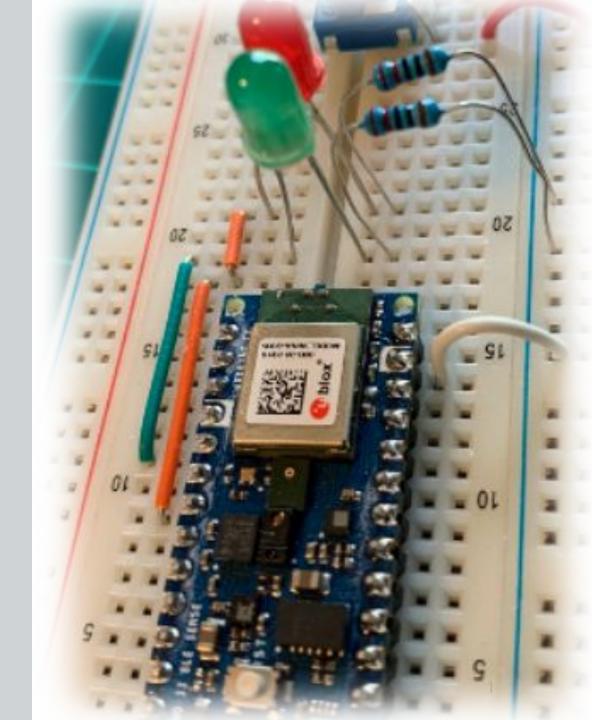
IESTI01 - TinyML

Embedded Machine Learning

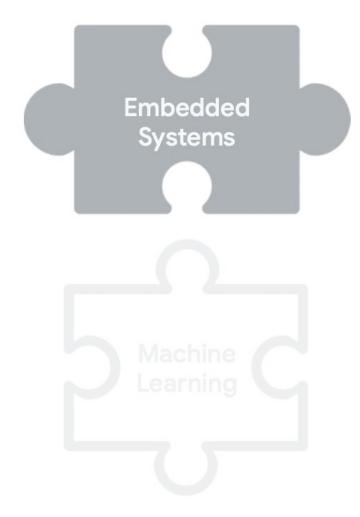
- 3. TinyML Challenges:
 - Embedded Systems



Prof. Marcelo Rovai
UNIFEI



What are the Challenges for TinyML?





