

Lecture 2: Data Labelling, Augmentation and Visualization

Wei Qi Yan

Auckland University of Technology

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What Is Deep Learning?

Deep Learning

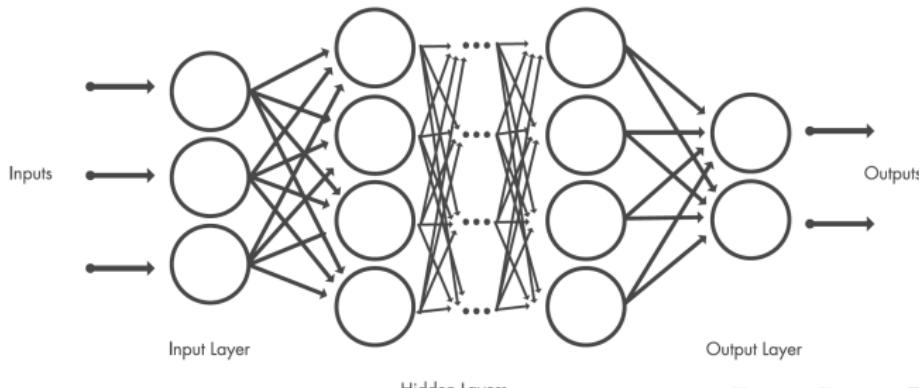
- Deep learning is a branch of machine learning that trains computers to do what comes naturally to humans: Learn from experience.
- Machine learning algorithms use computational methods to “learn” information directly from data without relying on a predetermined equation as a model.
- Deep learning is especially suitable for computer vision, which is important for solving problems such as face recognition, motion detection, and many advanced driver assistance technologies.

Web: Mark Hudson Beale Martin T. Hagan Howard B. Demuth. MATLAB R2019b Deep Learning Toolbox User's Guide.

Deep Learning

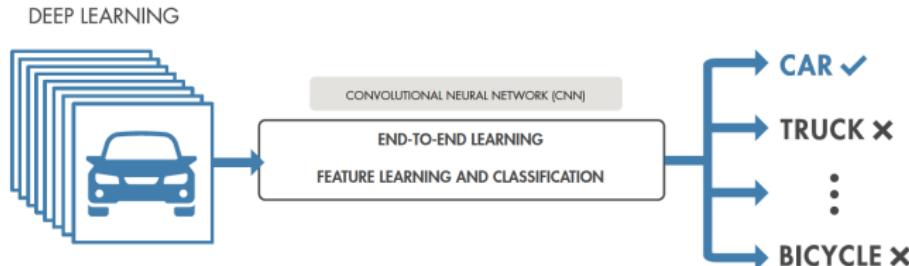
Deep Neural Networks(DNNs)

- A deep neural network combines multiple nonlinear processing layers, using simple element operating in parallel and inspired by biological nervous systems.
- A deep neural network consists of an input layer, several hidden layers, and an output layer.
- The layers are interconnected via nodes, or neurons, with each hidden layer using the output of previous layer as its input.



Deep Learning

Machine Learning(ML) vs Deep Learning(DL)



Machine Learning	Deep Learning
+ Good results with small data sets	- Requires very large data sets
+ Quick to train a model	- Computationally intensive
- Need to try different features and classifiers to achieve best results	+ Learns features and classifiers automatically
- Accuracy plateaus	+ Accuracy is unlimited

Questions?



Data Labelling and Augmentation

MATLAB Online

MATLAB Online

Search MathWorks.com

Overview | Specifications and Limitations | System Requirements | What's New

MATLAB Online

Use MATLAB through your web browser

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Use MATLAB with no downloads or installations.

Collaborate with others through online sharing and publishing

Store, manage, and access your files anywhere.

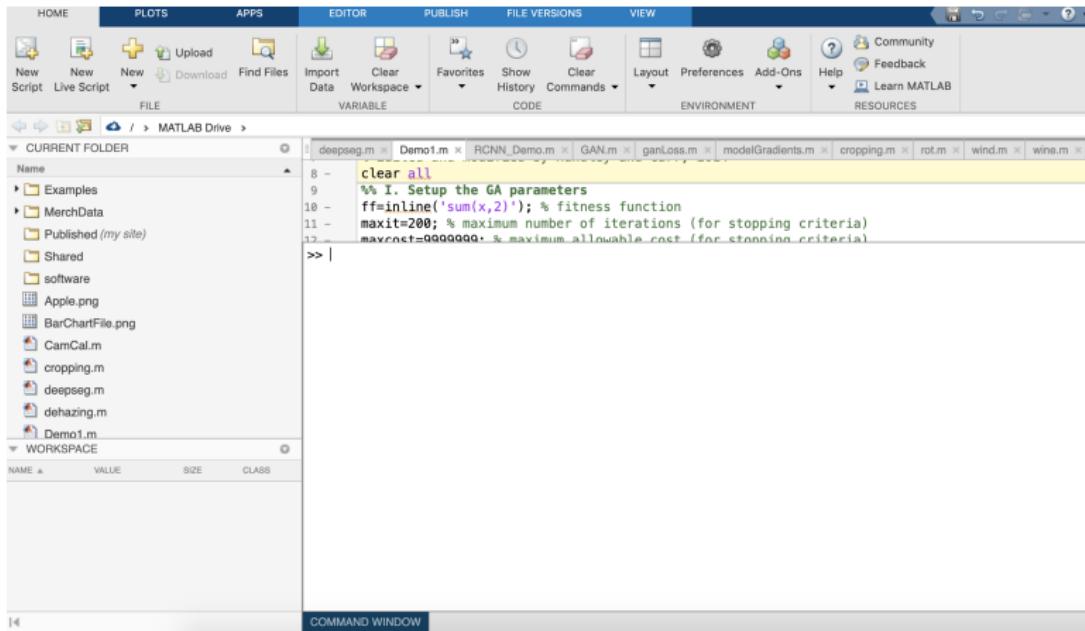
Web: <https://www.mathworks.com/products/matlab-online.html>

- MATLAB Online provides access to MATLAB from any standard web browsers.
- It is ideal for teaching and learning as well as convenient and lightweight access.
- With MATLAB Online, scripts, live scripts, and other MATLAB files are shared directly.
- MATLAB Online automatically updates to the latest version.
- There is 5GB store to access and manage files from anywhere.
- Use MATLAB Drive Connector to sync files, eliminating the need for manual upload or download.

