms such as YOLO , SSD, and ACF. For semantic and instance segmentation, you can use deep learning algorithms such as U-Net and Mask R-CNN. The toolbox provides object detection and

Show more

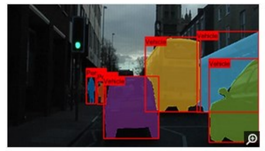



What Is Computer Vision Toolbox?

### Image and Video Ground Truth Labeling

Automate labeling for object detection, semantic segmentation, instance segmentation, and scene classification using the Video Labeler and Image Labeler apps.

Documentation | Examples



### Deep Learning and Machine Learning

Train or use pretrained deep learning and machine learning based object detection and segmentation networks. Evaluate the performance of these networks and deploy them as C/C++ or CUDA® code.

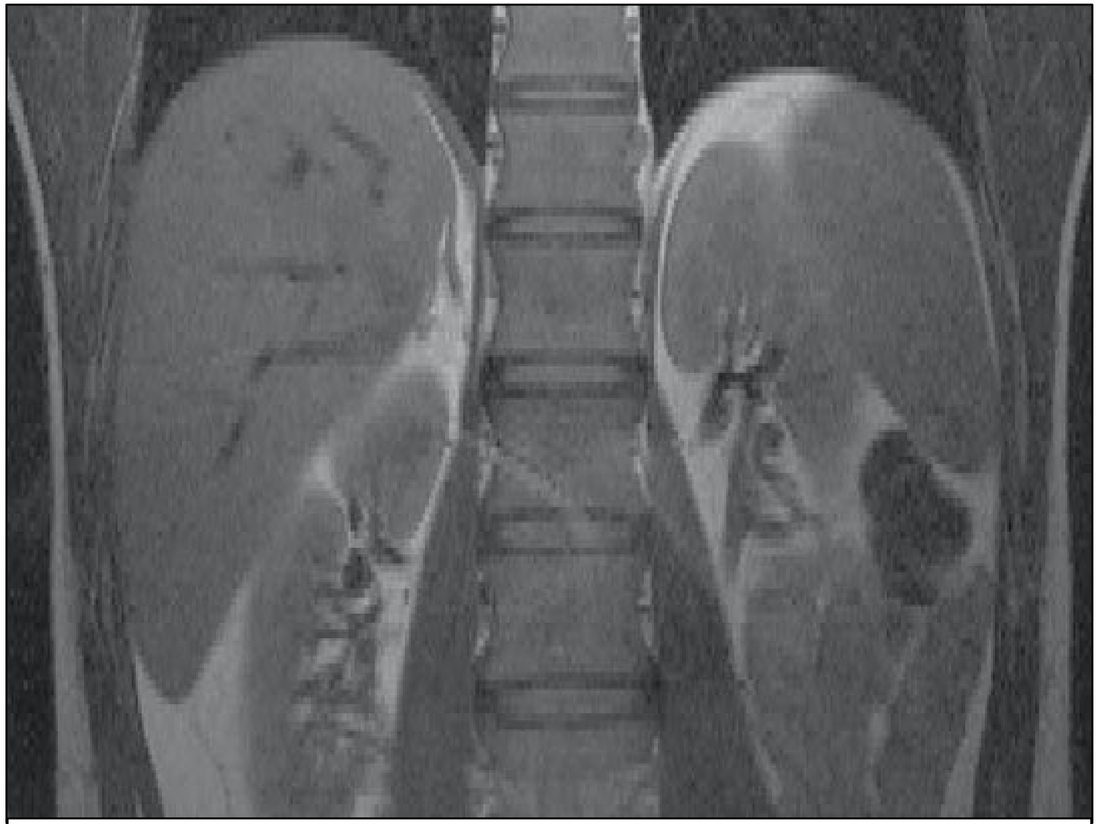
Documentation | Examples

### Automated Visual Inspection

Use the Automated Visual Inspection Library in Computer Vision Toolbox to identify anomalies or defects to assist and improve quality assurance processes in manufacturing.

