TinyML: Machine Learning meets the Internet of Things

Pietro Manzoni

- Universitat Politècnica de València (UPV)
- Valencia - SPAIN
- pmanzoni@disca.upv.es

http://grc.webs.upv.es/

TinyML = IoT + ML

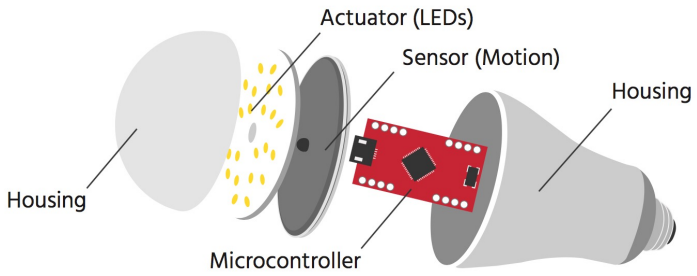
- The **Internet of Things** (IoT) refers to a system of interrelated, Internet-connected objects ("*things*"), that can collect and transfer data.

- **Machine Learning** is typically associated with computationally heavy cloud-based solutions with relatively high latencies, high power consumption, and the need for high bandwidths links.

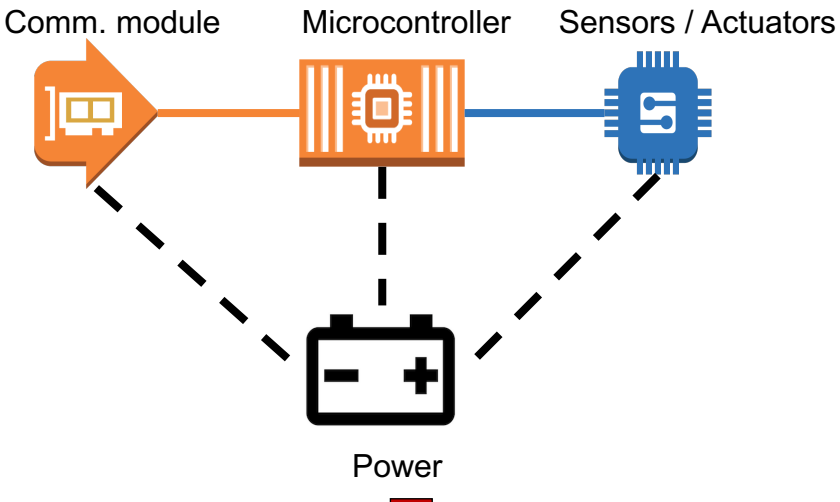
- **With TinyML, IoT and ML come together by shrinking deep learning networks to fit on tiny hardware, thus requiring low energy, low bandwidth links, and reduced latencies.**

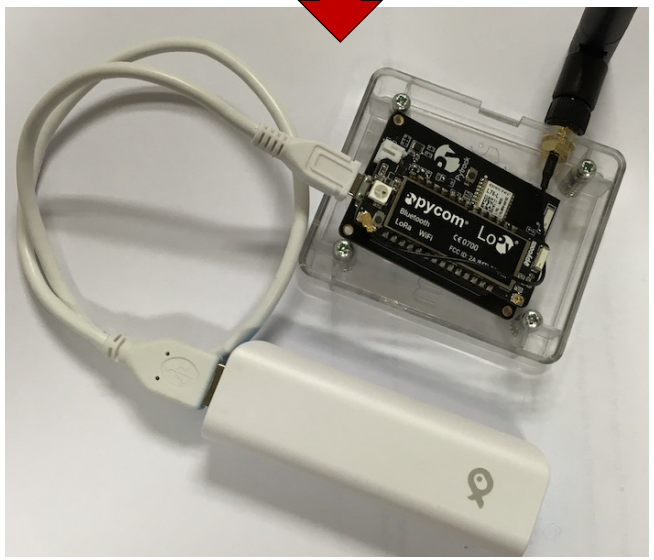
Things

- A "thing" generally consists of **four main parts:**
  - Sensors & actuators
  - Microcontroller
  - Communication unit
  - Power supply
- A "thing" has the **following properties**:
  - It's usually powered by battery. This implies limited source of energy.
  - It's generally small in size and low in cost. This limits their computing capability.



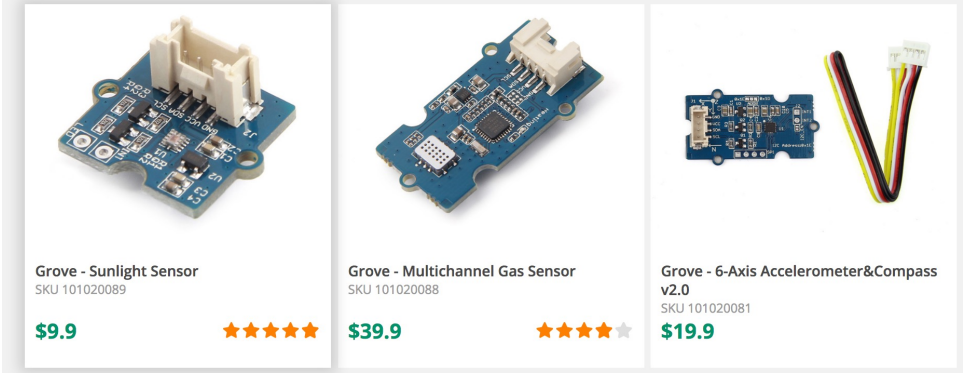
A Reference Guide to the Internet of Things Copyright © 2017 Bridgera LLC, RIoT

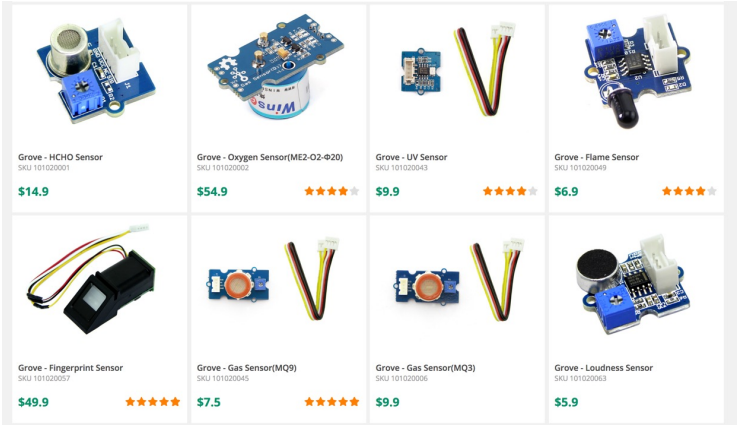




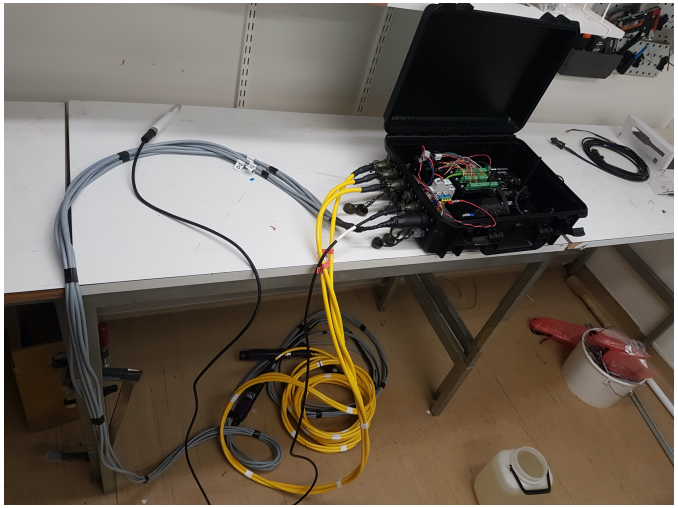
Classic Sensors

cheap...

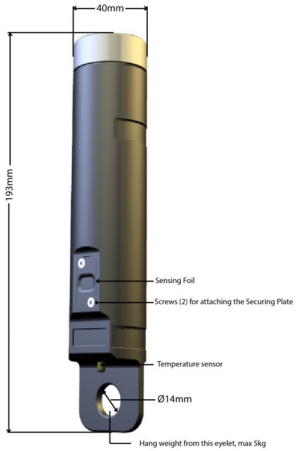




expensive...



1.2 **Oxygen Optode 4531 dimensions**

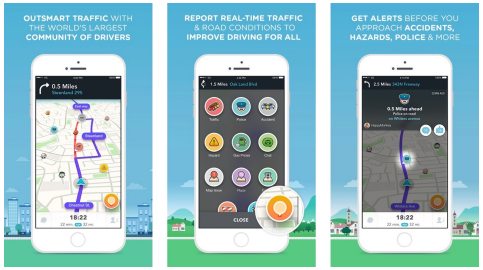


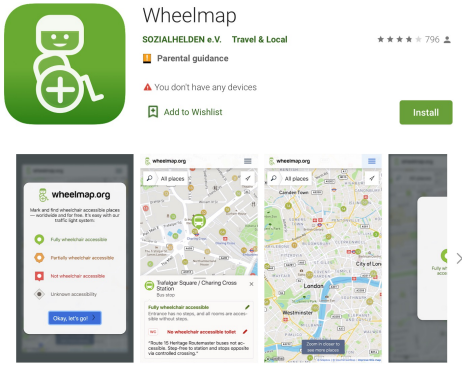
Parameter	Output	Default range[2)]	Calibrated range	Accuracy	Resolution
Oxygen Concentration	0 - 5V	0 to 800µM	0 to 500µM	<8µM or 5% whichever is greater	< 1µM
	4 - 20mA	0 to 800µM	0 to 500µM	<9µM or 5.2% whichever is greater	< 1µM
Oxygen Saturation	0 - 5V	0 – 200%	0 - 120%	<5 %	<0.4%
	4 - 20mA	0 – 200%	0 - 120%	<5.2 %	<0.4%
Temperature	0 - 5V	-5 to + 35°C	0 - 36°C	±0.1°C	±0.01°C
	4 - 20mA	-5 to + 35°C	0 - 36°C	±0.15°C	±0.02°C

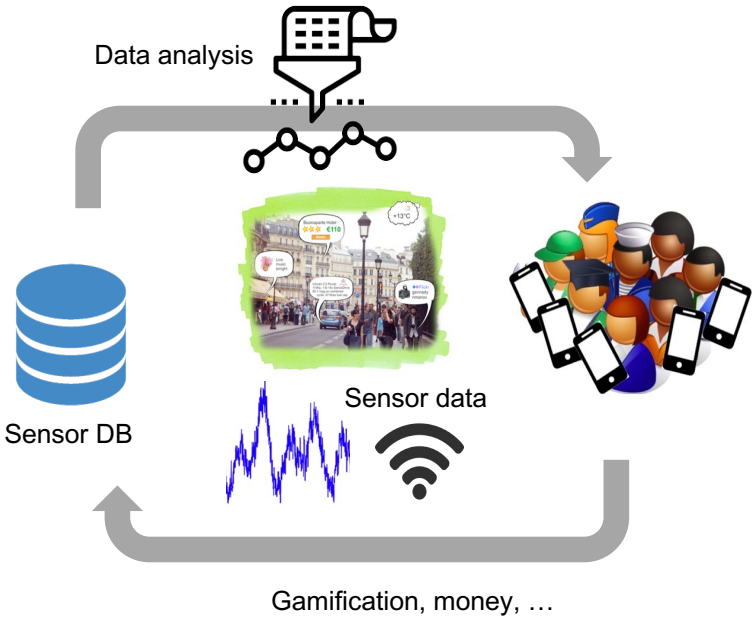
Beyond conventional sensors: humans as sensors