Web: <https://www.mathworks.com/products/matlab-online.html>

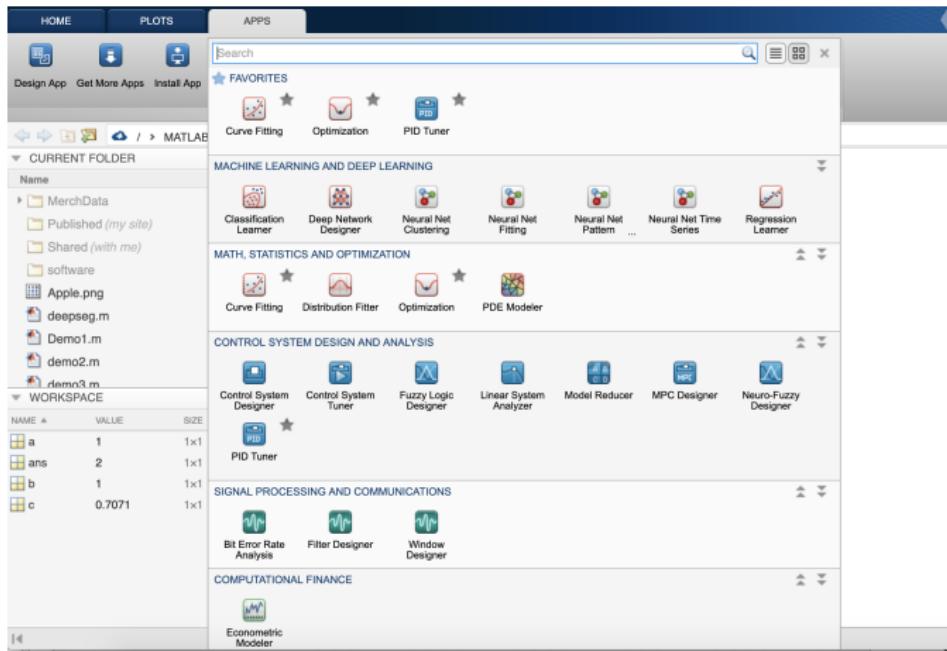
Data Labelling and Augmentation

MATLAB Interface



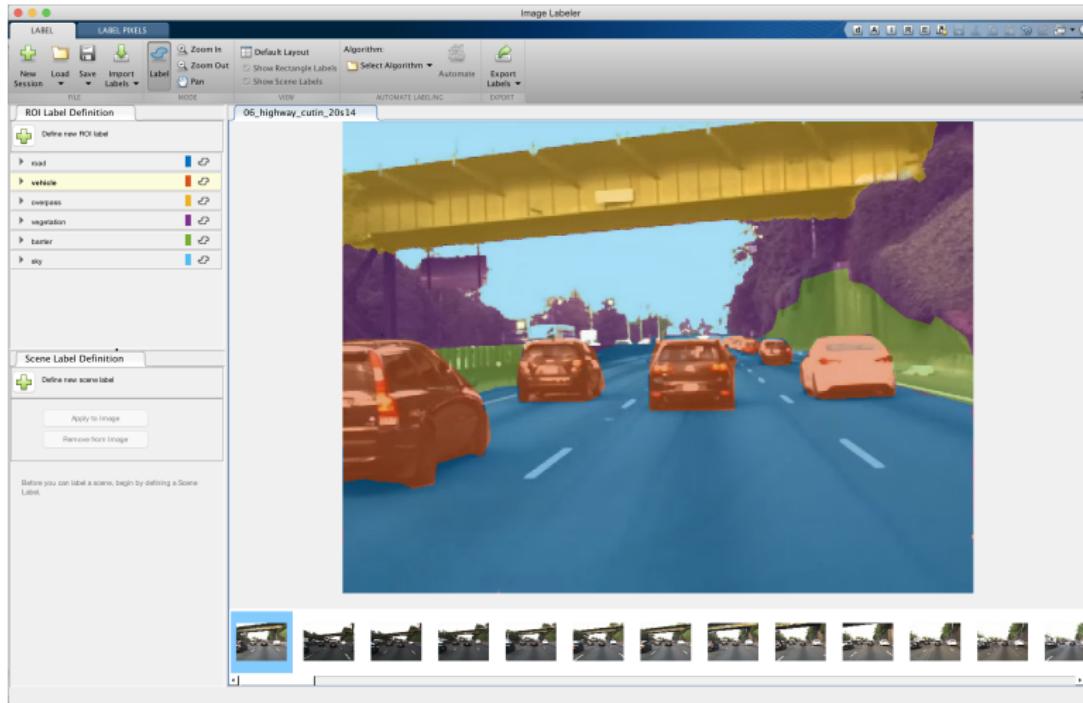
Web: <https://www.mathworks.com/products/matlab-online.html>

Getting Started



Data Labelling and Augmentation

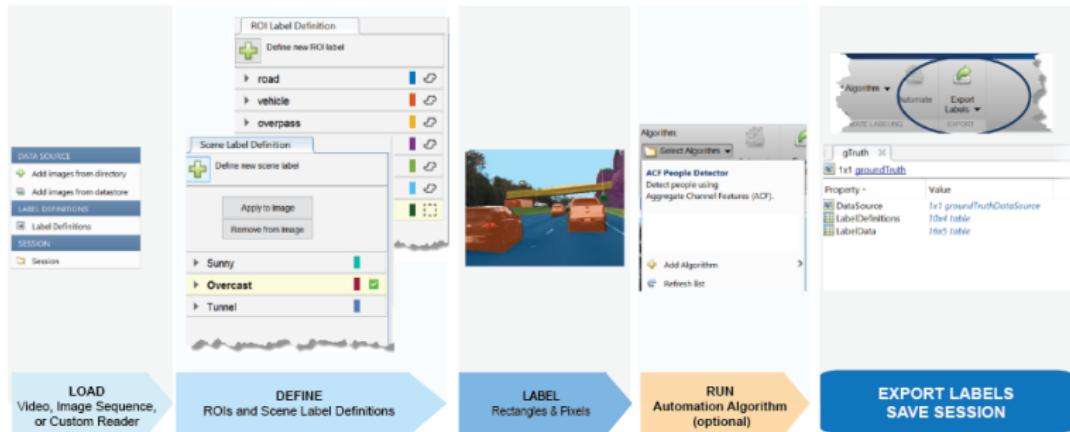
MATLAB Image Labeler



Web: <https://au.mathworks.com/help/vision/ref/imagelabeler-app.html>

Data Labelling and Augmentation

MATLAB Labeling Workflow



Web: <https://au.mathworks.com/help/vision/ref/imagelabeler-app.html>

MATLAB Datastore for Deep Learning

- Because deep learning often requires large amounts of data, datastores are an important part of deep learning.
- Datastores can be used directly as input for network training, validation, and inference.
- The data read from these datastores must be preprocessed into a format required by a deep learning network.
- Deep learning frequently requires the data to be preprocessed and augmented before the data is in an appropriate form to input to a network.

