

# JETSON DEVELOPER KITS

for Engineers, Makers, and Learners

JETSON NANO 2GB



5W | 10W  
0.5 TFLOPS (FP16)  
\$59

JETSON NANO



5W | 10W  
0.5 TFLOPS (FP16)  
\$99

JETSON XAVIER NX



10W | 15W  
6 TFLOPS (FP16) | 21 TOPS (INT8)  
\$399

JETSON AGX XAVIER



10 | 15W | 30W  
11 TFLOPS (FP16) | 32 TOPS (INT8)  
\$699

Multiple developer kits - Same software

Full specs at [developer.nvidia.com/jetson](http://developer.nvidia.com/jetson)

# Lesson Plan

## Artificial Intelligence

- Introduction to Recent Developments in Artificial Intelligence
- Machine Learning, Deep Learning, and Reinforcement Learning
- Statistics and Machine Learning Tools
- RL Agents: Markov Decision Processes
- Q-Learning and Deep Q-Network (DQN) Agents
- Actor-Critic Approach and Policy Gradient
- Supervised Artificial Neural Networks
- Unsupervised Artificial Neural Networks
- Workflow Application in Deep Learning
- Object Detection
- Image Classification
- Transfer Learning
- Pose Estimation
- Case Studies and its Walkthrough

# Modules Overview

## Introduction to Recent Developments in Artificial Intelligence

- 1.1: Teaching Kit Modules Overview
- 1.2: AI Introduction
- 1.3: AI Hardware
- 1.4: Introduction to Jetson Nano
- 1.5: Edge, AloT, Big Data

### Lab: Mandelbrot CPU vs. GPU

### Lab: Parallel Programming with CUDA

### Lab: Image and Video Processing

### Lab: Prediction and Classification using Machine Learning

```
Basics of GPU programming
We'll see how to write and read data to and from the GPU's memory, and how to write some very simple elementwise GPU functions in CUDA C.

PyCUDA's gpuarray class
PyCUDA's gpuarray class has important role within GPU programming in Python. This has all of the features from NumPy—multidimensional vector/matrix/tensor shape structuring, array-style point-wise computations (for example, +, -, ./, and *).

Transferring data to and from the GPU with gpuarray
GPU has its own memory apart from the host computer's memory, which is known as device memory. In CUDA C, data is transferred back and forth between the CPU to the GPU (with cudaMemcpyDeviceToHost()).
Fortunately, PyCUDA covers all of the overhead of memory allocation, deallocation, and data transfers with the gpuarray class.

[ 1]: # Create the host data
host_data = np.array([1,2,3,4,5], dtype=np.float32)
# Copy host data to GPU and create a new GPU array
device_data = gpuarray.to_gpu(host_data)

# Perform pointwise multiplication on the GPU
device_data *= 2

# Retrieve the GPU data into a new with the gpuarray.get function
host_data_x2 = device_data.get()
print(host_data_x2)

Example: Doubling the value of elements in an array
Here, we will take an array and double the element of it on the GPU.

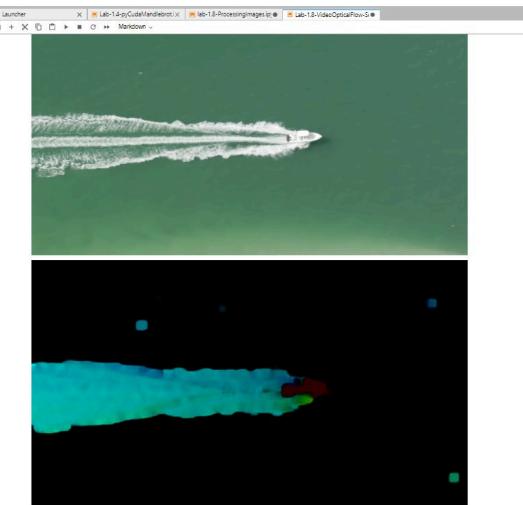
Step1: Getting started
[ 1]: # Declare the array as follows:
np.random.seed(1729)
a = np.random.randn(4,4).astype(np.float32)

Step 2: Transferring Data to the GPU
The next step in most programs is to transfer data onto the device. In PyCuda, you will mostly transfer data from numpy arrays on the host.

[ 1]: # First, we need to allocate memory on the device
a_gpu = gpuarray.AllocEmpty(4,4)

[ 1]: # we need to transfer the data to the GPU
a_gpu.memcpy_host_ipynb()

Step 3: Executing a Kernel
For this tutorial, we will write code each entry in a_gpu. To this end, we write the corresponding CUDA C code, and feed it into the constructor of a pycuda.compiler.SourceModule
```



```
OpenCV and CUDA
This second code block uses a GPU. Here you will note that each frame must be uploaded to the GPU device before applying the OpenCV CUDA enabled transformation.

[ 1]: # Now we start OpenCV
import cv2
import numpy as np
import pycuda.driver as cuda
import pycuda.autoinit
display = cv2.display()
```

```
"mandel_ker"
def gpu_mandelbrot(width, height, real_low, real_high, imag_low, imag_high, max_iters, upper_bound):

    # we set up our complex lattice as such
    real_vals = np.linspace(real_low, real_high, width, dtype=np.complex64) # 1
    img_vals = np.linspace(imag_low, imag_high, height, dtype=np.complex64) # 2
    mandel_lattice = np.meshgrid(real_vals + img_vals.transpose(), dtype=np.complex64) # 3

    # copy complex lattice to the GPU
    mandel_lattice_gpu = gpuarray.to_gpu(mandel_lattice) # 4

    # allocate an empty array on the GPU
    mandel_graph_gpu = gpuarray.empty(shape=mandel_lattice_gpu.shape, dtype=np.float32) # 5

    mandel_ker(mandel_lattice_gpu, mandel_graph_gpu, np.int32(max_iters), np.float32(upper_bound)) # 6

    mandel_graph = mandel_graph_gpu.get() # 7

    return mandel_graph

t1 = time()
mandel = gpu_mandelbrot(512,512,-2,-2,512, 2)
t2 = time()

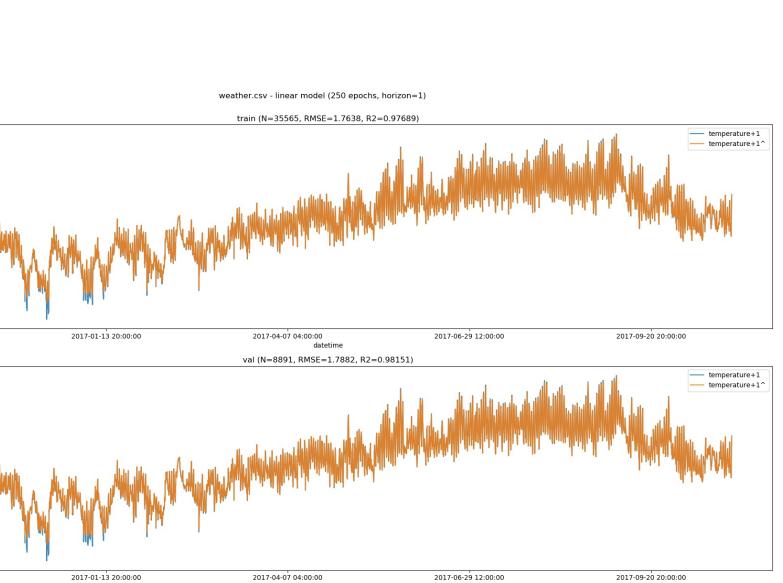
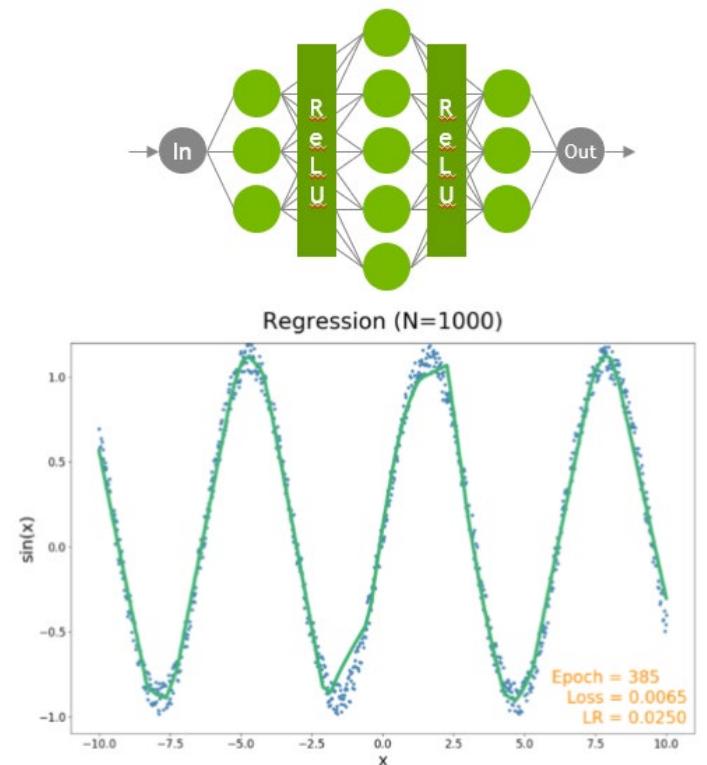
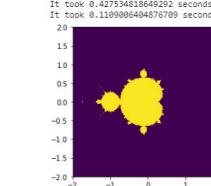
mandel_time = t2 - t1

t1 = time()
fig = plt.figure(1)
plt.imshow(mandel, extent=(-2, 2, -2, 2))
plt.savefig("mandelbrot.png", dpi=fig.dpi)
t2 = time()

dump_time = t2 - t1

print ("It took {} seconds to calculate the Mandelbrot graph.".format(mandel_time))
print ("It took {} seconds to dump the image.".format(dump_time))

#note the significant reduction in execution time
It took 0.427340185449292 seconds to calculate the Mandelbrot graph.
It took 0.1109006464876798 seconds to dump the image.
```



# Teaching Kit Modules Overview

## Introduction to Jetson Nano

- Jetson Nano 2 GB Developers Kit at core of content
- Sparkfun DLI Add on Kit <https://www.sparkfun.com/products/16389>
- Option to use Jetbot Kits <https://www.nvidia.com/en-us/autonomous-machines/embedded-systems/jetbot-ai-robot-kit/>
- Add on kits provides essential accessories such as camera, power cables, SD cards as an all-in-one kit rather than purchasing each item separately
- Most kits supply 32GB SD cards but consider purchasing 64GB or higher SD cards



Sparkfun DLI kit



Waveshare Jetbot kit



Assembled DLI and Jetbot kits

# Teaching Kit Module Overview

Jetson Hardware Differences from first Teaching Kit

Affordable, minimum requirement is Jetson Nano 2GB plus accessories (camera, cables, SD card)

Reduced hardware build and software configuration:

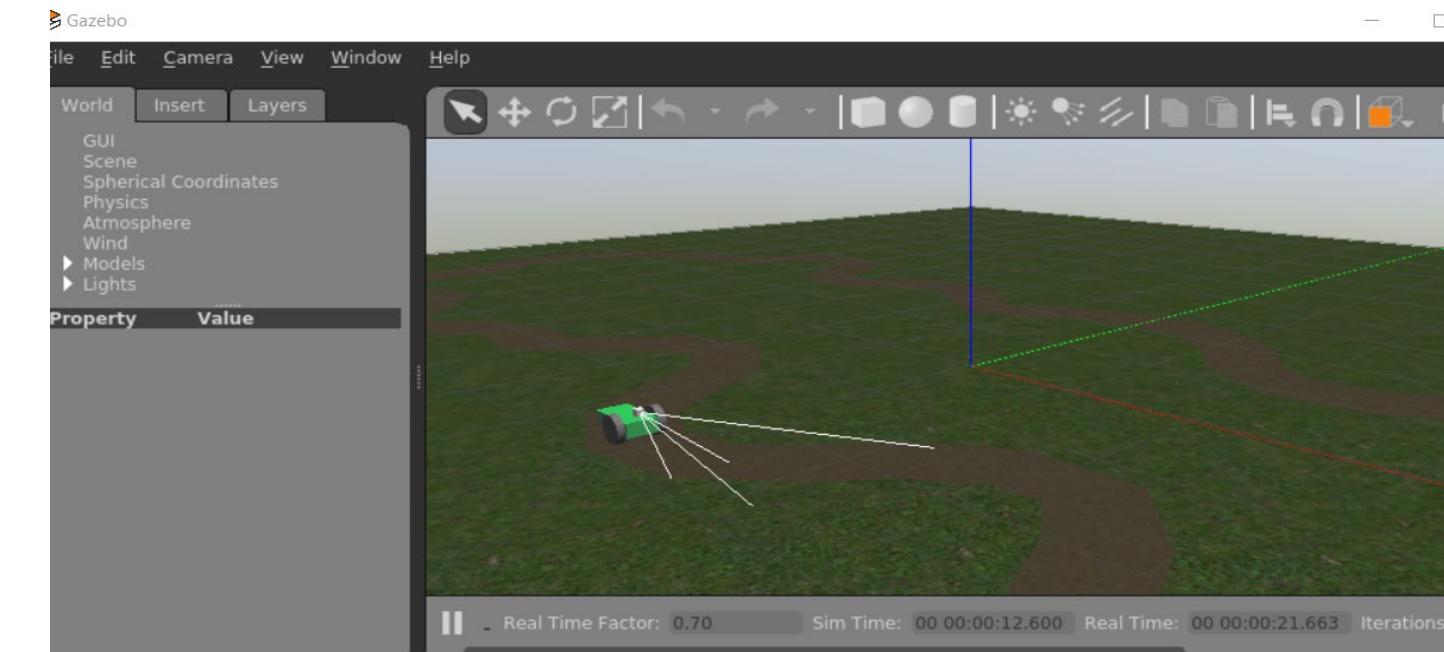
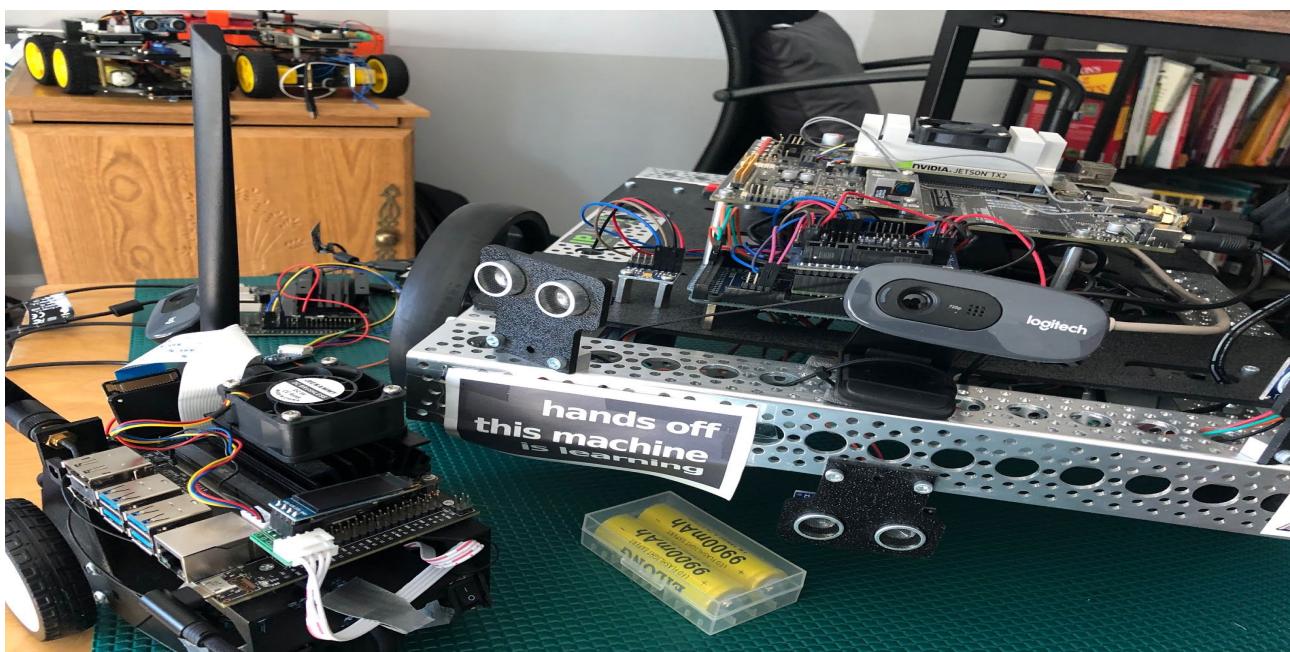
- Less than 30 minutes for minimum Jetson DLI kit

- Less than 2 hours for Jetbot

- Headless connection from host to Jetson

- SD images and NVIDIA prebuilt containers

Option to work with virtual Jetbot



# CUDA

**Kernels:** CUDA kernels are C functions that get executed in parallel on GPU.

**Threads:** Kernels execute as a set parallel threads.

**Blocks:** A group of threads that can execute task in parallel.

**Grids:** CUDA blocks are grouped into grids with each block having same number of threads.

A CUDA kernel is executed by an array of threads.

- All threads run the same code
- Each thread has an ID that it uses to compute memory addresses and make control decisions

*Standard C Code*

```
void saxpy(int n, float a,
           float *x, float *y)
{
    for (int i = 0; i < n; ++i)
        y[i] = a*x[i] + y[i];
}

int N = 1<<20;

// Perform SAXPY on 3M elements
saxpy(N, 2.0, x, y);
```

*C with CUDA extensions*

```
__global__
void saxpy(int n, float a,
           float *x, float *y)
{
    int i = blockIdx.x*blockDim.x + threadIdx.x;
    if (i < n) y[i] = a*x[i] + y[i];
}

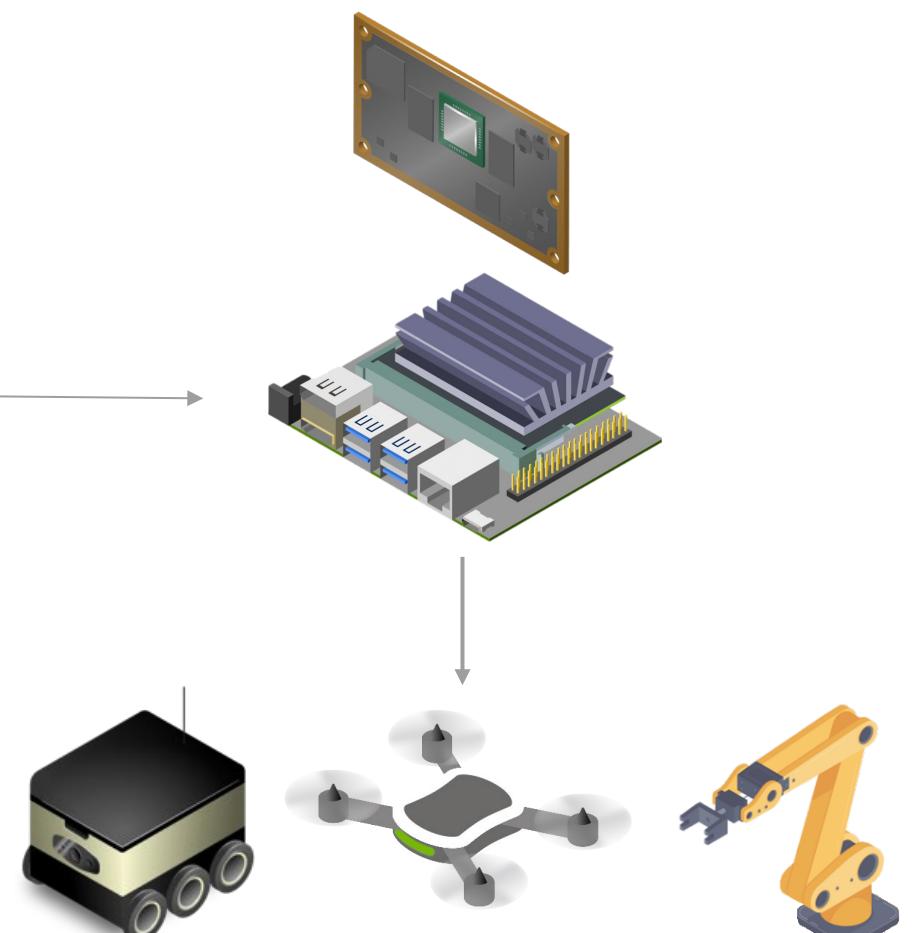
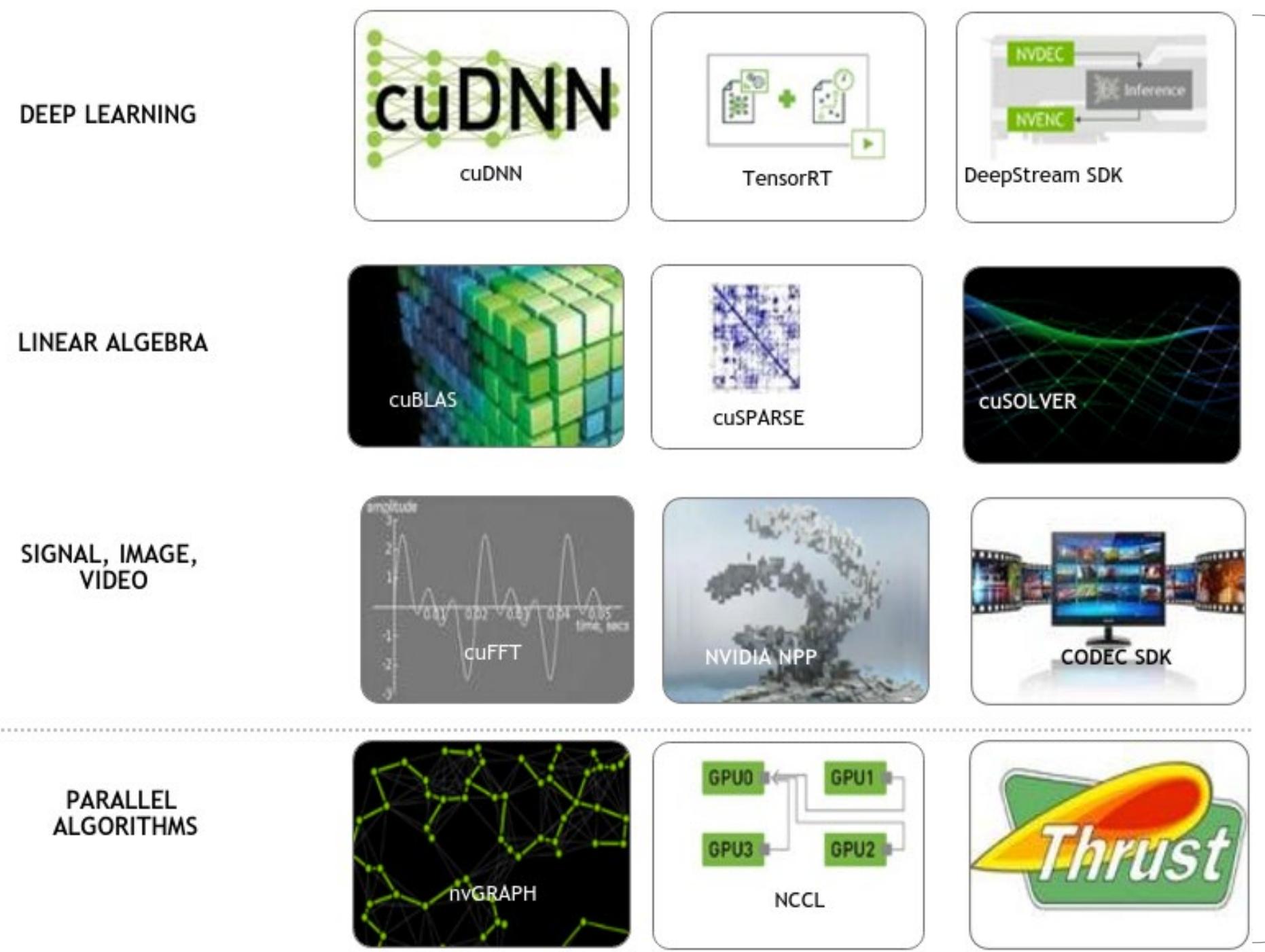
int N = 1<<20;
cudaMemcpy(x, d_x, N, cudaMemcpyHostToDevice);
cudaMemcpy(y, d_y, N, cudaMemcpyHostToDevice);

// Perform SAXPY on 3M elements
saxpy<<<4096,256>>>(N, 2.0, x, y);

cudaMemcpy(d_y, y, N, cudaMemcpyDeviceToHost);
```

# CUDA accelerated libraries

## JetPack SDK



# Code in Action

## Introduction to CUDA and PyCUDA

PyCUDA gives you easy, Pythonic access to Nvidia's CUDA parallel computation API.