Documentation | Examples

# Computer Vision User Case



Beth Israel Medical Center Improves MRI Accuracy

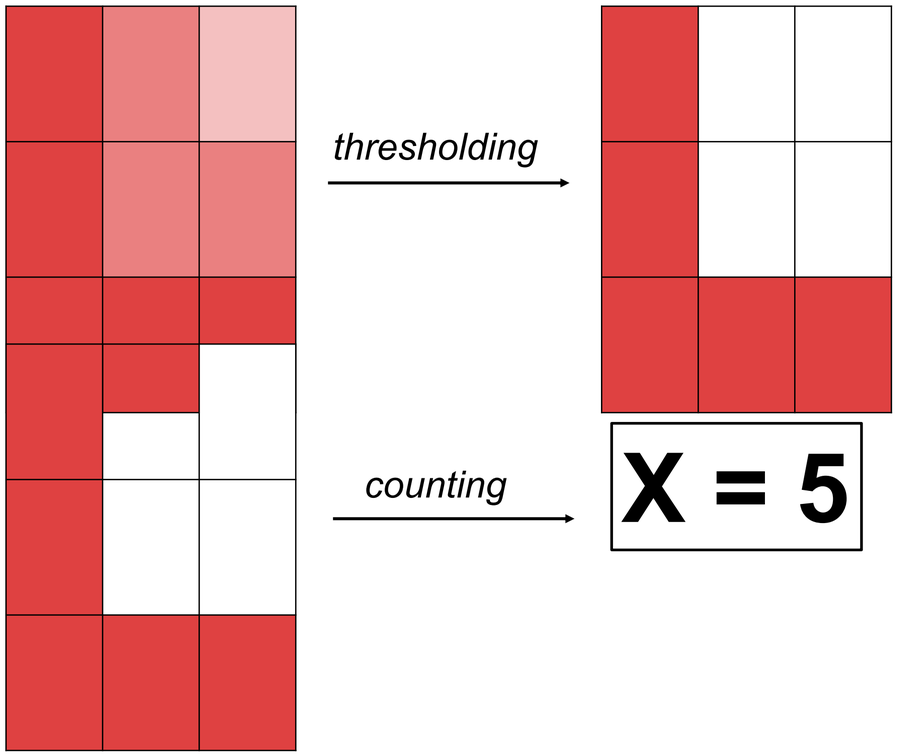
**IPCV user stories**

**Deep Learning user stories**

# Image Processing and Computer Vision Connection

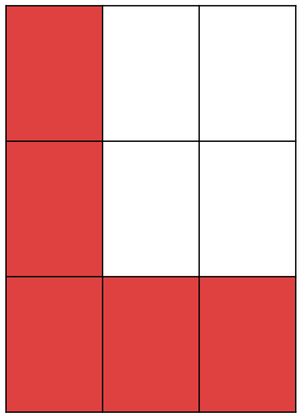
## Image Processing

*Manipulation of images to extract meaningful information*



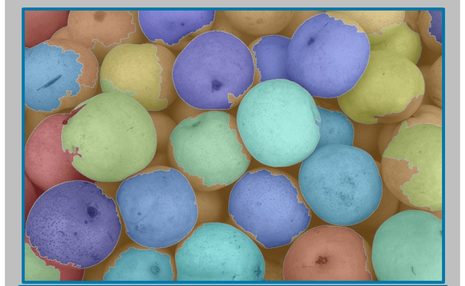

## Computer Vision

*Teaching computers to understand images and video*



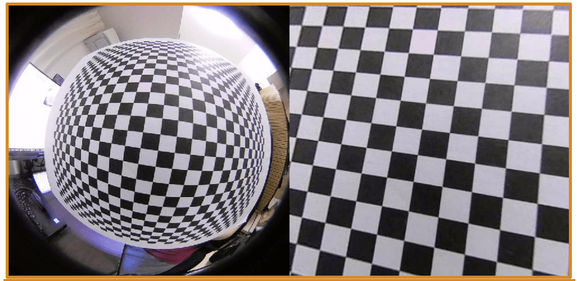
This is the letter “L”

# Image Processing and Computer Vision Techniques



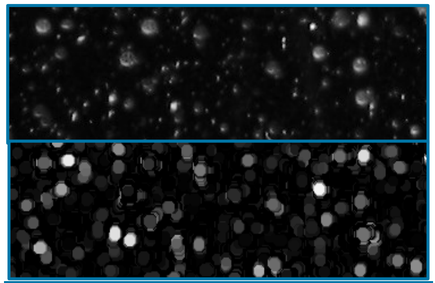
Segmentation

Edge Detection



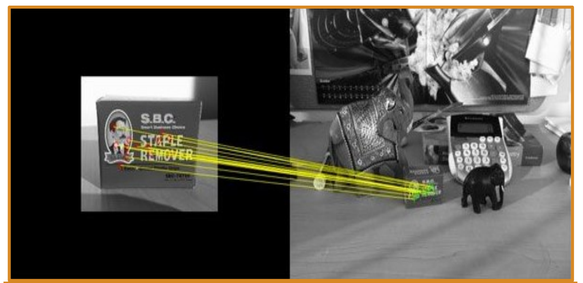
Camera Calibration

Labeling

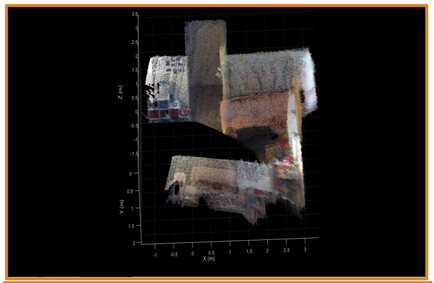


Morphology


3D Image Processing




Feature Detection



Point Cloud Processing

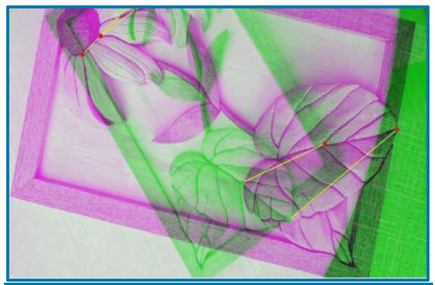


Image Registration

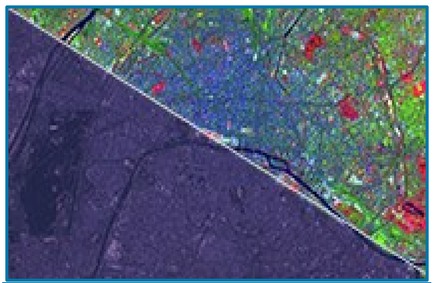
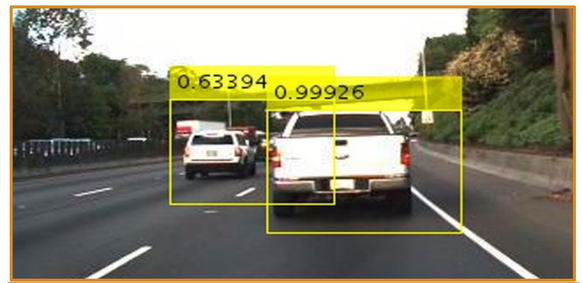


Image Enhancement




Object Detection


Tracking

# Labeler Apps

- Label ground truth for image, video, lidar and medical data

- Important for training networks for:
  - Classifiers
  - Object Detectors
  - Segmentation

- Features:
  - Create label definitions and attributes.
  - Semi automated or automated labeling with built-in or custom algorithms
  - Blocked processing support (image)
  - Superpixel automation (Image, Video)

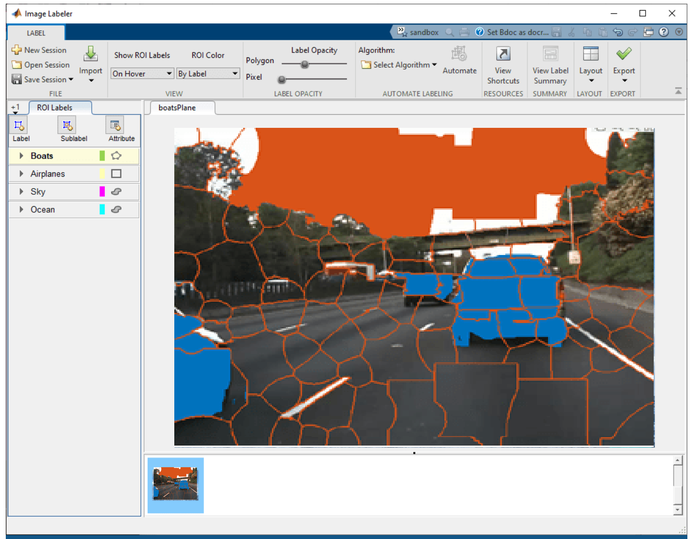
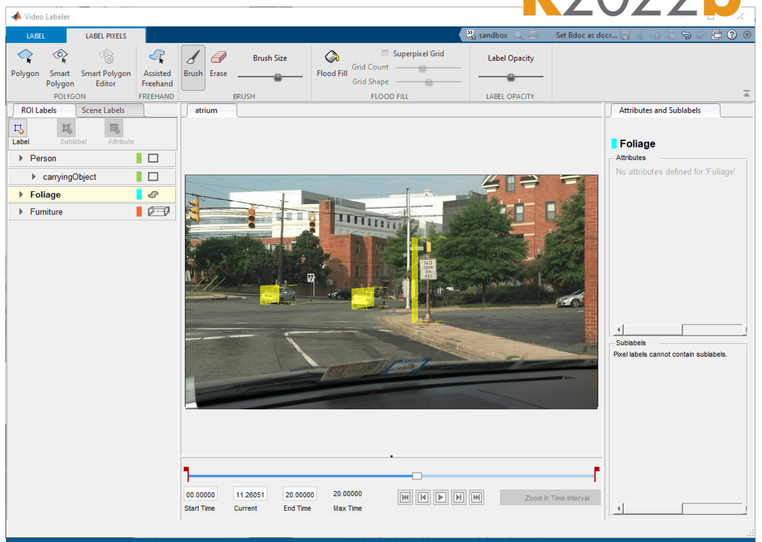
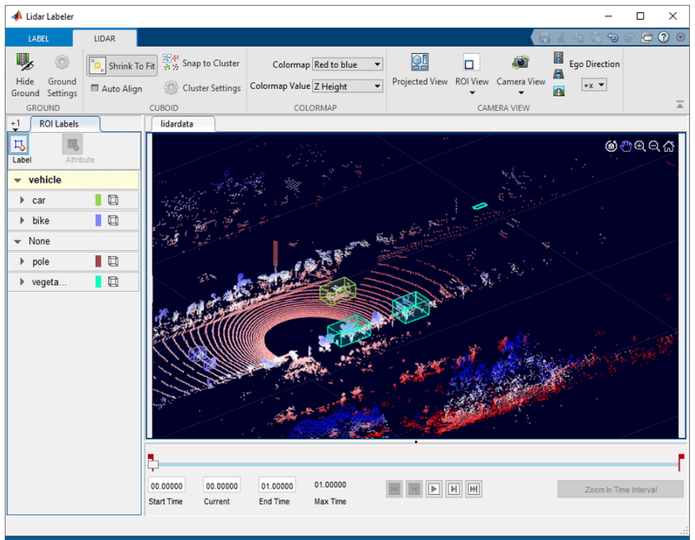