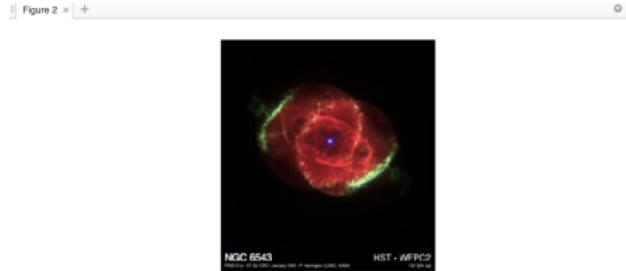
MATLAB Image Augmentation

- Resize images using rescaling and cropping.
- Multiply the height and width of images by using a scaling factor.
- Extract a subregion of the image and preserve the spatial extent of each pixel.
- Augment images with a random combination of resizing, rotation, reflection, shearing, and translation transformations.
- Combine datastores with image data.
- Associate image and label data.
- Transform volumetric data in image datastore.

Web: <https://au.mathworks.com/help/deeplearning/ug/preprocess-images-for-deep-learning.html>

Data Labelling and Augmentation

MATLAB Image Augmentation: Image Resizing



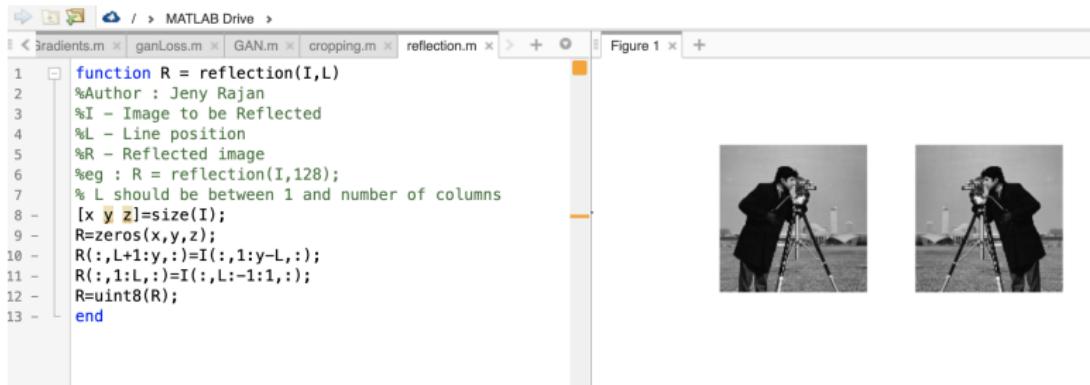
```
>>I = imread('ngc6543a.jpg');
>>J = imresize(I, 0.5);% resize half
>> figure, imshow(I), figure, imshow(J)
```

```
COMMAND WINDOW
>> I = imread('ngc6543a.jpg');
>> J = imresize(I, 0.5);
>> figure, imshow(I), figure, imshow(J)
>> figure, imshow(I), figure, imshow(J)
>>
```

Web: <https://au.mathworks.com/help/images/ref/imresize.html>

Data Labelling and Augmentation

MATLAB Image Augmentation: Image Reflecting



The screenshot shows the MATLAB IDE interface. On the left, the code editor displays the `reflection.m` script:

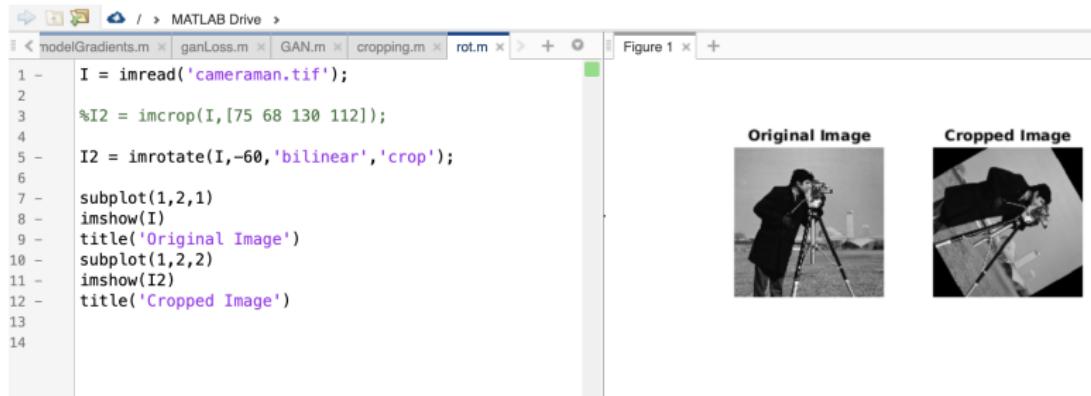
```
1 function R = reflection(I,L)
2 %Author : Jeny Rajan
3 %I - Image to be Reflected
4 %L - Line position
5 %R - Reflected image
6 %eg : R = reflection(I,128);
7 % L should be between 1 and number of columns
8 [x y z]=size(I);
9 R=zeros(x,y,z);
10 R(:,L+1:y,:)=I(:,1:y-L,:);
11 R(:,1:L,:)=I(:,L:-1:1,:);
12 R=uint8(R);
13 end
```

On the right, there are two images labeled "Figure 1". The left image shows a person standing behind a tripod, facing away from the camera. The right image shows the same person, but their reflection is visible in the tripod's mirror, creating a symmetrical effect.

