MicroPython - Python for microcontrollers and Embedded Linux

with focus on sensor-oriented applications

https://github.com/emlearn/emlearn-micropython

FOSDEM 2025, Brussels
Embedded devroom

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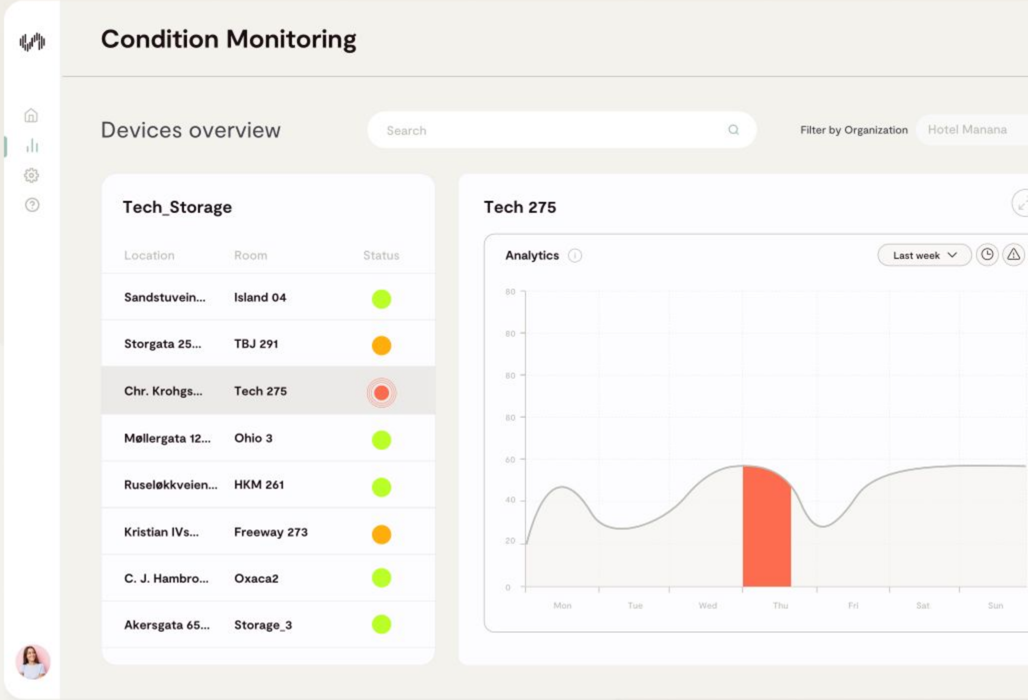
We utilise sound and vibration analysis to detect and warn you of upcoming errors in your technical infrastructure before they happen.