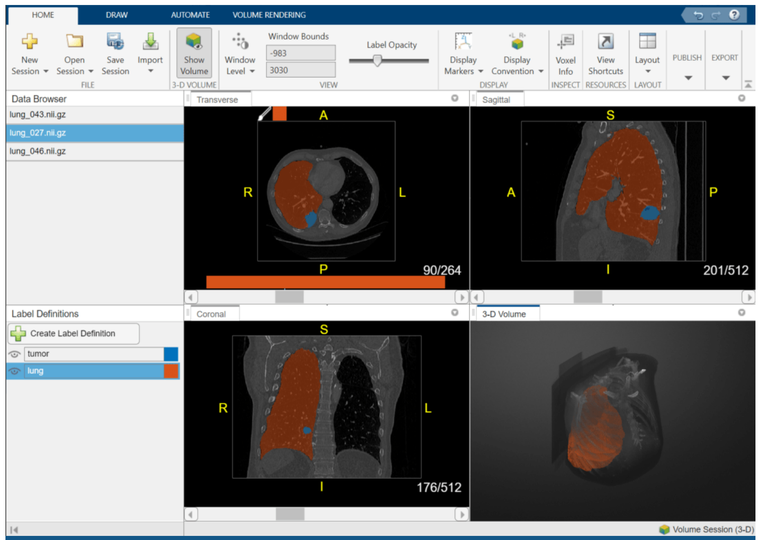

Image Labeler (Computer Vision Toolbox)




Video Labeler (Computer Vision Toolbox)



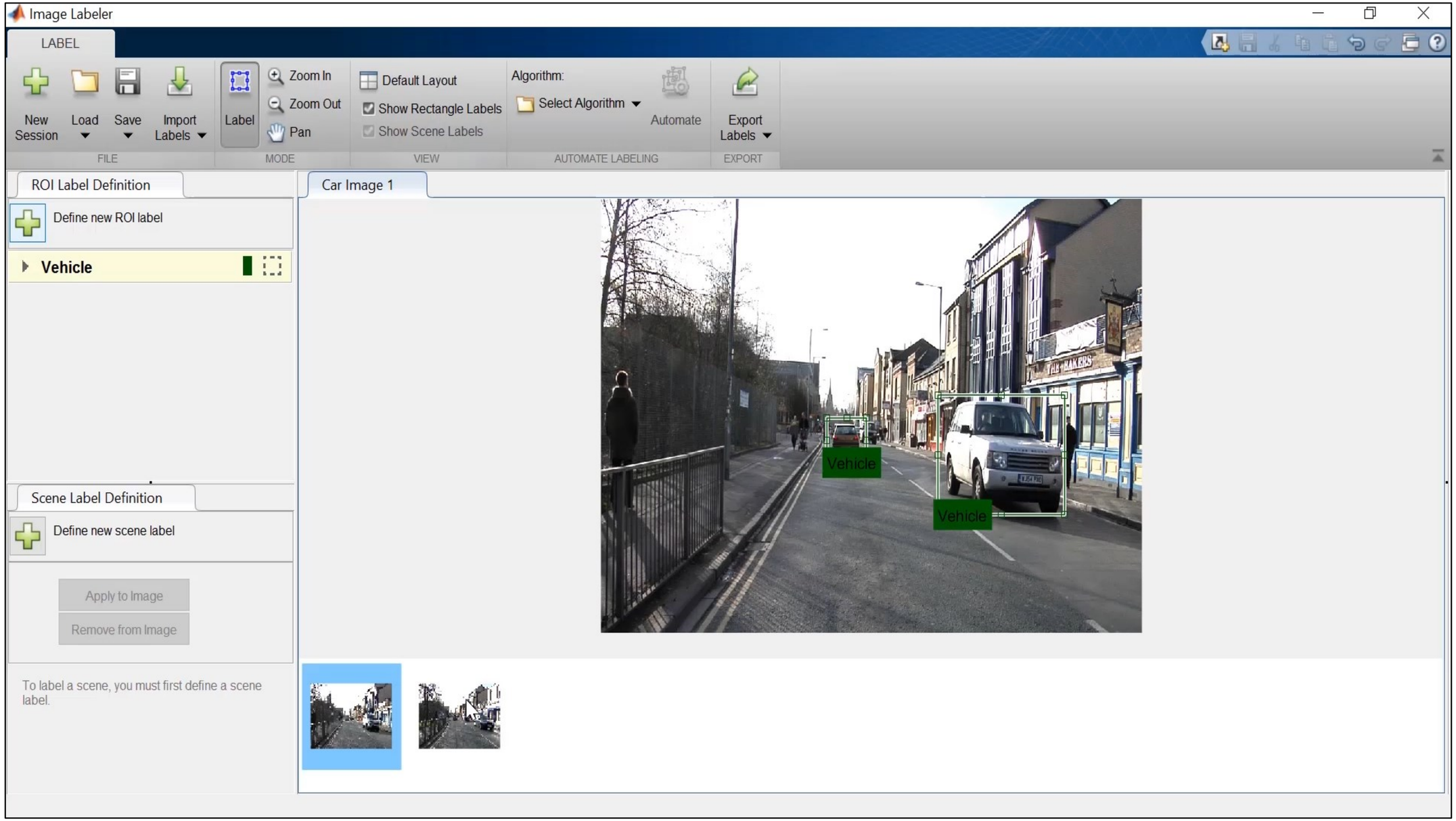

Lidar Labeler (Lidar Toolbox)