- Abstractions make CUDA programming easier
- Full power of CUDA API if needed
- Automatic error checking and cleanup

### Initialization

A few modules have to be loaded to initialize communication to the GPU:

```
[ 1]: # Import PyCUDA and several modules associated with the PyCUDA
!pip install pycuda
import pycuda
import pycuda.driver as cuda
cuda.init()

import pycuda.autoinit
from pycuda.compiler import SourceModule
import pycuda.gpuarray as gpuarray
from pycuda.curand import rand as curand
from pycuda.elementwise import ElementwiseKernel

import numpy as np
import numpy.linalg as la
```

### CUDA device query

A GPU query is a very basic operation that will tell us the specific technical details of our GPU, such as available GPU memory and core count.

```
[ 1]: print('CUDA device query (PyCUDA version) \n')
print('Detected {} CUDA Capable device(s) \n'.format(cuda.Device.count()))
for i in range(cuda.Device.count()):

    gpu_device = cuda.Device(i)
    print('Device {}:\n{}\tcompute capability: {}\n{}\tTotal Memory: {} megabytes'.format(i, gpu_device.name(), gpu_device.compute_capability(), gpu_device.total_memory()//(1024**2)))
```

### Basics of GPU programming

We'll see how to write and read data to and from the GPU's memory, and how to write some very simple elementwise GPU functions in CUDA C.

## Introduction to CUDA Python with Numba

### CONCEPT 1: What is Numba?

Numba is a just-in-time, type-specializing, function compiler for accelerating numerically-focused Python. Let's break down those terms:

- **function compiler:** Numba compiles Python functions, not entire applications, and not parts of functions. Numba does not replace your Python interpreter, but is just another Python module that can turn a function into a (usually) faster function.
- **type-specializing:** Numba speeds up your function by generating a specialized implementation for the specific data types you are using. Python functions are designed to operate on generic data types, which makes them very flexible, but also very slow. In practice, you only will call a function with a small number of argument types, so Numba will generate a fast implementation for each set of types.
- **just-in-time:** Numba translates functions when they are first called. This ensures the compiler knows what argument types you will be using. This also allows Numba to be used interactively in a Jupyter notebook just as easily as a traditional application
- **numerically-focused:** Currently, Numba is focused on numerical data types, like int, float, and complex. There is very limited string processing support, and many string use cases are not going to work well on the GPU. To get best results with Numba, you will likely be using NumPy arrays.

The most common way to use Numba is through its collection of decorators that can be applied to your functions to instruct Numba to compile them. When a call is made to a Numba decorated function it is compiled to machine code "just-in-time" for execution and all or part of your code can subsequently run at native machine code speed!

Numba supports CUDA GPU programming by directly compiling a restricted subset of Python code into CUDA kernels and device functions following the CUDA execution model. Kernels written in Numba appear to have direct access to NumPy arrays. NumPy arrays are transferred between the CPU and the GPU automatically.

[Documentation](#)

#### Terminology

- **host:** the CPU
- **device:** the GPU
- **host memory:** the system main memory
- **device memory:** onboard memory on a GPU card
- **kernels:** a GPU function launched by the host and executed on the device
- **device function:** a GPU function executed on the device which can only be called from the device (i.e. from a kernel or another device function)

Most CUDA programming facilities exposed by Numba map directly to the CUDA C language offered by NVIDIA. Therefore, it is recommended you read the official [CUDA C programming guide](#).

### CONCEPT 2: How does Numba work?

Numba reads the Python bytecode for a decorated function and combines this with information about the types of the input arguments to the function. It analyzes and optimizes your code, and finally uses the LLVM compiler library to generate a machine code version of your function, tailored to your CPU capabilities. This compiled version is then used every time your function is called.

[Numba flowchart](#)

#### Other things of interest:

Numba has quite a few decorators:

- **@jit** - compile the decorated function on-the-fly to produce efficient machine code. [Docs are here](#)
- **@jit -d** is an alias for @jit(nopython=True) as it is so commonly used!
- **@vectorize** - produces NumPy ufunc's (with all the ufunc methods supported). [Docs are here](#)
- **@guvectorize** - produces NumPy generalized ufunc's. [Docs are here](#)
- **@stencil** - declare a function as a kernel for a stencil like operation. [Docs are here](#)
- **@jitclass** - for jit aware classes. [Docs are here](#)
- **@cfunc** - declare a function for use as a native call back (to be called from C/C++ etc). [Docs are here](#)
- **@overload** - register your own implementation of a function for use in nopython mode, e.g. @overload(scipy.special.j0). [Docs are here](#)

## Introduction to Parallel Programming

Traditionally, computers were only focused on computer programs serially. These programs were broken into series instructions that are executed on a single processor sequentially. In contrast with parallel programming, you can break down the computer programs into the sub-programs which will be executed on multiple processor in parallel.

**CUDAS** is a parallel computing platform and programming model developed by NVIDIA for general computing on graphical processing units (GPUs). With CUDA, developers are able to dramatically speed up computing applications by harnessing the power of GPUs.

The [CUDA Toolkit](#) from NVIDIA provides everything you need to develop GPU-accelerated applications. The CUDA Toolkit includes GPU-accelerated libraries, a compiler, development tools and the CUDA runtime.

### Getting started

In this tutorial, we will perform some operations with traditional computing and parallel computing.

```
[ 1]: # import libraries
import numpy as np
from numpy import testing
from numba import cuda, types
```

### Array summation: Traditional computing

In this section, we will create two arrays using NumPy, we will sum them up and check the time.

```
[ 1]: # declare an array
n = 2048
x = np.arange(n, dtype=np.int32)
y = np.ones_like(x)
z = np.zeros_like(x)
```

```
[ 1]: # print out the result
print(x)
print(y)
```

```
[ 1]: # create a function that will sum up the arrays
def add(x, y, z):
    for idx in range(0, len(x)):
        z[idx] = x[idx] + y[idx]
    return z
```

```
[ 1]: # print out time
@time
z = add(x, y, z)
z
```

### Array summation: Parallel computing

Support for NumPy arrays is a key focus of Numba development and is currently undergoing extensive refactoring and improvement. Most capabilities of NumPy arrays are supported by Numba in object mode, and a few features are supported in nopython mode too (with much more to come).

A few noteworthy limitations of arrays at this time:

- Arrays can be passed in to a function in nopython mode, but not returned. Arrays can only be returned in object mode.
- New arrays can only be created in object mode.
- Currently there are no bounds checking for array indexing and slicing, although negative indices will wrap around correctly.
- A small number of NumPy array ufuncs are only supported in object mode, but the vast majority work in nopython mode.
- Array slicing only works in object mode

## Performance best practices

Array operations with GPUs can provide considerable speedups over CPU computing.

**CuPy** is an open-source array library for GPU-accelerated computing with Python. CuPy utilizes CUDA Toolkit libraries including cuBLAS, cuRAND, cuSOLVER, cuSPARSE, cuFFT, cuDNN and NCCL to make full use of the GPU architecture.

- Most operations perform well on a GPU using CuPy. CuPy speeds up some operations more than 100X.
- CuPy's interface is highly compatible with NumPy. CuPy supports various methods, indexing, data types, broadcasting and more. This [comparison table](#) shows a list of NumPy and their corresponding CuPy implementations.

**NumPy** is the fundamental package for scientific computing in Python. It is a Python library that provides a multidimensional array object, various derived objects (such as masked arrays and matrices), and an assortment of routines for fast operations on arrays, including mathematical, logical, shape manipulation, sorting, selecting, I/O, discrete Fourier transforms, basic linear algebra, basic statistical operations, random simulation and much more.

### Benchmarking speed- NumPy vs CuPy

In this tutorial, we will perform some operations using NumPy and CuPy library and we will benchmark the time.

```
[ 1]: # import libraries
import numpy as np
import cupy as cp
import copy
```

Let's start with creating an array using NumPy and CuPy and compare the time.

### Creating an array with NumPy

```
[ 1]: %time
np_var1 = np.random.random((10000, 10000))
np_var2 = np.random.random((10000, 10000))
```

### Creating and array with CuPy

```
[ 1]: %time
cp_var1 = cupy.random.random((10000, 10000))
cp_var2 = cupy.random.random((10000, 10000))
cupy.cuda.Stream.null.synchronize()
```

```
[ 1]: # print the numpy array
cp_var1
```

```
[ 1]: # print the cupy array
cp_var2
```

### Trigonometric function

Let's do some trigonometric operations and compare the time.

```
[ 1]: %timeit bool((np.sin(np_var1)**2 + np.cos(np_var1)**2 == 1).all())
```

```
[ 1]: %timeit bool((cupy.sin(cp_var2)**2 + cupy.cos(cp_var2)**2 == 1).all())
```

# ML Fundamentals

## Learning Objectives

- Define artificial intelligence
- Define machine learning
- Define deep learning
- Define neural network and types of layers
- Explain convolution neural network
- Explain types of artificial neural networks

# Code in Action

- Weather Forecasting
- Solar Power Prediction
- Space Shuttle Classification

## pytorch-timeseries

Time-series forecasting and prediction on tabular data using PyTorch. Supports Jetson Nano, TX1/TX2, AGX Xavier, and Xavier NX.

### Starting the Container

```
$ git clone https://github.com/dusty-nv/pytorch-timeseries
$ cd pytorch-timeseries
$ docker/run.sh
$ cd pytorch-timeseries
```

### Weather Forecasting

In this [hourly weather dataset](#), we are forecasting the future weather of a city based on it's past weather. The following data is provided on 1-hour intervals (over a timespan of 40,000 hours):

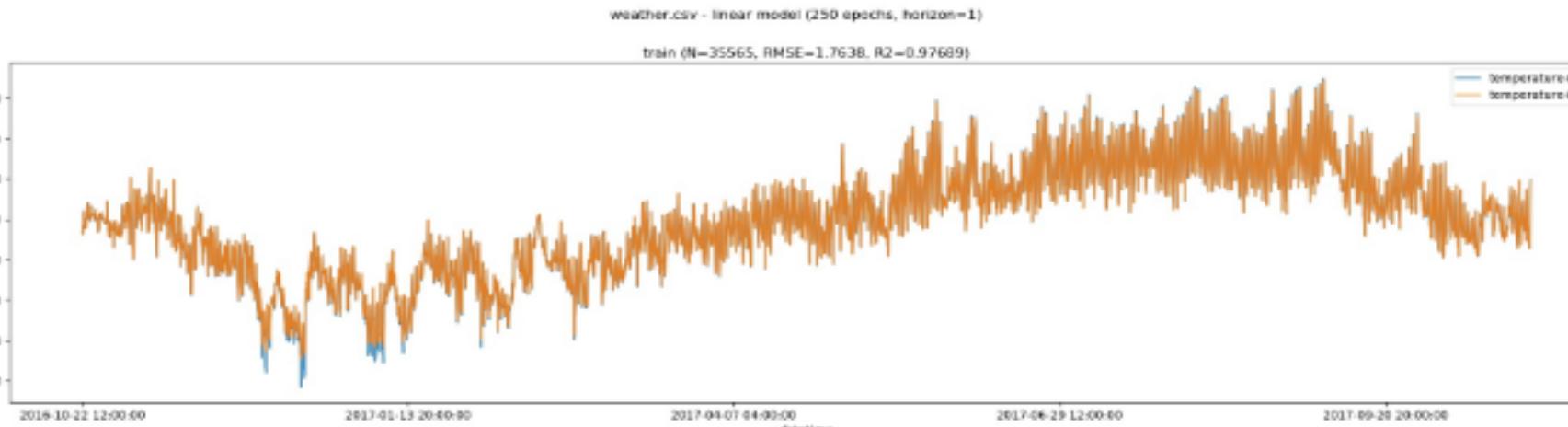
```
temperature
humidity
pressure
wind_direction
wind_speed
```

Let's start by forecasting just the temperature:

```
$ python3 train.py --data data/weather.csv --inputs temperature --outputs temperature --horizon 1

train RMSE: [1.7638184641368702]
train R2:   [0.9768890819461414]

val RMSE:   [1.788160646675811]
val R2:     [0.9815134518452414]
```