soundsensing



Trusted by Nordic market leaders

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Goal

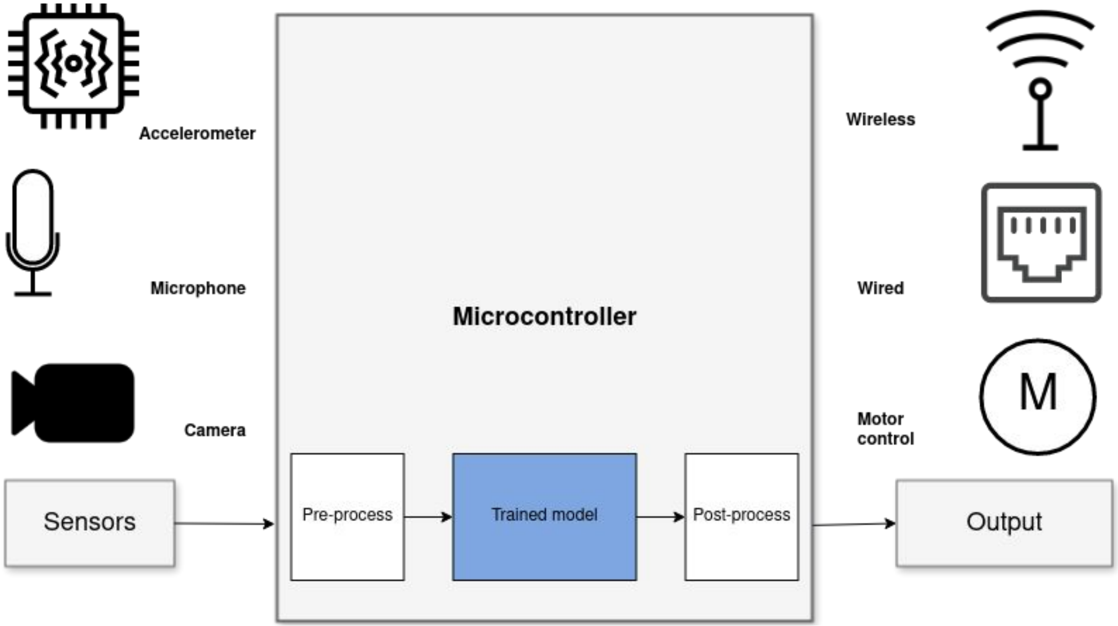
Purpose of this presentation

You as an
embedded / software developer
(professional or hobbyist)

will **learn enough about MicroPython**

to ***consider* it for a future project**

Focus: Sensor node systems



"Internet of Things"

"Wearable devices"

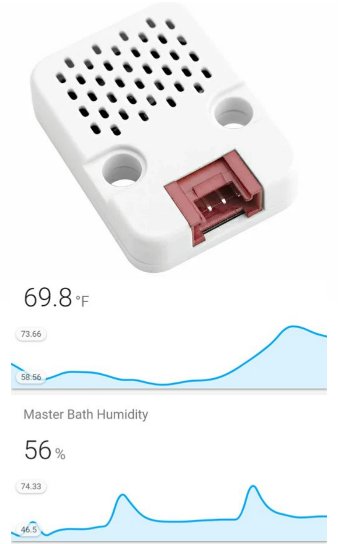
Robotics,
Industrial automation

1) Read sensors –> 2) Process data * –> 3) Transmit/act on data data

* including Digital Signal Processing (DSP) and Machine Learning (ML)

Environment logger

Temperature



Activity tracker

Accelerometer

emlearn

Random Forest classifier

emlearn_trees

Noise monitor

Microphone

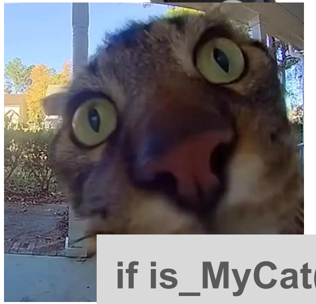
emlearn

Infinite Impulse Response filters

emlearn_iir

Image Classifier

Camera



```
if is_MyCat(img):
    open_door()
```

emlearn

Convolutional Neural Network

emlearn_cnn

Outline / agenda

1. MicroPython project overview
2. Tour of MicroPython features
    - …
    - Sensor communication
    - Connectivity
    - **Native C modules** for efficient data processing
3. Sensors using Digital Signal
4. MicroPython on (Embedded) Linux

MicroPython introduction

Jumping right into it

MicroPython introduction

Started in 2014

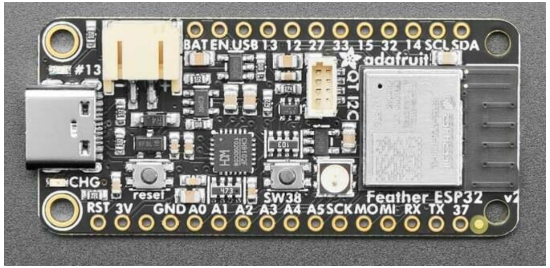
For devices with 64 kB+ RAM (256 kB+ recommended)
Supports 8+ microcontroller families

Tries to be as compatible with CPython as possible, within constraints.
Python 3.6 mostly implemented, partial after that.

Package manager “**mip install**”
Has support for loading C modules at runtime!

