# MATLAB EXPO 2019

Pixels to Features to Models

**Object Detection and Image Segmentation** 

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### Agenda

- Introduction
  - Applications
  - Computer vision tasks
  - Choosing an approach
- Examples
  - 'Traditional' image processing
  - Deep learning
- Getting started



### **Computer Vision Tasks**



#### Automated Driving

Manufacturing





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#### Medical Imaging



#### **Computer Vision Tasks**



Where are the cars?

Where can I drive?

How many parts?

Are they damaged?



Is this a tumour?

How large is it?





#### **Computer Vision Tasks**



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### Two approaches to computer vision



#### 'Traditional' Image Processing



### Two approaches to computer vision



#### Machine Learning



### **Machine Learning v Deep Learning**



#### Machine Learning learns tasks using manually extracted features

**Deep Learning** learns both features and tasks directly from data





#### **Examples**

Two examples to demonstrate these approaches:

- 1. Traditional image processing for segmentation
- 2. Deep learning for object detection



#### **Example 1: Part Inspection**

Challenge:

- Find all of the items in the image
- Classify them hook, nut or washer

#### Data

- Small number of images, unlabelled
- Taken from fixed position, controlled lighting





### Two approaches to computer vision



'Traditional' Image Processing



### Load Image

#### Import image

I = imread('nutsAndBolts.png');

#### Convert to grayscale

Igray = rgb2gray(I); imshow(Igray)





#### **Segmentation**

- Next we want to segment the image
- Two routes:
  - Writing MATLAB code
  - Apps (and then generating code)





BW = imbinarize(Igray, 'adaptive', 'Sensitivity', 0.52,... 'ForegroundPolarity', 'dark');





BW = imbinarize(Igray, 'adaptive', 'Sensitivity', 0.52,... 'ForegroundPolarity', 'dark');

BW = imcomplement(BW);





BW = imbinarize(Igray, 'adaptive', 'Sensitivity', 0.52,... 'ForegroundPolarity', 'dark');

BW = imcomplement(BW);

radius = 9; decomposition = 0; se = strel('disk', radius, decomposition); BW = imclose(BW, se);



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BW = imbinarize(Igray, 'adaptive', 'Sensitivity', 0.52,... 'ForegroundPolarity', 'dark');

BW = imcomplement(BW);

radius = 9; decomposition = 0; se = strel('disk', radius, decomposition); BW = imclose(BW, se);

se2 = strel('disk', 3, 0); BW = imopen(BW, se2);





BW = imbinarize(Igray, 'adaptive', 'Sensitivity', 0.52,... 'ForegroundPolarity', 'dark');

BW = imcomplement(BW);

radius = 9; decomposition = 0; se = strel('disk', radius, decomposition); BW = imclose(BW, se);

se2 = strel('disk', 3, 0); BW = imopen(BW, se2);

BW = imfill(BW, 'holes');



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### **Classification**

Going to classify the parts based on their area

[regions, numPixelRegions] = bwlabel(BW);

imshow(label2rgb(regions))





### **Classification**

#### Going to classify the parts based on their area

sprintf('%04d',stats(k).Area),'Hor','Center','Vert','middle')

```
[regions, numPixelRegions] = bwlabel(BW);
imshow(label2rgb(regions))
stats = regionprops(regions, 'all');
for k=1:length(stats)
    text(stats(k).Centroid(1),stats(k).Centroid(2),...
```

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end



#### **Classification**

histogram(Area, 1000:100:4000)
xlabel('Area (pixels)')
ylabel('Number of Parts')



