IESTI01 – TinyML

Embedded Machine Learning

3. TinyML Challenges:
   - Embedded Systems

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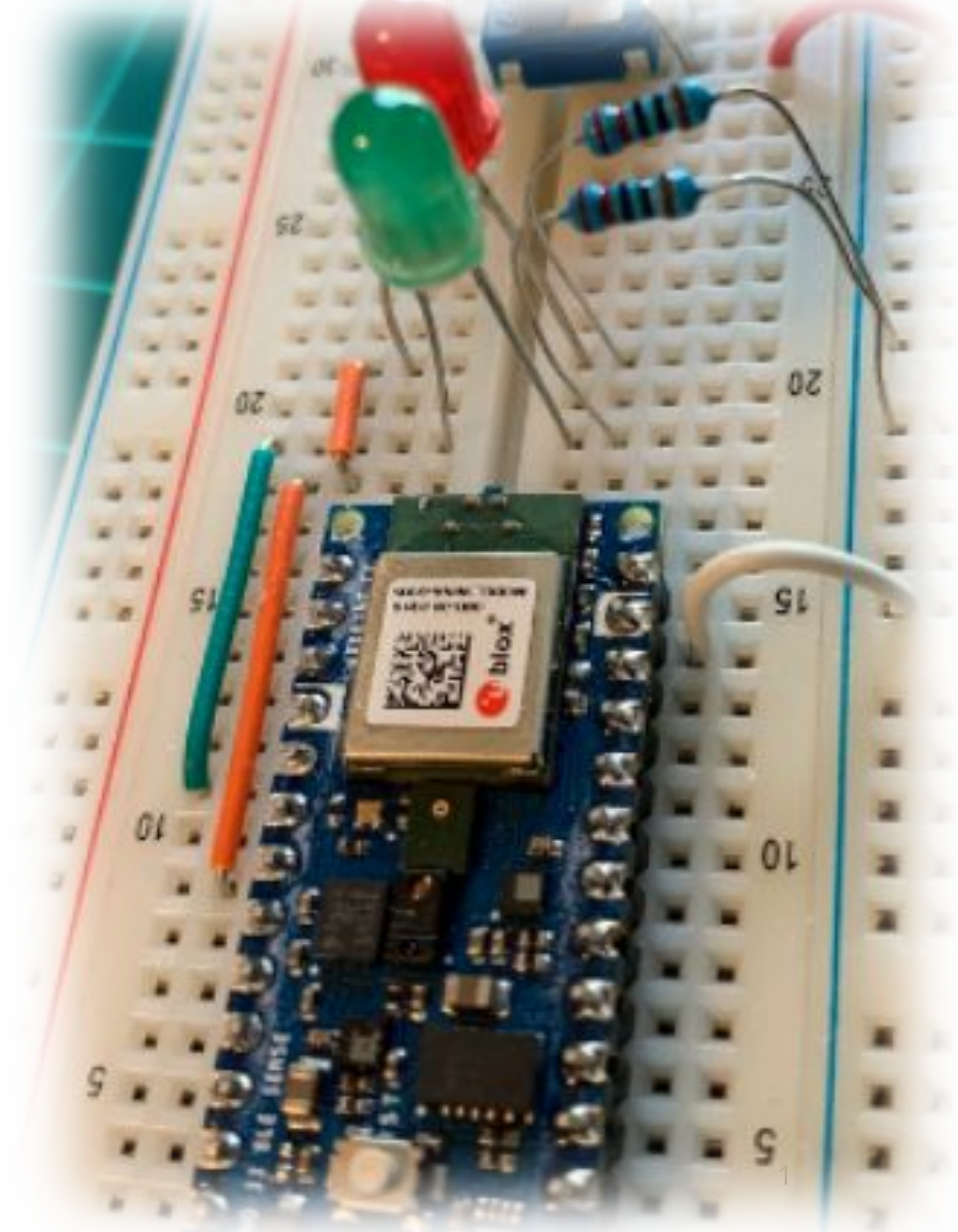
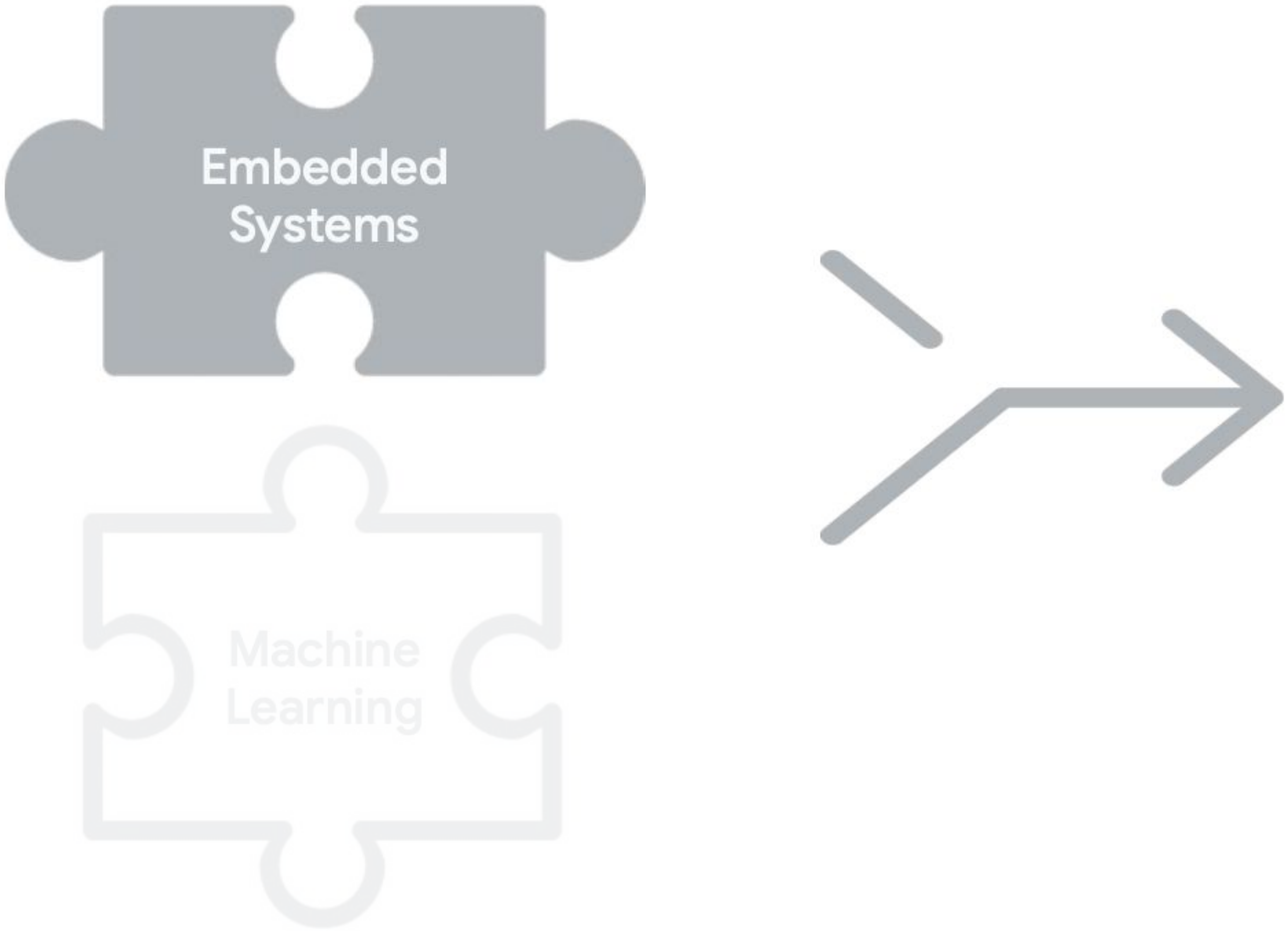
UNIFEI