- Social sensing: E.g., tweeting real-world data and/or events

https://www.waze.com





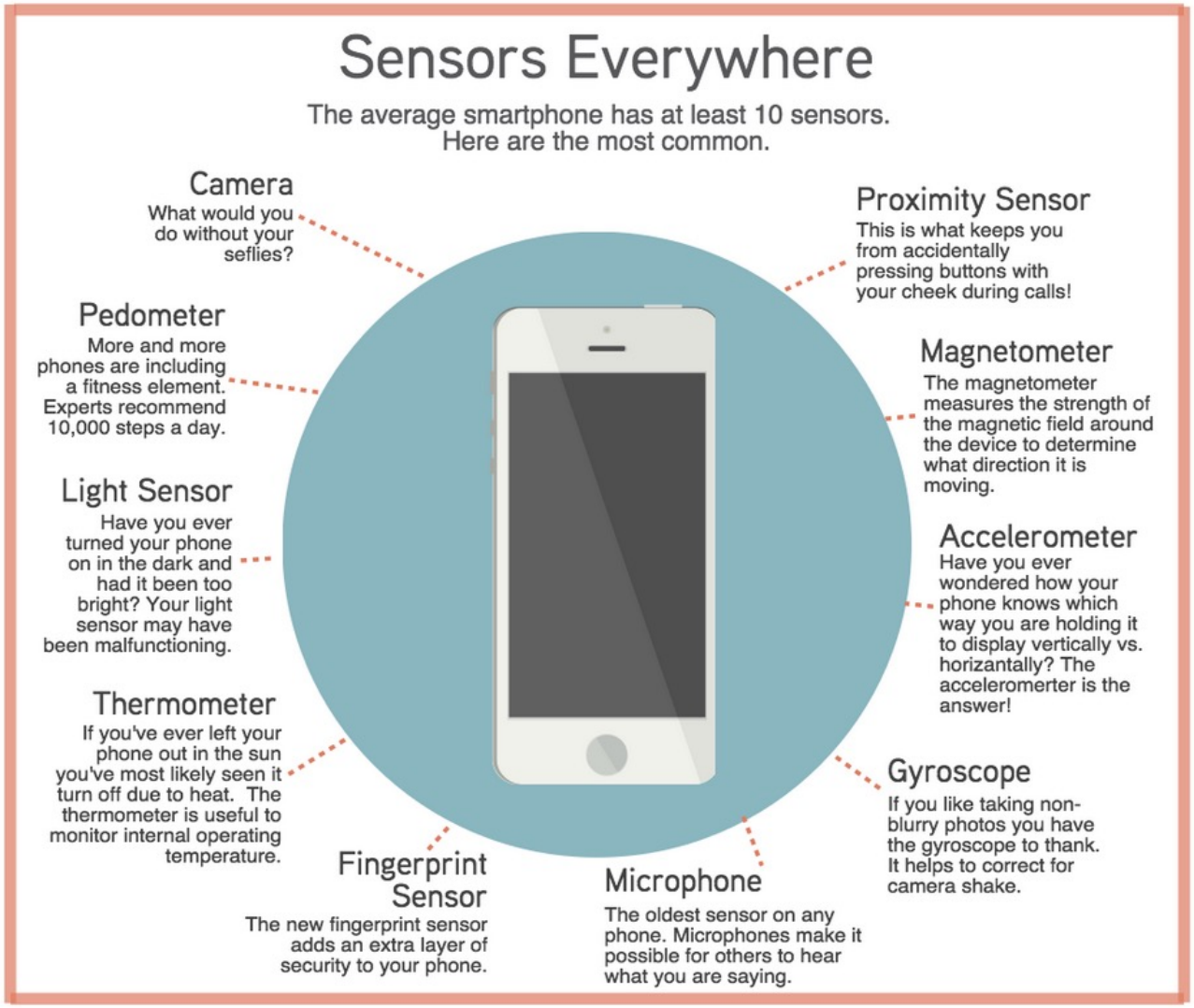


Crowdsensing, crowdsourcing

Participatory crowdsensing, where the users voluntarily participate in contributing information.

Opportunistic crowdsensing, where the data is sensed, collected, and shared automatically without user intervention and in some cases, even without the user's explicit knowledge.

Endpoints have sensors… tons of sensors



https://github-wiki-see.page/m/Apt3kStudio/Phone/wiki/Sensors-on-Smartphones

Power sources

- Today, the **most common power source is a battery**, but there are several other possibilities for power, such as **solar cells, piezoelectricity, radio-transmitted energy, and other forms of power scavenging.**
- Rechargeable batteries are not particularly well-suited to smart objects.
  - Instead of using rechargeable batteries, battery-equipped smart objects are typically designed so a single battery should last the entire lifetime of the smart object.

LiPo

LiPo

Li-ion

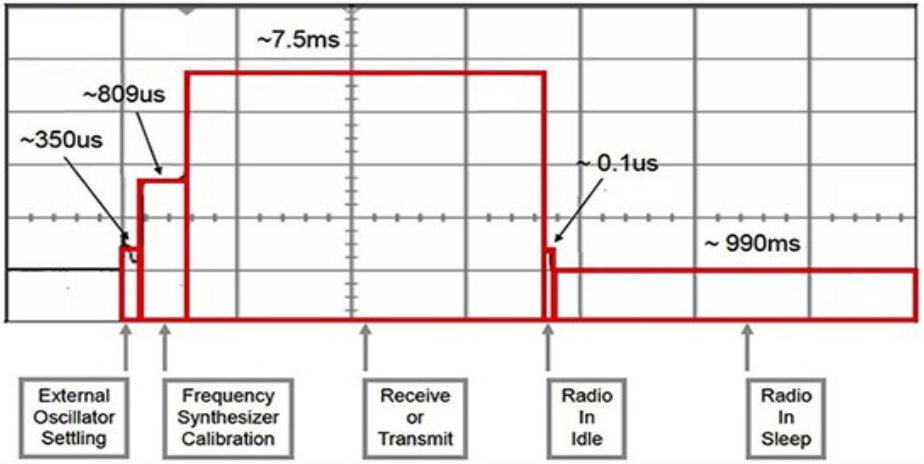
Lithium Ion (Li-ion)
Lithium-Ion Polymer (Li-Po)

How much power can you get from an AA?

- There are around 10,000 Joules in an AA battery.
- There are 31,536,000 seconds in a year.
- So, if you rely on one AA battery, in theory you've got an average 0.000317 watts of continuous power, or 317 µW
- Actually in practice it's a lot more complex with battery characteristics, but a rule of thumb is that three AAs might give you about 1 mW of power for a year, if you're lucky.

Communication Device

- **Of the hardware components of a "thing", the radio is usually the most power-consuming component.**
  - Compared to the power consumption of the microcontroller or the sensors, the radio transceiver often uses ten times as much power.
- For low-power radios, only a small portion of the power consumption is used to send the radio signal into the air.
  - ➔ listening is as power consuming as sending.



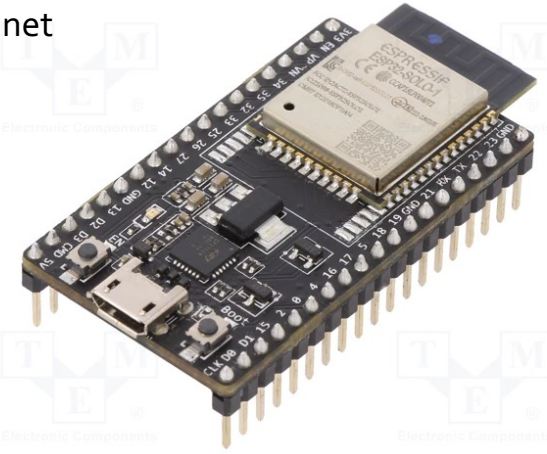
Microcontroller: ESP32

- The ESP32 series employs a Tensilica Xtensa LX6 microprocessor in both dual-core and single-core variations. ESP32 is created and developed by Espressif System

- CPU: Xtensa dual-core (or single-core) 32-bit LX6 microprocessor, operating at 160 or 240 MHz and performing at up to 600 DMIPS
- Memory: 520 KiB SRAM
- Wireless connectivity:
  - Wi-Fi: 802.11 b/g/n
  - Bluetooth: v4.2 BR/EDR and BLE
- Peripheral interfaces:
  - 12-bit SAR ADC up to 18 channels
  - 2 × 8-bit DACs
  - 10 × touch sensors (capacitive sensing GPIOs)
  - ...

https://www.espressif.com/en/products/socs/esp32

http://esp32.net



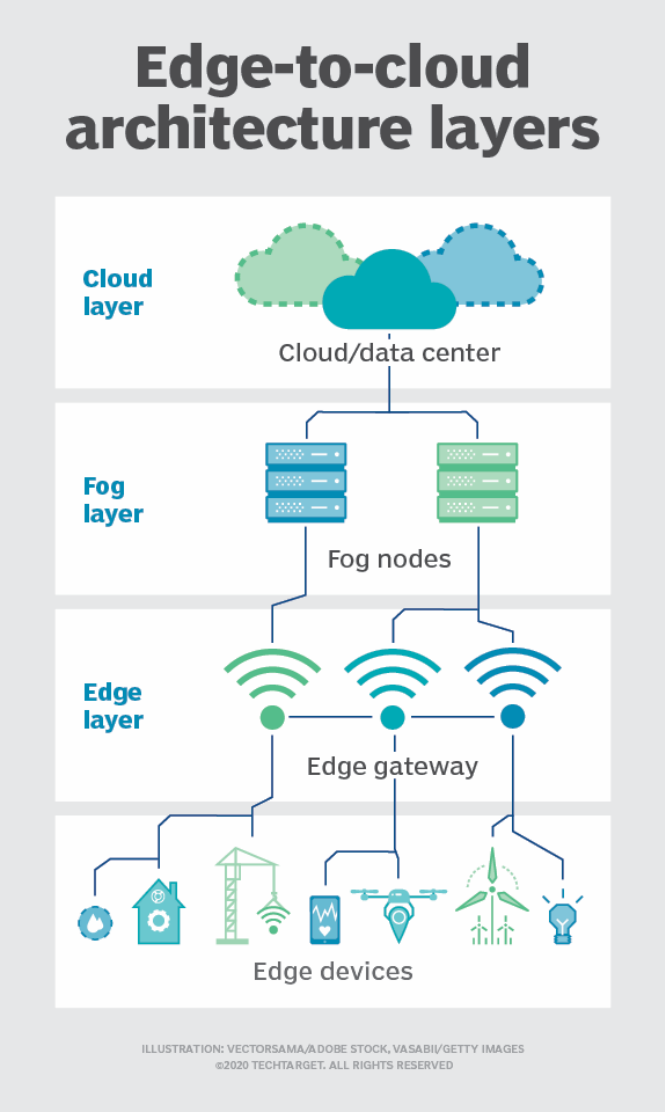
Mode	Min	Typ	Max	Unit
Transmit 802.11b, DSSS 1 Mbps, POUT = +19.5 dBm	-	240	-	mA
Transmit 802.11g, OFDM 54 Mbps, POUT = +16 dBm	-	190	-	mA
Transmit 802.11n, OFDM MCS7, POUT = +14 dBm	-	180	-	mA
Receive 802.11b/g/n	-	95 ~ 100	-	mA
Transmit BT/BLE, POUT = 0 dBm	-	130	-	mA
Receive BT/BLE	-	95 ~ 100	-	mA

Power mode	Description			Power consumption
Modem-sleep	The CPU is powered on.	240 MHz *	Dual-core chip(s)	30 mA ~ 68 mA
			Single-core chip(s)	N/A
		160 MHz *	Dual-core chip(s)	27 mA ~ 44 mA
			Single-core chip(s)	27 mA ~ 34 mA
		Normal speed: 80 MHz	Dual-core chip(s)	20 mA ~ 31 mA
			Single-core chip(s)	20 mA ~ 25 mA
Light-sleep	-			0.8 mA
Deep-sleep	The ULP coprocessor is powered on.			150 μA
	ULP sensor-monitored pattern			100 μA @1% duty
	RTC timer + RTC memory			10 μA
Hibernation	RTC timer only			5 μA
Power off	CHIP_PU is set to low level, the chip is powered off.			1 μA

What does that all mean?