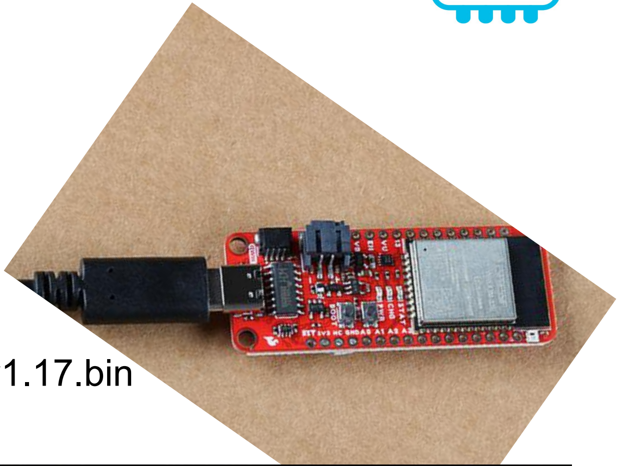
More info: https://micropython.org

Hardware recommendation
- start with a **ESP32** device



Complete device with sensors etc.:	20 - 50 USD
Development boards:	5 - 20 USD
Chips / modules	1 - 5 USD

Installing MicroPython



Download prebuilt firmware

https://micropython.org/download/?port=esp32

Flash firmware to device

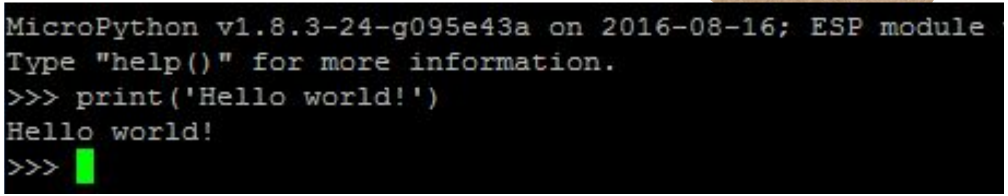
pip install esptool

esptool.py --chip esp32 --port … erase_flash
esptool.py --chip esp32 --port … write_flash -z 0 micropython-v1.17.bin

Connect to device

pip install mpremote

mpremote repl



IDE (optional): Viper IDE, Thonny, VS Code, et.c.

Temperature sensor - code

1. Read the sensor in a loop
2. Send data using MQTT
3. Wait until next measurement

The same approach usable for other slow-changing phenomena

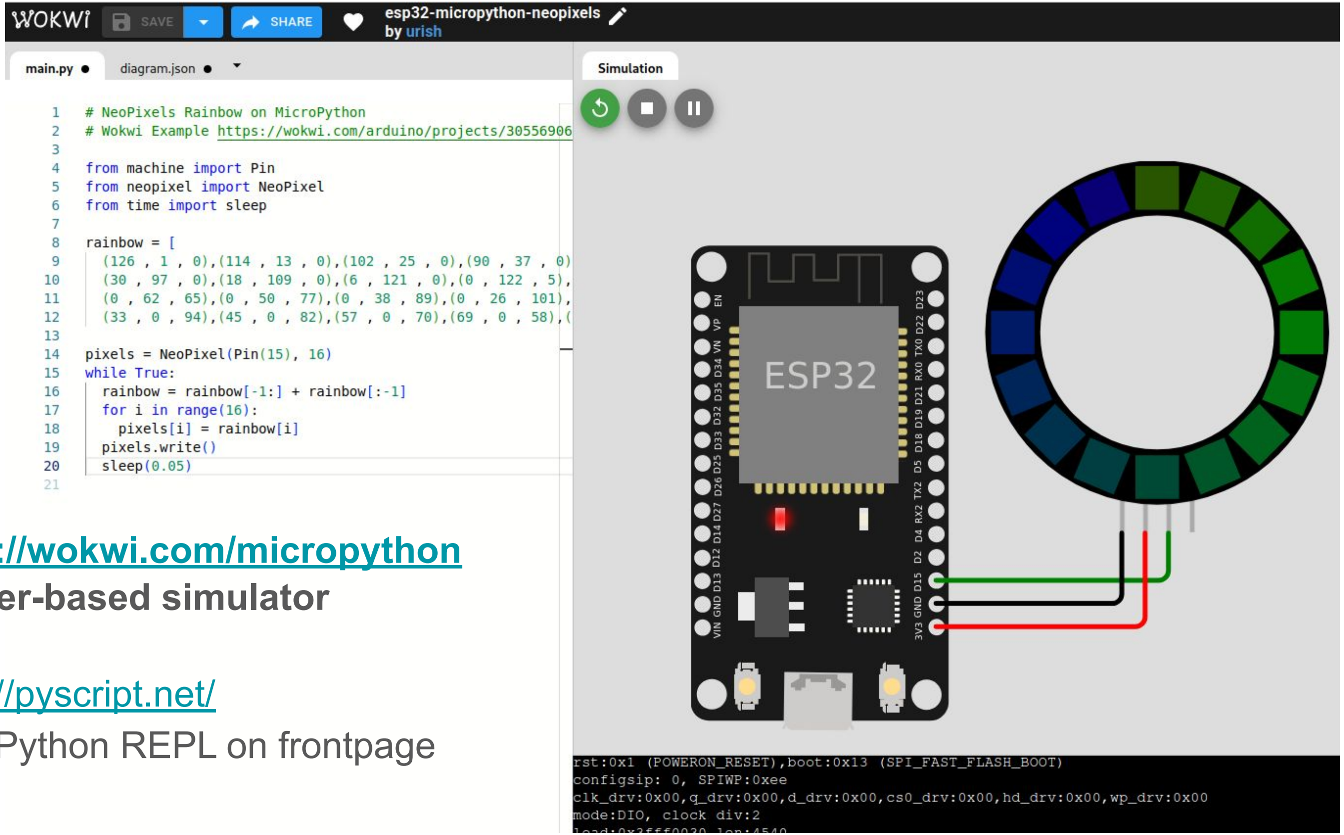
Using https://viper-ide.org/ with Chromium