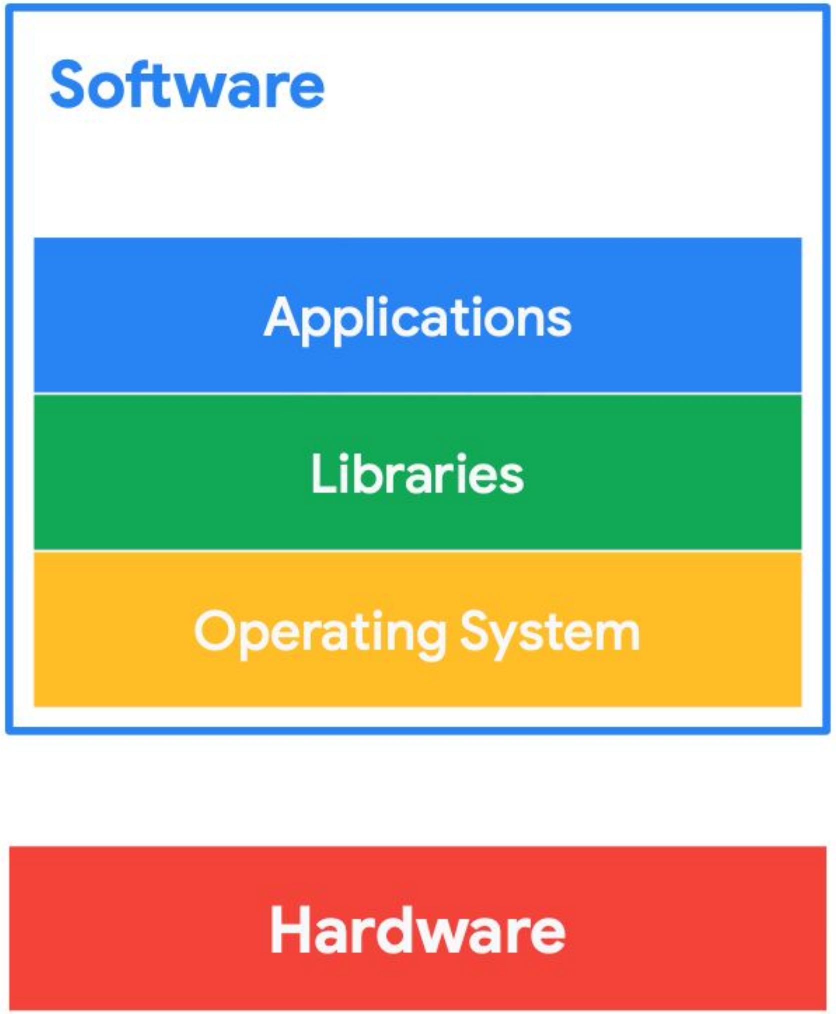


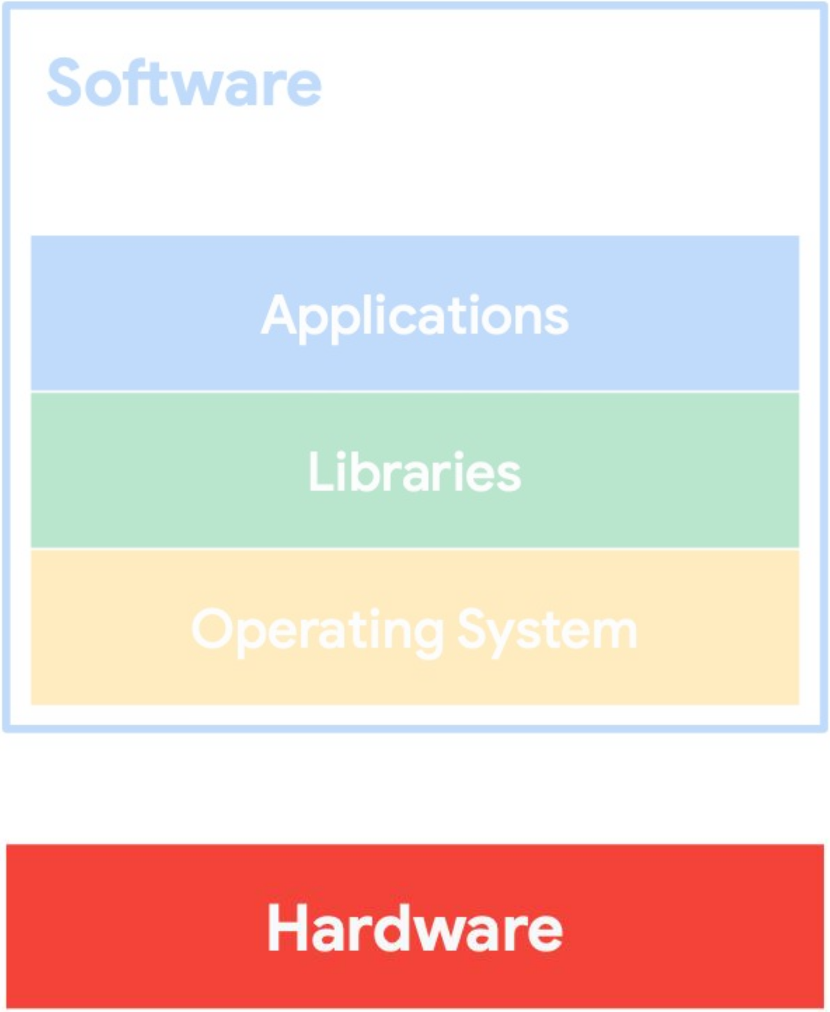
What are the Challenges for TinyML?