TinyML

Applications

Libraries

Operating System

Hardware

Applications

Libraries

Operating System

Hardware

Building Blocks of Computing Hardware



Hardware



Software

Compute

Memory

Storage

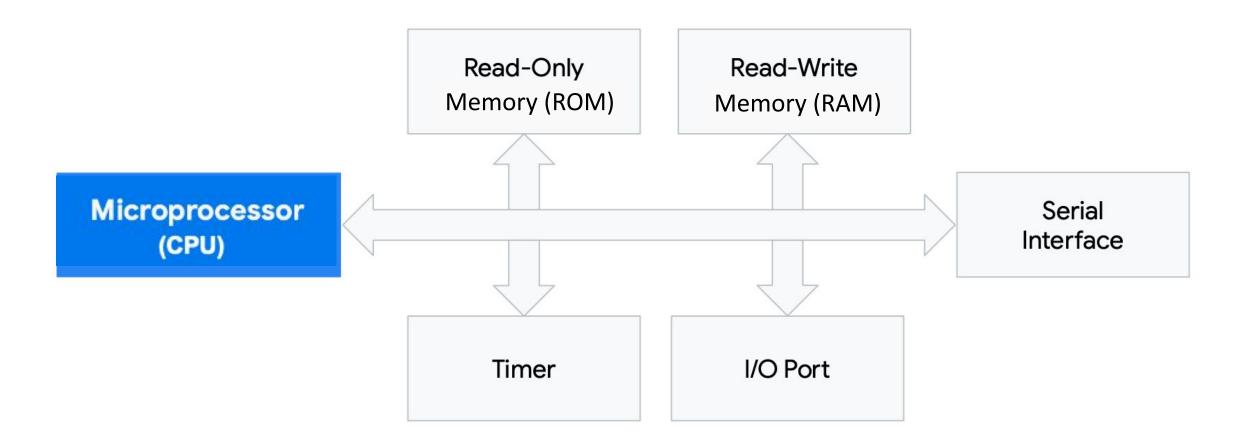






Microprocessor *v.*Microcontroller

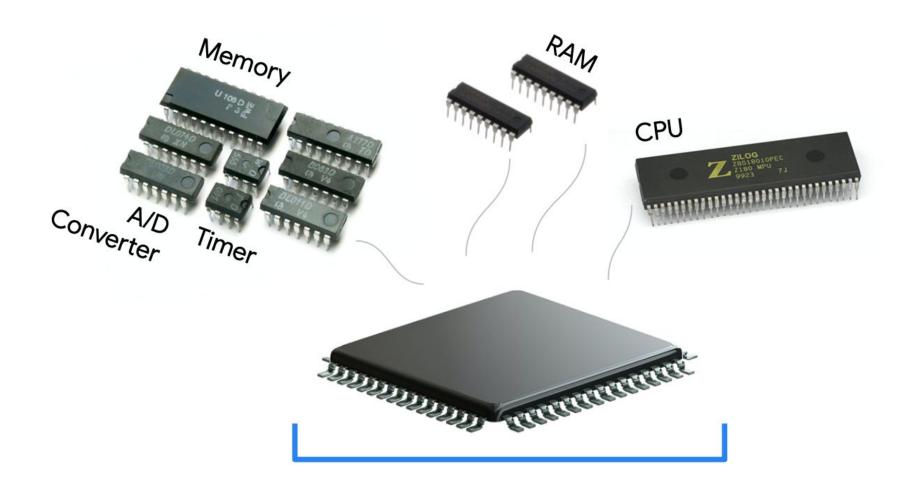
Microprocessor: only one part of the puzzle



Microcontroller

CPU	Read-Only Memory (ROM)	Read-Write Memory	
Timer	I/O Port	Serial Interface	

Microcontroller: a complete package



Microprocessor (CPU)

- Heart of a computer system
- Just the processor, memory and storage are external
- Mainly used in general purpose systems like laptops, desktops and servers
- Offers flexibility in design
- System size is big

Microcontroller

- Heart of an embedded system
- Memory and storage are all internal to the system
- Mainly used in specialized,
 fixed function systems like
 phones, MP3 players, etc.
- Limited flexibility in design
- System size is tiny

Orders of Magnitude Difference

Platform

Compute

Memory

Storage

Power

Microprocessor	>	> Microcontroller	
			Nano
1GHz-4GHz	~10X	1MHz-400MHz	64MHz
512MB-64GB	~10000X	2KB-512KB	256KB
64GB-4TB	~100000X	32KB-2MB	1MB
30W-100W	~1000X	150µW-23.5mW	

Implications

- How complicated is the running task?
- How much memory does it need to have?
- How long does the job have to perform?

Microcontroller



1MHz-400MHz

2KB - 512KB

32KB - 2MB

150µW-23.5mW

Hardware



Power

EdgeML

TinyML

Video Classification 2 MB+



















Jetson Nano RaspberryPi **SmartPhone** (Cortex-A + GPU) (Cortex-A)











KeyWord Spotting Audio Classification 50 KB



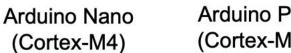


Image

250 KB+







Arduino Pro (Cortex-M7)



Anomaly Detection Sensor Classification 20 KB

(Cortex-M0+)

Source: Edge Impulse

Computing Hardware











	Raspberry Pico	Arduino Nano Sense	ESP 32	Seeed Wio Terminal	Arduino Portenta
32Bits CPU	Dual-core Arm Cortex-M0+	Arm Cortex-M4F	Xtensa LX6 Dual Core	Arm Cortex-M4F	Dual Core Arm Cortex M7/M4
CLOCK	133MHz	64MHz	240MHz	120MHz	480/240MHz
RAM	264KB	256KB	520KB	192KB	1MB
ROM	2MB	1MB	2MB	4MB	2MB
Radio		BLE	BLE/WiFi	BLE/WiFi	BLE/WiFi
Sensors	No	Yes	No	Yes	No