Medical Image Labeler (Medical Imaging Toolbox)

[Labeling Apps]

# Semi-Automated Labeling with Apps



# *Let's go to MATLAB!*

# Deep Learning for Computer Vision

```
>> net = alexnet;
```

# Import Deep Learning Models

- `alexnet`
- `vgg16`
- `vgg19`
- `googlenet`
- `inception-v3`
- `resnet-18`
- `resnet-50`
- `resnet-101`
- `inception-resnet-v2`
- `squeezenet`
- `densenet-201`

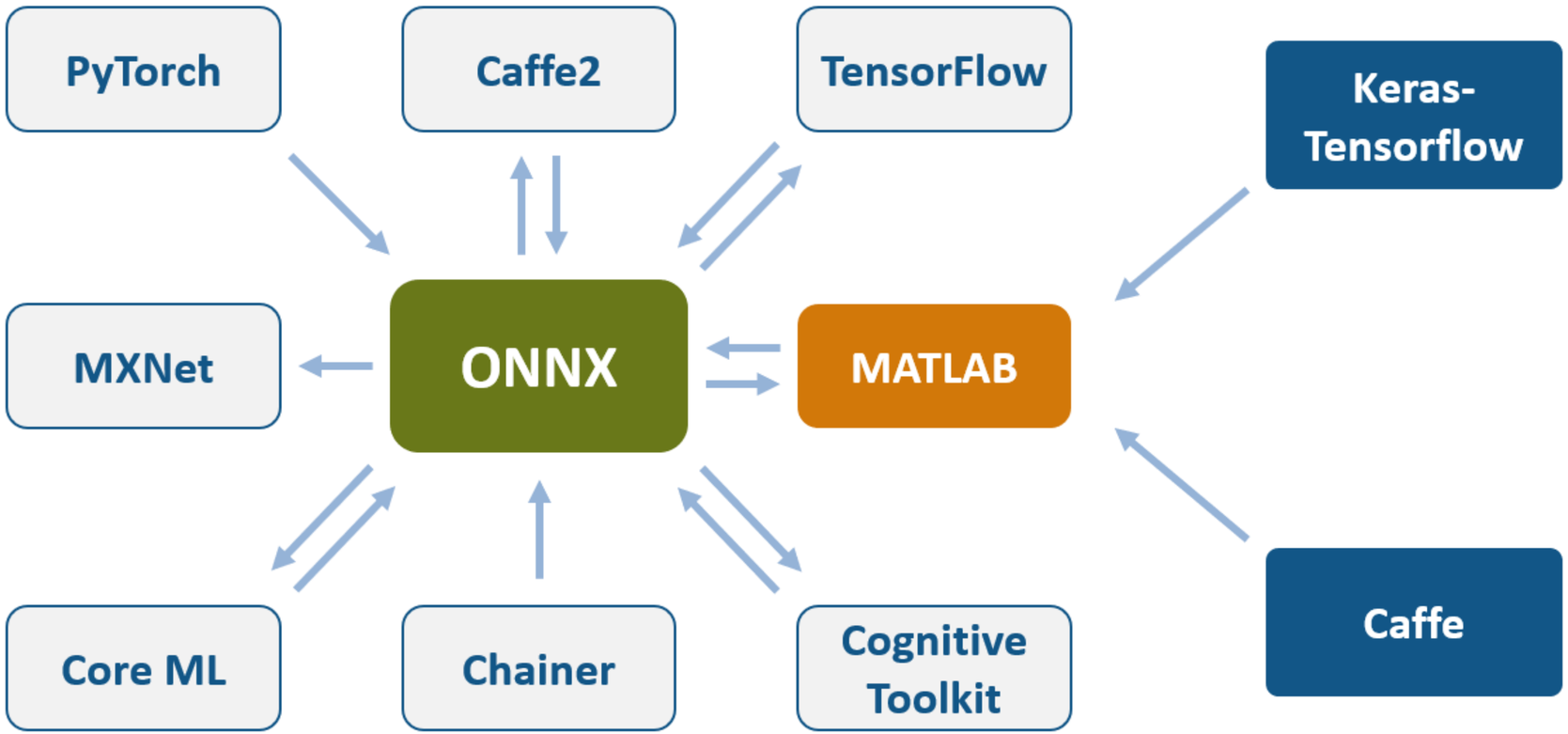
… (growing list over time)

**Download from within MATLAB**


Single line of code to access models -

```
net = alexnet;
net = vgg16;
net = vgg19;
```