TinyML

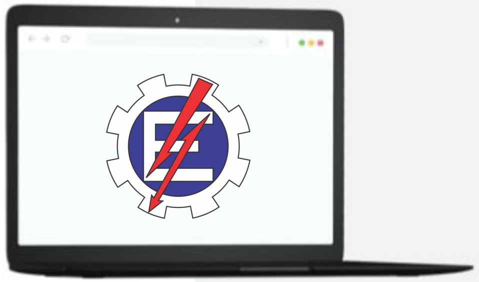
Computer System




Software
Applications
Libraries
Operating System
Hardware

Building Blocks of Computing Hardware

Hardware



Software

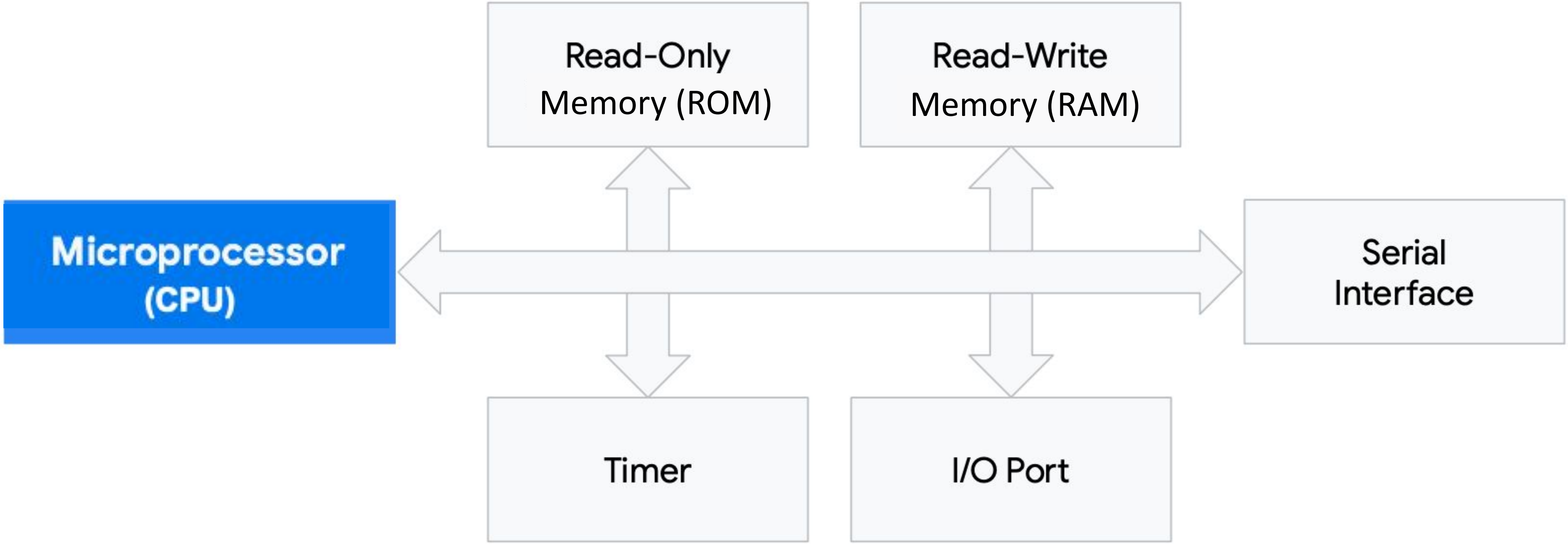
Compute

Memory

Storage

Microprocessor
v.
Microcontroller

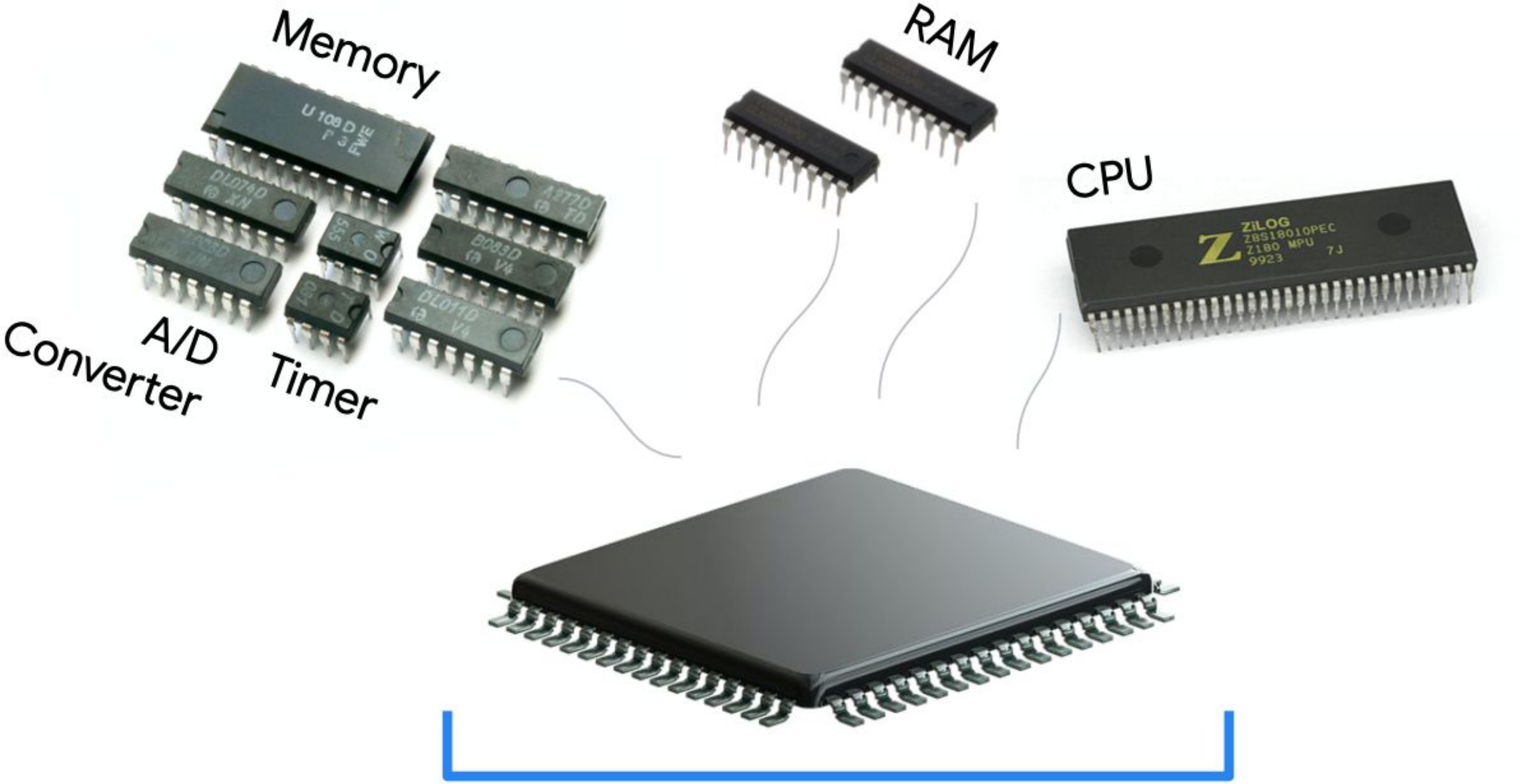
Microprocessor: only **one part** of the puzzle



Microcontroller

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

Microcontroller: a **complete package**



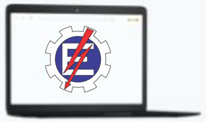
Microprocessor **(CPU)**

- 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

	Microprocessor	>	Microcontroller	
Platform				Nano
Compute	1GHz–4GHz	**~10X**	1MHz–400MHz	64MHz
Memory	512MB–64GB	**~10000X**	2KB–512KB	256KB
Storage	64GB–4TB	**~100000X**	32KB–2MB	1MB
Power	30W–100W	**~1000X**	150µW–23.5mW	