Zero-install. Connect to device via USB

Using peterhinch/micropython-mqtt and jonnor/micropython-mpu6886

```python
from mqtt_as import MQTTClient, config
import asyncio
from mpu6886 import MPU6886
from machine import I2C

# Local configuration
config['ssid'] = 'FIXME'  # Optional on ESP8266
config['wifi_pw'] = 'FIXME'
config['server'] = 'test.mosquitto.org'

mpu = MPU6886(I2C(0, sda=21, scl=22, freq=100000))

async def main(client):
    print('main-start')
    await client.connect()
    print('connected')

    while True:
        t = mpu.temperature
        print('publish-data', t)
        await client.publish('pydataglobal2024/send', f'{t:.2f}'
        await asyncio.sleep(30)

MQTTClient.DEBUG = True  # Optional: print diagnostic messages
client = MQTTClient(config)
try:
    asyncio.run(main(client))
finally:
    client.close()
```

Try it now - running in the browser!



https://wokwi.com/micropython

Brower-based simulator

https://pyscript.net/

MicroPython REPL on frontpage

MicroPython tour

MicroPython *is* Python - but not CPython

High degree of compatibility - but never 100%
Continuous job to keep up with CPython
Some differences inherent - from < 1 MB RAM and FLASH

Included libraries are minimal
micropython-lib has more extensisive/featured
https://github.com/micropython/micropython-lib

Known incompatibilities
https://docs.micropython.org/en/latest/genrst/index.html#micropython-differences-from-cpython

Not implemented (by CPython major release)
https://github.com/micropython/micropython/issues/7919#issuecomment-1025221807

No CFFI or C module compatibility!
But there is another C API

Garbage collected
One GC cycle *will take 1-10 ms* (typ)
Some control, limited (gc module)

TLDR:

- Will be very familiar to Python devs
- Small scripts will mostly work with minor mods.
- Larger programs/modules may need refactoring or rewrite to fit target

Hardware access - the **machine** module

https://docs.micropython.org/en/latest/library/machine.html

- class Pin – control I/O pins
- class Signal – control and sense external I/O devices
- class ADC – analog to digital conversion
- class ADCBlock – control ADC peripherals
- class PWM – pulse width modulation
- class UART – duplex serial communication bus
- class SPI – a Serial Peripheral Interface bus protocol (controller side)
- class I2C – a two-wire serial protocol
- class I2S – Inter-IC Sound bus protocol
- class RTC – real time clock
- class Timer – control hardware timers
- class WDT – watchdog timer
- class SD – secure digital memory card (cc3200 port only)
- class SDCard – secure digital memory card
- class USBDevice – USB Device driver

Hardware Abstraction Layer
for microcontroller peripherals

Same on all hardware/ports
* with exceptions

File system

Enabled on most ports/hardware
(with sufficient resources)