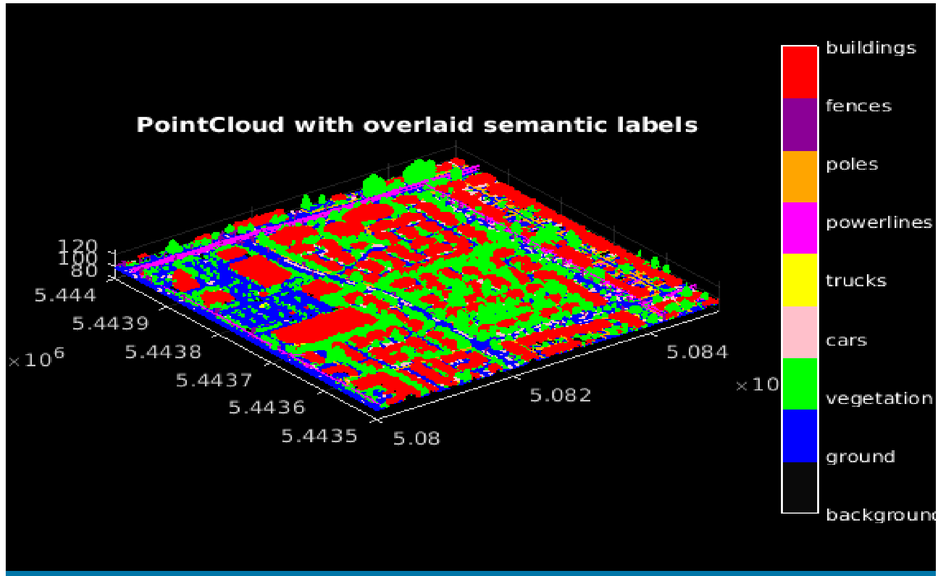
# Import Deep Learning Models



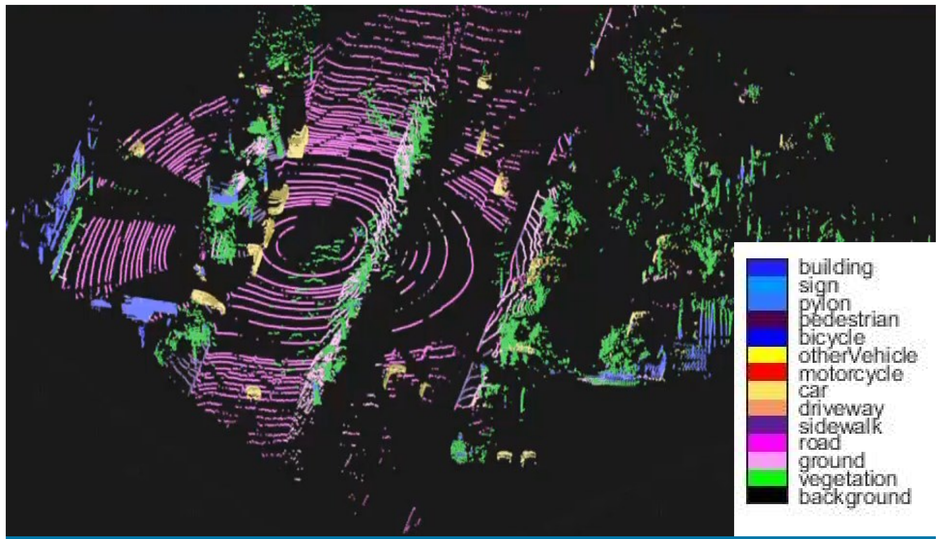
# Semantic Segmentation

- Develop semantic segmentation models using:
  - Segnet and PointSeg networks on organized data
  - segment images, point cloud data, lidar data etc.
- Important for:
  - Associating pixels to class labels.
  - Tracking and labeling workflows.
  - Segmenting ground, vegetation, buildings, etc.

- Key features:
  - Store training and test data using Datastore objects
  - Expand datasets using augmentation techniques
  - Speedup network training using GPU
  - Evaluate models using inbuilt function




Aerial Lidar Data Semantic Segmentation

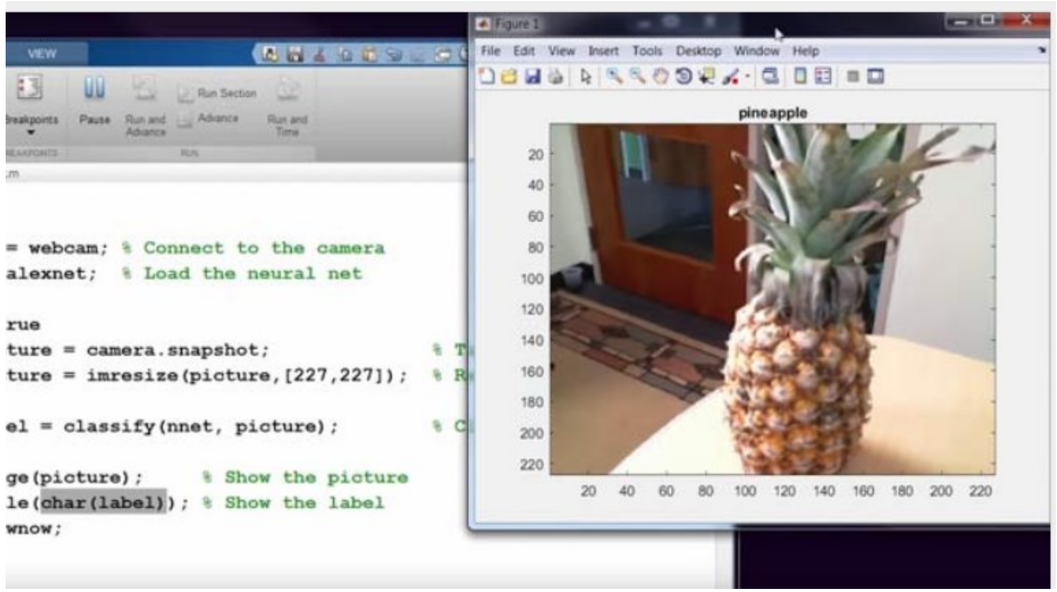


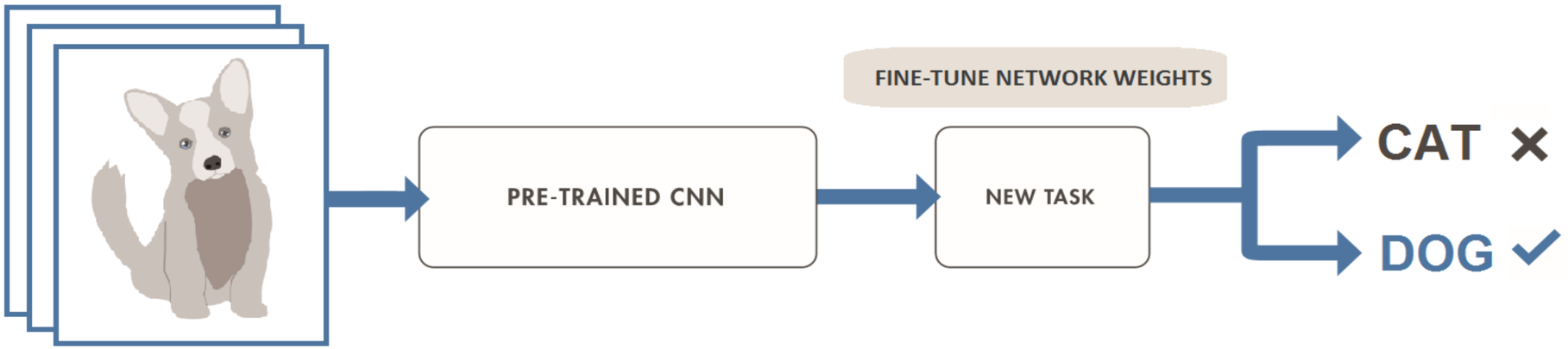

Automotive Point Cloud Data Semantic Segmentation

# *Let's go to MATLAB!*

# Deep Learning: Transfer Learning

*Pre-trained CNN, Alexnet in use*



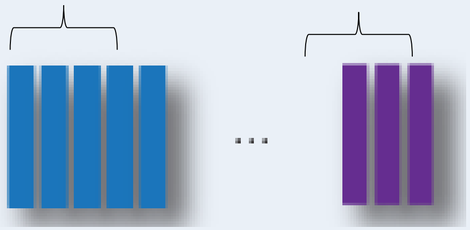



# Transfer Learning Workflow

## Load pretrained network

Early layers that learned low-level features (edges, blobs, colors)

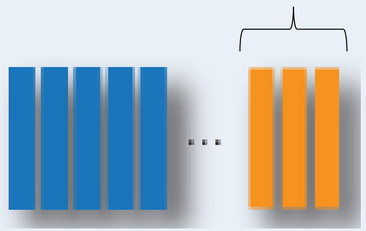
Last layers that learned task specific features