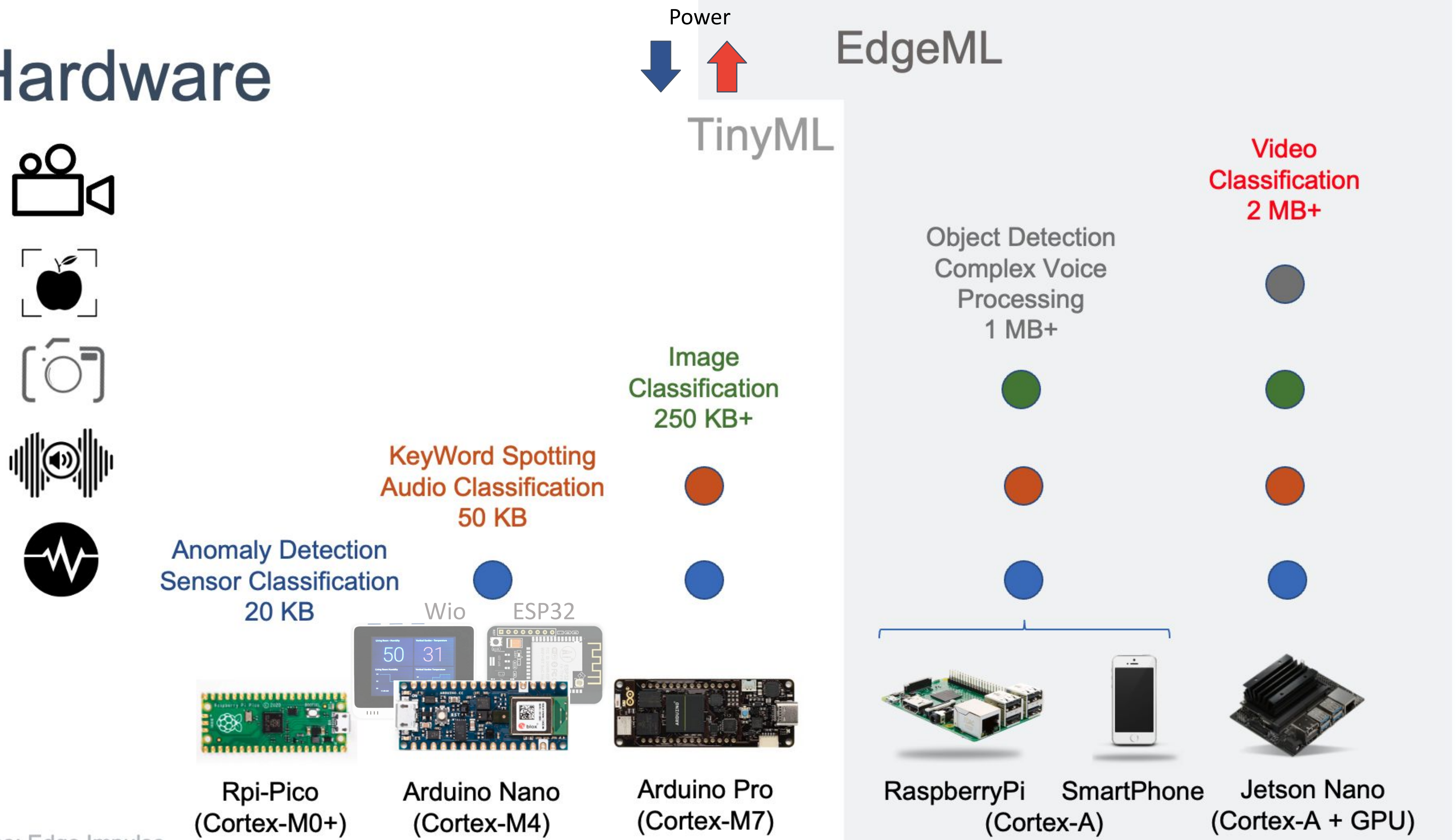
Implications

- 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

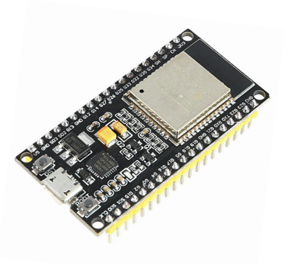
Hardware

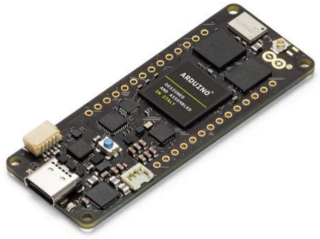


Source: Edge Impulse

Computing Hardware

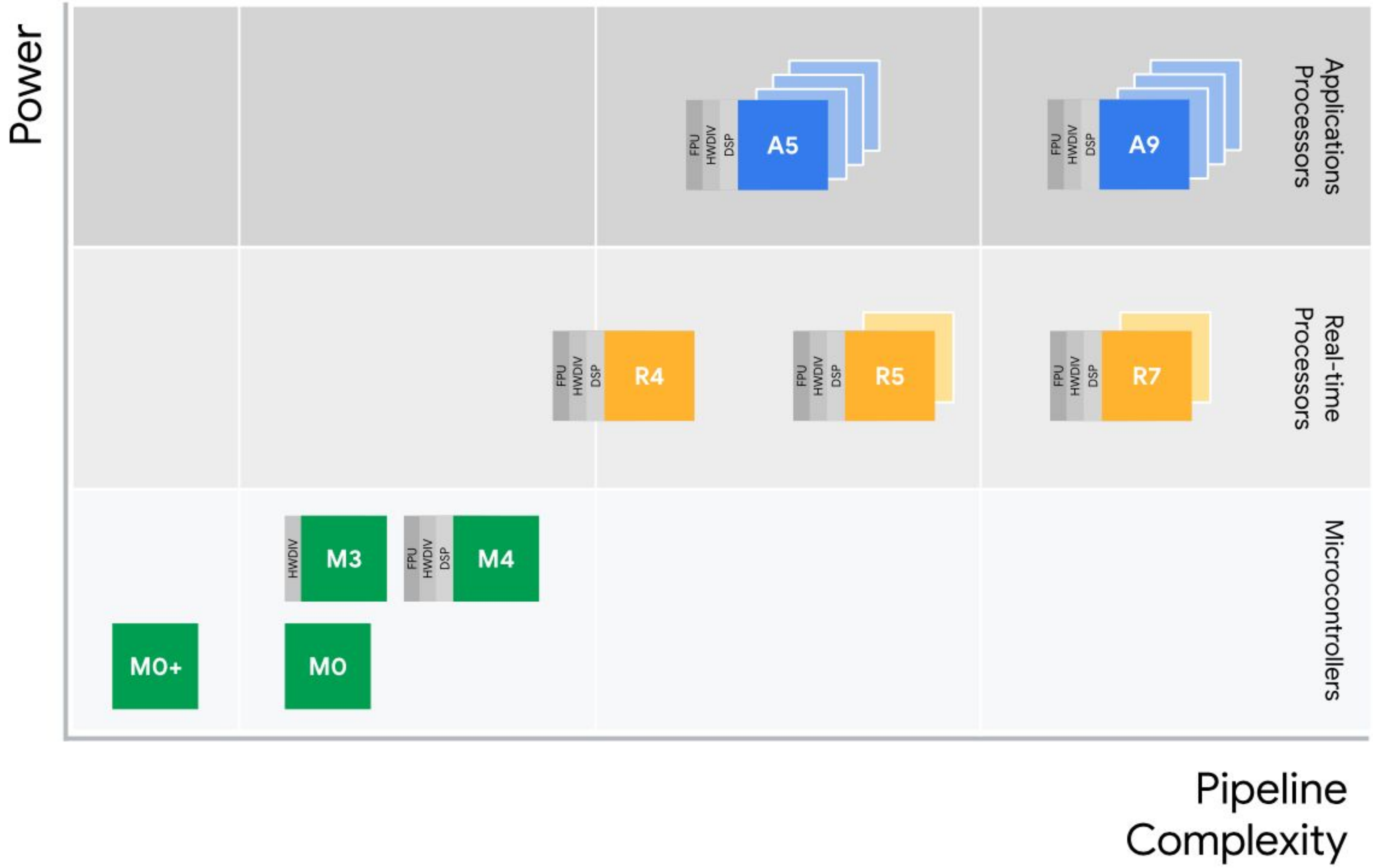




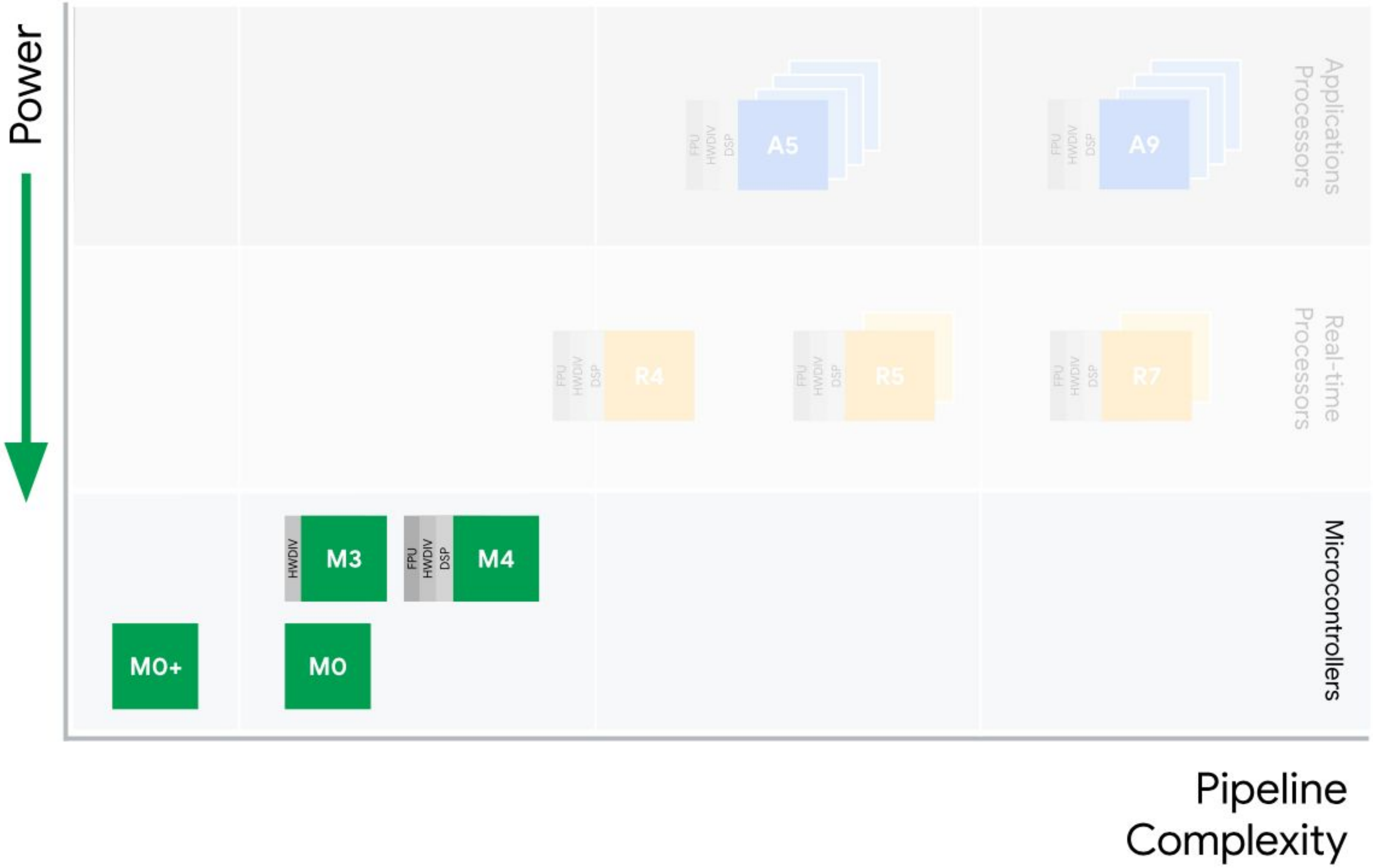


	Raspberry Pico	Arduino Nano Sense	ESP 32	Seeed Wio Terminal	Arduino Portenta
32Bits CPU	Dual-core Arm Cortex-M0+	Arm Cortex-M4F	Xtensa LX6 Dual Core	Arm Cortex-M4F	Dual Core Arm Cortex M7/M4
CLOCK	133MHz	64MHz	240MHz	120MHz	480/240MHz
RAM	264KB	256KB	520KB	192KB	1MB
ROM	2MB	1MB	2MB	4MB	2MB
Radio	---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