Internal FLASH and/or **SDCard**

LittleFS or **FAT32**

Save/load from standard files

https://docs.micropython.org/en/latest/reference/filesystem.html

Using micropython-npyfile to read/write Numpy .npy files
https://github.com/jonnor/micropython-npyfile/

mpremote

Tool for PC <-> microcontroller communication

https://docs.micropython.org/en/latest/reference/mpremote.html

Copy from device

```
mpremote cp -r :images/ ./data/
```

Copy to device

```
mpremote cp ./model.trees.csv ./models/
```

mip - package manager

Install from micropython-lib

mpremote install requests

Third party packages

mpremote install github:jonnor/micropython-zipfile

Can run directly on device *

```
import mip
mip.install('requests')
```

* Assuming device has Internet over WiFi/Ethernet

Install native C modules at runtime

*mpremote mip install https://example.net/ **xtensawin_6.2***/emlearn_trees.mpy*

* Specify architecture + MicroPython ABI version

Connectivity

BLE - Bluetooth Low Energy

aioble - high-level application API, asyncio
bluetooth - low-level hardware-layer
Ports: ESP32, RP2, Unix

WiFi

network.WLAN
Ports: ESP32, RP2, STM32, etc

Ethernet

network.LAN
Ports: ESP32, RP2, STM32, etc
Hardware: Wiznet, +++

C modules *

Defines a Python module with API. functions/classes et.c.

Implemented by users, **libraries,** or be **part of MicroPython core**.

Can be **portable** or **hardware/platform specific**

* Or **other language** which **compiles to C**, or **exposes C API** https://github.com/vshymanskyy/wasm2mpy
C++, Rust, Zig, TinyGo, TypeScript

```c
// Include the header file to get access to the MicroPython API
#include "py/dynruntime.h"

// Helper C function to compute factorial
static mp_int_t factorial_helper(mp_int_t x) {
    if (x == 0) {
        return 1;
    }
    return x * factorial_helper(x - 1);
}

// DEFINE FUNCTION. Callable from Python
static mp_obj_t factorial(mp_obj_t x_obj) {
    mp_int_t x = mp_obj_get_int(x_obj);
    mp_int_t result = factorial_helper(x);
    return mp_obj_new_int(result);
}
static MP_DEFINE_CONST_FUN_OBJ_1(factorial_obj, factorial);


// MODULE ENTRY
mp_obj_t mpy_init(mp_obj_fun_bc_t *self, size_t n_args, size_t n_kw, mp_obj_t *args) {
    // Must be first, it sets up the globals dict and other things
    MP_DYNRUNTIME_INIT_ENTRY

    // Register function in the module's namespace
    mp_store_global(MP_QSTR_factorial, MP_OBJ_FROM_PTR(&factorial_obj));

    // This must be last, it restores the globals dict
    MP_DYNRUNTIME_INIT_EXIT
}
```

emlearn

Native module (.mpy) VS External C module

	Native module	External C module
Installable at runtime	Yes, as .mpy file	No. Must be included in firmware image
Requires SDK/toolchain	No (only to build)	Yes
Code executes from	RAM	FLASH
Limitations	No libc / libm linked * No static BSS *	None
Maturity	Low *	Excellent
Documentation	https://docs.micropython.org/en/latest/develop/natmod.html	https://docs.micropython.org/en/latest/develop/cmodules.html

* Improved greatly in upcoming MicroPython (1.25+).
Contributions by Volodymyr Shymanskyy, Alessandro Gatti, Damien George, and others