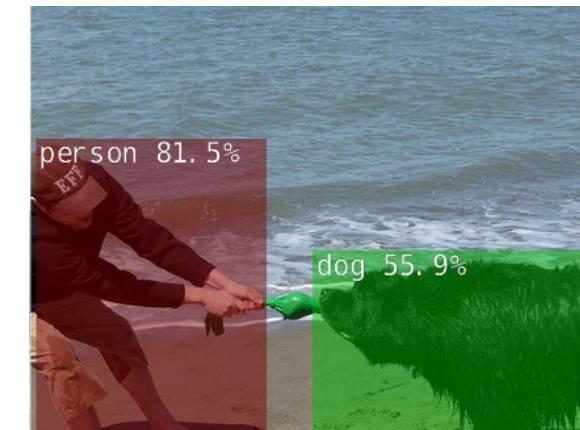
# Teaching Kit Modules Overview

## Vision Deep Neural Networks (DNNs)

- 2.1: Image Classification
  - 2.2: Object Detection
  - 2.3: Semantic Segmentation
  - 2.4: Pose Estimation
- Lab: Hello AI World**



Image Classification



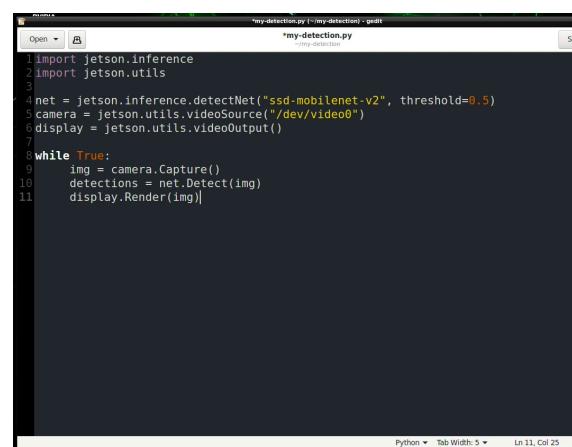
Object Detection



Semantic Segmentation

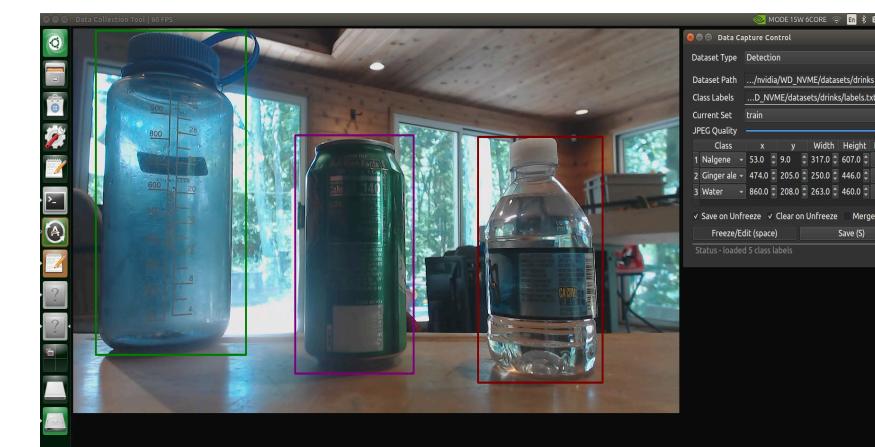


Pose Estimation

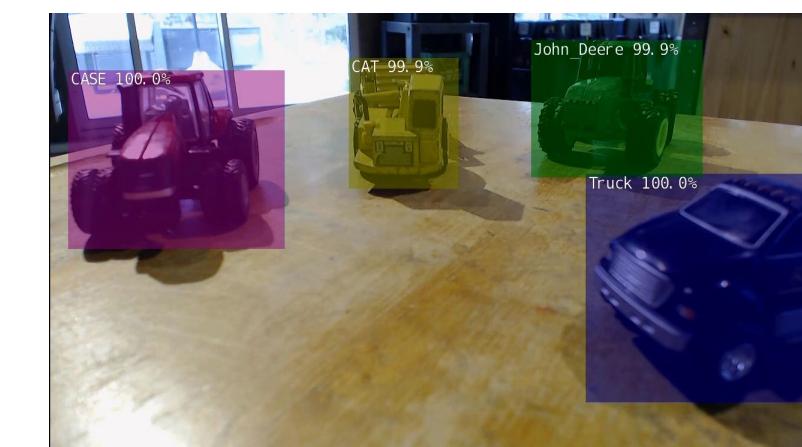


```
my-detection.py
my-detection.py
import jetson.inference
import jetson.utils
net = jetson.inference.detectNet("ssd-mobilenet-v2", threshold=0.5)
camera = jetson.utils.videoSource("/dev/video0")
display = jetson.utils.videoOutput()
while True:
    img = camera.Capture()
    detections = net.Detect(img)
    display.Render(img)
```

Code Your Own Programs  
(Python or C++)



Collect Your Own Datasets



Train Your Own Models

# Image Classification

## Learning Objectives

- Define image classification
- Explain challenges in image classification
- Describe different dataset for image classification
- Describe image classification architectures
- Discuss performance and accuracy benchmarks

### Objective:

Recognize the main subject in the image and assign a label to the image



# Datasets for Image Classification



6 5 0 0 7 5 1 0 3 9  
2 7 8 2 6 3 6 7 4 0  
1 3 8 7 2 6 9 1 7 9  
3 1 8 5 6 0 3 7 2 6  
4 1 3 4 2 3 5 0 2 7  
8 2 6 3 1 6 9 2 3 4

# Architectures

- LeNet
- AlexNet
- VGG-16
- Inception V1
- ResNet-50
- Xception
- MobileNet

# Object detection

## Learning Objectives

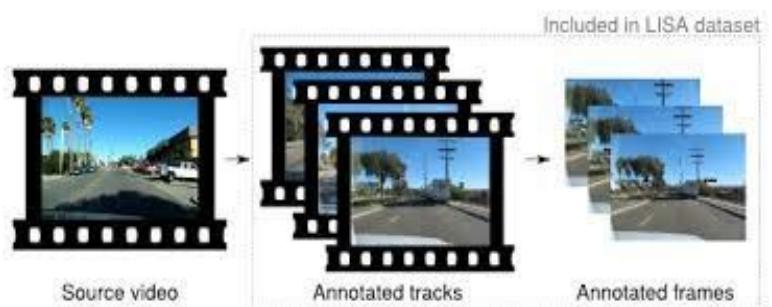
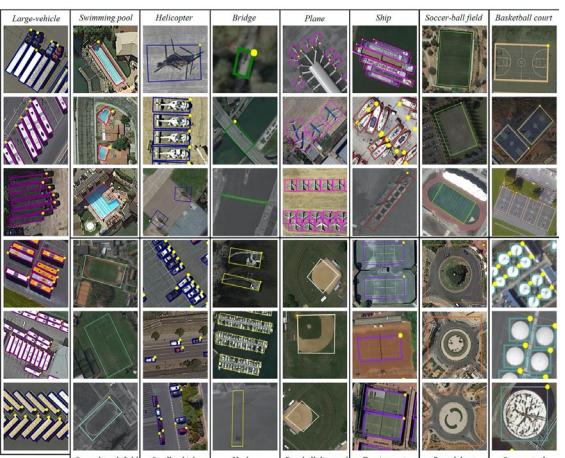
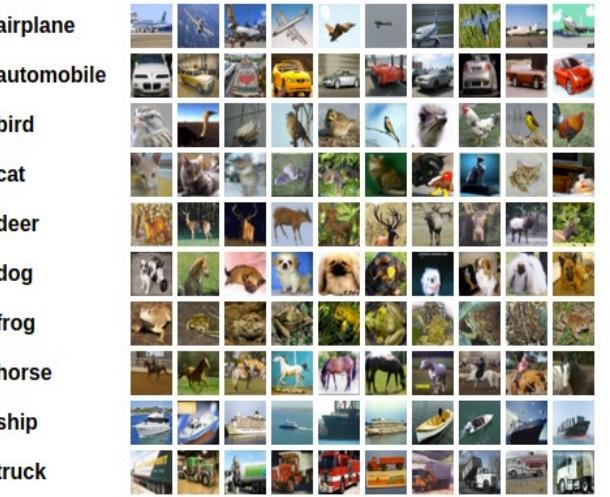
- Define object detection
- Describe different datasets for object detection
- Describe object detection architectures
- Discuss performance benchmarks

### Objective:

Predict the class and the position of multiple objects in the image



# Datasets for object detection



# Architectures

- Sliding Window
- R-CNN
- Fast R-CNN
- Faster R-CNN
- YOLO
- SSD
- Transformers

# Semantic Segmentation

## Learning Objectives

- Define image segmentation
- Define semantic segmentation
- Define instance segmentation
- Describe image segmentation architectures
- Learn about popular datasets and applications
- Discuss about performance

### Semantic Segmentation Objective:

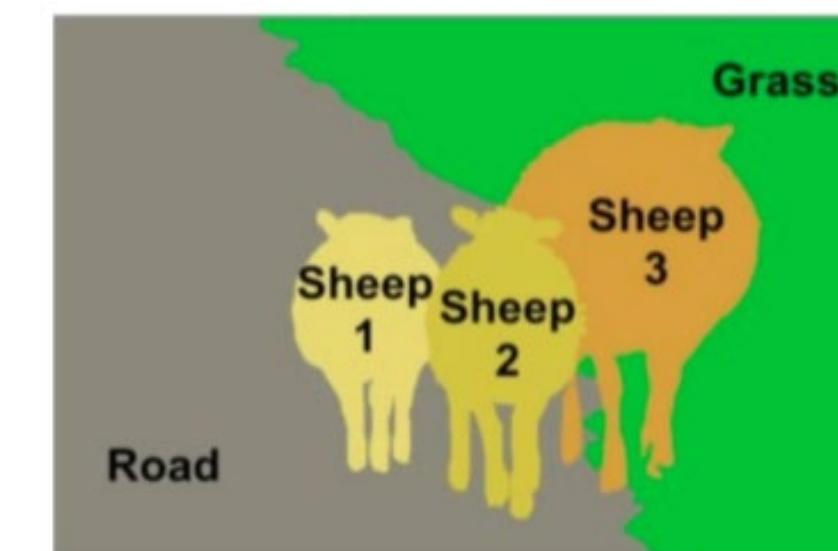
Classify all pixels

Don't differentiate instances.



### Instance Segmentation Objective:

Classify pixels but differentiate instances (predict segmentation mask)



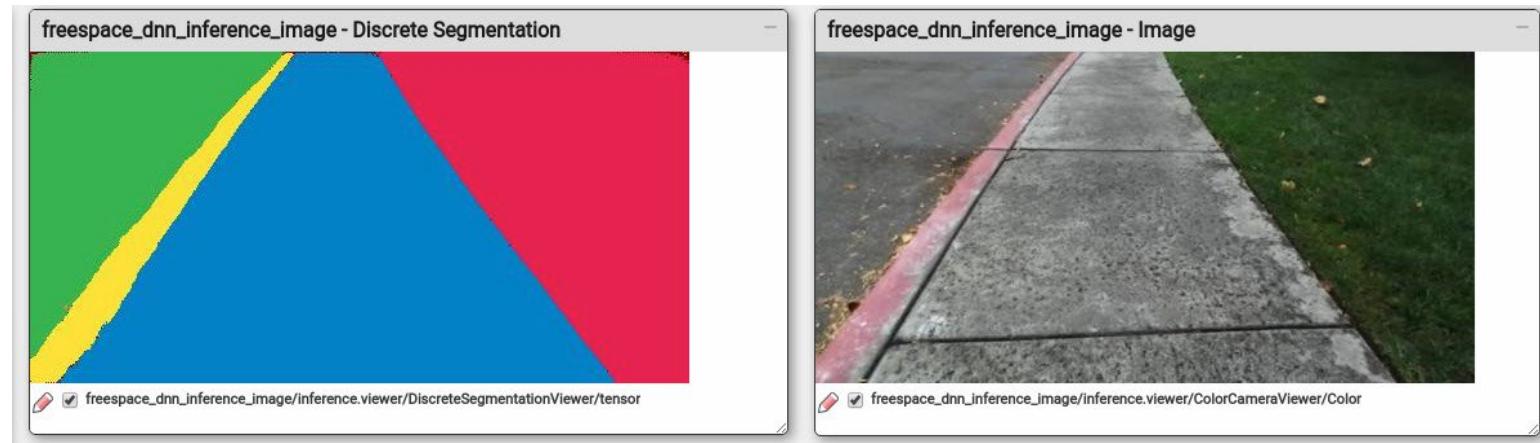
# Popular Datasets



# Architectures

- Fully Convolutional Networks
- SegNet
- U-Net
- RefineNet
- Learning Deconvolution Network
- Mark R-CNN