1 million images
1000s classes

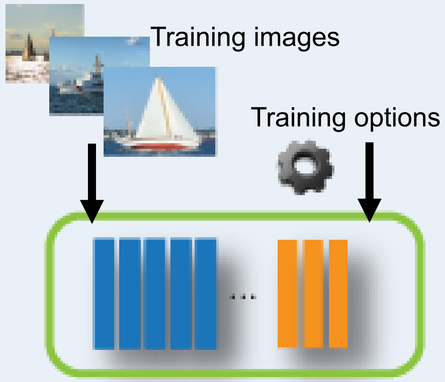
## Replace final layers

New layers to learn features specific to your data



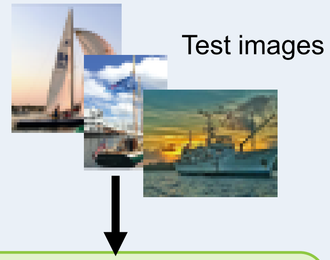
Fewer classes
Learn faster

## Train network



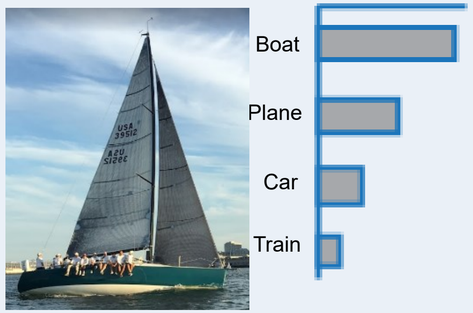

100s images
10s classes

## Predict and assess network accuracy

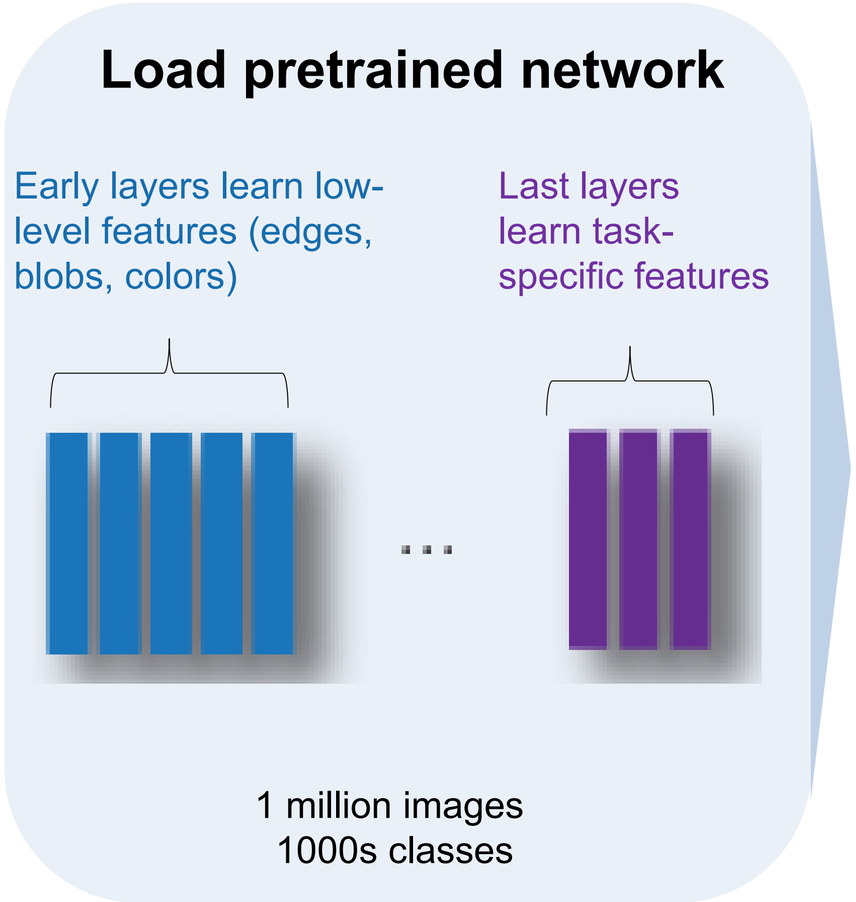



Trained Network

## Deploy results



# Transfer Learning Workflow – Step 1

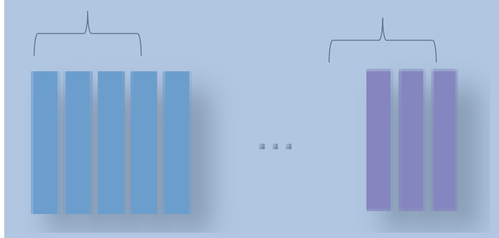


# Transfer Learning Workflow – Step 2

## Load pretrained network

Early layers that learned low-level features (edges, blobs, colors)

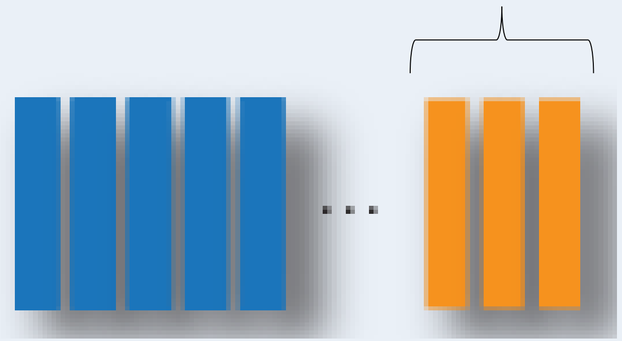
Last layers that learned task specific features



1 million images
1000s classes

## Replace final layers

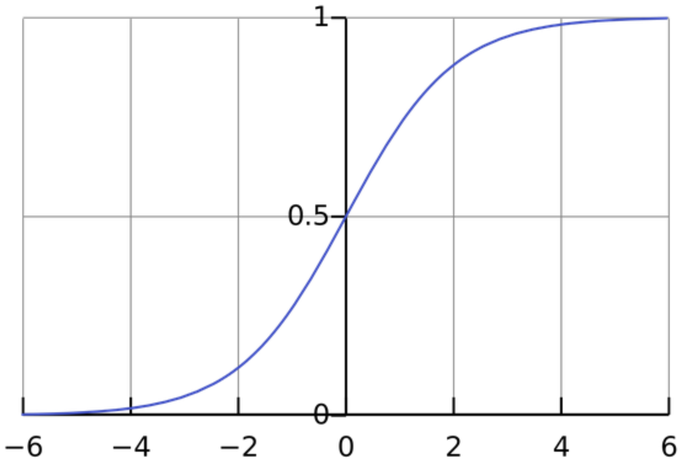
New layers learn features specific to your data



Fewer classes
Learn faster

# Classification Problems End with 3 Layers

- Fully Connected Layer
  - Looks at which high-level features correspond to a specific category
  - Calculates scores for each category (highest score wins)