So… Edge Computing

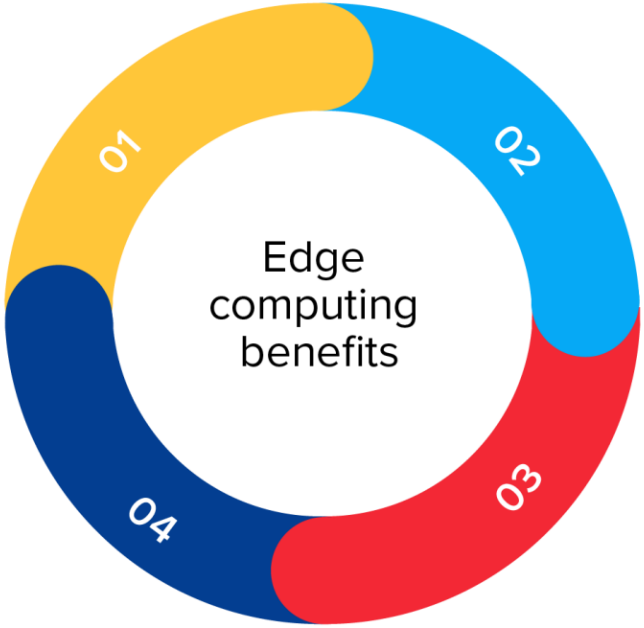
- A possible definition of edge computing is: "a part of a distributed computing topology in which information processing is located close to the edge — where things and people produce or consume that information."



Advantages of Edge Computing

Latency
Reduction of latency by processing the data closer to the customer

Security ➔ Privacy
Computing at the edge provides more security than computing at the cloud because it is less vulnerable to numerous variety of threats due to its scope

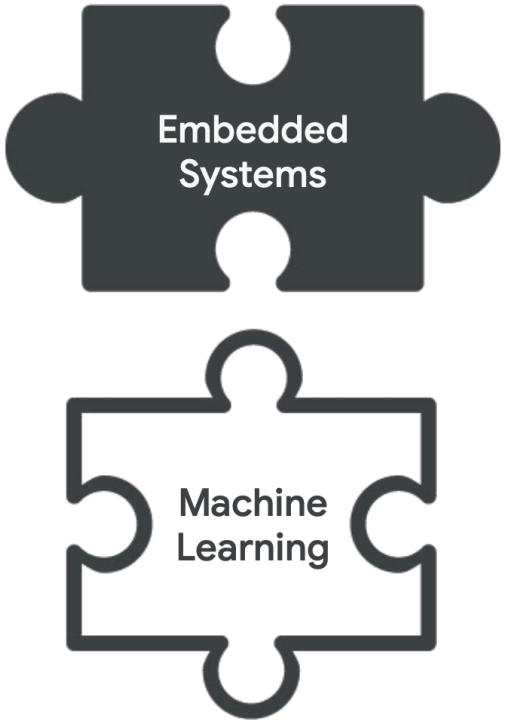


Bandwidth
Sending data from edge to the cloud takes up spectral resources; there's just not enough bandwidth for data transportation

Reliability
By processing data at the edge, you eliminate network reliability problems

https://www.wwt.com/article/show-me-the-money-drive-new-revenue-streams-with-edge-computing

What is TinyML?



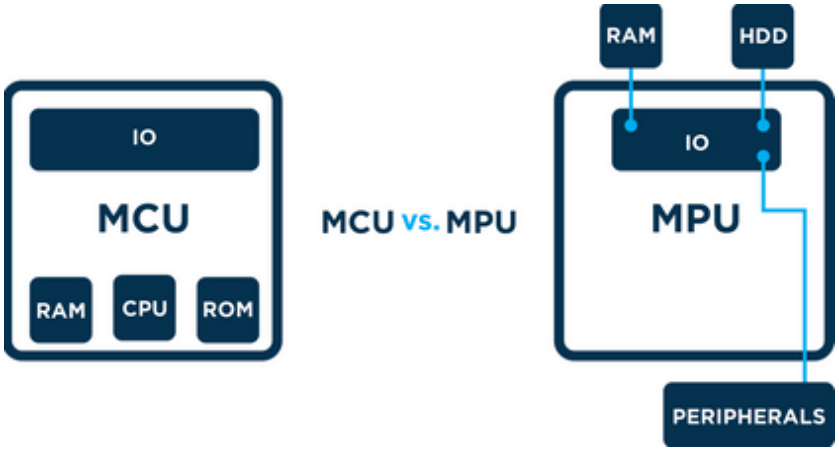
Original definition: "…a neural network model that runs at an energy cost of below 1 mW."
© "TinyML" by Pete Warden, Daniel Situnayake

TinyML

"Tiny machine learning (TinyML) is a fast-growing field of machine learning technologies and applications including algorithms, hardware, and software capable of performing on-device sensor data analytics at extremely low power consumption, **typically in the mW range and below**, enabling a variety of always-on ML use-cases on battery-operated devices."

Microcontroller

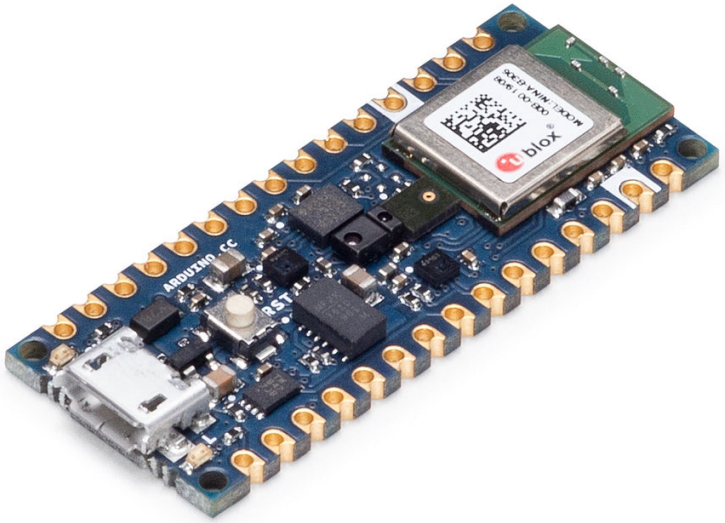
- A microcontroller is a microprocessor with built-in memory, timers, and hardware for connecting external devices such as sensors, actuators, and radio transceivers.
- Typically, a smart object microcontroller has a few kilobytes of on-chip memory and is run at a clock speed of a few megahertz.



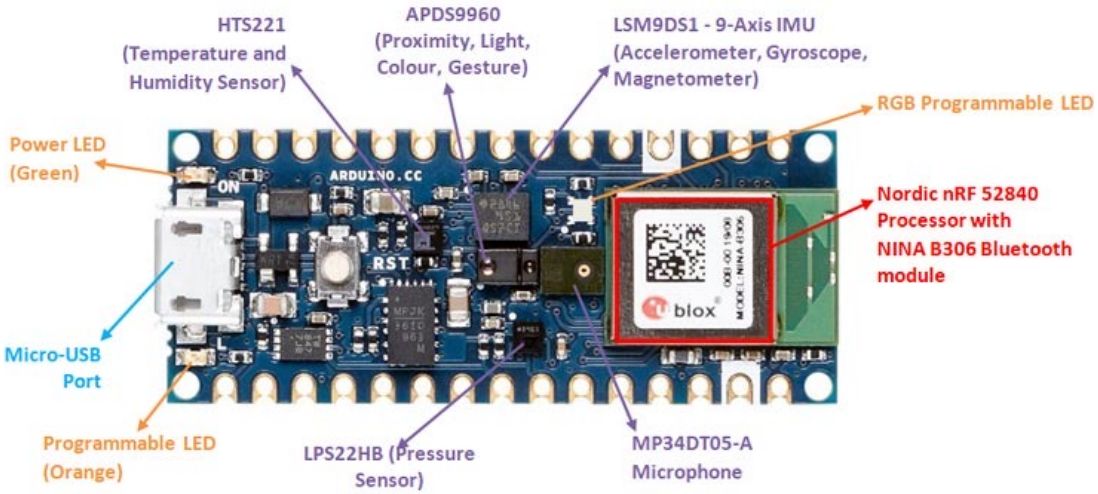
Orders of magnitude

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

Most widely used HW for TinyML (currently)



Arduino Nano 33 BLE Sense
64 MHz **Arm® Cortex-M4**F (with FPU)
1 MB Flash + 256 KB RAM
Bluetooth® 5 multiprotocol radio



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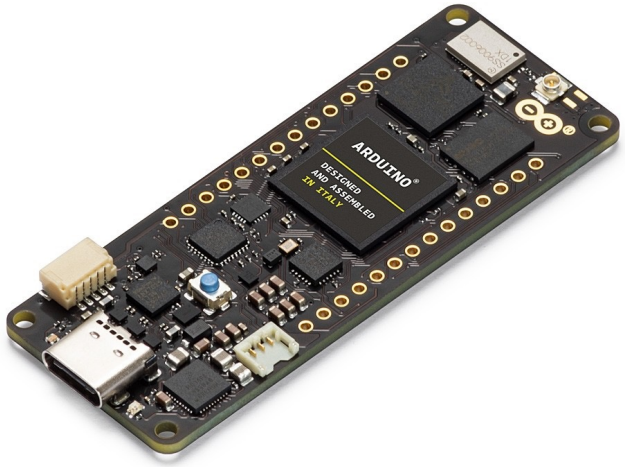
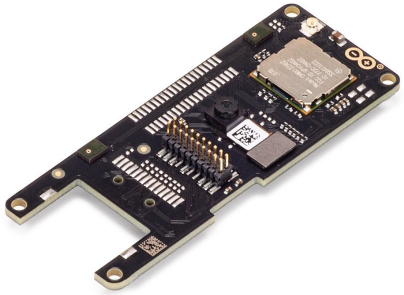
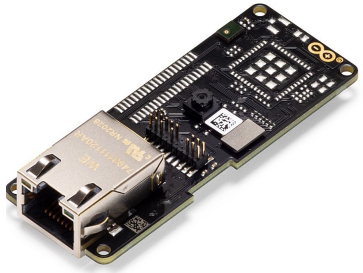






Portenta H7 is probably one of the currently most powerful MCUs.

H7's main processor is the dual core STM32H747 including a Cortex® M7 running at 480 MHz and a Cortex® M4 running at 240 MHz.

The two cores communicate via a *Remote Procedure Call* mechanism.