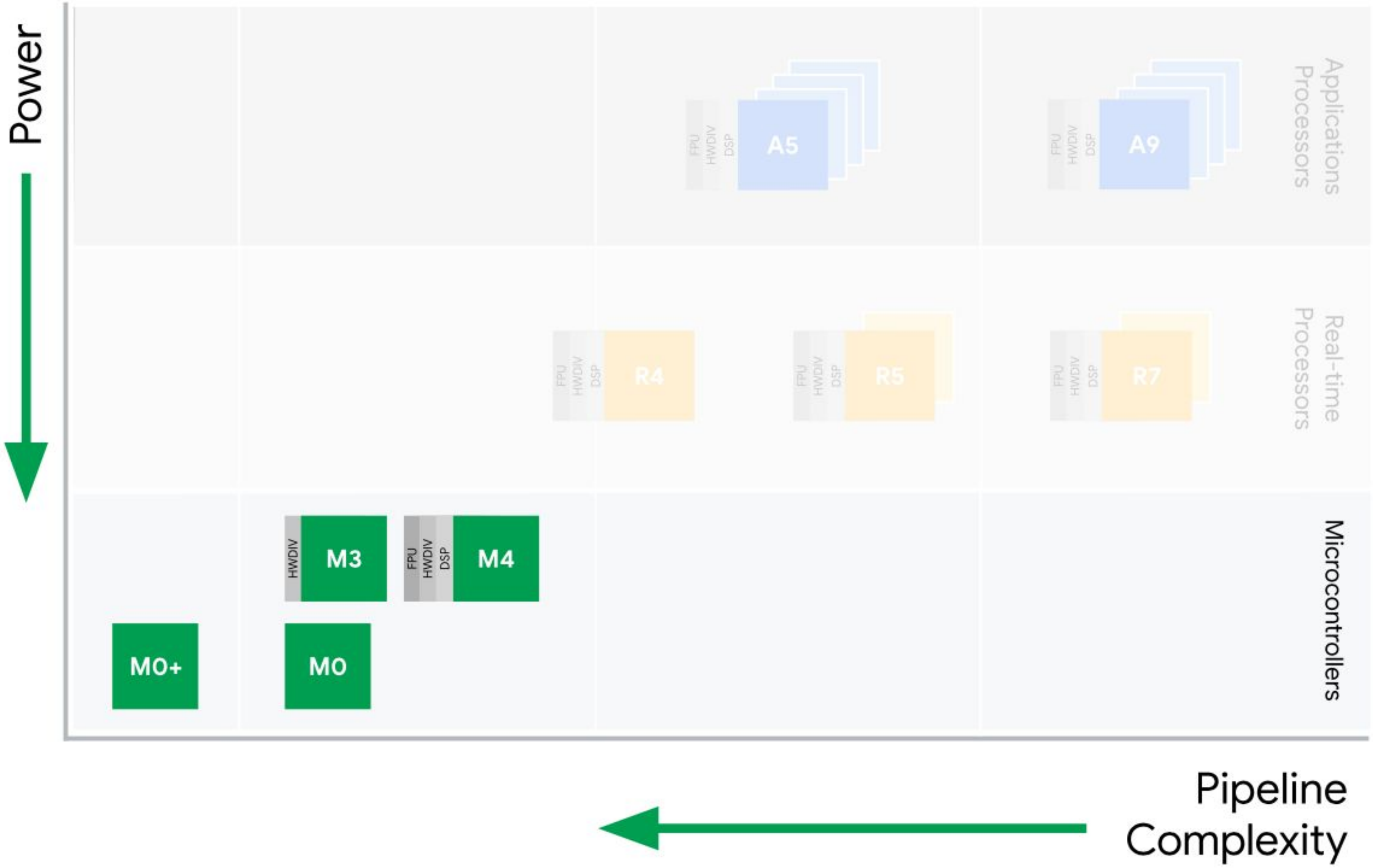
ARM Cortex Processor Profiles



ARM Cortex Profiles



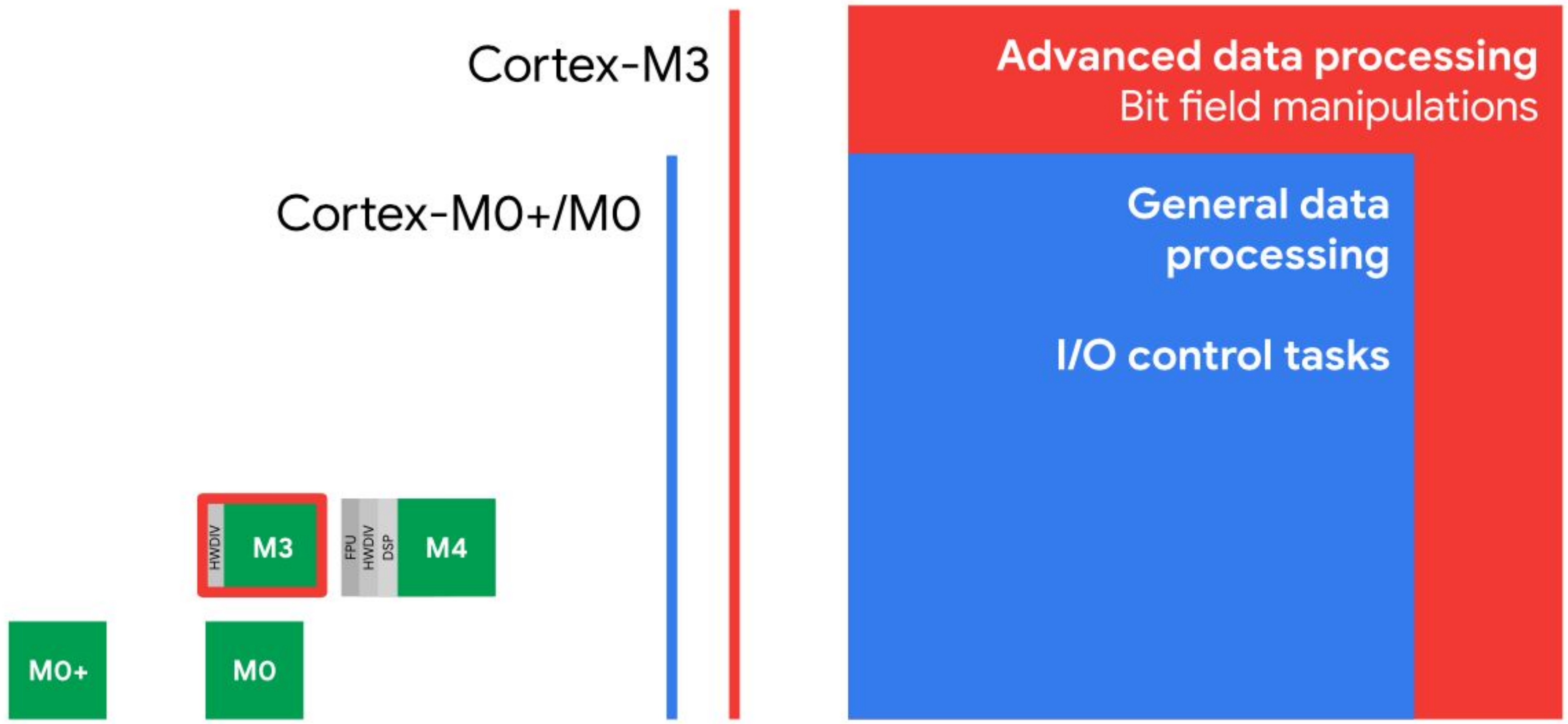
ARM Cortex Profiles



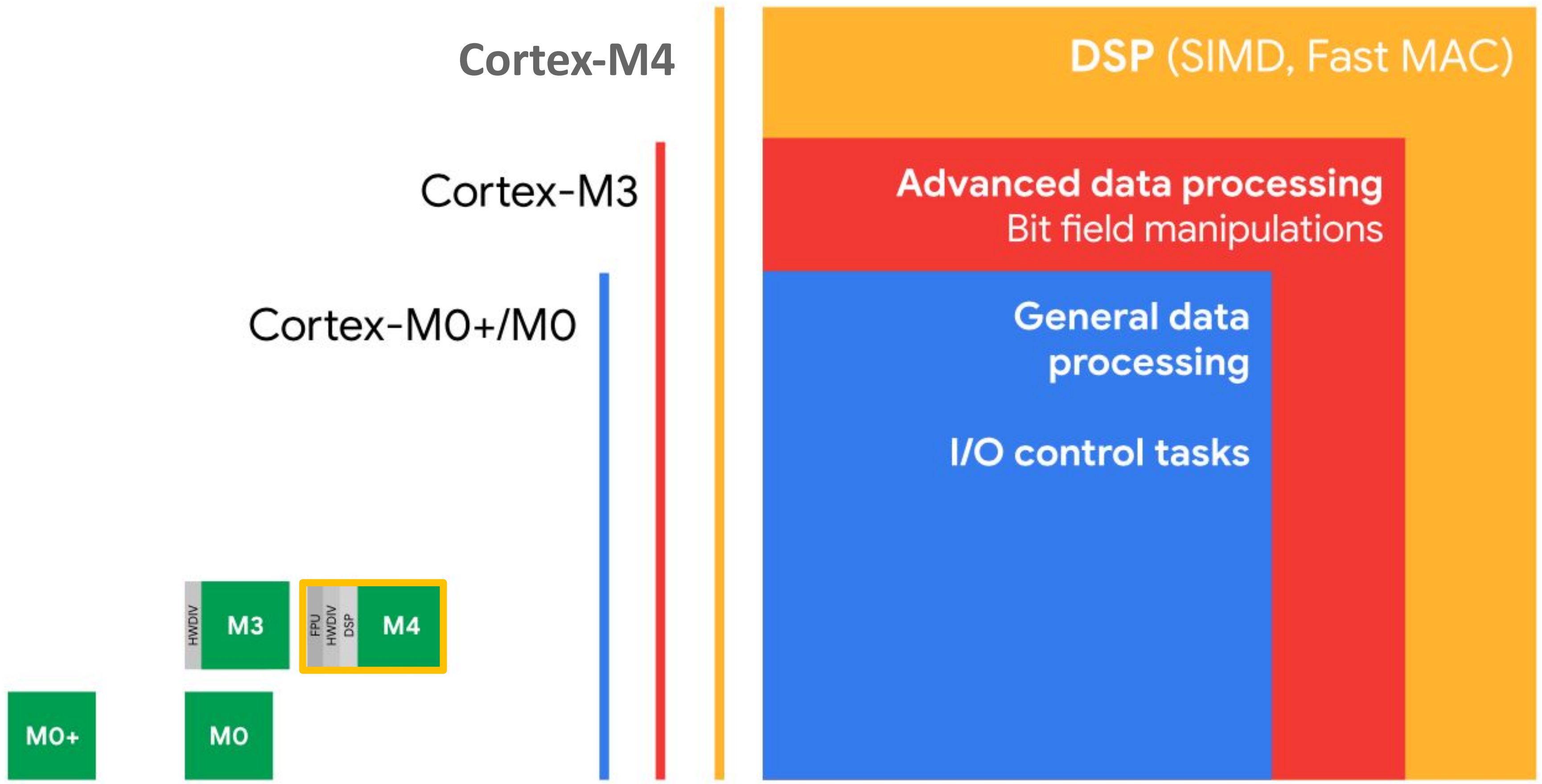
ARM **Cortex-M** ISA

Cortex-M0+/M0

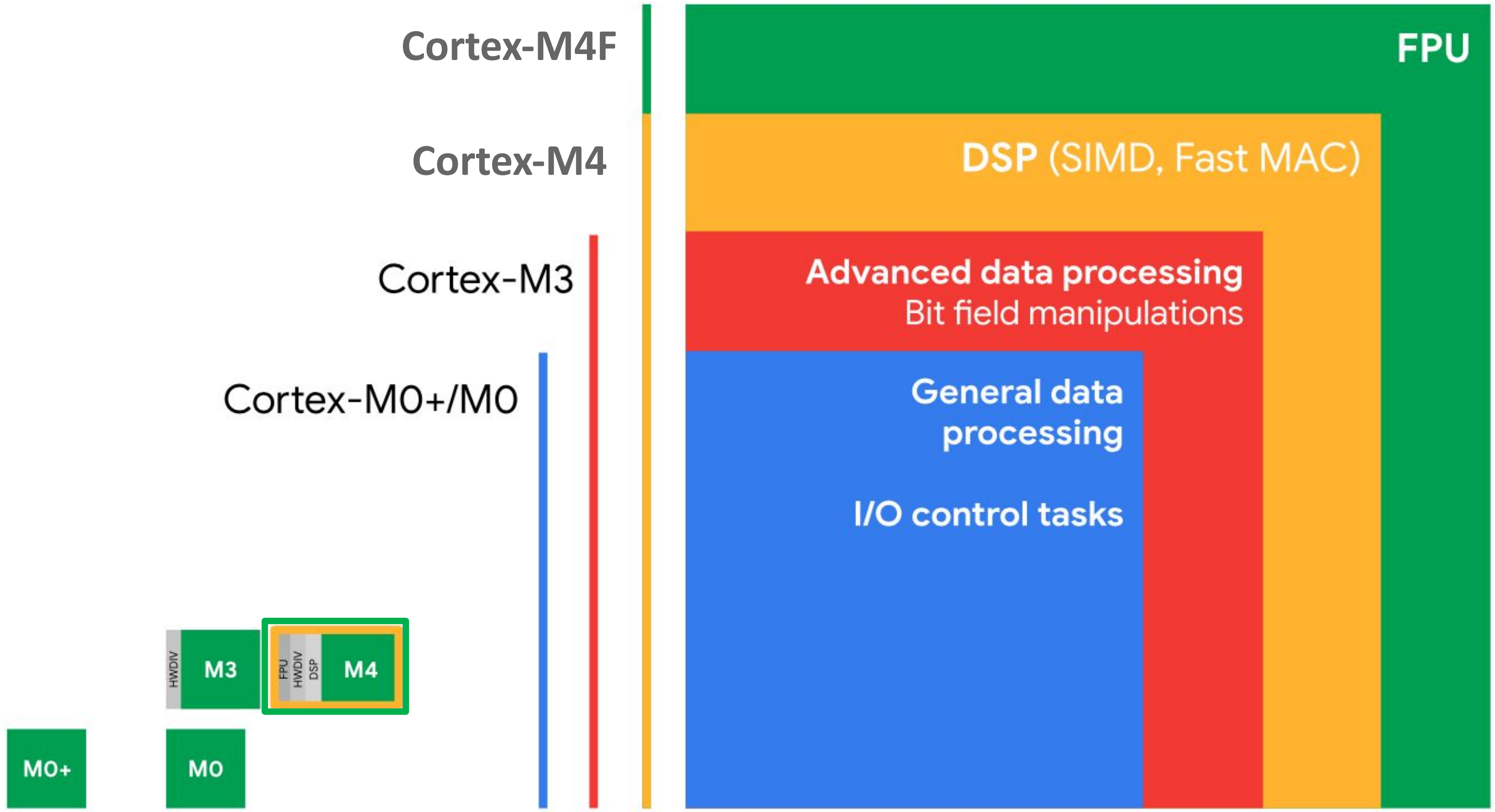