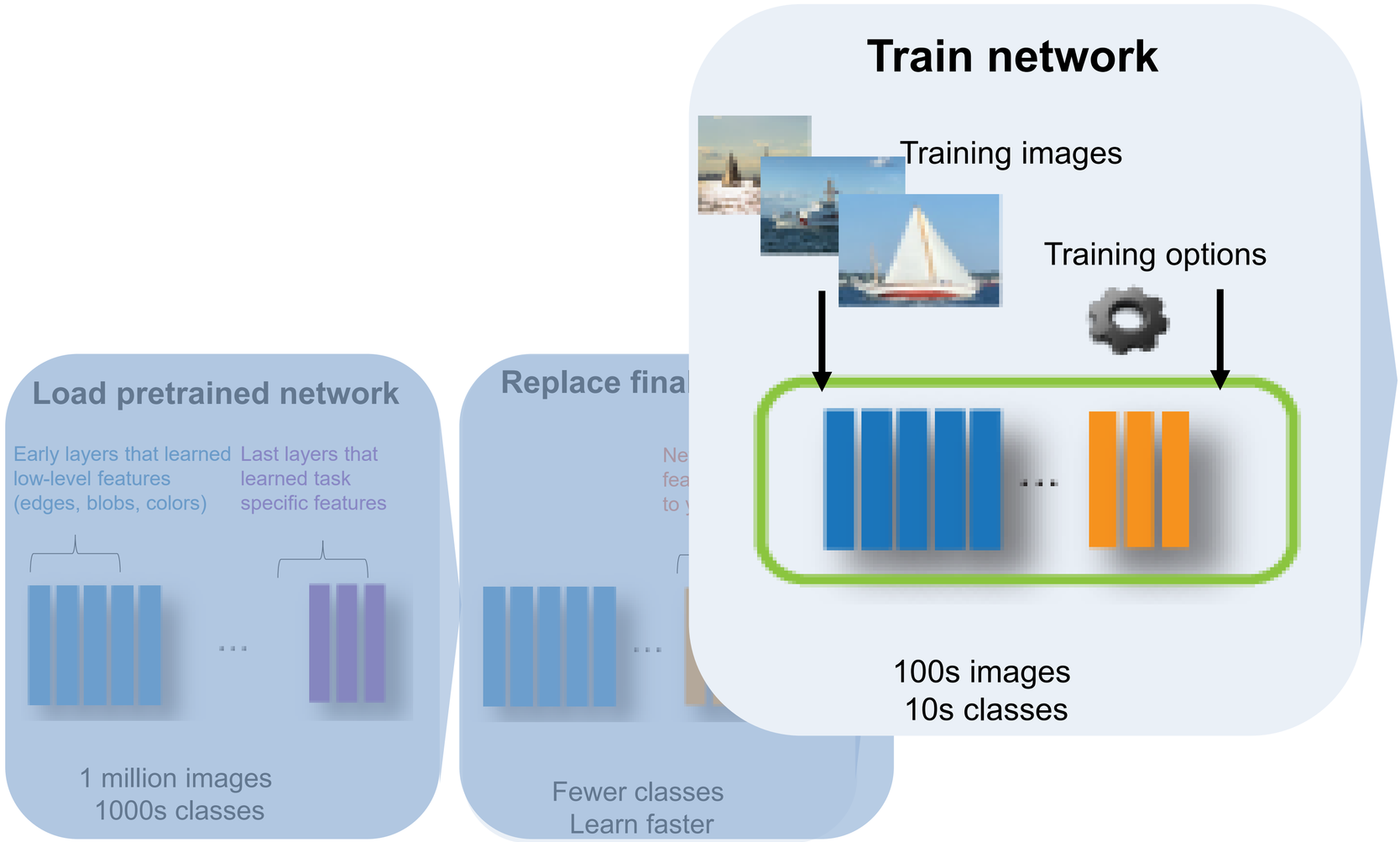



- Softmax Layer
  - Turns scores into probabilities.

- Classification Layer
  - Categorizes image into one of the classes that the network is trained on

*Note: Regression problems end with a fully connected layer and regression layer*

# Transfer Learning Workflow – Step 3



# Transfer Learning Workflow – Step 4

**Load pretrained network**

Early layers that learned low-level features (edges, blobs, colors)

Last layers that learned task specific features

1 million images
1000s classes

**Replace final**

Fewer classes
Learn faster

100s images
10s classes

**Predict and assess network accuracy**

Test images

Trained Network

# Transfer Learning Workflow – Step 5

## Load pretrained network

Early layers that learned low-level features (edges, blobs, colors)