# Applications: Free Space Detection



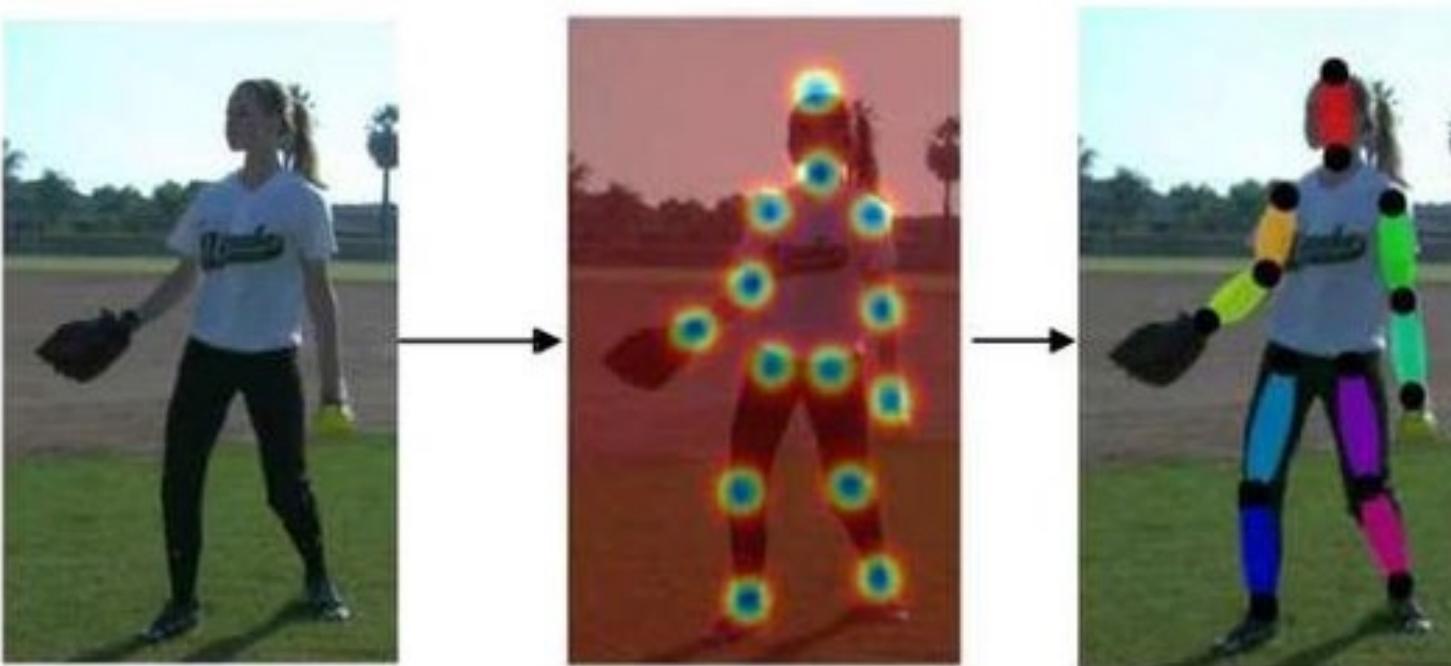
# Pose Estimation

## Learning Objectives

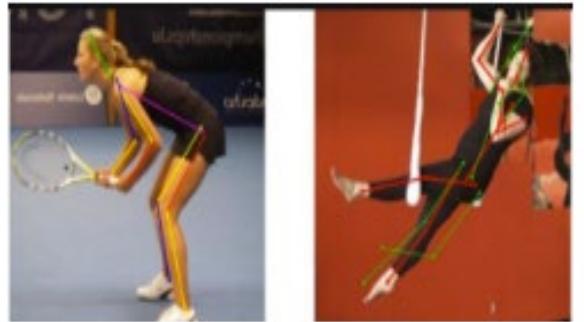
- Define pose estimation
- Describe pose estimation architectures
- Learn about popular datasets and applications
- Discuss about performance

### Objective:

Predict the pose of a person/object from an image or a video



# Datasets for Pose Estimation

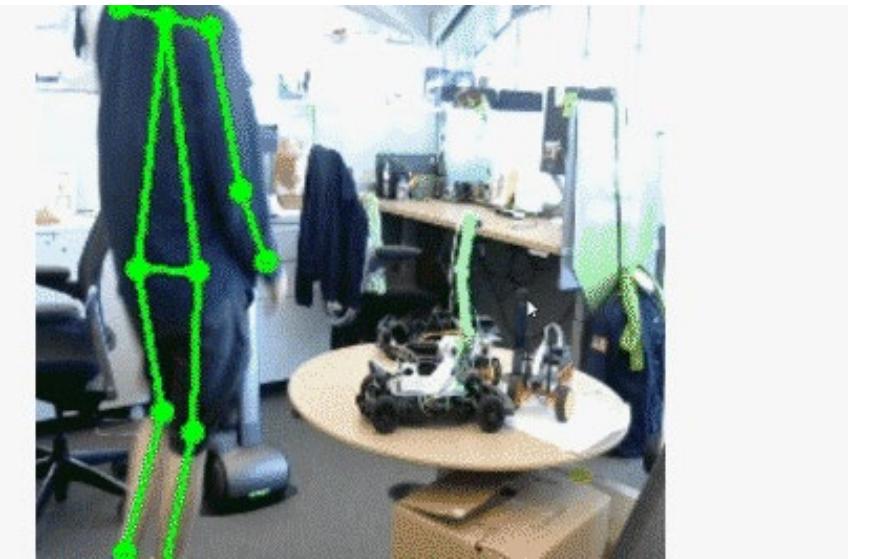
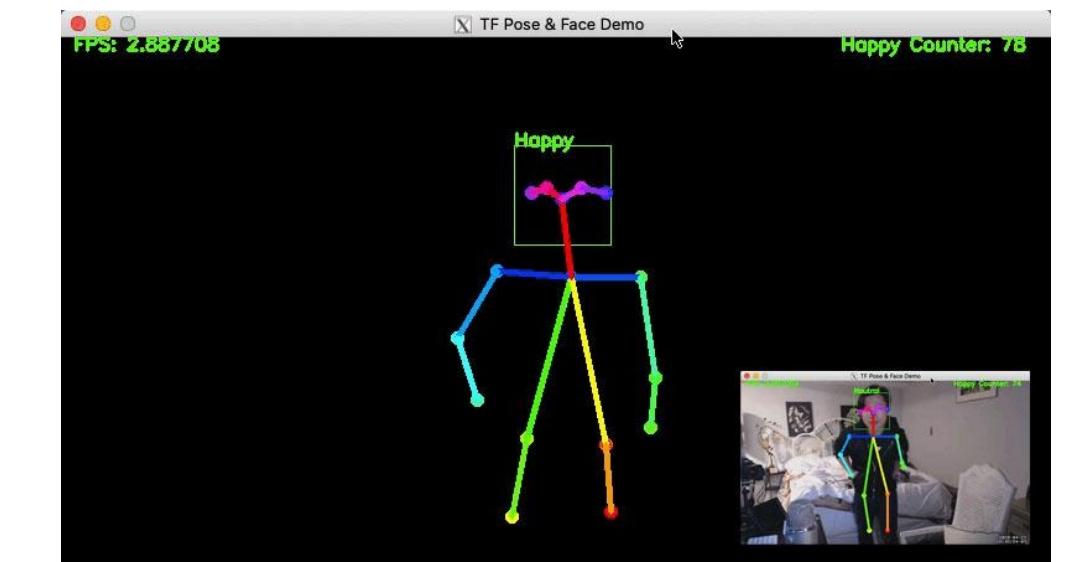
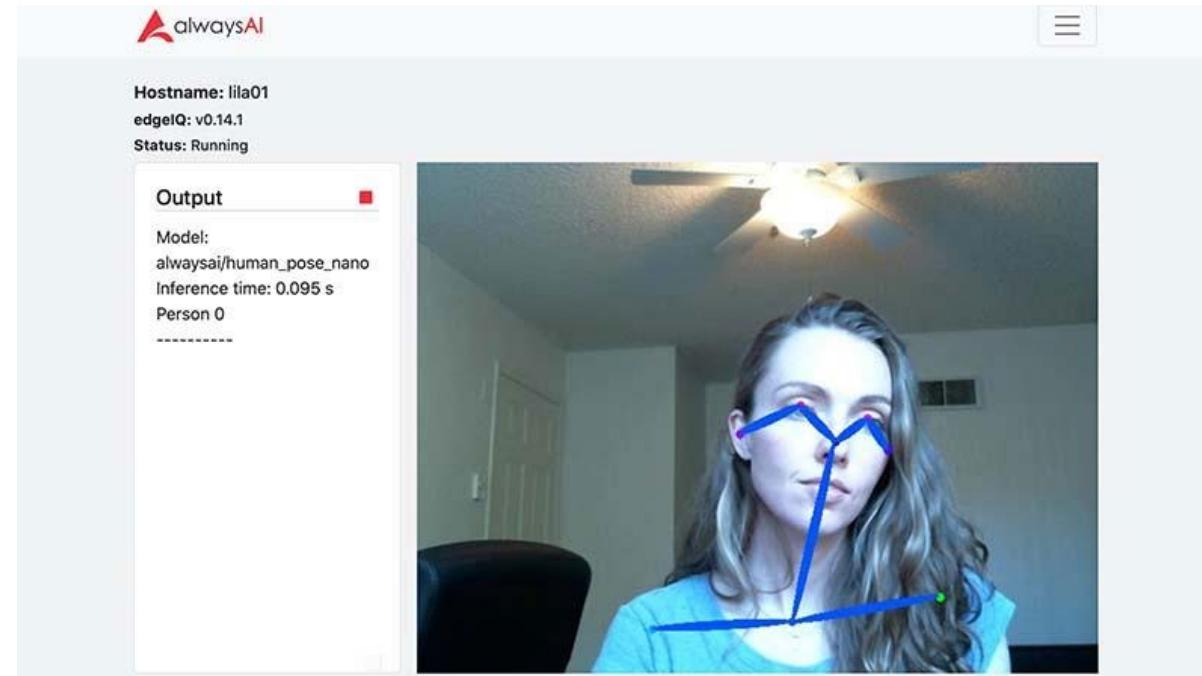


# List of architectures models

- [OpenPose](#)
- [High Resolution Net \(HRNet\)](#)
- [DeepCut](#)
- [Regional Multi-Person Pose Estimation \(AlphaPose\)](#)
- [Deep Pose:](#)
- [PoseNet:](#)
- [DensePose](#)

# Applications

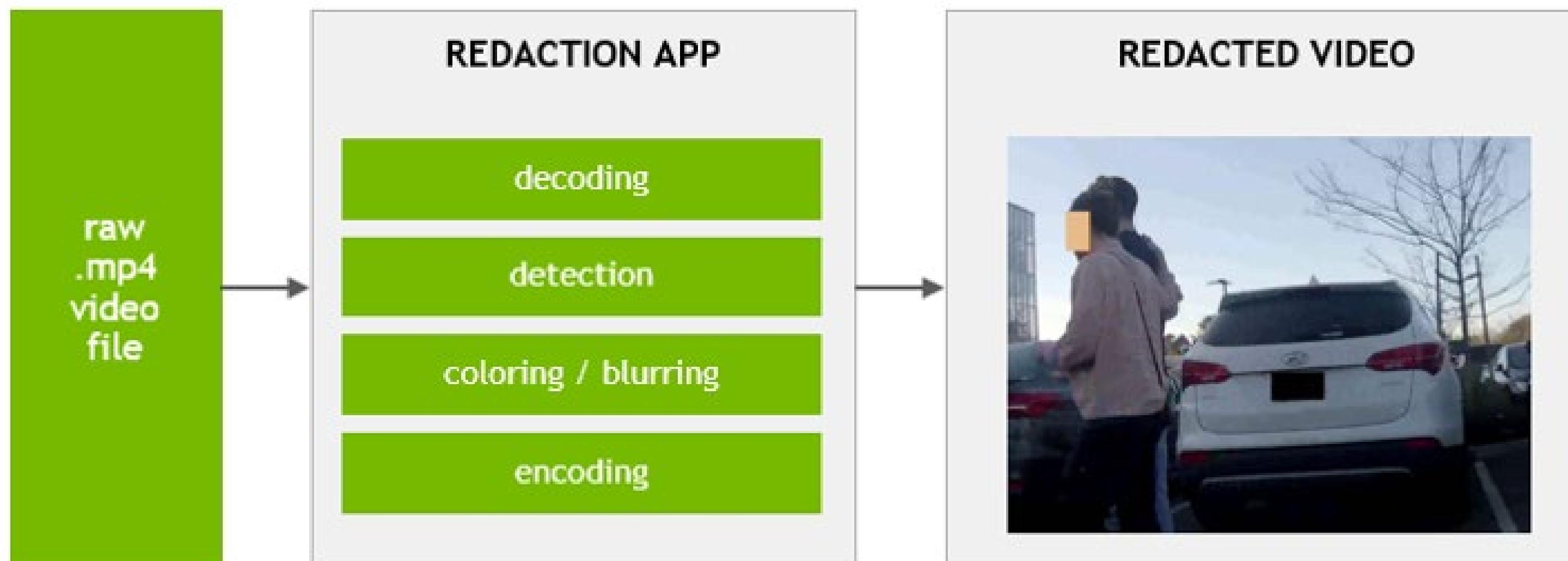
- Gesture Recognition
- Virtual Reality
- Activity Recognition
- Posture Analysis