Web: <https://au.mathworks.com/matlabcentral/fileexchange/13914-image-reflection>

Data Labelling and Augmentation

MATLAB Image Augmentation: Image Rotating



The screenshot shows a MATLAB IDE window. The current file is 'rot.m'. The code reads a 'cameraman.tif' image, crops it to [75 68 130 112], rotates it by -60 degrees using bilinear interpolation, and then displays both the original and rotated images.

```
I = imread('cameraman.tif');
I2 = imcrop(I,[75 68 130 112]);
I2 = imrotate(I,-60,'bilinear','crop');
subplot(1,2,1)
imshow(I)
title('Original Image')
subplot(1,2,2)
imshow(I2)
title('Cropped Image')
```

Original Image



Cropped Image



Web: <https://au.mathworks.com/help/images/ref/imrotate.html>

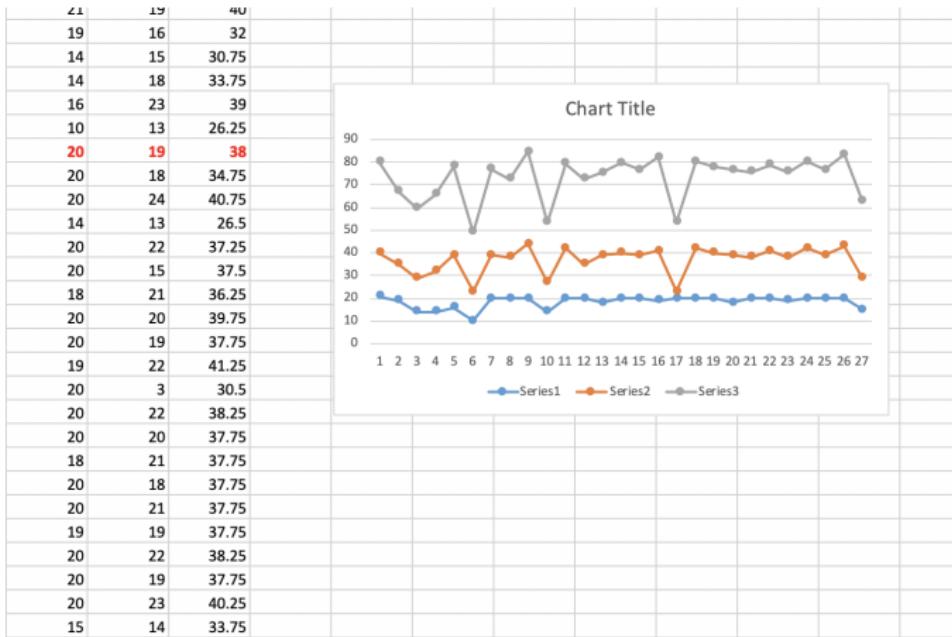
Data Labelling and Augmentation

Questions?

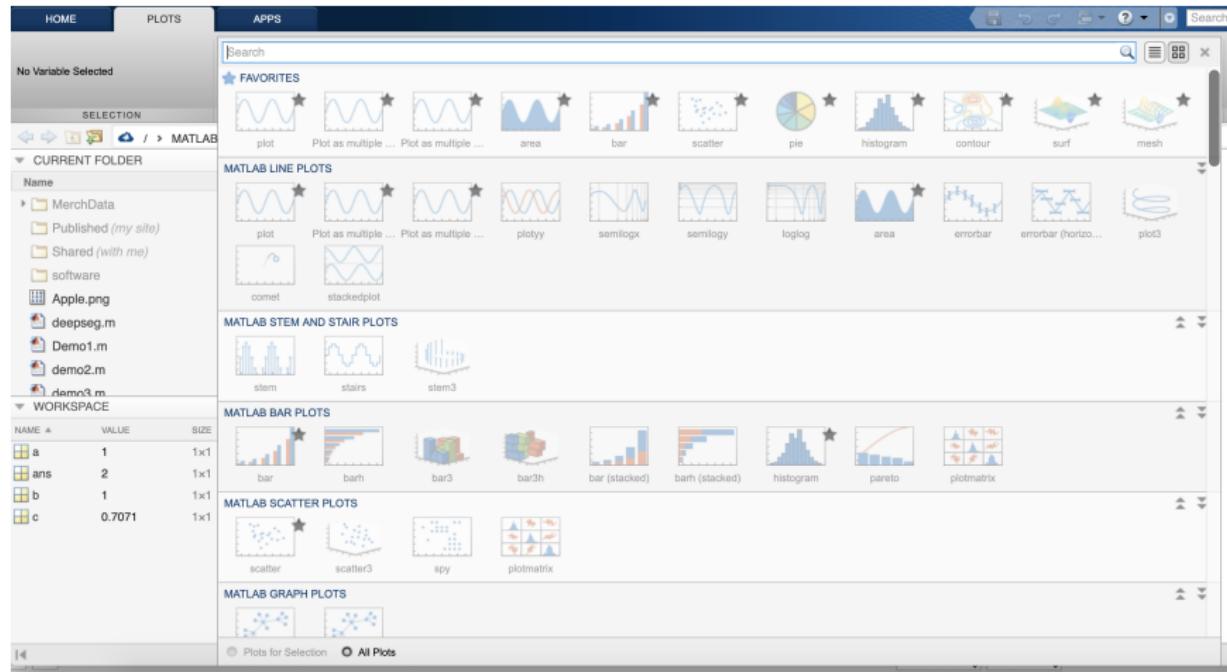


Basic Knowledge of Data Visualization

Microsoft Office: Excel



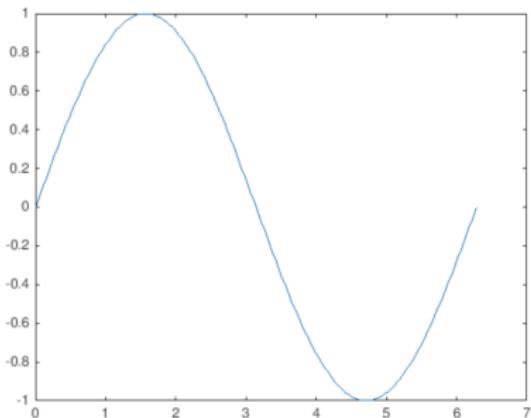
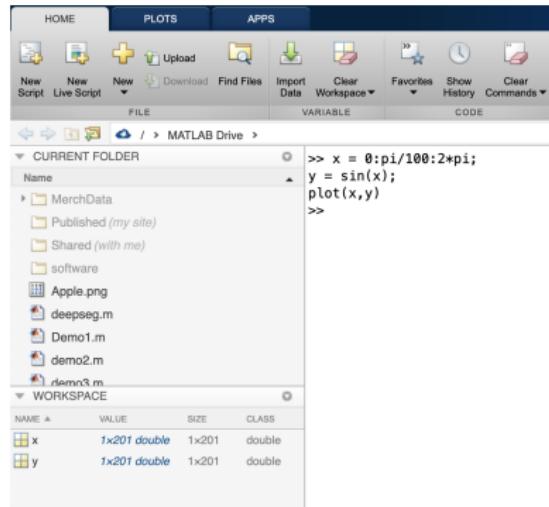
MATLAB: Data Visualization