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```
minArea = [1300 1900 3200];
maxArea = [1800 2200 4100];
partNames = {'nut', 'ring', 'screw'};
partColors = {'magenta'; 'green'; 'cyan'};
Iparts = I;
for k=1:3
    idx = Area > minArea(k) & Area < maxArea(k);
    Iparts = insertObjectAnnotation(Iparts,...
        'rectangle', vertcat(stats(idx).BoundingBox),...
        partNames{k}, 'Color', partColors{k});
end
```

imshow(Iparts)



#### **Example 1: Part Inspection**

- 'Basic' image processing can solve this problem well
- Single feature (area) can be used to classify
- Fast, and east to interpret

MATLAB provides:

- High-level functions to chain together
- Apps to get started/learn functions
- Simple route to deployment





### **Adding more features**

- More complex classifications will require more features
- More features leads to a more complicated model
  - Machine Learning
- Other ways to extract features
  - e.g Visual bag of words



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#### **Example 2: Deep Learning**

Challenge:

Build an object detector to find cars

Data:

- Many images, each containing one or more cars
- Large variations in angle, lighting etc
- Labelled with bounding boxes (hopefully)





### Two approaches to computer vision



#### Machine Learning



# **Deep Learning Workflow**

#### **Prepare Data**



Data access and preprocessing



Ground truth labeling



Model exchange

across frameworks

Hardware-accelerated training



Enterprise Deployment





#### **Prepare Data**

- Dedicated MATLAB apps for automating and simplifying the labelling process
- Split data in training and test sets
- Datastore objects to manage collections of data

```
imdsTrain = imageDatastore(trainingDataTbl{:,'imageFilename'});
bldsTrain = boxLabelDatastore(trainingDataTbl(:,'vehicle'));
trainingData = combine(imdsTrain,bldsTrain);
```



#### **Train Model**

- Using YOLOv2 model architecture
  - Start-of-the-art object detector
  - Capable of running on real time video
  - Documented example
- Two stages:
  - Feature extraction layers use a pretrained research network
  - Detector layers build ourselves
- Use Deep Network Designer to build the network graphically

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#### **Train Model**

#### Next define training options

```
options = trainingOptions('sgdm', ...
'MiniBatchSize', 16, ....
'InitialLearnRate',1e-3, ...
'MaxEpochs',20);
```

#### And train the model

detector = trainYOLOv2ObjectDetector(trainingData, lgraph, options);



### Testing

#### Evaluate model performance on validation images

```
I = imread(testDataTbl.imageFilename{1});
```

```
% Run the detector.
[bboxes,scores] = detect(detector,I);
```

```
% Annotate detections in the image.
I = insertObjectAnnotation(I, 'rectangle', bboxes, scores);
imshow(I)
```







### **Testing**

Evaluate model performance across training and test sets:

- Recall what proportion of the cars do I detect?
- Precision of the detections I make, what proportion are correct

Look out for:

- Underfitting performance poor on training and test data
- Overfitting good performance on training data, poor on test data

Iterate to improve the model





#### **Example 2: Deep Learning**

- Deep learning a good fit because of variation in the data
- Learns both a feature representation and a detection model

MATLAB provides:

- Graphical tools for labelling and network design
- Pretrained models to build on top of



### **Deploying Algorithms**





## Musashi Seimitsu Industry Co.,Ltd.

**Detect Abnormalities in Automotive Parts** 



Automated visual inspection of 1.3 million bevel gear per month

#### MATLAB use in project:

- Preprocessing of captured images
- Image labelling and annotation
- Deep learning based analysis
  - Various transfer learning methods
     (Combinations of CNN models, Classifiers)
  - Estimation of defect area using Class Activation Map
  - Abnormality/defect classification
- Deployment to NVIDIA Jetson using GPU Coder





### **Summary**

- Segmentation and object detection form the basis of many common computer vision tasks
- Select image processing or machine learning approaches based on specifics of your problem
- MATLAB supports full workflow for both routes:
  - Easy data management
  - Apps to get started
  - Robust implementations of mathematical methods
  - Visualisations tools
  - Deployment to enterprise and embedded systems
- Wide range of examples to adapt to your projects



### What Next?

- Deep Learning Onramp
- Other talks
  - AI techniques for Signal, Time-series and Text Data
  - Automated Driving System Design
- Demo stands
  - Deep Learning and Reinforcement Learning
  - Driverless Science Museum exhibition stand
- Doc examples
- Application Engineer support