# Teaching Kit Modules Overview

Diversity, Ethics,  
and Security

3.1: Diversity and Bias in Datasets  
3.2: Ethics and Security  
**Lab: Image and Video Redaction**



# Teaching Kit Module Overview

## Module 3 - Diversity, Bias and Security

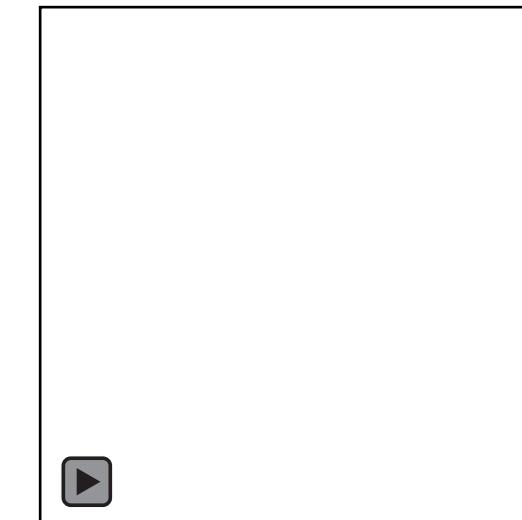
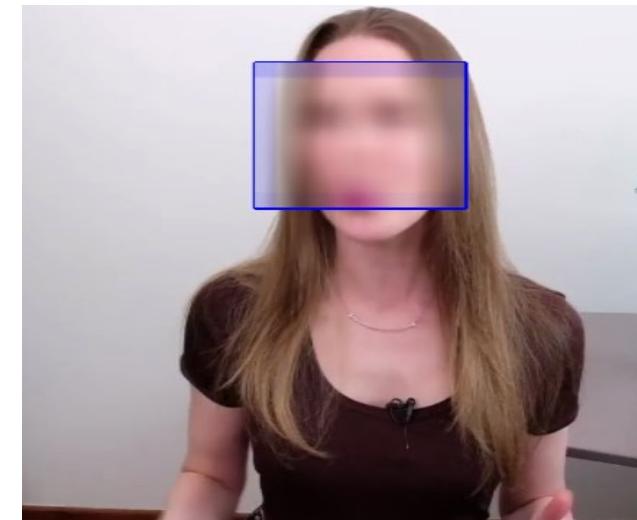
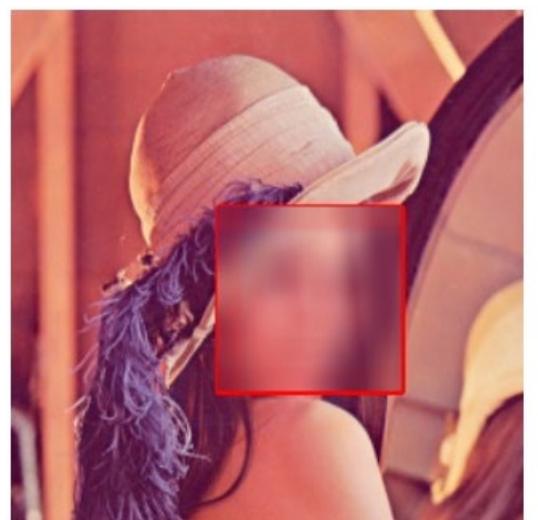
Outlines issues of Data Bias and ways to solve

Outlines principles of Responsible AI and importance of transparency

Discusses ethics and influences of AI

Highlights security considerations and data governance

Provides hands on example using OpenCV CUDA libraries and CUDA enabled haar cascades algorithms to detect and redact faces from images and video

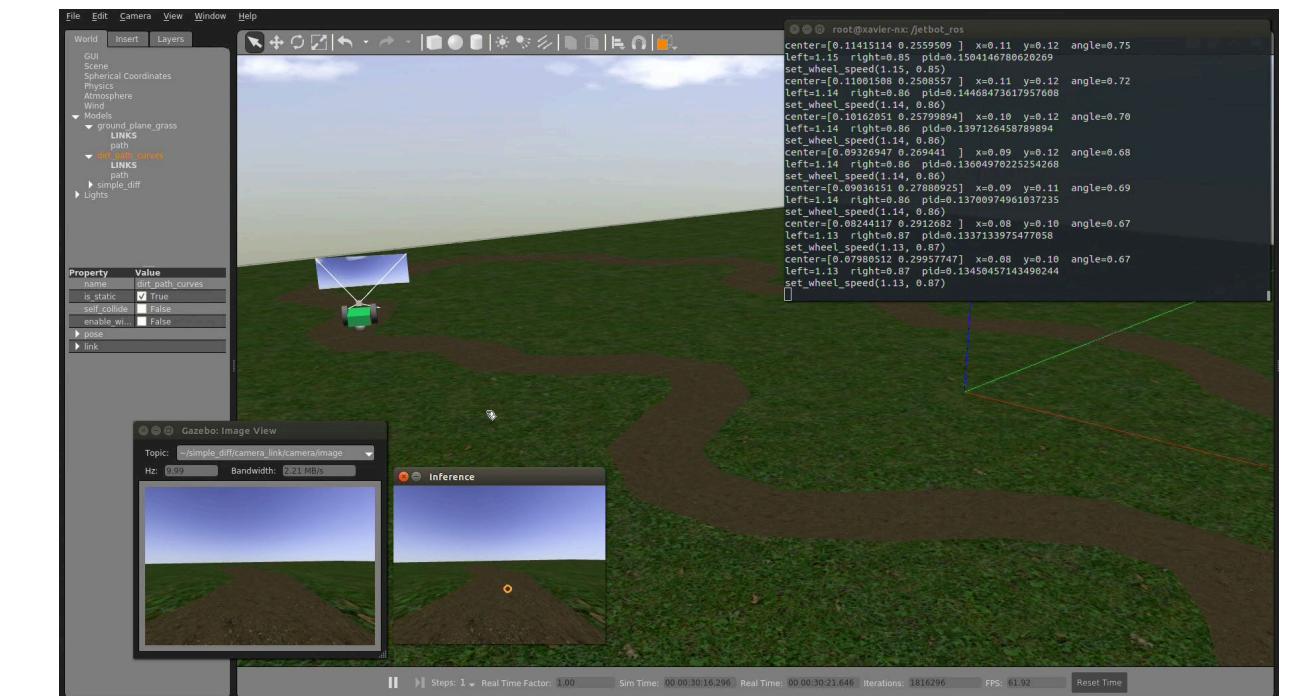
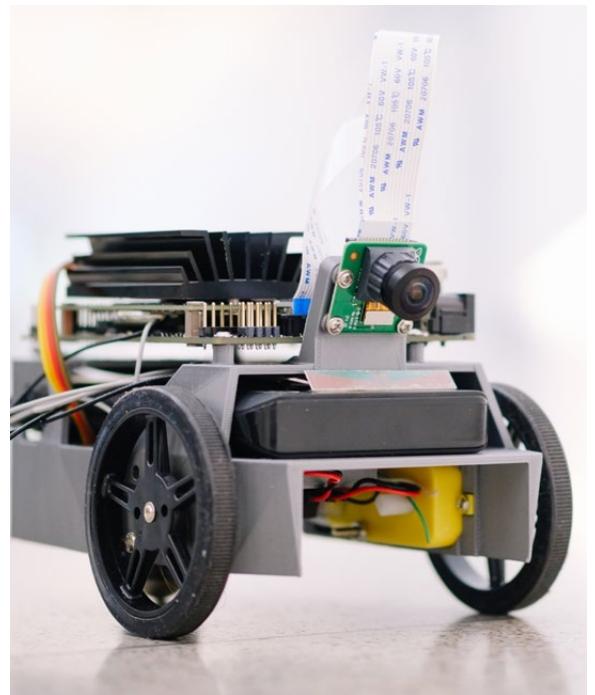


# Teaching Kit Modules Overview

## Module 4: Autonomous Robotics

- 4.1: Agent Architectures
- 4.2: Teaching Machines to Act
- 4.3: Introduction to ROS2
- 4.4: Robot Navigation

**Lab: Autonomous JetBot Navigation with ROS and Gazebo**

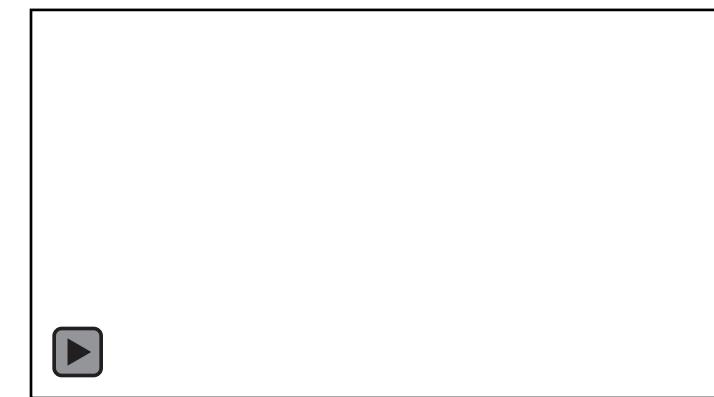


# Teaching Kit Module Overview

## Module 4 Autonomous Vehicles

Introduces the JetBot Getting Started Kit and covers essentials of:

- Robot as an Intelligent Agent
- Control and training machine to act
- Collects image data and trains to avoid obstacles and follow identified path
- Leverages Pytorch to train data and Tensor to optimize



# Teaching Kit Overview

## Module 4 ROS2 and Gazebo

The virtual JetBot uses both Robot Operating System 2 (ROS2) and Gazebo  
Leverages the prebuilt NVIDIA Jetbot\_Ros container  
Provides an overview of the ROS2 commands  
Lab exercises cover obstacle avoidance and road following using ROS2 and Gazebo

### Launch Gazebo

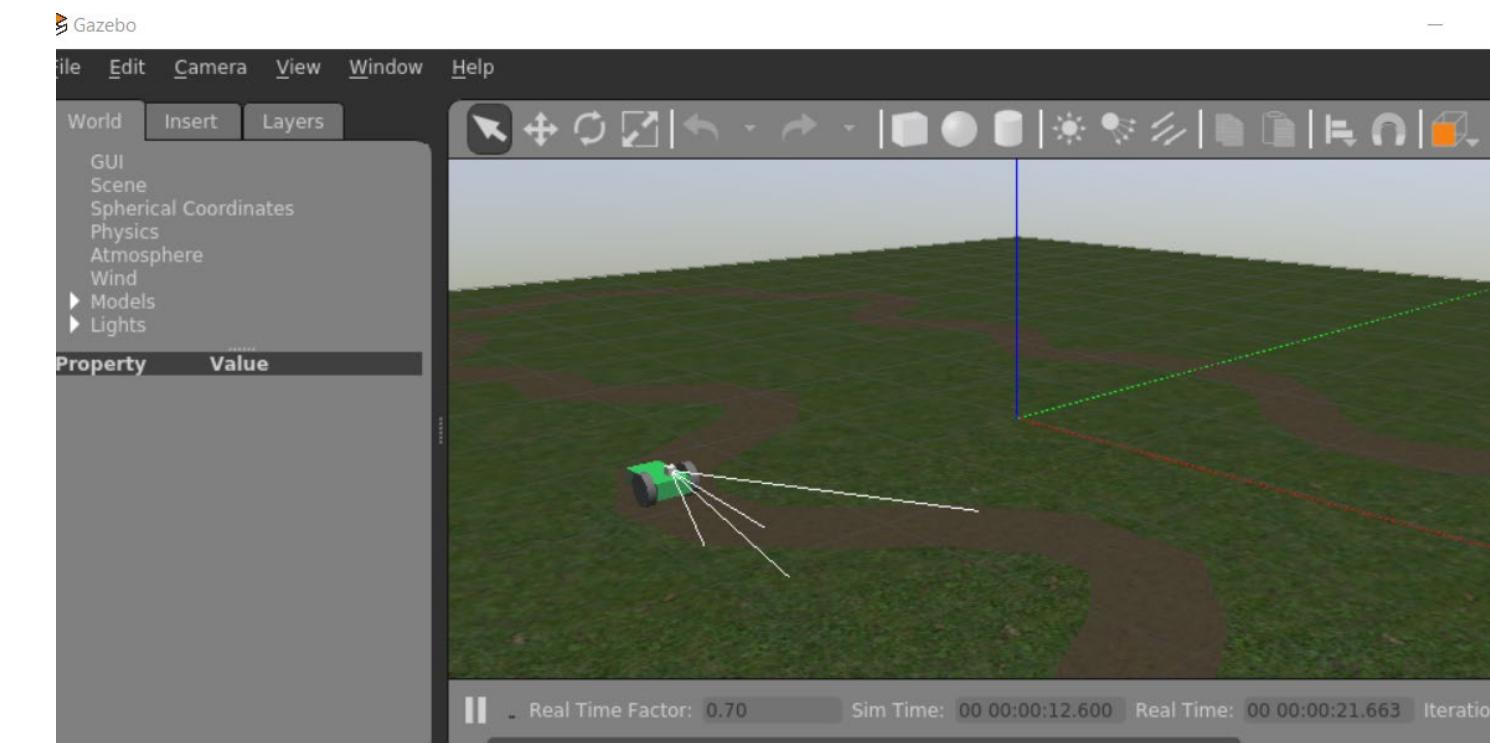
```
ros2 launch jetbot_ros gazebo_world.launch.py
```