Web: <https://www.mathworks.com/products/matlab-online.html>

MATLAB: Data Visualization

Basics: 2D Plot

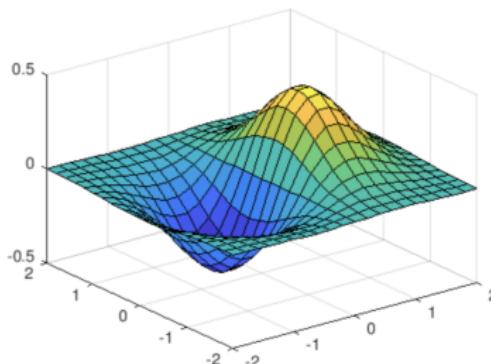
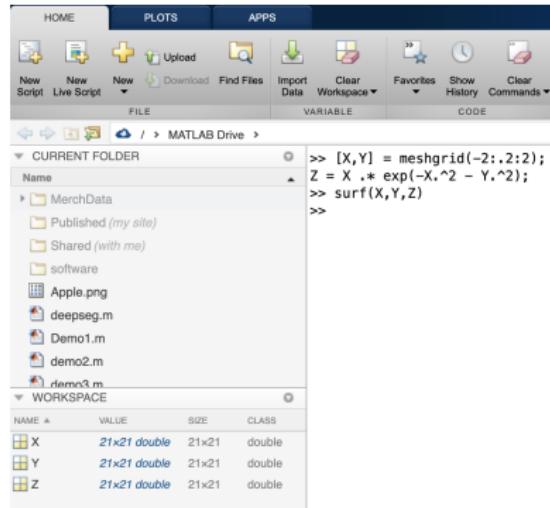


Web:

https://au.mathworks.com/help/matlab/examples.html?category=graphics&s_tid=CRUX_lftnav_examples_plots

MATLAB: Data Visualization

Basics: 3D Plot

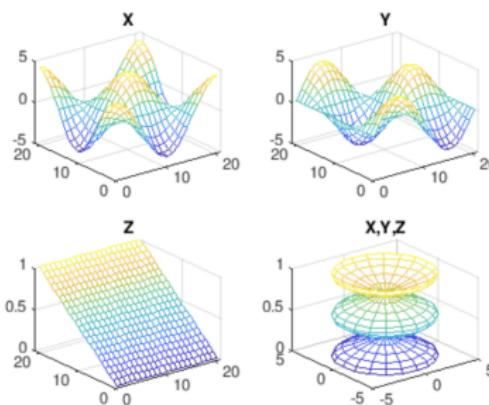
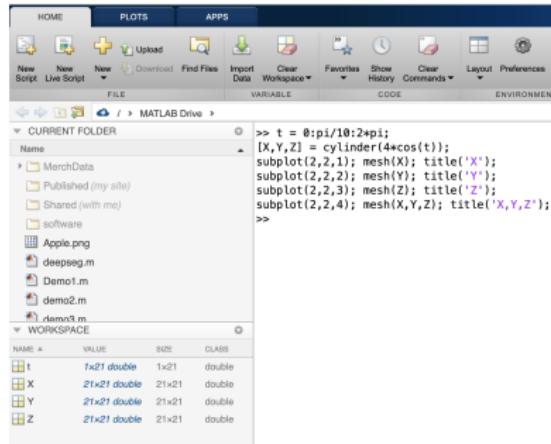


Web:

https://au.mathworks.com/help/matlab/examples.html?category=graphics&s_tid=CRUX_lftnav_exemplar_plots

MATLAB: Data Visualization

Basics: Subplot



Web:

https://au.mathworks.com/help/matlab/examples.html?category=graphics&s_tid=CRUX_lftnav_examples

Matplotlib: Data Visualization



Version 3.1.3

[Installation](#) [Documentation](#) [Examples](#) [Tutorials](#) [Contributing](#)

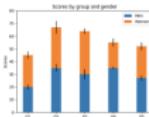
[home](#) | [contents](#) »

Gallery

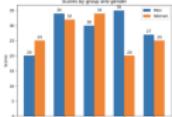
This gallery contains examples of the many things you can do with Matplotlib. Click on any image to see the full image and source code.

For longer tutorials, see our [tutorials page](#). You can also find [external resources](#) and a [FAQ](#) in our [user guide](#).

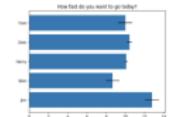
Lines, bars and markers



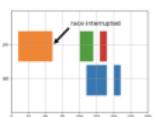
Stacked Bar Graph



Grouped bar chart with labels



Horizontal bar chart



Broken Barh

<https://matplotlib.org/gallery/mplot3d/wire3d.html#sphx-glr-gallery-mplot3d-wire3d-py>

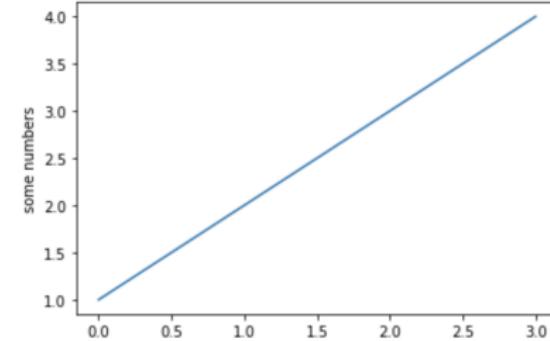
CoLaboratory: Data Visualization

Untitled0.ipynb 

File Edit View Insert Runtime Tools Help All changes saved

+ Code + Text

import matplotlib.pyplot as plt
plt.plot([1, 2, 3, 4])
plt.ylabel('some numbers')
plt.show()



some numbers

<https://matplotlib.org/gallery/mplot3d/wire3d.html#sphx-glr-gallery-mplot3d-wire3d-py>