ARM **Cortex-M** ISA

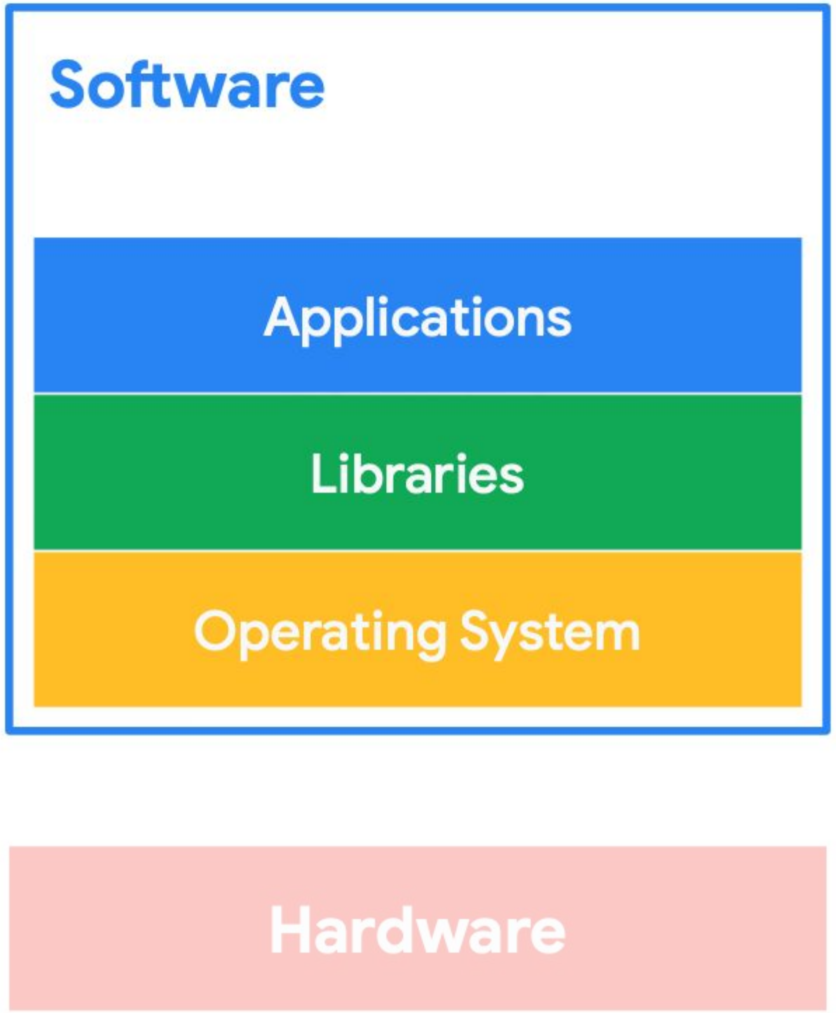


ARM **Cortex-M** ISA



ARM **Cortex-M** ISA

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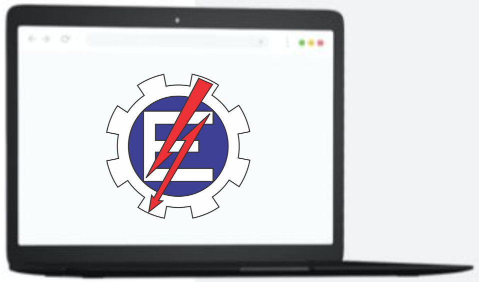
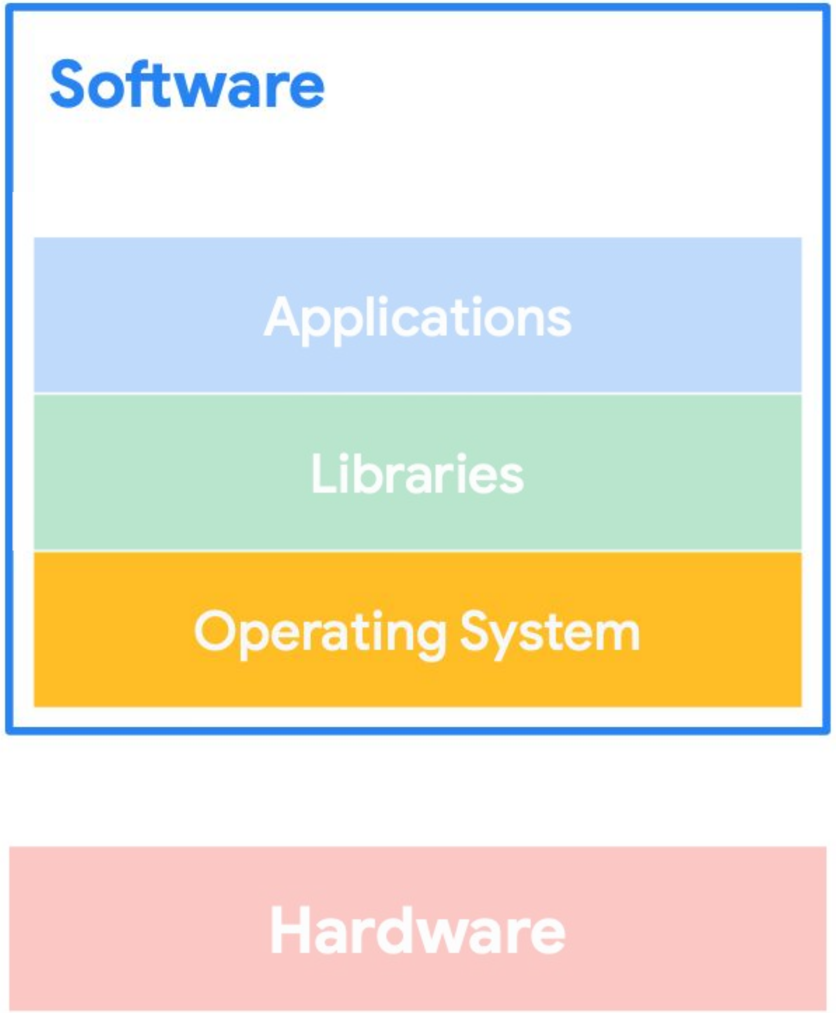
Hardware