Then to run the following commands, launch a new terminal session into the container:

```
sudo docker exec -it jetbot_ros /bin/bash
```

### Test Teleop

```
ros2 launch jetbot_ros teleop_keyboard.launch.py
```

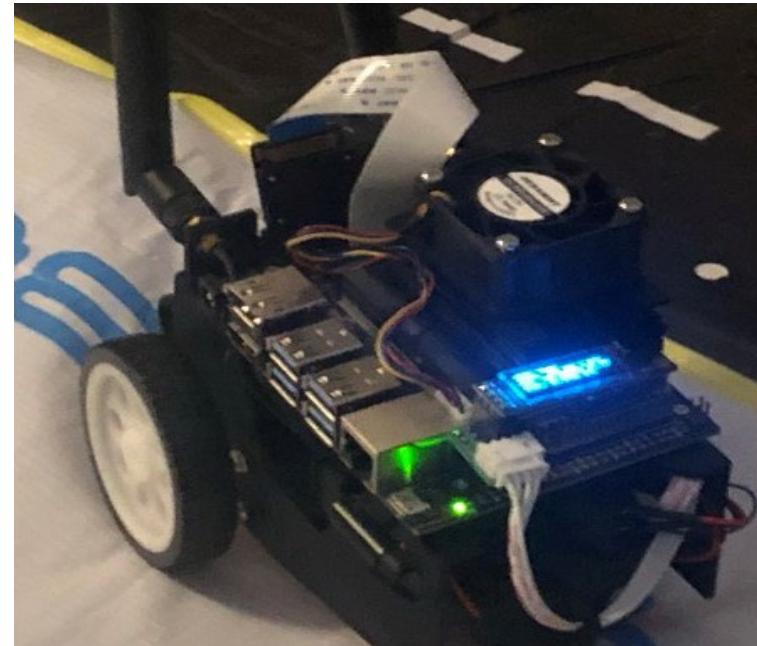


# Teaching Kit Tips

Feedback from the classroom

## UMBC Data 690 Applied AI for Data Science Practitioners

- Early content
- Spring 2021 Virtual Course
- Fall 2021 In Person Course



### Challenges:

Linux may be new to many students  
Difficult to troubleshoot hardware remotely  
Streaming video and images requires extra setup  
Software ecosystem is still emerging

### Tips:

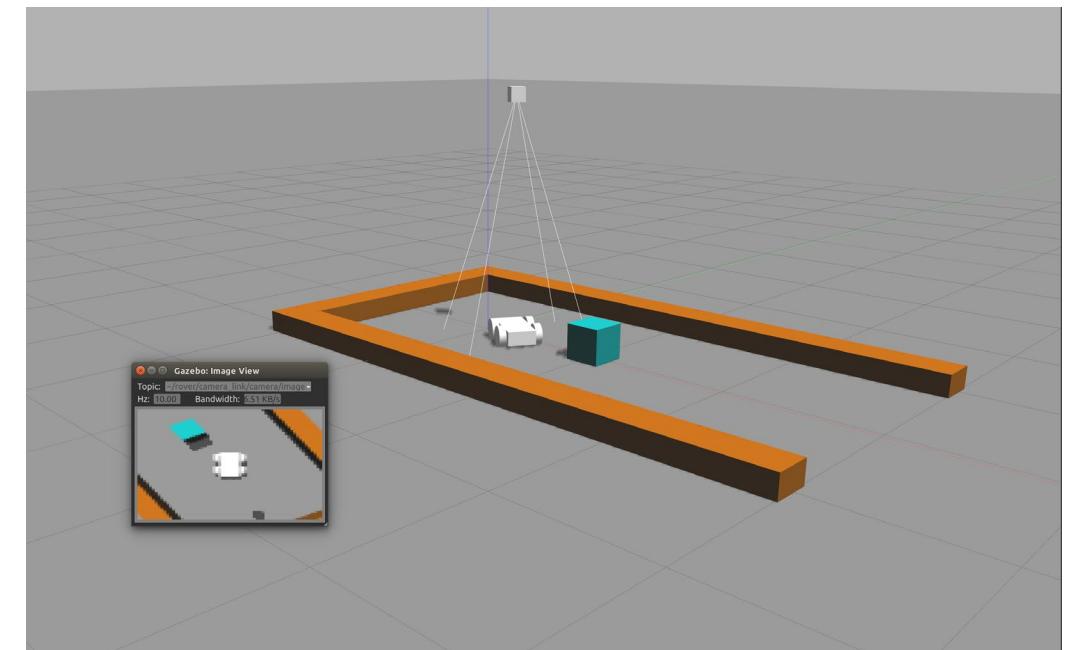
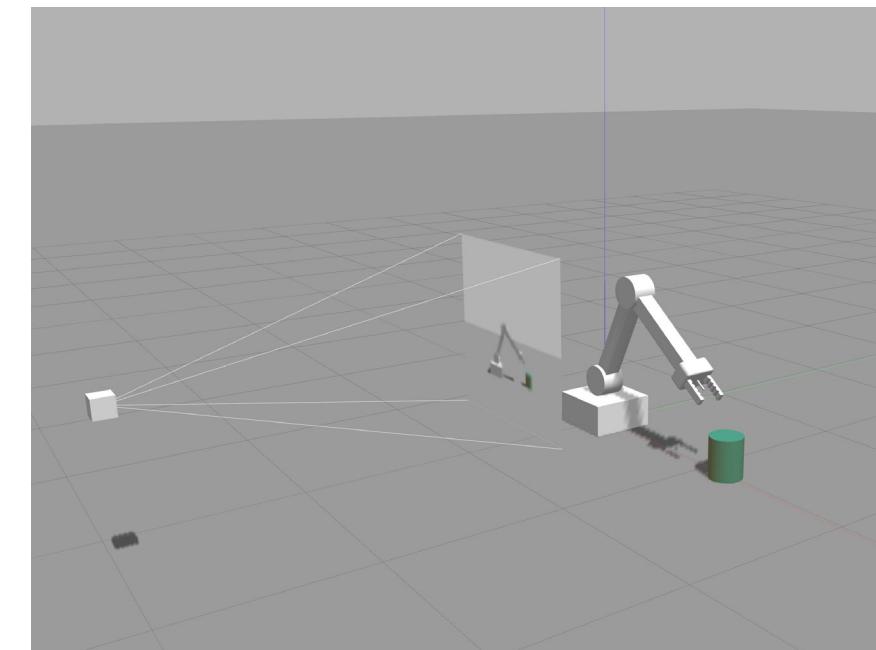
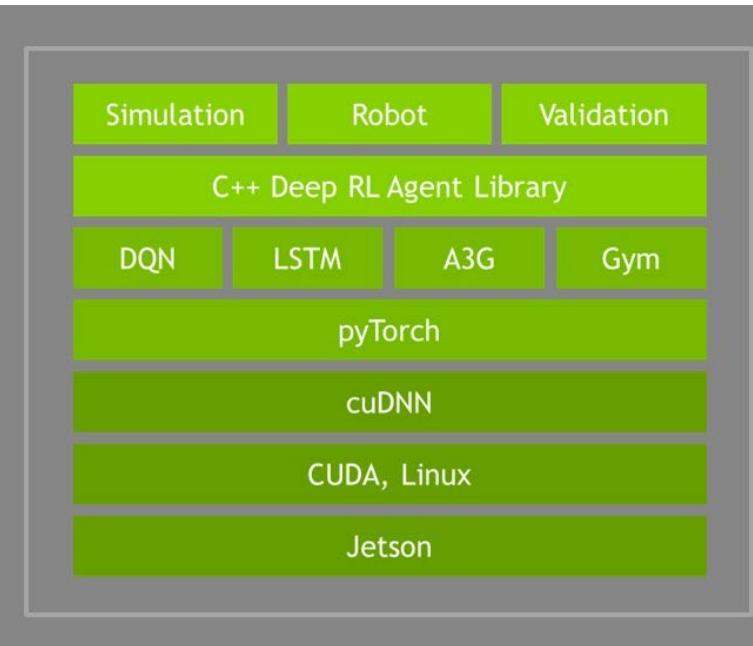
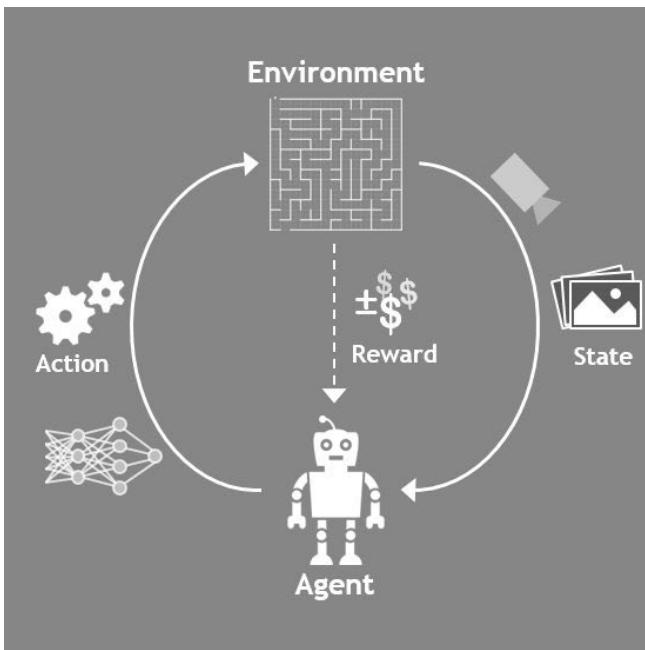
Use containers help reduce setup time  
Allow extra time for hardware setup  
Have students demonstrate in person  
Have spare Jetson kits and accessories on hand (SD cards, cables, Nanos)

```
git clone https://github.com/dusty-nv/jetbot_ros  
cd jetbot_ros  
docker/run.sh
```