Matplotlib: Data Visualization

```
[1] import matplotlib.pyplot as plt
import numpy as np

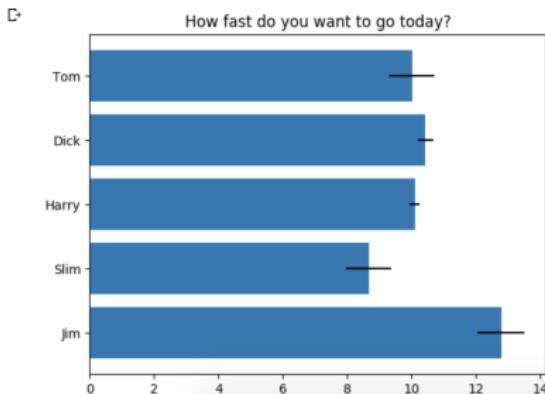
# Fixing random state for reproducibility
np.random.seed(19680801)

plt.rcdefaults()
fig, ax = plt.subplots()

# Example data
people = ('Tom', 'Dick', 'Harry', 'Slim', 'Jim')
y_pos = np.arange(len(people))
performance = 3 + 10 * np.random.rand(len(people))
error = np.random.rand(len(people))

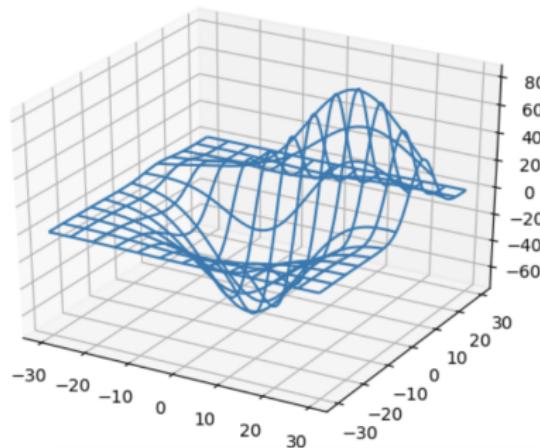
ax.barh(y_pos, performance, xerr=error, align='center')
ax.set_yticks(y_pos)
ax.set_yticklabels(people)
ax.invert_yaxis() # labels read top-to-bottom
ax.set_xlabel('Performance')
ax.set_title('How fast do you want to go today?')

plt.show()
```



Matplotlib: Data Visualization

```
▶ from mpl_toolkits.mplot3d import axes3d  
import matplotlib.pyplot as plt  
  
fig = plt.figure()  
ax = fig.add_subplot(111, projection='3d')  
  
# Grab some test data.  
X, Y, Z = axes3d.get_test_data(0.05)  
  
# Plot a basic wireframe.  
ax.plot_wireframe(X, Y, Z, rstride=10, cstride=10)  
  
plt.show()
```



<https://matplotlib.org/gallery/mplot3d/wire3d.html#sphx-glr-gallery-mplot3d-wire3d-py>



Matplotlib: Data Visualization

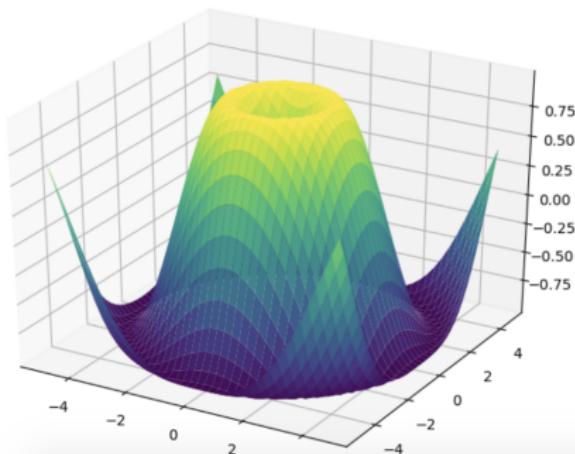
```
import matplotlib.pyplot as plt
from matplotlib import cm
from mpl_toolkits.mplot3d import Axes3D

X = np.arange(-5, 5, 0.25)
Y = np.arange(-5, 5, 0.25)
X, Y = np.meshgrid(X, Y)
R = np.sqrt(X**2 + Y**2)
Z = np.sin(R)

fig = plt.figure()
ax = Axes3D(fig)
ax.plot_surface(X, Y, Z, rstride=1, cstride=1, cmap=cm.viridis)

plt.show()
```

▶



<https://matplotlib.org/gallery/mplot3d/wire3d.html#sphx-glr-gallery-mplot3d-wire3d-py>

TensorFlow Graph

- TensorFlow graph: Creating the computational graph.
- The nodes (Operations) and edges (Tensors): Indicating how individual operations are composed together.
- TensorFlow collections: Storing metadata.

TensorBoard

- TensorBoard is to visualize a computation graph.
- TensorBoard needs to save the computation graph to a summary file (`tf.summary.FileWriter`).
- TensorBoard renders the structure of a graph visually in a browser.
- TensorBoard is launched by using:
c:> tensorboard - -logdir=".. \tensorflow\graph"