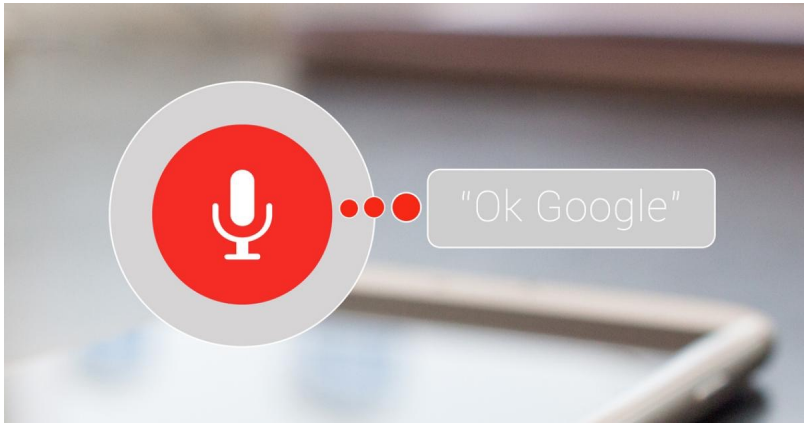
Both processors share all the in-chip peripherals and can run:

- Arduino sketches on top of the Arm® Mbed™ OS
- Native Mbed™ applications
- MicroPython / JavaScript via an interpreter
- TensorFlow™ Lite

Or even… https://ouraring.com/

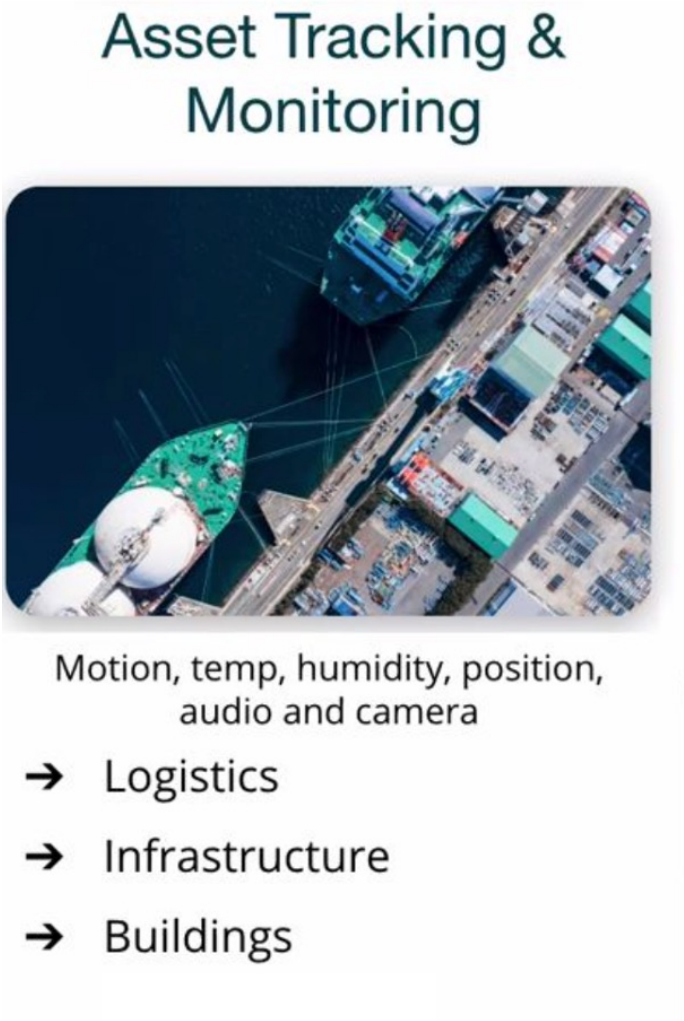
The future of health wrapped around your finger — monitoring your sleep, heart rate, activity, and temperature with personalized insights.

Applications of TinyML: the beginning



Applications examples: asset tracking and monitoring

- Locate and manage assets remotely using sensors in real time
- Track health condition through an interactive dashboard
- Measure machine performance and track missing assets



Applications examples: predictive maintenance

- Using sensors, data collation, analytics and machine learning to monitor equipment continuously and predict failure with far greater accuracy. See for example: https://www.scnsoft.com/blog/iot-predictive-maintenance-guide
  - **Florida Power & Light** has turned to IoT development to deploy a predictive maintenance solution that estimates when turbines are running ineffectively or about to fail
  - **Chevron** has turned to IoT development to roll out a predictive maintenance solution that helps to identify corrosion and pipeline damages.

RAM-1: An Advanced Grid Monitoring Solution

https://www.ram-center.com

But the range of applications is wide…

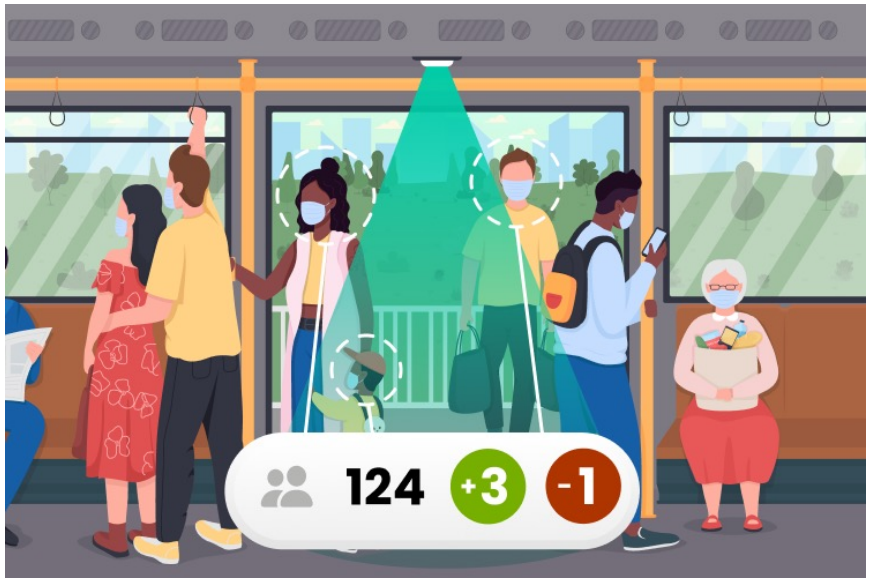
Plant Village: https://plantvillage.psu.edu

But the range of applications is wide…

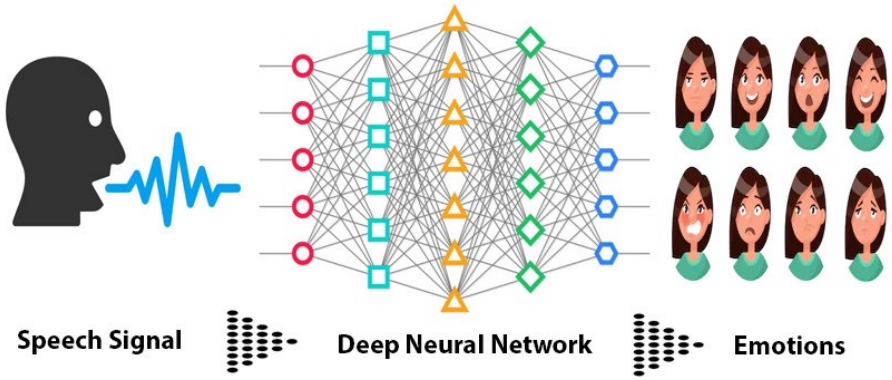
Rainforest Connection: https://rfcx.org/ecoacoustics

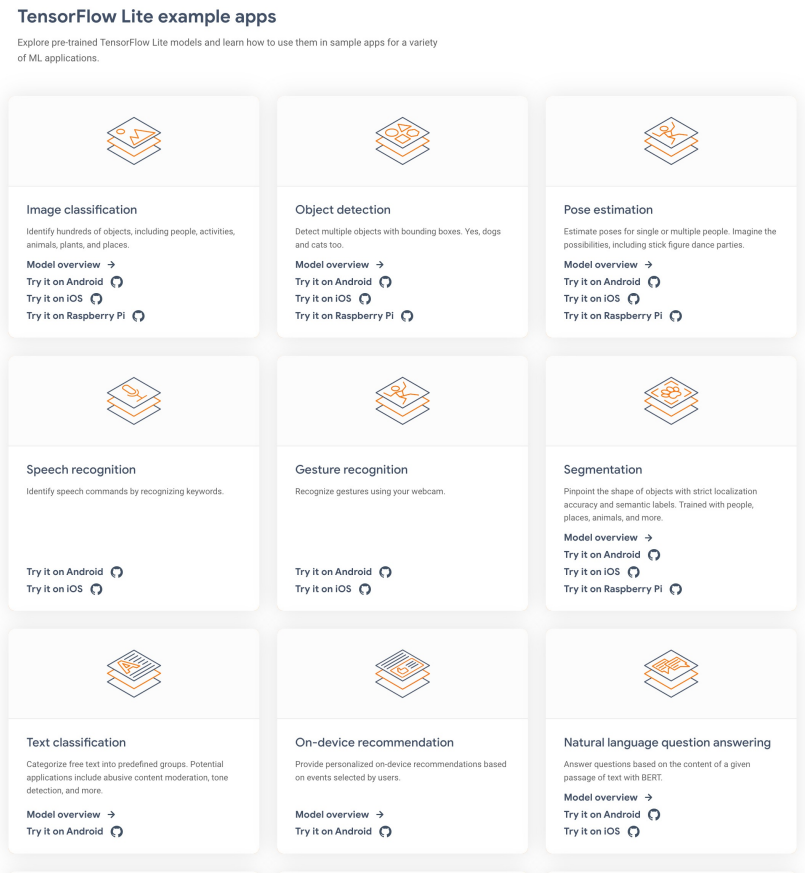
And...