Last layers that learned task specific features

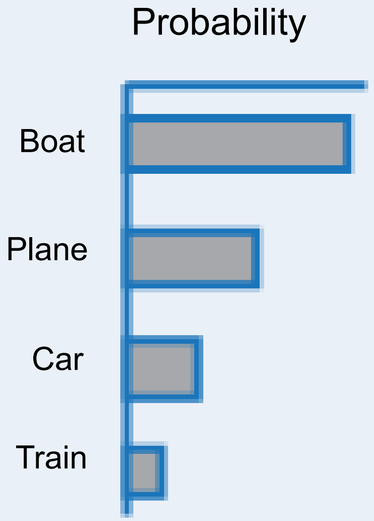
1 million images
1000s classes

## Replace final

Fewer classes
Learn faster

100s images
10s classes

## Deploy results




## lict and assess :work accuracy

Test images

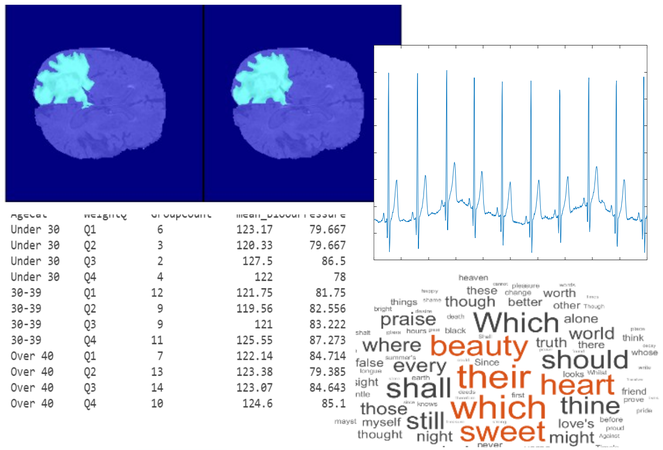


Trained Network

# *Let's go to MATLAB!*

# Improving and Understanding Network Accuracy

# Why is my neural network giving me “incorrect” results?

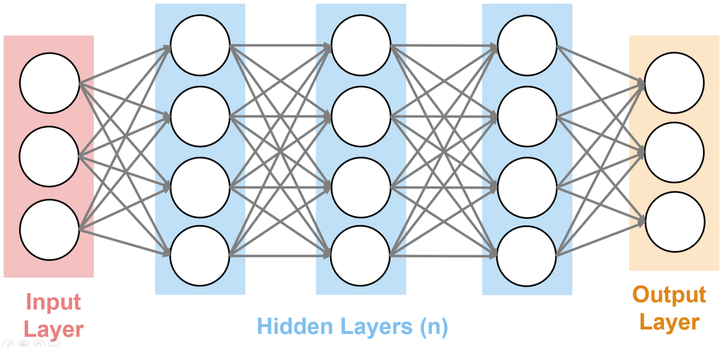


| Agecat | Weight | # Outpatient | Mean_Blood Pressure |
|---|---|---|---|
| Under 30 | Q1 | 6 | 123.17 | 79.667 |
| Under 30 | Q2 | 3 | 120.33 | 79.667 |
| Under 30 | Q3 | 2 | 127.5 | 86.5 |
| Under 30 | Q4 | 4 | 122 | 78 |
| 30-39 | Q1 | 12 | 121.75 | 81.75 |
| 30-39 | Q2 | 9 | 119.56 | 82.556 |
| 30-39 | Q3 | 9 | 121 | 83.222 |
| 30-39 | Q4 | 11 | 125.55 | 87.273 |
| Over 40 | Q1 | 7 | 122.14 | 84.714 |
| Over 40 | Q2 | 13 | 123.38 | 79.385 |
| Over 40 | Q3 | 14 | 123.07 | 84.643 |
| Over 40 | Q4 | 10 | 124.6 | 85.1 |




## Data

Is there enough data?
Is the data what is needed for the application?
What about the quality of the data?
Is data augmentation in use?
Have you checked results at each stage of training?




## Neural Network Architecture

What layers are being used and why?
Are the appropriate layers being used for the application?
Is there normalization and/or regularization?
What about the quality of the data?
Have you checked results at each stage of training?

etclearn-rate
batch-size
weights bias
regularization

## Parameters and Their Settings

What parameters are present?
Were the batch size, learn rate, weights, and other values set?

Source : http://theorangeduck.com/page/neural-network-not-working

# Hyperparameter Tuning in Deep Learning

“The challenge with hyperparameters is that there are no magic number that works everywhere. The best numbers depend on each task and each dataset.”

**Training Cycle**

Epoch:

Iteration:

Iterations per epoch:

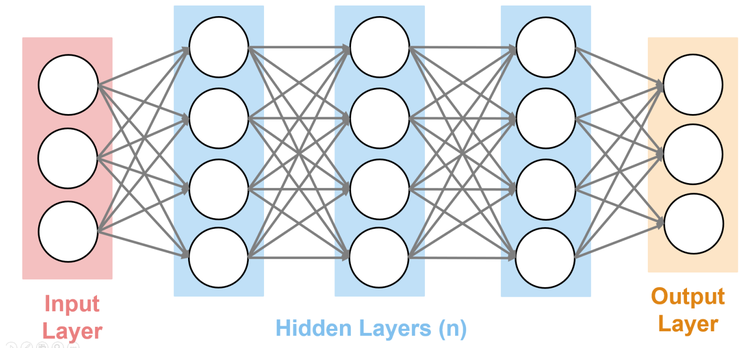
Maximum iterations:

**Other Information**

Hardware resource:

Learning rate schedule:

Learning rate:



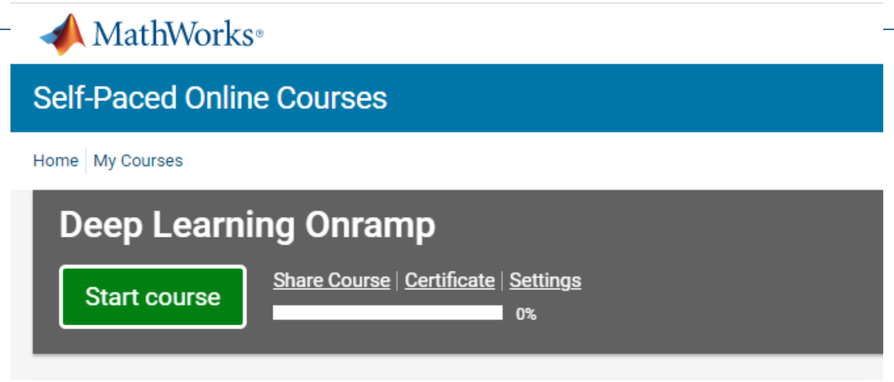

Source : https://towardsdatascience.com/hyperparameters-in-deep-learning-927f7b2084dd

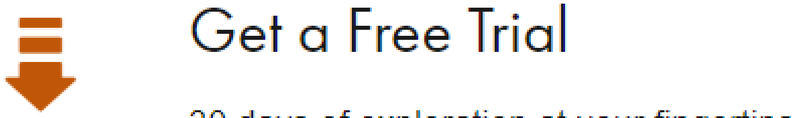
# Summary: Computer Vision with MATLAB

- **Comprehensive documentation and examples** make getting started easy
- **Ready-to-use algorithms** available for common tasks with ability to customize them
- **Interactive live scripts and apps** allow evaluating and selecting algorithms and their settings quickly
- **Deep learning ramp-up** in MATLAB is easy

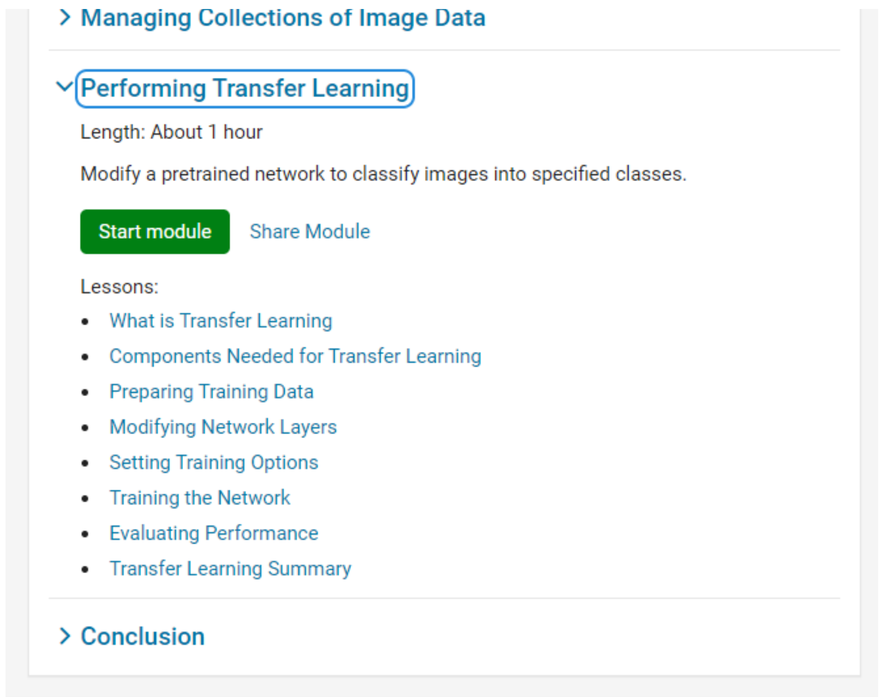
# Next Steps

- Computer Vision Toolbox
- Deep Learning Onramp
  - 2 hr online tutorial
- Product Trial
- Deep Learning Toolbox




Download now



# Thank You

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