TensorBoard: Data Visualization

YOLO-Based Flame Detection

```
import tensorflow as tf
import numpy as np
import BuildGraph as md
import DataProvider as dp
import time
import os
import shutil

dataPath = 'pydata'
savePath = 'model'

sess = tf.Session()
img, ism, box, lr, pre_train, pre_loss, pre_acc, train, loss, acc,
sess.run(tf.global_variables_initializer())

trainData = dp.trainData(dataPath)

if os.path.exists(savePath):
    shutil.rmtree(savePath)
os.mkdir(savePath)

sm = tf.summary.merge_all()
ckptSaver = tf.train.Saver()
ckptSaver.export_meta_graph(savePath + 'model.meta')
smWriter = tf.summary.FileWriter(savePath, sess.graph)
smWriter.add_graph(sess.graph, 0)
```

```
===== RESTART: C:\wyan\research\deep learning\SDQ_SRC\DFL\train.py =====
1 : loss = 1269.335693 , acc = 0.300000 , time = 7.203/24778.756
2 : loss = 873.849243 , acc = 0.700000 , time = 13.844/23811.254
3 : loss = 401.209290 , acc = 0.500000 , time = 20.422/23417.107
4 : loss = 248.261627 , acc = 0.600000 , time = 26.953/23179.691
5 : loss = 1315.869873 , acc = 0.200000 , time = 33.391/22972.752
6 : loss = 400.726990 , acc = 0.300000 , time = 39.719/22772.087
7 : loss = 809.821289 , acc = 0.400000 , time = 46.094/22651.789
8 : loss = 163.144196 , acc = 0.500000 , time = 52.391/22527.972
9 : loss = 305.354431 , acc = 0.400000 , time = 58.594/22395.836
10 : loss = 247.942047 , acc = 0.700000 , time = 64.859/22311.628
11 : loss = 209.520798 , acc = 0.300000 , time = 71.219/22272.049
12 : loss = 97.307373 , acc = 0.300000 , time = 77.641/22256.982
13 : loss = 192.668365 , acc = 0.300000 , time = 84.500/22360.003
14 : loss = 47.122841 , acc = 0.700000 , time = 91.156/22398.396
15 : loss = 88.590630 , acc = 0.600000 , time = 97.813/22431.670
16 : loss = 126.988731 , acc = 0.500000 , time = 104.500/22467.504
17 : loss = 29.922207 , acc = 0.700000 , time = 111.125/22486.474
18 : loss = 20.898193 , acc = 0.900000 , time = 117.484/22452.573
19 : loss = 191.536560 , acc = 0.300000 , time = 123.688/22393.951
20 : loss = 69.449844 , acc = 0.400000 , time = 129.797/22325.066
21 : loss = 81.624252 , acc = 0.600000 , time = 135.984/22275.539
22 : loss = 104.009354 , acc = 0.400000 , time = 142.469/22276.936
23 : loss = 65.351791 , acc = 0.700000 , time = 149.563/22369.351
24 : loss = 36.031826 , acc = 0.500000 , time = 157.031/22507.816
```

TensorBoard

SCALARS

IMAGES

AUDIO

GRAPHS

DISTRIBUTIONS

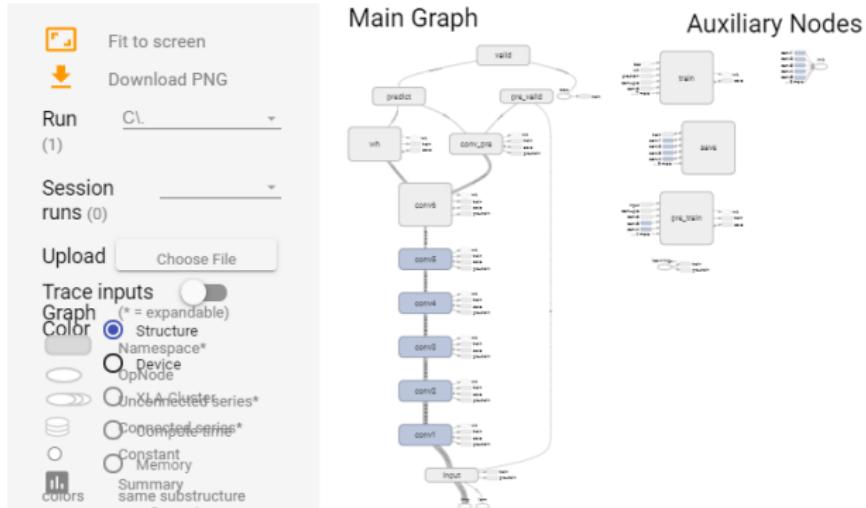
HISTOGRAMS

EMBEDDINGS

TEXT

TensorBoard: Data Visualization

YOLO-Based Flame Detection



TensorBoard

SCALARS

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HISTOGRAMS

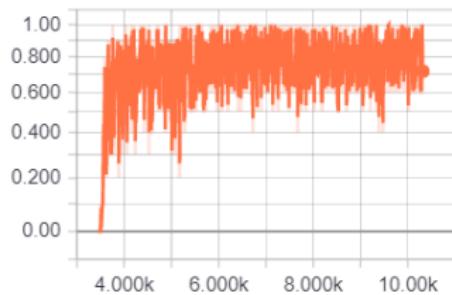
EMBEDDINGS

TEXT

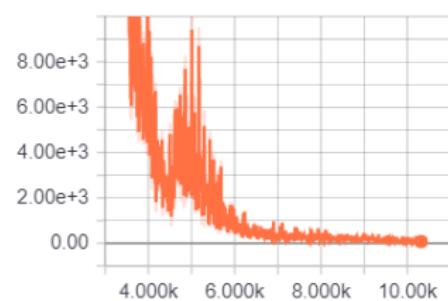
TensorBoard: Data Visualization

YOLO-Based Flame Detection

acc



loss



TensorBoard

SCALARS

IMAGES

AUDIO

GRAPHS

DISTRIBUTIONS

HISTOGRAMS

EMBEDDINGS

TEXT

Website: <http://localhost:6006/#graphs>

Basic Knowledge of Data Visualization

Questions?



How to Use the MATLAB Toolbox

MATLAB uses four graphical tools for training neural networks to solve problems in function fitting, pattern recognition, clustering, and time series. There are four ways to use the MATLAB Toolbox:

- Through the four graphical user interfaces (GUIs).
- Through basic command-line operations.
- Through customization.
- Through any of the functions contained in the toolbox.

Implementation of Machine Learning

MATLAB Toolboxes

- Function fitting (>> nftool)
- Pattern recognition (>>nprtool)
- Clustering (>> nctool)
- Time series analysis (>>ntstool)

Steps of Using the MATLAB Toolbox

- ① Collect data;
- ② Create a network;
- ③ Configure the network;
- ④ Initialize the weights and biases;
- ⑤ Train the network;
- ⑥ Validate the network;
- ⑦ Use the network.