People counting



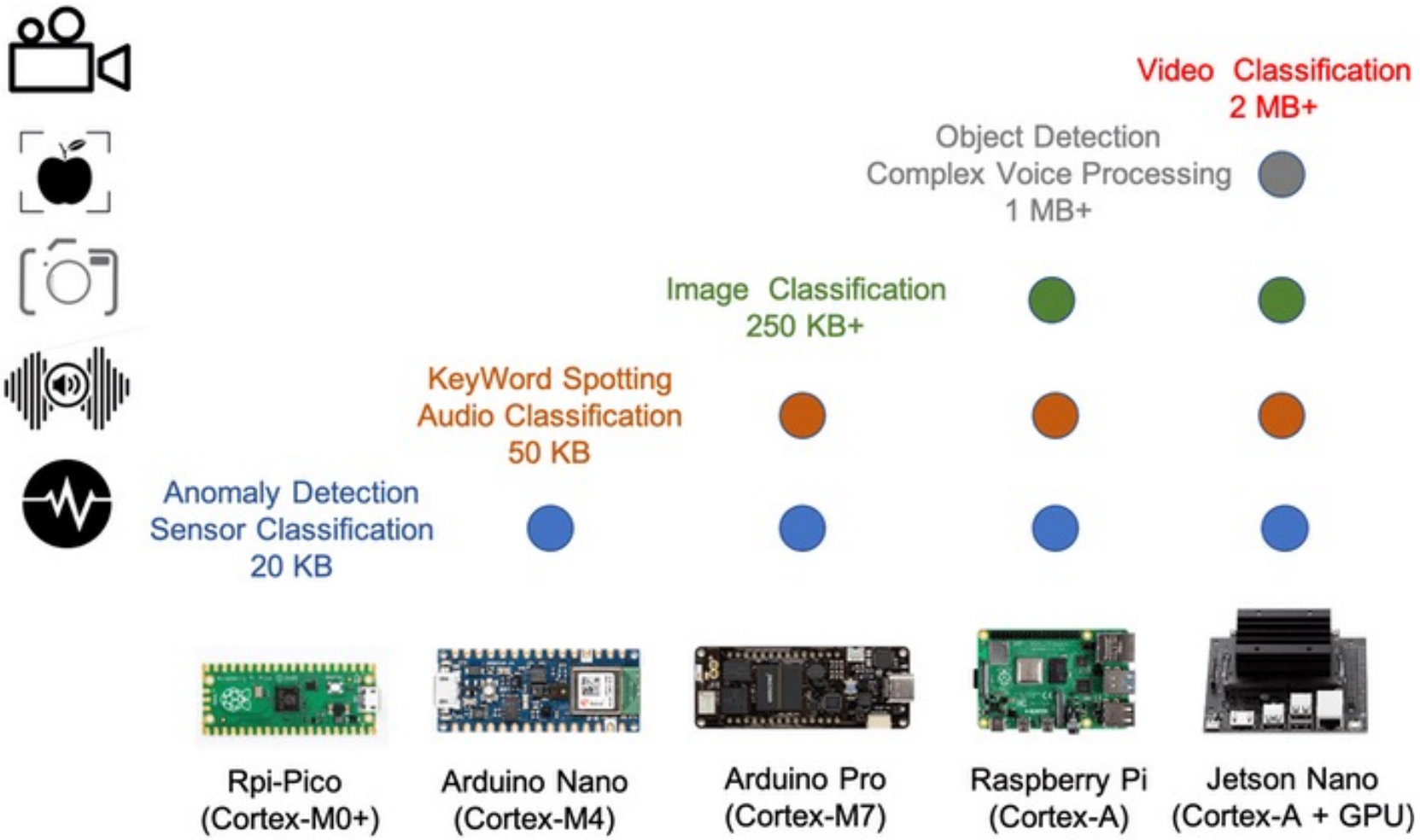
Sentiment analysis



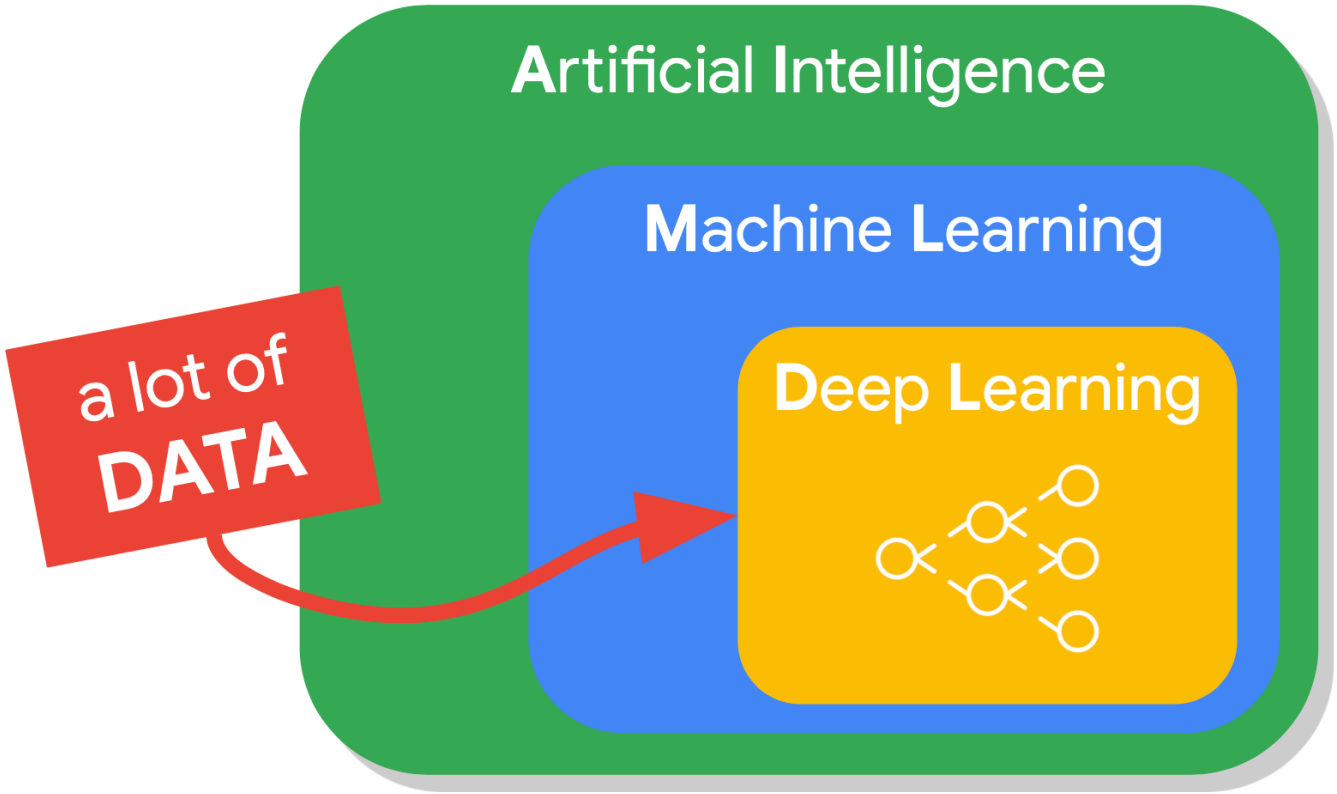


https://www.tensorflow.org/lite/examples

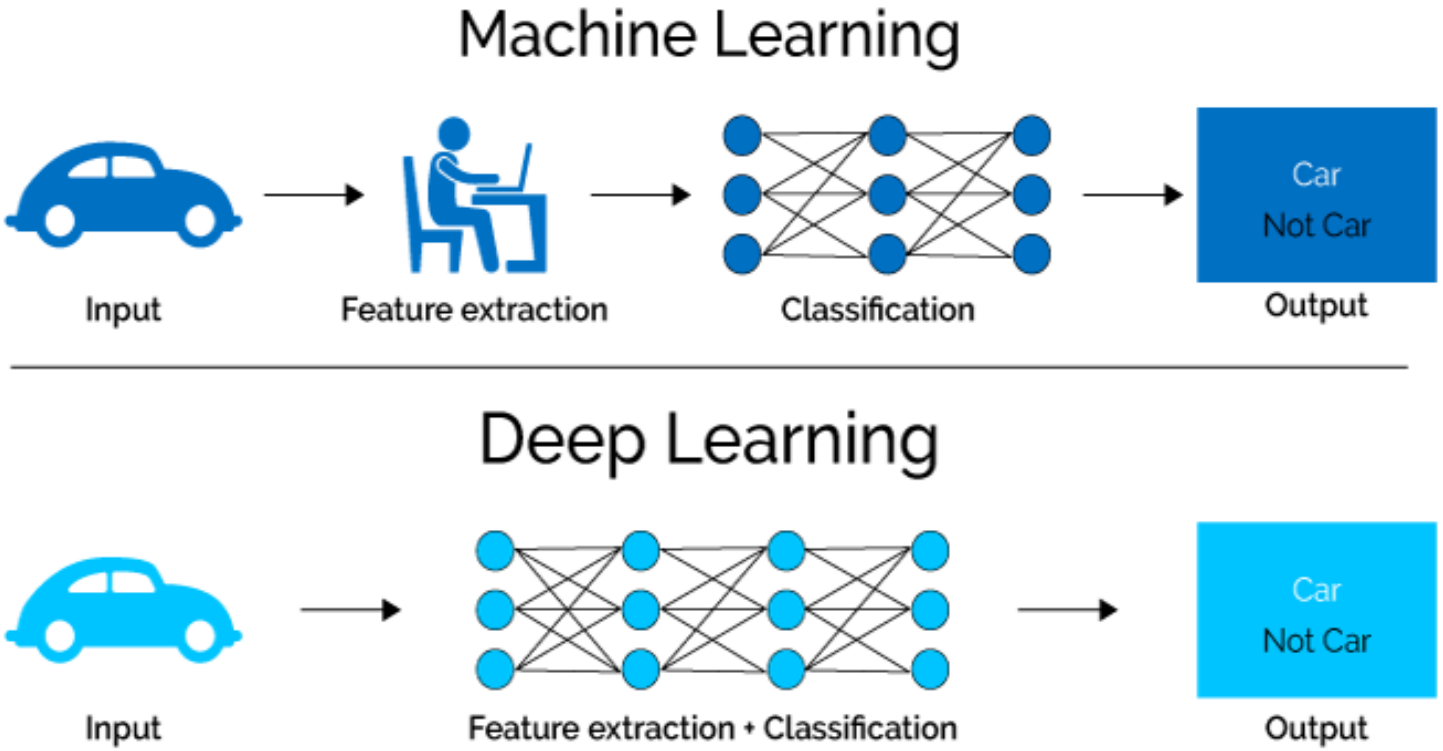
Current limitations



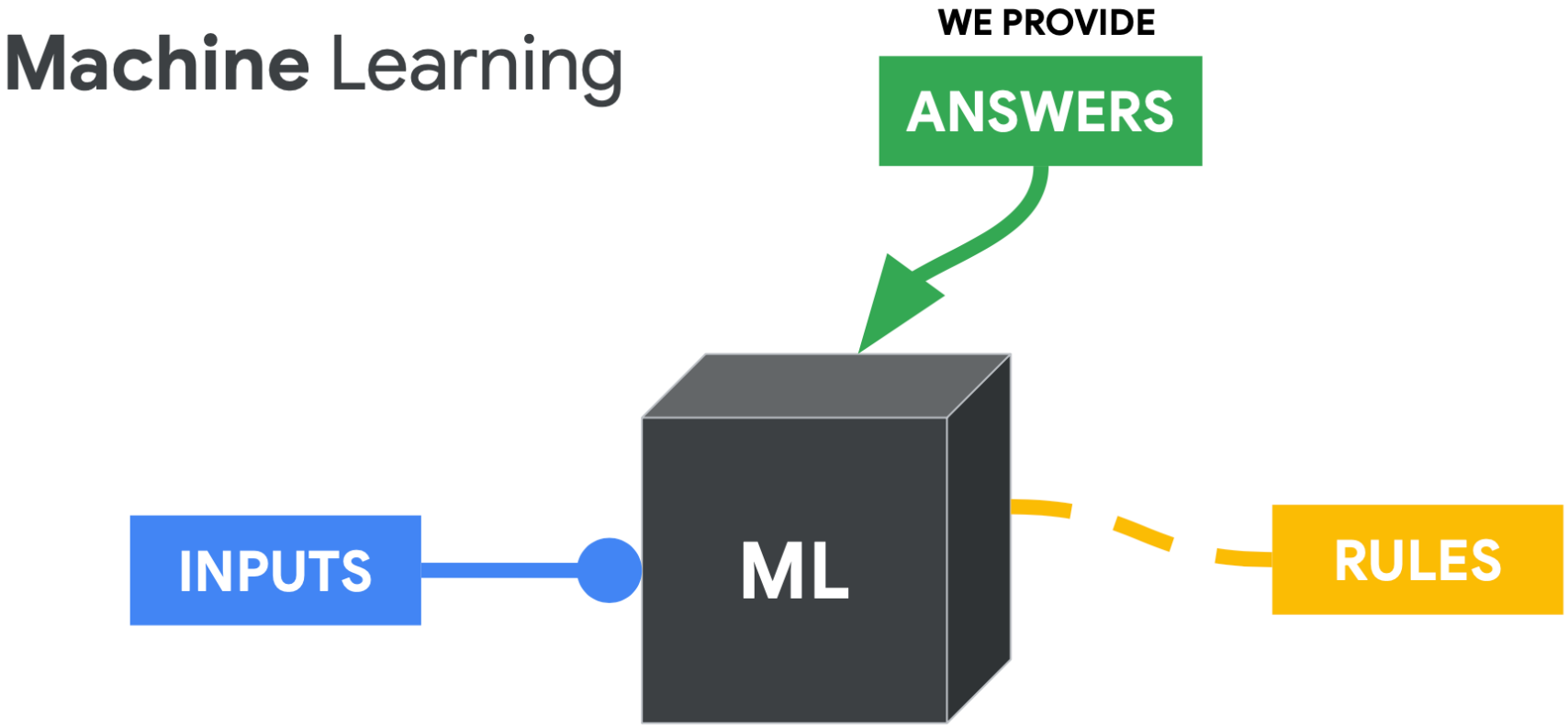
Machine Learning: Some initial definitions