Software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Widely Used Operating Systems

mac OS

Linux

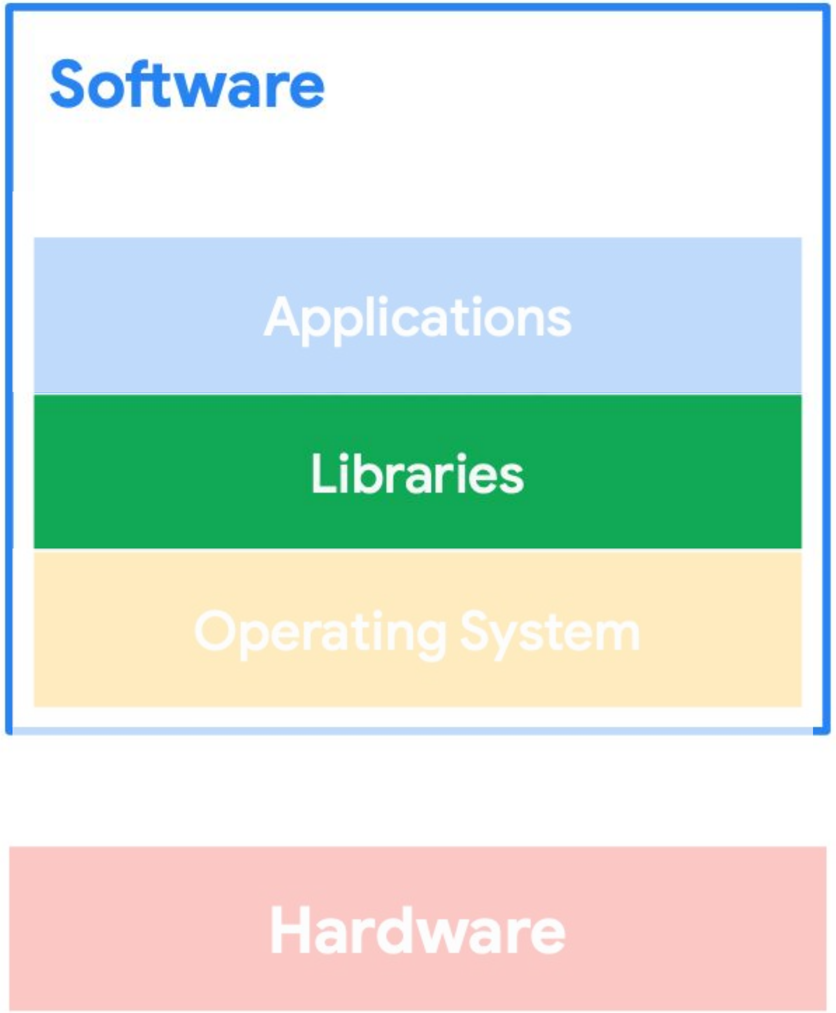
iOS

Mobile OS

free RTOS

arm MBED OS

Embedded Sys.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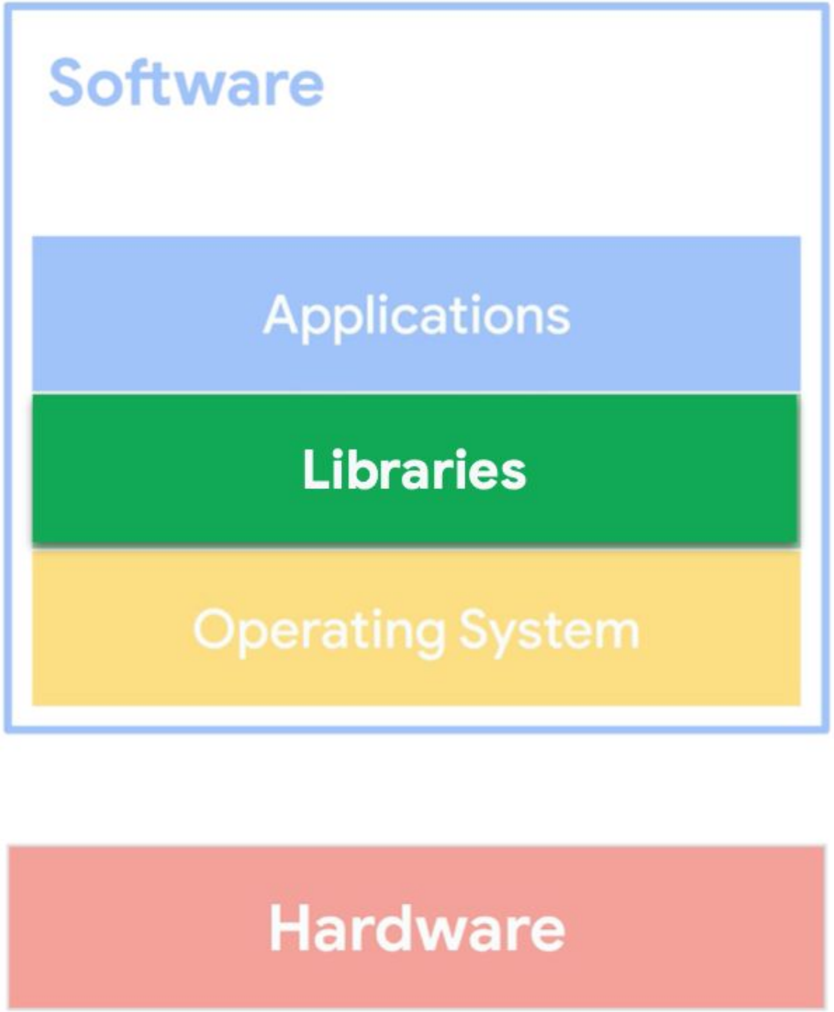
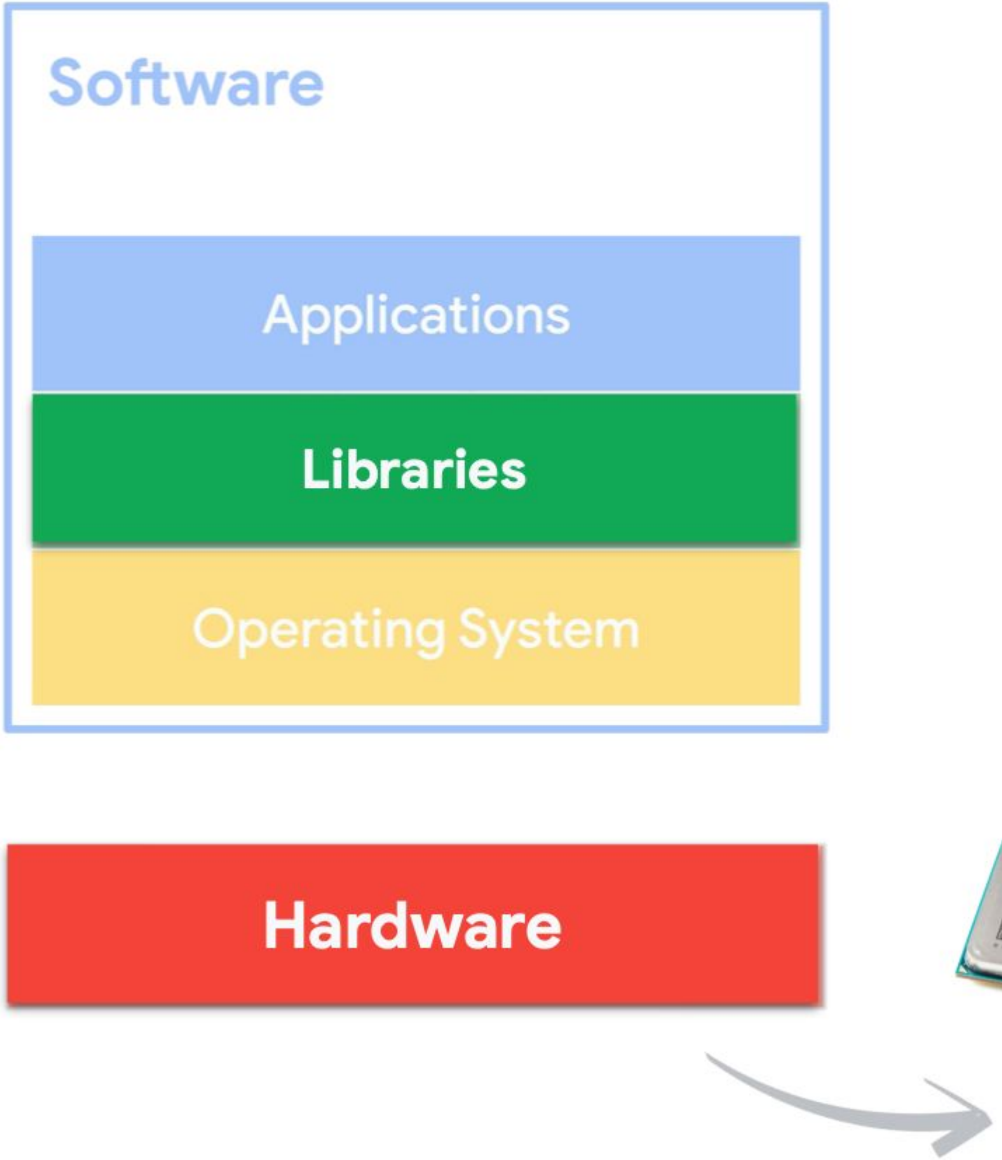