Implementation of Machine Learning

e.g., Fitting a Function

- ① Load dataset, e.g., $[inputs; targets] = house_dataset;$
- ② Create a network, e.g.,
 $hiddenLayerSize = 10$
 $net = \text{fitnet}(hiddenLayerSize);$
- ③ Set up the division of data, e.g.,
 $net.divideParam.trainRatio = 70/100;$
 $net.divideParam.valRatio = 15/100;$
 $net.divideParam.testRatio = 15/100;$
- ④ Train the network, e.g., $[net; tr] = train(net; inputs; targets);$
- ⑤ Test the network, e.g.,
 $outputs = net(inputs);$
 $errors = gsubtract(outputs, targets);$
 $performance = perform(net, targets, outputs)$
- ⑥ View the network, e.g., $view(net).$

Implementation of Machine Learning

e.g., Pattern Classification

- ① Load dataset, e.g.,

inputs = cancerInputs;
targets = cancerTargets;

- ② Create a network, e.g.,

hiddenLayerSize = 10

net = patternnet(hiddenLayerSize);

- ③ Set up the division of data, e.g.,

net.divideParam.trainRatio = 70/100;

net.divideParam.valRatio = 15/100;

net.divideParam.testRatio = 15/100;

- ④ Train the network, e.g., $[net; tr] = train(net; inputs; targets);$

- ⑤ Test the network, e.g.,

outputs = net(inputs);

errors = gsubtract(outputs, targets);

performance = perform(net, targets, outputs)

- ⑥ View the network, e.g., $view(net).$

Implementation of Machine Learning

e.g., Pattern Classification

Neural Network

Algorithms

Data Division: Random (dividerand)
Training: Scaled Conjugate Gradient (trainscg)
Performance: Cross-Entropy (crossentropy)
Calculations: MEX

Progress

Epoch:	0	46 iterations	1000
Time:		0:00:00	
Performance:	0.114	0.00297	0.00
Gradient:	0.0756	0.00131	1.00e-06
Validation Checks:	0	6	6

Plots

Performance	(plotperform)
Training State	(plottrainstate)
Error Histogram	(ploterrhist)
Confusion	(plotconfusion)
Receiver Operating Characteristic	(plotroc)

Navigation icons: back, forward, search, etc.

Implementation of Machine Learning

e.g., Pattern Classification

Training Confusion Matrix			
Output Class	Target Class		
	1	2	
1	303 62.0%	4 0.8%	98.7% 1.3%
2	9 1.8%	173 35.4%	95.1% 4.9%
	97.1% 2.9%	97.7% 2.3%	97.3% 2.7%

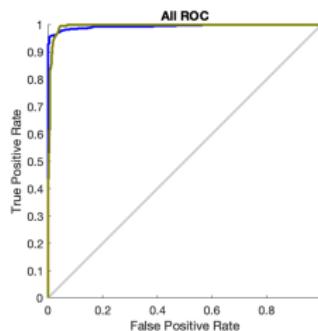
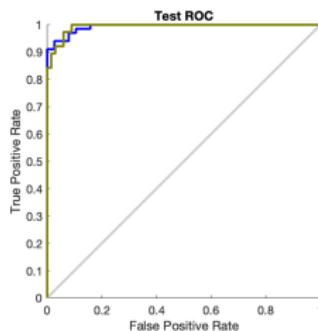
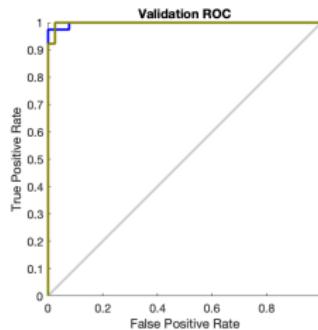
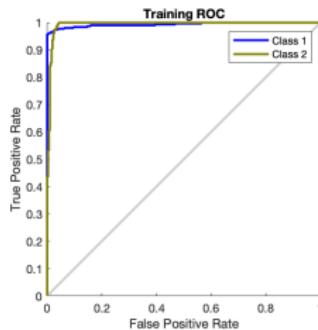
Validation Confusion Matrix			
Output Class	Target Class		
	1	2	
1	78 74.3%	2 1.9%	97.5% 2.5%
2	1 1.0%	24 22.9%	96.0% 4.0%
	98.7% 1.3%	92.3% 7.7%	97.1% 2.9%

Test Confusion Matrix			
Output Class	Target Class		
	1	2	
1	65 61.9%	4 3.8%	94.2% 5.8%
2	2 1.9%	34 32.4%	94.4% 5.6%
	97.0% 3.0%	89.5% 10.5%	94.3% 5.7%

All Confusion Matrix			
Output Class	Target Class		
	1	2	
1	446 63.8%	10 1.4%	97.8% 2.2%
2	12 1.7%	231 33.0%	95.1% 4.9%
	97.4% 2.6%	95.9% 4.1%	96.9% 3.1%

Implementation of Machine Learning

e.g., Pattern Classification



Implementation of Machine Learning

e.g., Clustering

- ① Load dataset, e.g.,
inputs = simpleclusterInputs;
- ② Create a Self-Organizing Map (SoM), e.g.,
dimension1 = 10;
dimension2 = 10;
net = selforgmap([dimension1dimension2]);
- ③ Train the network, e.g., *[net, tr] = train(net, inputs);*
- ④ Test the network, e.g.,
outputs = net(inputs);
- ⑤ View the network, e.g., *view(net).*

Implementation of Machine Learning

e.g., Time-Series Prediction and Modeling

- ① Load dataset, e.g.,
inputSeries = phInputs; targetSeries = phTargets;
- ② Create a nonlinear autoregressive network with external input,
e.g., *inputDelays = 1 : 4; feedbackDelays = 1 : 4;*
hiddenLayerSize = 10; net =
narxnet(*inputDelays, feedbackDelays, hiddenLayerSize*);
- ③ Set up division of data for training, validating, testing, e.g.,
net.divideParam.trainRatio = 70/100;
net.divideParam.valRatio = 15/100;
net.divideParam.testRatio = 15/100;
- ④ Train the network, e.g.,
[net, tr] = train(net, inputs, targets, inputStates, layerStates);
- ⑤ Test the network, e.g.,
outputs = net(inputs, inputStates, layerStates);
errors = gsubtract(targets, outputs);
performance = perform(net, targets, outputs);
- ⑥ ...

e.g., Time-Series Prediction and Modeling

- ...
- View the network, e.g., `view(net)`
- Plot the performance training record to check for potential overfitting, e.g., `figure, plotperform(tr);`
- Close the loop on the NARX network, e.g.,
`netc = closeloop(net);`
- Remove a delay from the network, e.g.,
`nets = removedelay(net);`

Implementation of Machine Learning

Questions?



Learning Objectives

- To justify the differences between machine learning and deep learning.
- To critically compare and evaluate the major tools of data labelling and augmentation.
- To critically compare and evaluate the major algorithms of machine learning and pattern recognition.