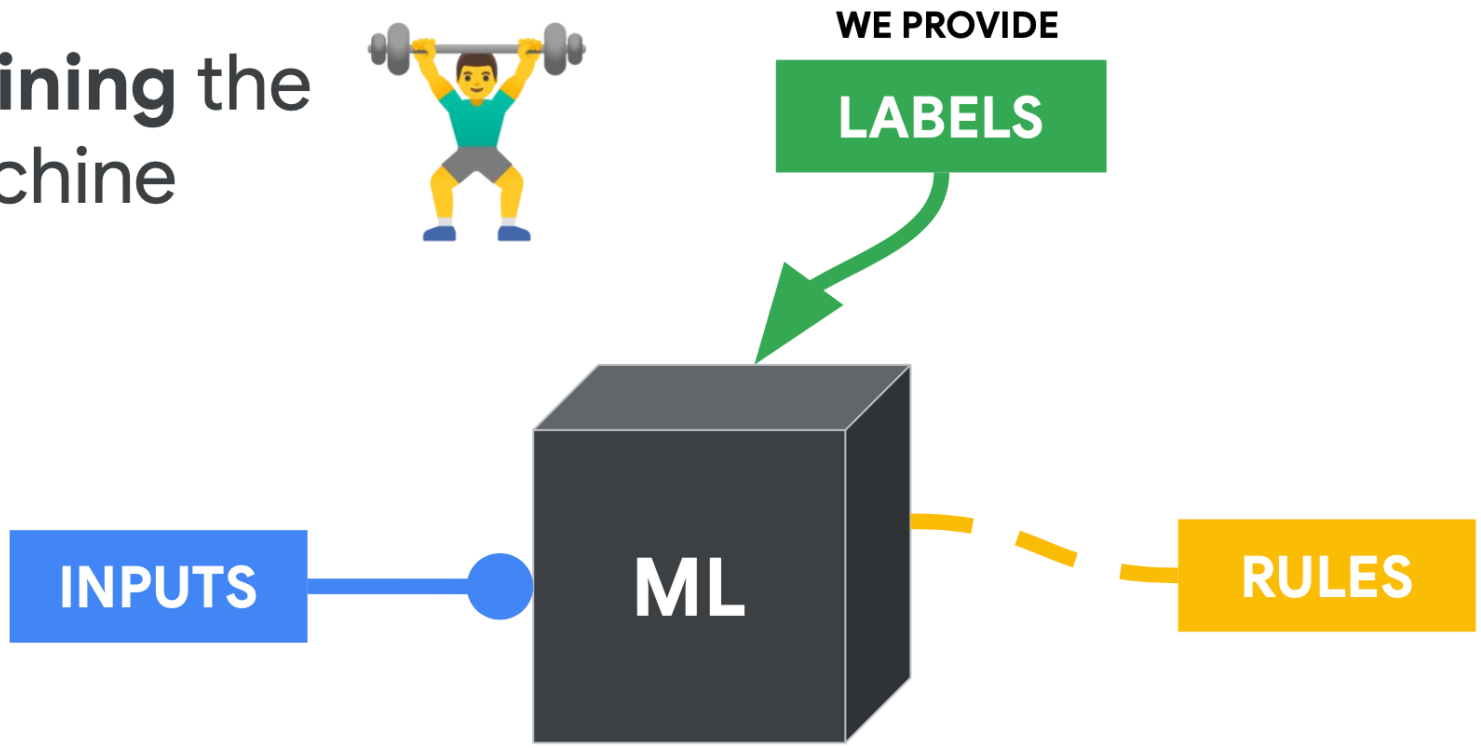
Machine Learning vs Deep Learning



Machine learning

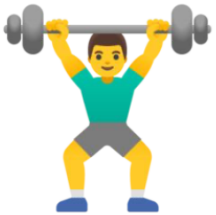


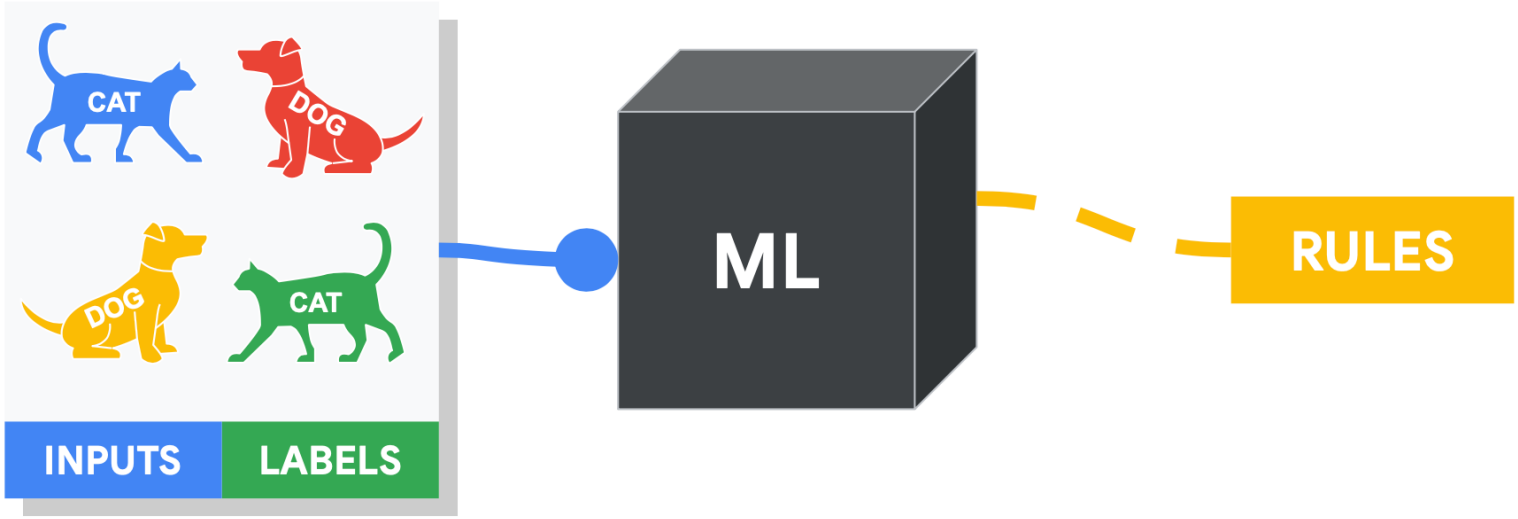
Training



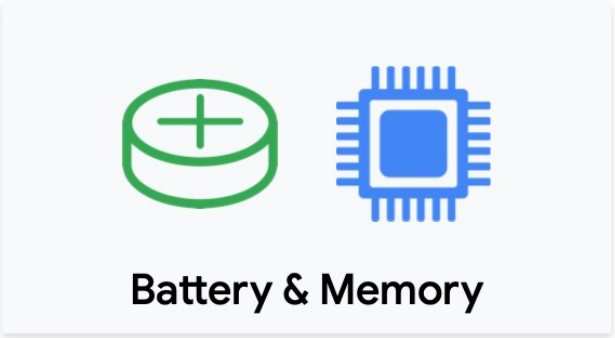
Training

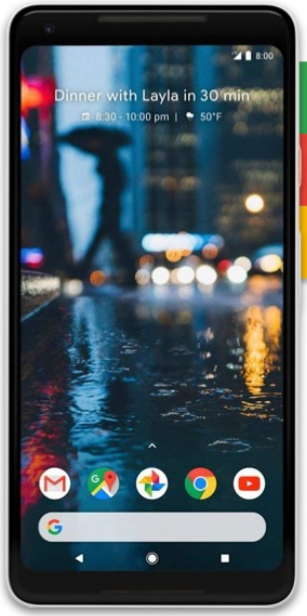
Training the machine





Deploying





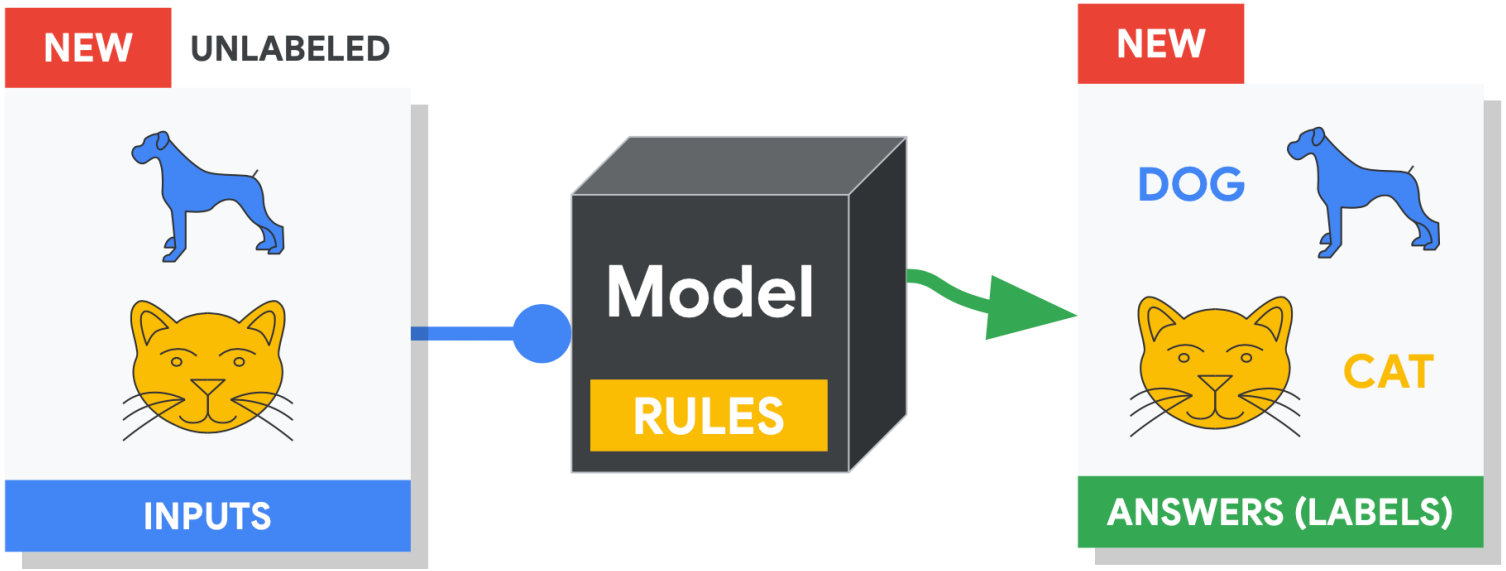
Less memory

Less compute power

Only focused on *inference*

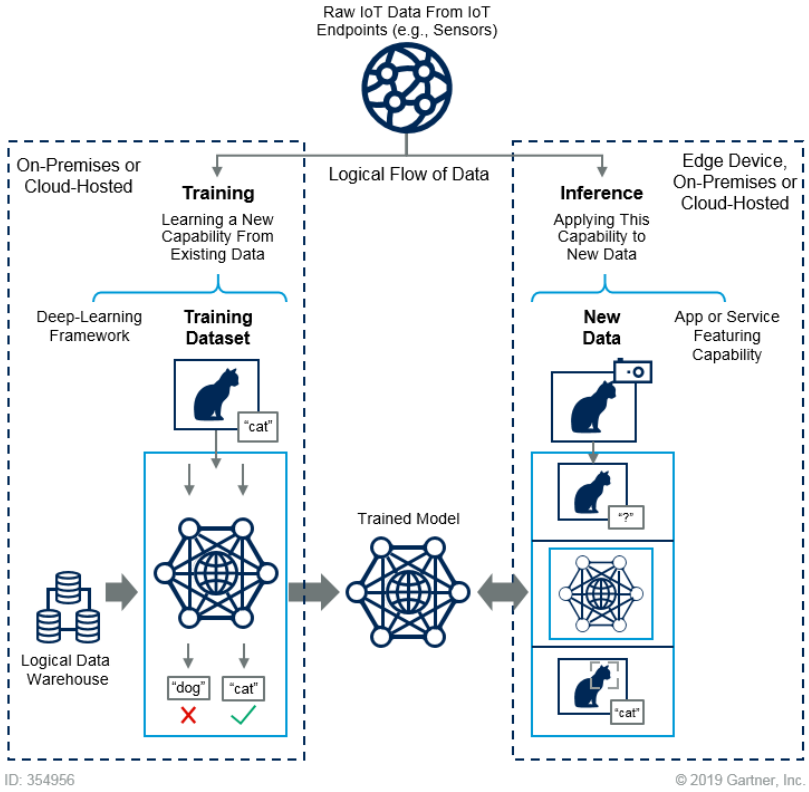
Predictions / Inferencing

Making **predictions:**



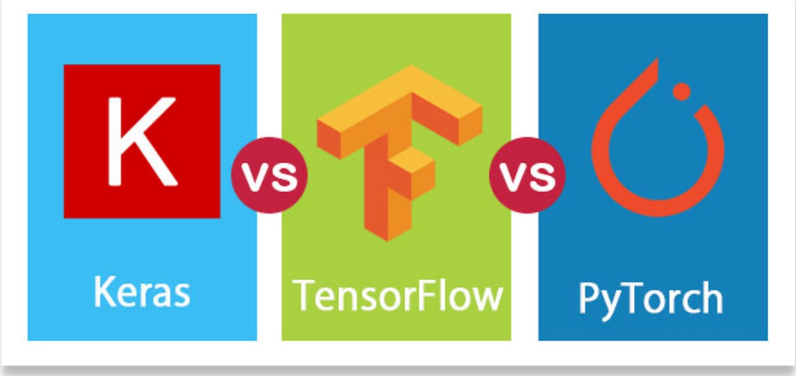
Training and Inference

- **Machine Learning** occurs in two stages – learning and inferencing. At present, TinyML only handles inferencing
- Training refers to the process of creating a machine learning algorithm. Training involves using a machine learning framework and a training dataset.
  - IoT data provides a source of training data that data scientists and engineers can use to train machine learning models.
- Inference refers to the process of using a trained machine-learning algorithm to make a prediction.
  - IoT data can be used as the input to a trained machine learning model, enabling predictions that can guide decision logic on the device, at the edge.