# Teaching Kit Modules Overview

## Reinforcement Learning

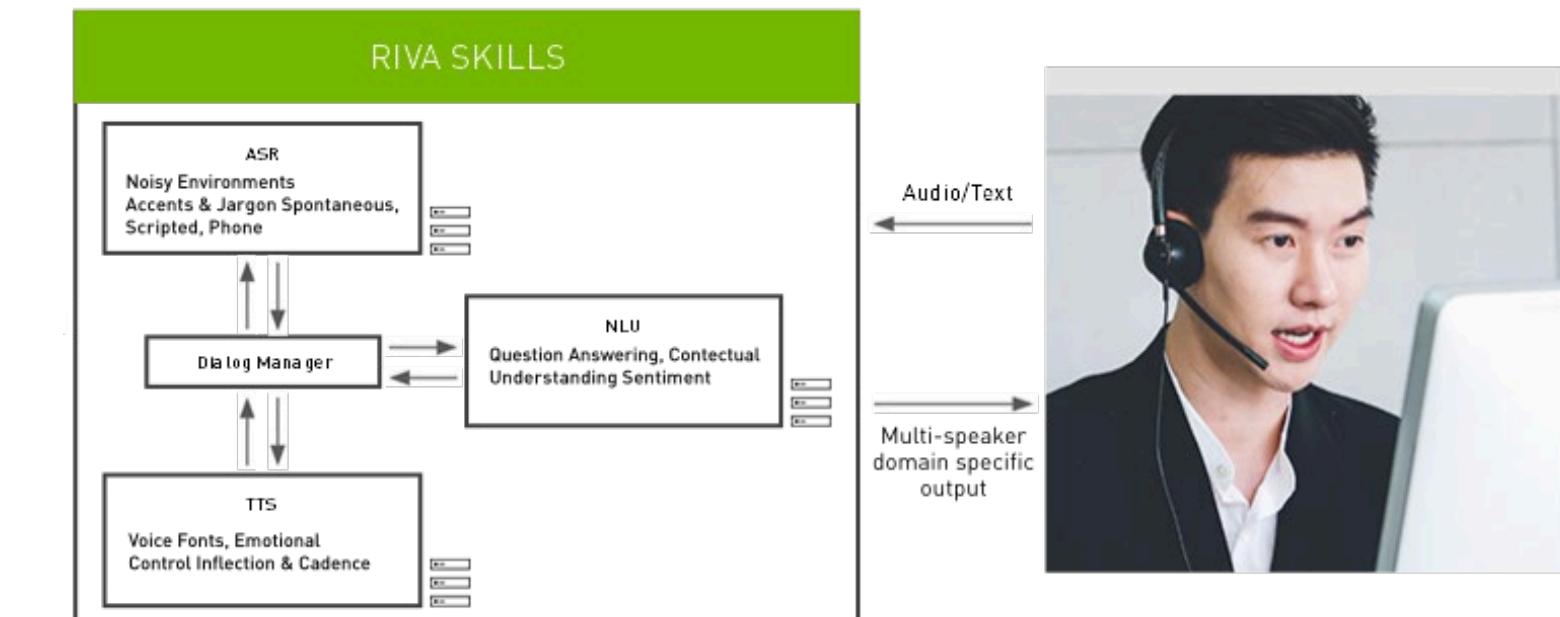
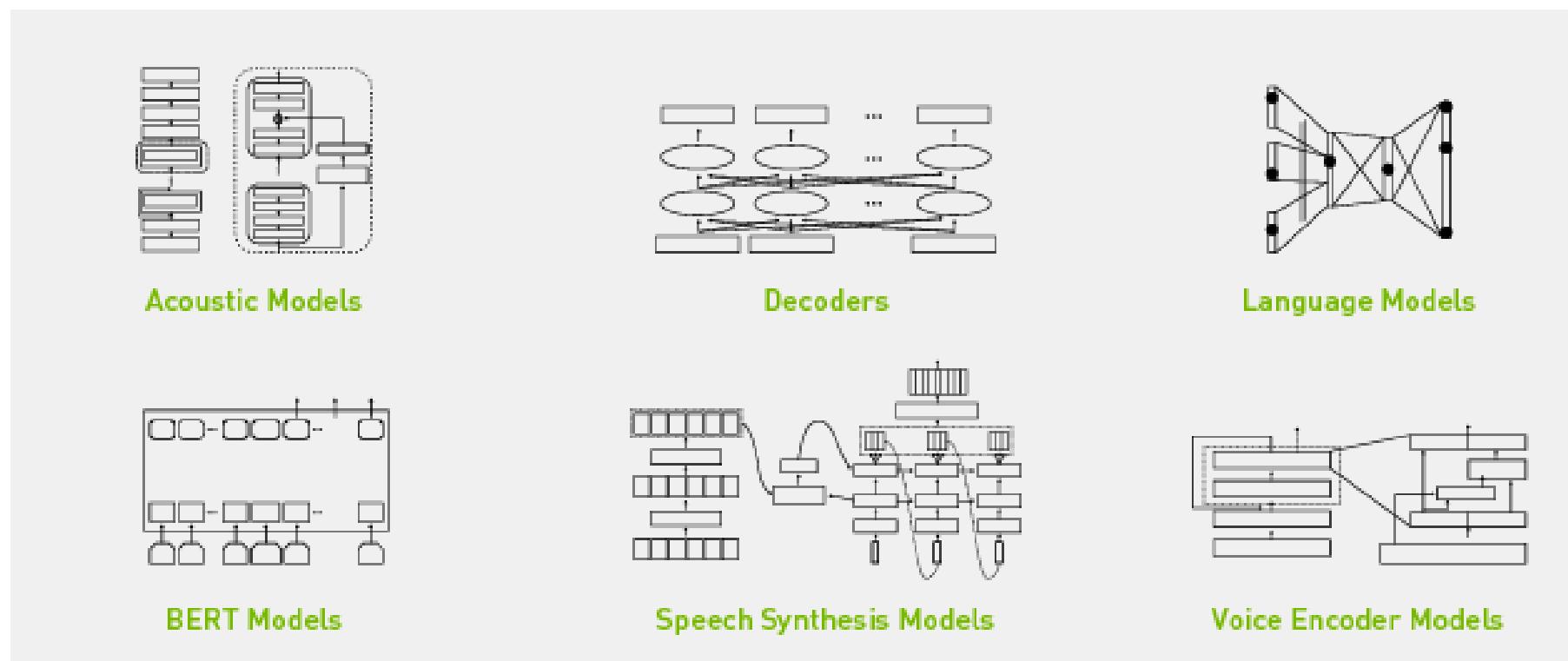
5.1: Introduction to RL Agents  
5.2: Deep RL for Vision  
**Lab: OpenAI Gym (Deep Q-Network)**  
**Lab: Robotic Arm Manipulation in Gazebo**



# Teaching Kit Modules Overview (For Future Release)

## Module 6: Natural Language Conversational AI

- 6.1: Natural Language Processing (NLP)
- 6.2: Speech Recognition (ASR)
- 6.3: Text-to-Speech (TTS)
- Lab: Python NLP**
- Lab: ASR, NLP, TTS Chatbot**

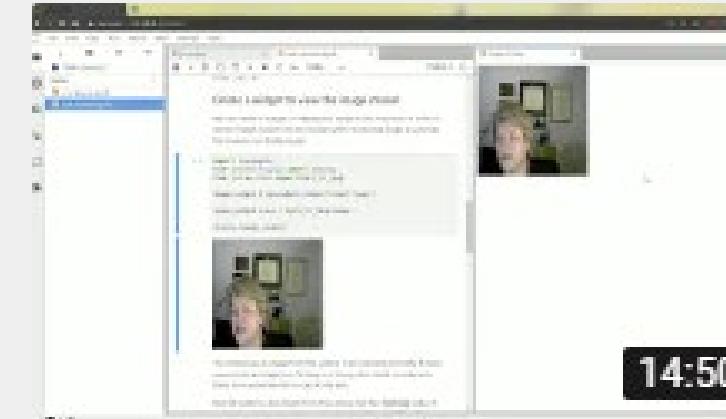


# AI Fundamentals

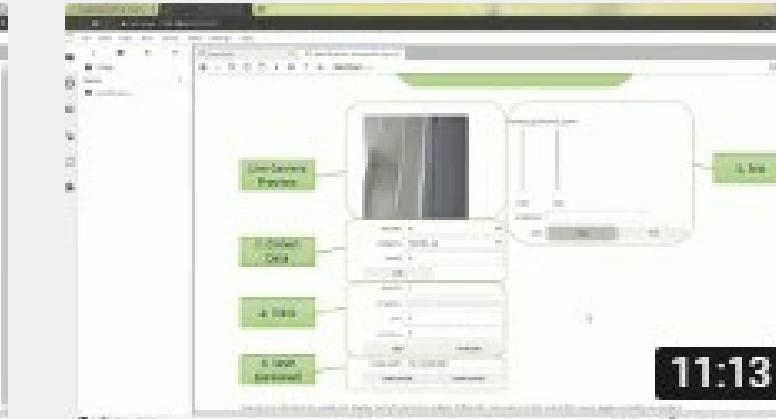
Getting Started  
with AI  
on Jetson Nano



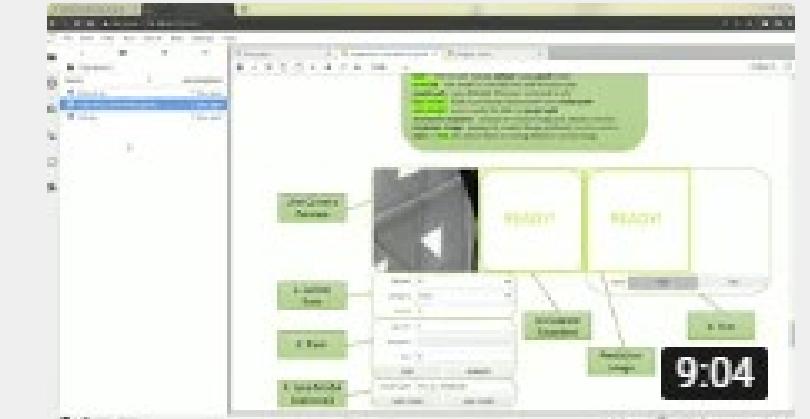
System Setup



Camera Capture



Classification



Regression

Hello AI World

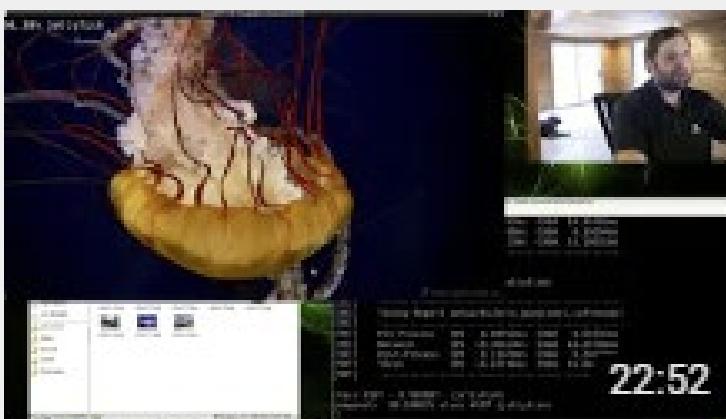
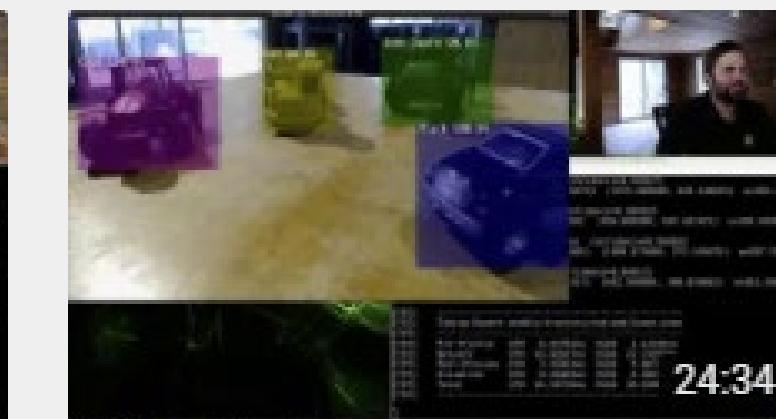


Image Recognition



Object Detection



Data Collection + Training



Semantic Segmentation

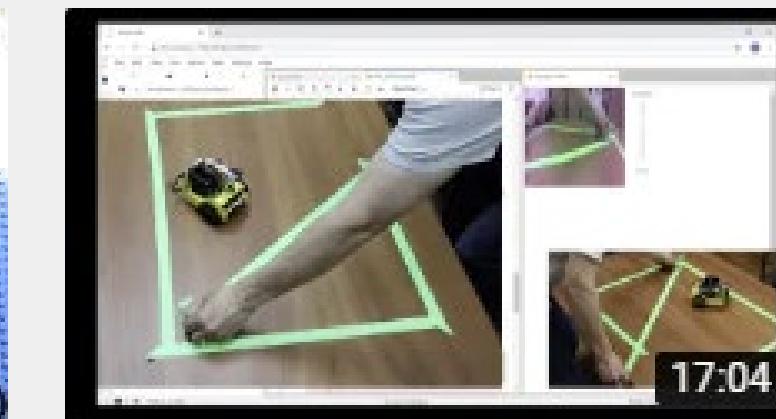
JetBot



Hardware Setup



Software Setup



Collision Avoidance



Road Following