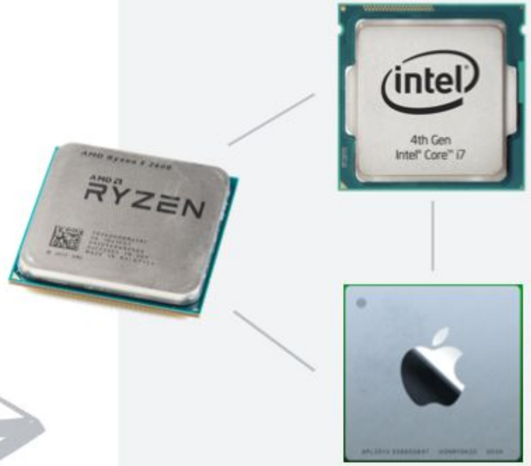

```python
import numpy as np

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

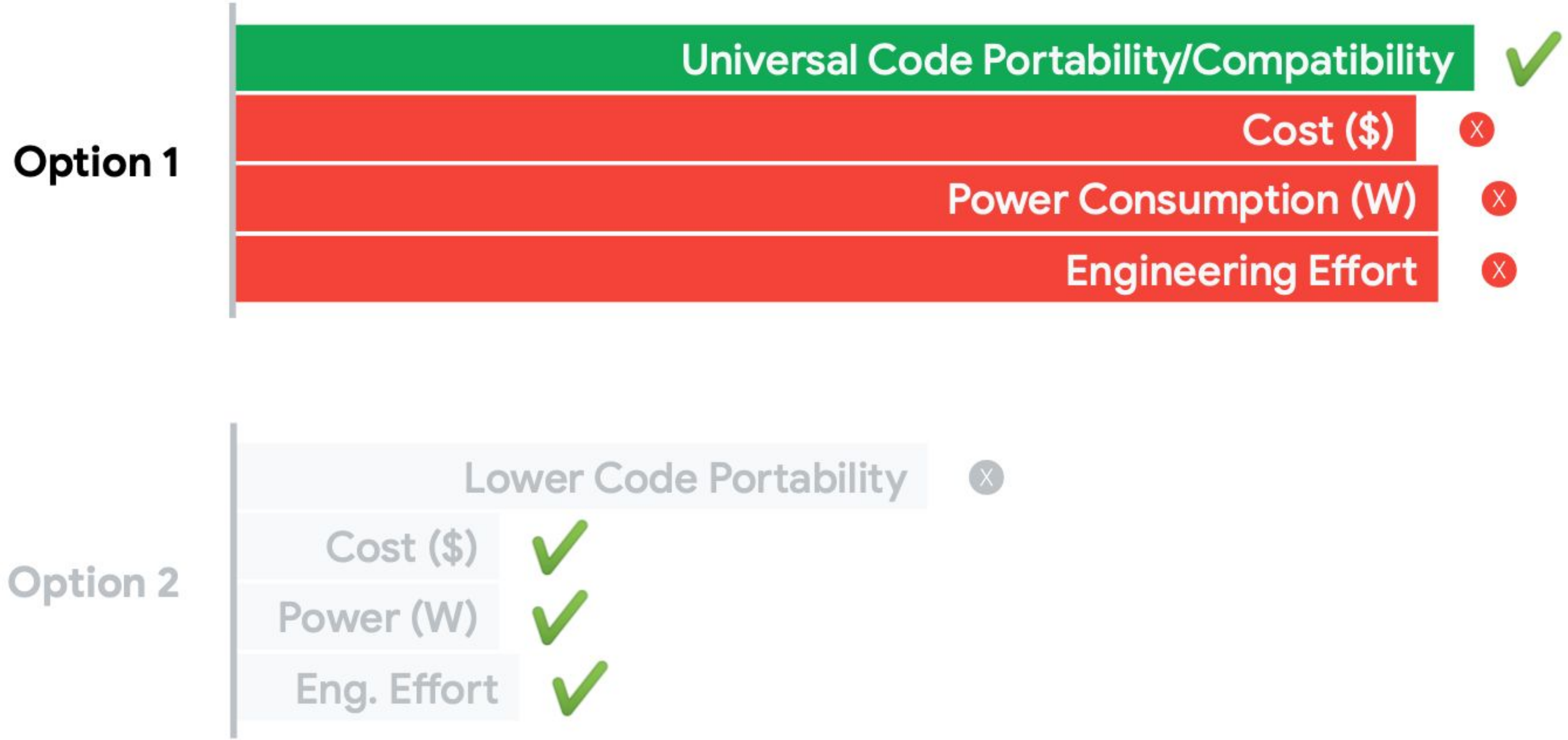


Portability Opportunity

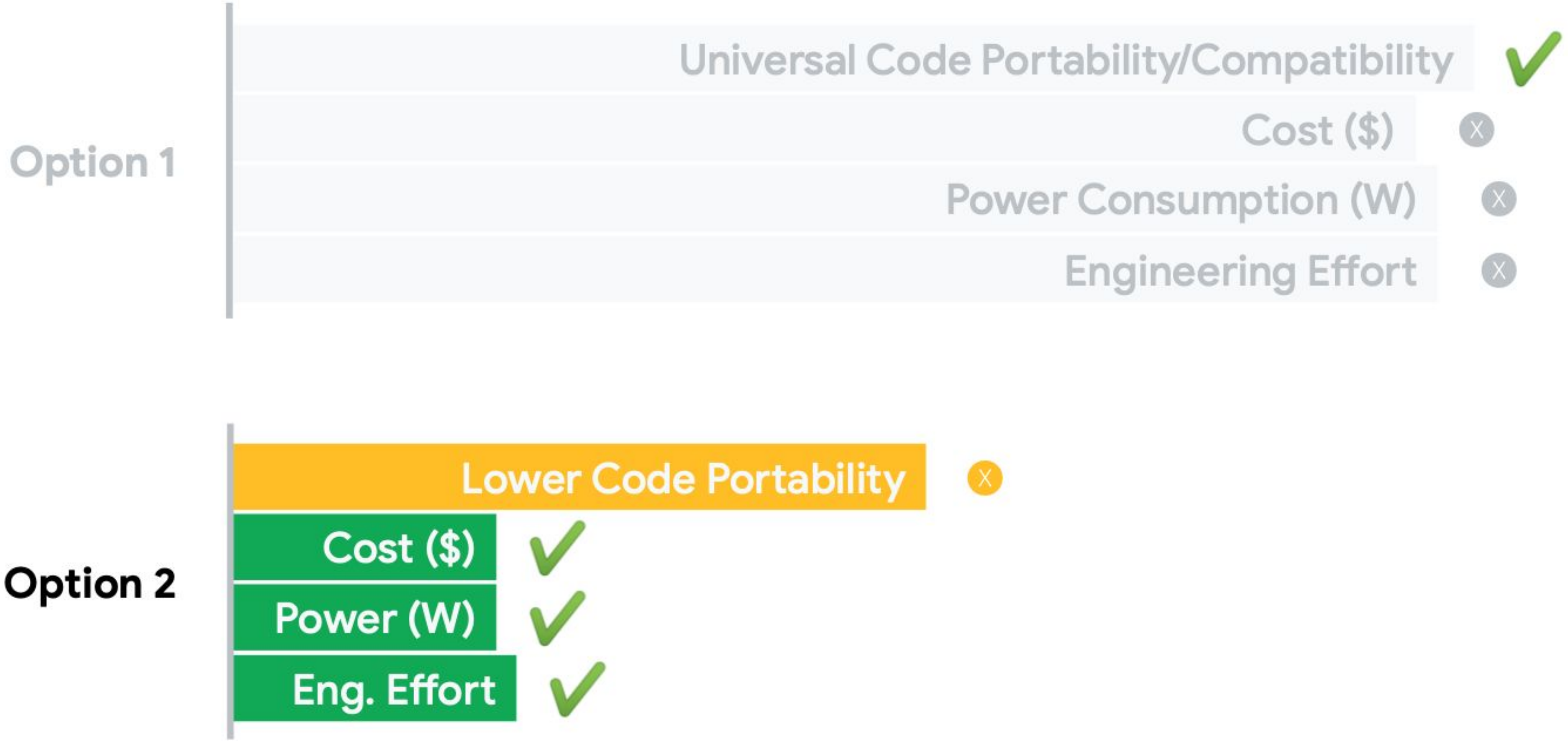
Able to execute the same code on different microprocessor hardware and architectures.



Portability **Trade-offs**

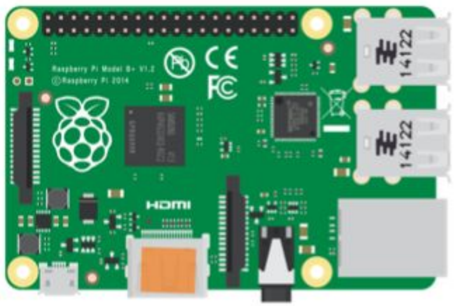


Portability **Trade-offs**



Portability **Trade-offs**

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



X	✓
Specific HW Implementation of a Library	

Option 2

Lower Code Portability	X
Cost ($)	✓
Power (W)	✓
Eng. Effort	✓

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: “TinyML” by Pete Warden, Daniel Situnayake
- Deploy textbook “TinyML Cookbook” by Gian Marco Iodice

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 TinyML4D, an initiative to make TinyML education available to everyone globally.

Thanks

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