About the available software frameworks

- The three main frameworks which are available as an open-source library are opted by data scientist in deep learning are TensorFlow, Keras, and PyTorch.
  - **TensorFlow** is used to perform multiple tasks in data flow programming and machine learning applications.
  - **Keras** is a neural network library scripted in Python and executes on the top layer of TensorFlow.
  - **PyTorch** is a machine learning library that is mainly used in natural language processing.

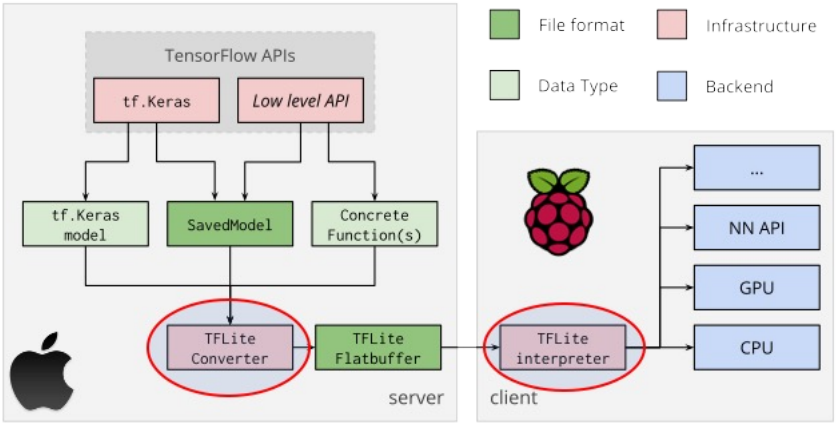


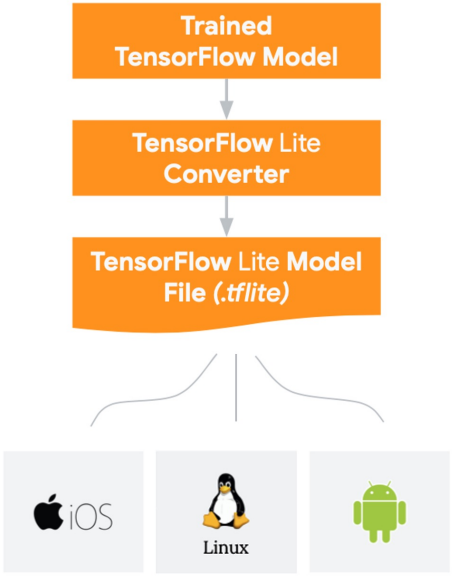
TensorFlow Lite for microcontrolers

- https://www.tensorflow.org/lite/microcontrollers
- TensorFlow is Google's open-source machine learning framework which helps in developing machine learning models quickly.
- For TinyML, there is TensorFlow Lite Micro, which is a specialised version of TensorFlow for microcontrollers.
  - TFLite Micro is written in C++ 11 and requires a 32-bit platform and is mostly compatible with Arm Cortex-M Series processors.
  - An ESP32 port is available as well
- TFLite Micro allows you to easily compress regular TensorFlow models into just a few kilobytes and comes with numerous example models.

TensorFlow Lite (TFLite)

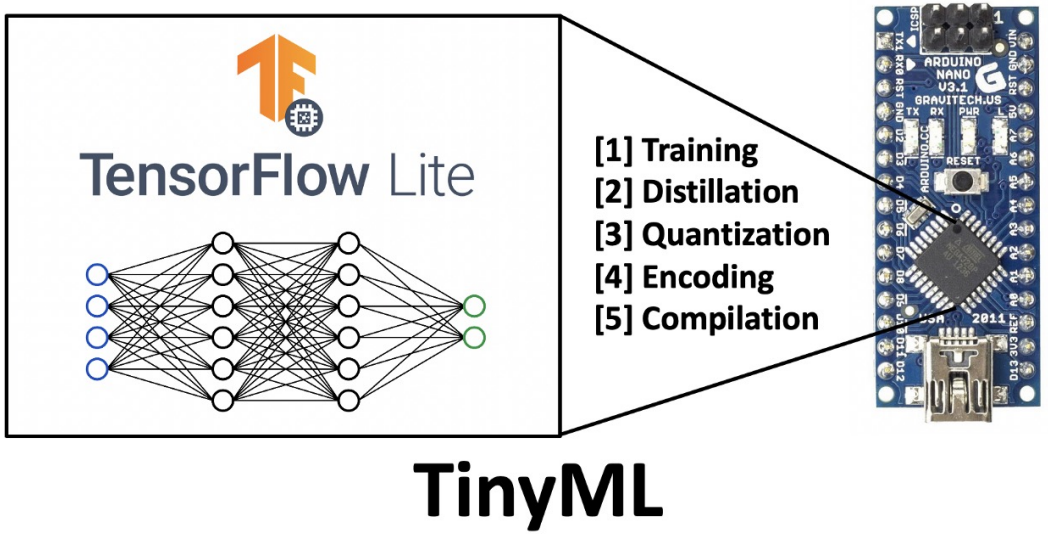
- Consists of two main components:
  - The **TFLite converter**, which converts TensorFlow models into an efficient form for use by the interpreter and can introduce optimizations to improve binary size and performance.
  - The **TFLite interpreter** runs with specially optimized models on many different hardware types, including mobile phones, embedded Linux devices, and microcontrollers.





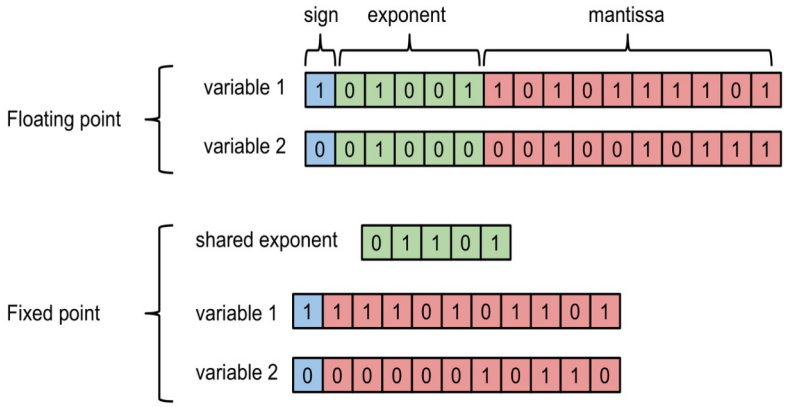
TensorFlow Lite optimizations

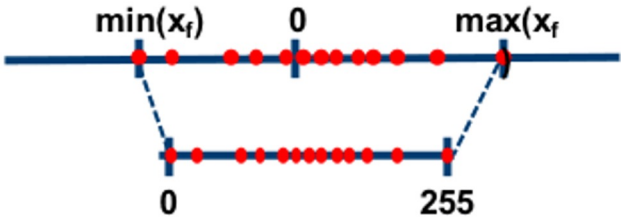
- Problem:
  - Less Compute Power, Less Memory, High Accuracy
- Some optimizations:
  - Quantization
  - Pruning
- ..and
  - Separable Convolutions
  - Knowledge Distillation



Quantization

- Neural Networks generally use 32 bit floating point weights
- These require more memory to save and custom logic to execute efficiently (which many micro-controllers do not have)
- By converting weights to INT8 (8 bits), we can save memory and compute faster
- However, it leads to a loss in accuracy since we lose precision





source: heartbeat.fritz.ai

TensorFlow Lite on the Raspberry Pi

- The example below shows how to use TensorFlow Lite on the Raspberry Pi to run object detection models.

https://www.youtube.com/watch?v=b7Yul7NxNq0

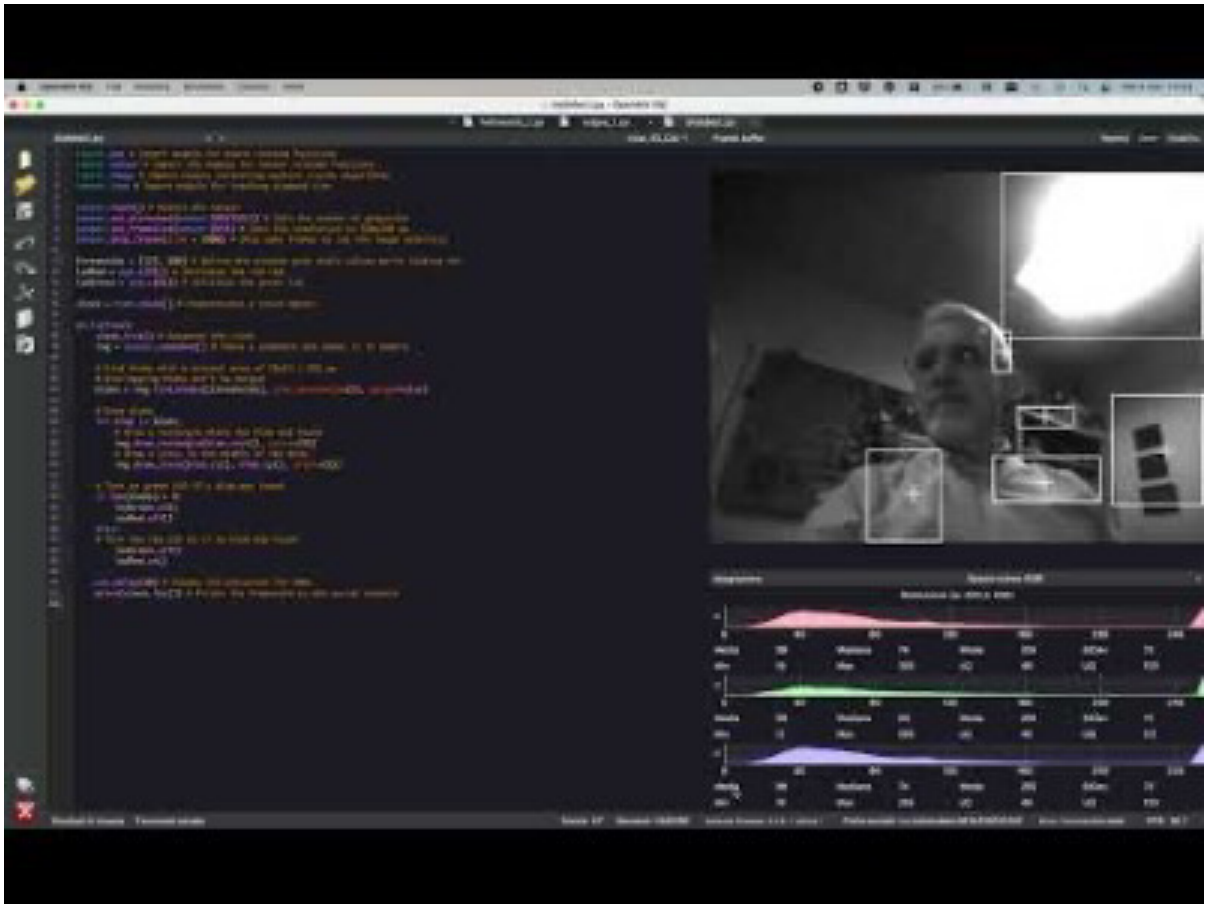
- http://openmv.io/

- OpenMV is another TinyML development platform, this time specialising in computer vision applications. This includes machine learning applied onto any kind of image or video like object recognition or image classification.
- The platform is built around their OpenMV Cam H7, which is a microcontroller board that runs on the ARM Cortex M7 processor and is Micropython programmable.