ARM Cortex Processor Profiles



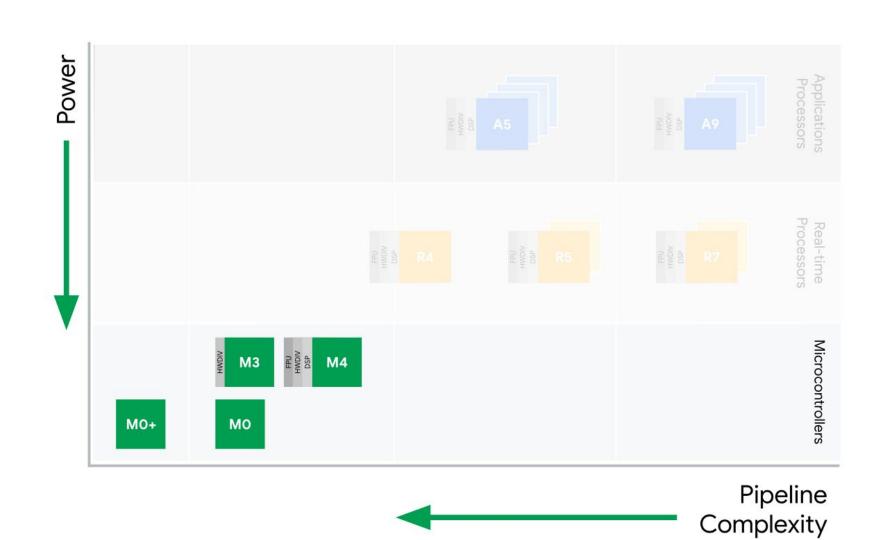
Pipeline Complexity

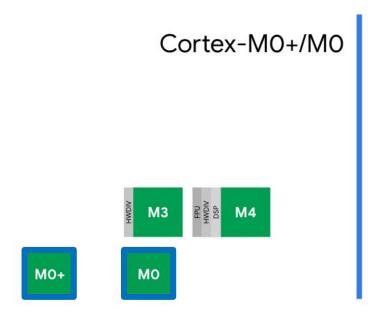
ARM Cortex Profiles



Pipeline Complexity

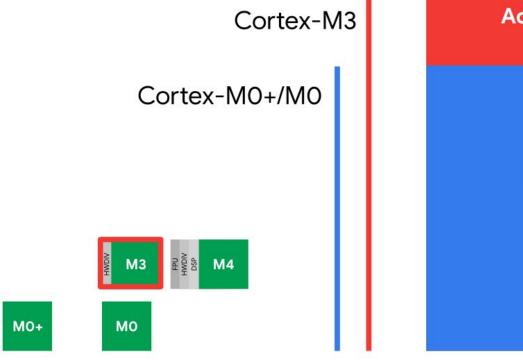
ARM Cortex Profiles



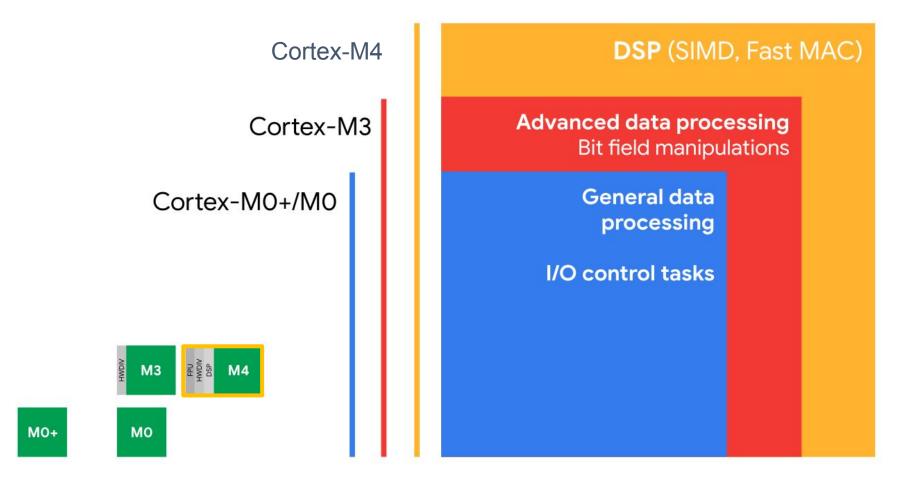


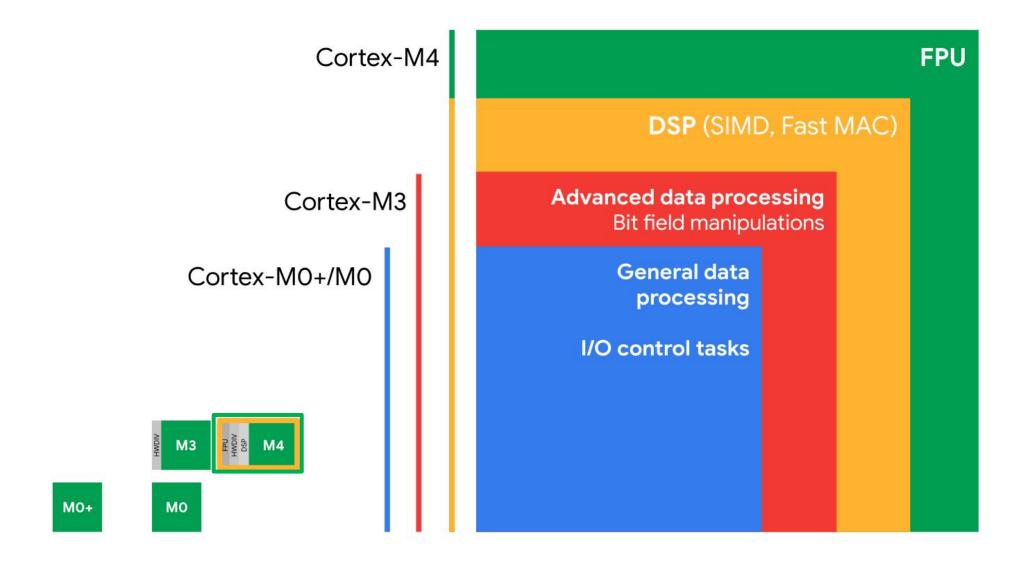
General data processing

I/O control tasks









Applications

Libraries

Operating System

Hardware

Hardware



Software

Applications

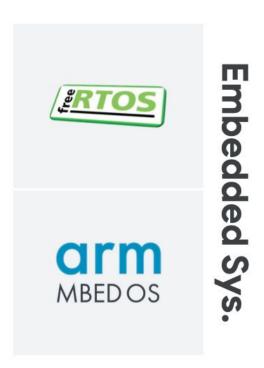
Libraries

Operating System

Hardware

Widely Used Operating Systems





Applications

Libraries

Operating System

Hardware

Applications

Libraries

Operating System

Hardware

import numpy as np

for x in range(10):
 np.SaveTheWorld()

Applications

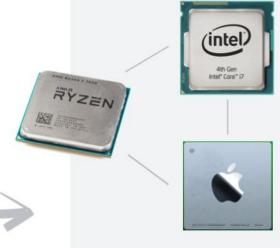
Libraries

Operating System

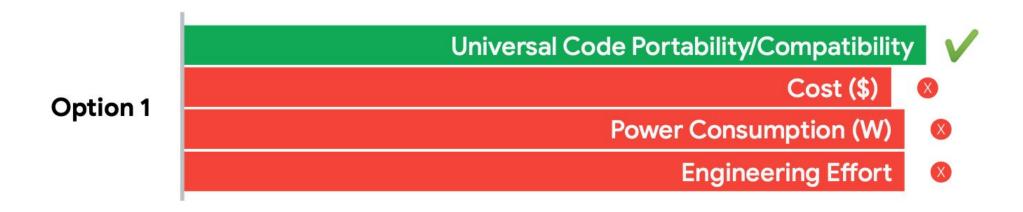
Hardware

Portability Opportunity

Able to execute the same code on different microprocessor hardware and architectures.

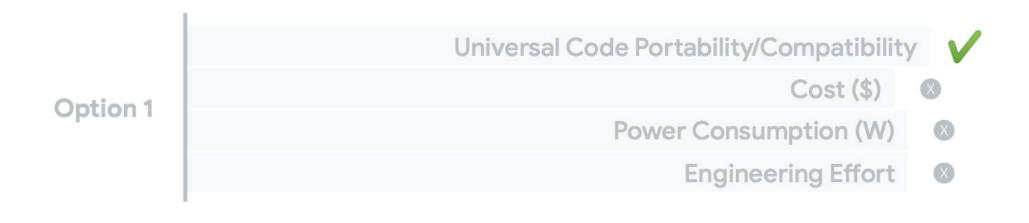


Portability Trade-offs





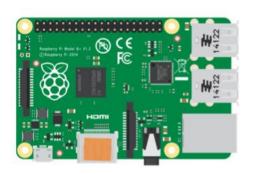
Portability Trade-offs





Portability Trade-offs

Sacrifice portability across systems for efficiency in system performance and power efficiency









Summary

 Embedded hardware is extremely limited in performance, power consumption and storage Embedded software is not as portable and flexible as mainstream computing

Reading Material

Main references

- Harvard School of Engineering and Applied Sciences CS249r: Tiny Machine Learning
- Professional Certificate in Tiny Machine Learning (TinyML) edX/Harvard
- Introduction to Embedded Machine Learning Coursera/Edge Impulse
- Computer Vision with Embedded Machine Learning Coursera/Edge Impulse
- Fundamentals textbook: "Deep Learning with Python" by François Chollet
- Applications & Deploy textbook: <u>"TinyML" by Pete Warden, Daniel Situnayake</u>
- Deploy textbook <u>"TinyML Cookbook" by Gian Marco Iodice</u>

I want to thank Shawn Hymel and Edge Impulse, Pete Warden and Laurence Moroney from Google, Professor Vijay Janapa Reddi and Brian Plancher from Harvard, and the rest of the TinyMLedu team for preparing the excellent material on TinyML that is the basis of this course at UNIFEI.

The IESTI01 course is part of the <u>TinyML4D</u>, an initiative to make TinyML education available to everyone globally.

Thanks