- In addition, OpenMV offers a cross-platform IDE that features a powerful code editor, debug terminal, and framebuffer viewer with histogram display – all of which are key components of developing computer vision applications in TinyML!

OpenMV: Blob detection with Portenta

- This example performs "Blob Detection" with a Portenta detecting the presence and the position of objects in a camera image.



OpenMV: Blob detection with Portenta: the code

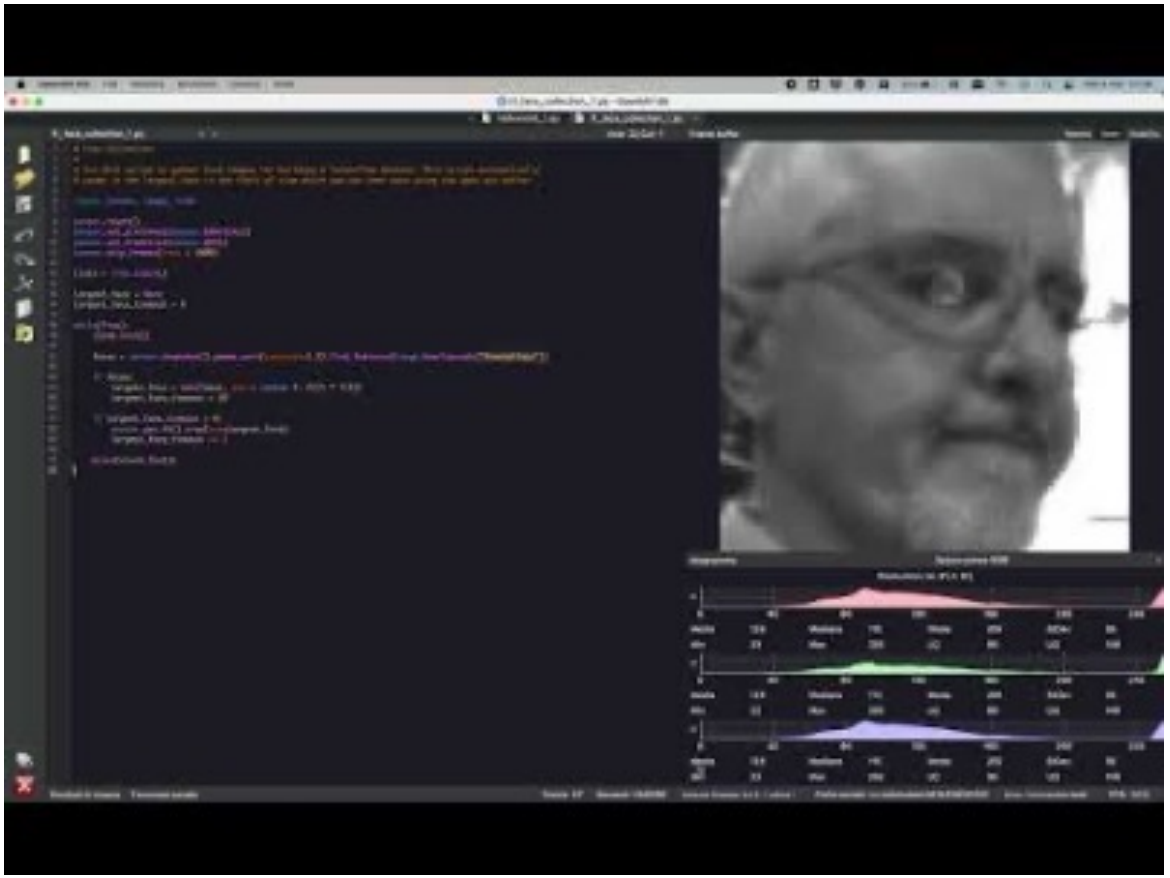
blobdect.py — UNREGISTERED

```python
import pyb # Import module for board related functions
import sensor # Import the module for sensor related functions
import image # Import module containing machine vision algorithms
import time # Import module for tracking elapsed time

sensor.reset() # Resets the sensor
sensor.set_pixformat(sensor.GRAYSCALE) # Sets the sensor to grayscale
sensor.set_framesize(sensor.QVGA) # Sets the resolution to 320x240 px
sensor.skip_frames(time = 2000) # Skip some frames to let the image stabilize

thresholds = (125, 200) # Define the min/max gray scale values we're looking for
ledRed = pyb.LED(1) # Initiates the red led
ledGreen = pyb.LED(2) # Initiates the green led

clock = time.clock() # Instantiates a clock object

while(True):
    clock.tick() # Advances the clock
    img = sensor.snapshot() # Takes a snapshot and saves it in memory

    # Find blobs with a minimal area of 15x15 = 225 px
    # Overlapping blobs won't be merged
    blobs = img.find_blobs([thresholds], area_threshold=225, merge=False)

    # Draw blobs
    for blob in blobs:
        # Draw a rectangle where the blob was found
        img.draw_rectangle(blob.rect(), color=255)
        # Draw a cross in the middle of the blob
        img.draw_cross(blob.cx(), blob.cy(), color=255)

    # Turn on green LED if a blob was found
    if len(blobs) > 0:
        ledGreen.on()
        ledRed.off()
    else:
    # Turn the red LED on if no blob was found
        ledGreen.off()
        ledRed.on()

    pyb.delay(50) # Pauses the execution for 50ms
    print(clock.fps()) # Prints the framerate to the serial console
```

Line 43, Column 1 — Spaces: 4 — Python

OpenMV: Face detection with Portenta

- This other example performs recognizes faces



tf_face_collection_1.py

OpenMV: Face detection with Portenta: the code

tf_face_collection_1.py — UNREGISTERED

```python
# Face Collection
#
# Use this script to gather face images for building a TensorFlow dataset. This script automatically
# zooms in the largest face in the field of view which you can then save using the data set editor.

import sensor, image, time

sensor.reset()
sensor.set_pixformat(sensor.RGB565)
sensor.set_framesize(sensor.QVGA)
sensor.skip_frames(time = 2000)

clock = time.clock()

largest_face = None
largest_face_timeout = 0

while(True):
    clock.tick()

    faces = sensor.snapshot().gamma_corr(contrast=1.5).find_features(image.HaarCascade("frontalface"))

    if faces:
        largest_face = max(faces, key = lambda f: f[2] * f[3])
        largest_face_timeout = 20

    if largest_face_timeout > 0:
        sensor.get_fb().crop(roi=largest_face)
        largest_face_timeout -= 1

    print(clock.fps())
```

Line 30, Column 1 — Spaces: 4 — Python

Edge Impulse

- http://edgeimpulse.com

- Edge Impulse is a platform that specifically targets the development of TinyML applications. With an easy-to-use web-based interface, Edge Impulse is arguably the easiest solution for anyone to collect data, train a model, and finally deploy it on a microcontroller. Best of all, it's free for developers, albeit with some limits on the number of projects you can create and compute time.
- Developing TinyML with Edge Impulse also allows you to take advantage of their Edge Optimised Neural (EON) compiler, which can run a neural network with 25-55% less RAM and 35% less storage compared to TFLite for Microcontrollers – a significant point to consider!
- Like TFLite Micro, Edge Impulse supports a substantial list of microcontrollers and development boards, also including the Arduino Nano 33 BLE Sense and Wio Terminal. Supported devices can easily record and upload datasets in a matter of minutes, but other devices can also use their Data forwarder to do the same with just a little more effort.

An alternative: https://www.lobe.ai

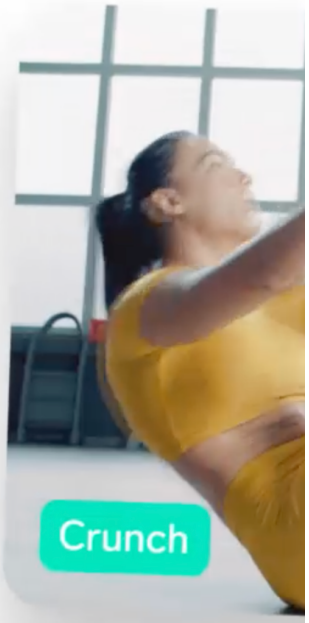
lobe

Overview Examples Tour Blog Help

Train apps to count reps

Lobe helps you train machine learning models with a free, easy to use tool.

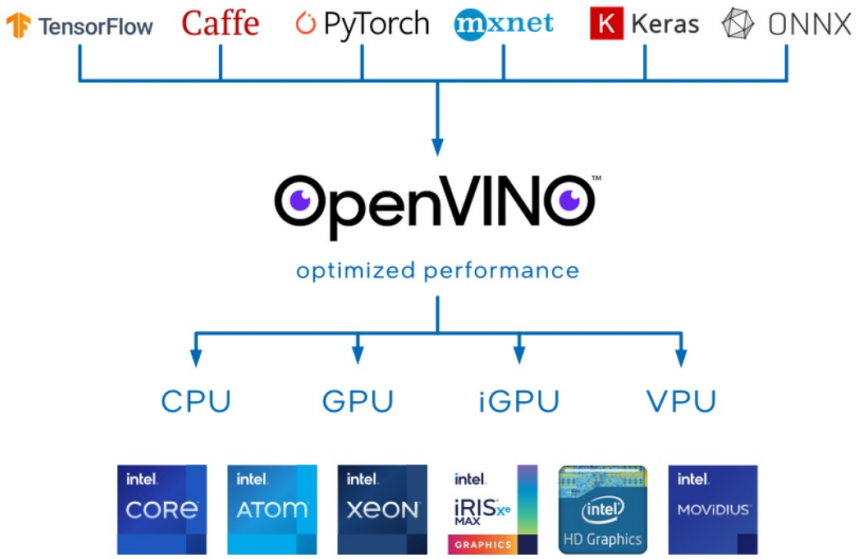
Download Watch Tour



And finally: OpenVINO

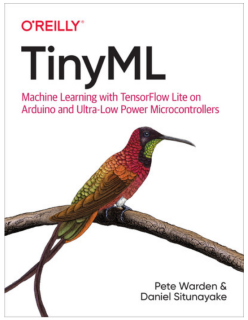
- OpenVINO™ is an open-source toolkit for optimizing and deploying AI inference.
  - Boost deep learning performance in computer vision, automatic speech recognition, natural language processing and other common tasks
  - Use models trained with popular frameworks like TensorFlow, PyTorch and more
  - Reduce resource demands and efficiently deploy on a range of Intel® platforms from edge to cloud

https://docs.openvino.ai/



On-line references

- Main refs
  - https://learning.oreilly.com/library/view/tinyml/9781492052036/
  - video Pete Warden: Building with TensorFlow Lite for microcontrollers | Workshop



- Tiny Machine Learning Community
  - https://discuss.tinymlx.org
- HarvardX Profession Certificate in Tiny Machine Learning (TinyML)
  - https://github.com/tinyMLx/courseware
- Tensorflow lite:
  - https://www.tensorflow.org/lite/
  - https://experiments.withgoogle.com/collection/tfliteformicrocontrollers
- Seeedstudio: Everything About TinyML – Basics, Courses, Projects & More!

TinyML: Machine Learning meets the Internet of Things

Thanks to:

- **Marcelo Rovai**
  - https://github.com/Mjrovai/UNIFEI-IESTI01-TinyML-2021.2
- **Vijay Janapa Reddi**
  - https://tinyml.seas.harvard.edu/SciTinyML/schedule/
- Archana Vaidheeswaran
- Soham Chatterjee
- ...and many more!
  - https://tinyml.seas.harvard.edu/CRESTLEX3/