Audio input - **machine.I2S**

Digital microphone or **external audio ADC**

Can be done using I2S protocol

On ports **ESP32, STM32, RP2, NRF52**

PDM protocol not supported :(

Example code
https://github.com/emlearn/emlearn-micropython/tree/master/examples/soundlevel_iir
https://github.com/miketeachman/micropython-i2s-examples

```python
# I2S audio input
from machine import I2S
audio_in = I2S(0, sck=Pin(26), ws=Pin(32), sd=Pin(33),
    mode=I2S.RX, bits=16,format=I2S.MONO, rate=16000,
)

# allocate sample arrays
chunk_samples = int(AUDIO_SAMPLERATE * 0.125)
mic_samples = array.array('h', (0 for _ in range(chunk_samples))) # int16
# memoryview used to reduce heap allocation in while loop
mic_samples_mv = memoryview(mic_samples)
# global to share state between callback and main
soundlevel_db = 0.0

meter = SoundlevelMeter(buffer_size=chunk_samples, samplerate=16000)

def audio_ready_callback(arg):
    # compute soundlevel
    global soundlevel_db
    soundlevel_db = meter.process(mic_samples)
    # re-trigger audio callback
    _ = audio_in.readinto(mic_samples_mv)

def main():
    # Use Non-Blocking I/O with callback
    audio_in.irq(audio_ready_callback)
    # Trigger first audio readout
    audio_in.readinto(mic_samples_mv)

    while True:
        render_display(db=soundlevel_db)
        time.sleep_ms(200)

if __name__ == '__main__':
    main()
```

Camera input

Not part of standard APIs yet

micropython-camera-API
Proposed API and implementation
(ESP32 only, for now)
https://github.com/
cnadler86/micropython-camera-API

OpenMV
https://openmv.io/
Custom MicroPython distribution
Focused on Computer Vision / Machine Vision

Sensor nodes

with MicroPython
and emlearn

emlearn
-micropython

https://github.com/emlearn/emlearn-micropython

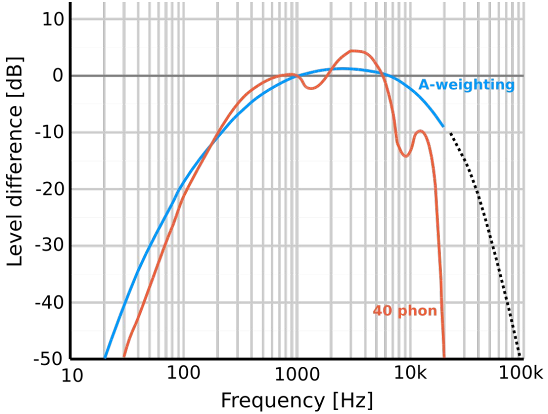
Noise sensor using **emlearn_iir**

Using **machine.I2S**
16 kHz samplerate

A weighting implemented with
Infinite Impulse Response (IIR) filter

emlearn_iir
25% CPU usage total

pure MicroPython
900% CPU - not feasible




```
# 6th order filter. 3x Second Order Sections "biquad"
a_filter_16k = [
    1.0383002230320646, 0.0, 0.0, 1.0, -0.016647242439959593, 6.928267
    1.0, -2.0, 1.0, 1.0, -1.7070508390293027, 0.7174637059318595,
    1.0, -2.0, 1.0, 1.0, -1.9838868447331497, 0.9839517531763131
]
self.frequency_filter = IIRFilter(a_filter_16k)
...
self.frequency_filter.process(samples)
```

Complete example code
https://github.com/emlearn/emlearn-micropython/tree/master/examples/soundlevel_iir

Human Activity Detection with **emlearn_trees**

Using **Random Forest** classifier trained with **scikit-learn**

```
import emltrees
model = emltrees.new(10, 1000, 10)
with open('eml_digits.csv', 'r') as f:
    emltrees.load_model(model, f)

features = array.array('h', ...)
out = model.predict(features)
```

https://github.com/emlearn/emlearn-micropython/tree/master/examples/har_trees

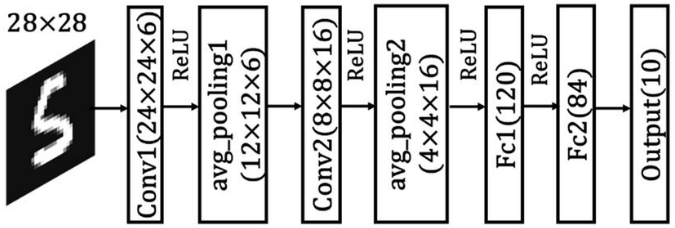
Performance comparison

10 trees, max 100 leaf nodes, “digits” dataset

	Inference time	Program space
m2cgen	60.1 ms	179 kB
everywhereml	17.7 ms	154 kB
emlearn	**1.3 ms**	**15 kB**

emlearn is **10x faster and 10x more space efficient** compared to generating Python code

Image classification with **emlearn_cnn**



Convolutional Neural Network (CNN)

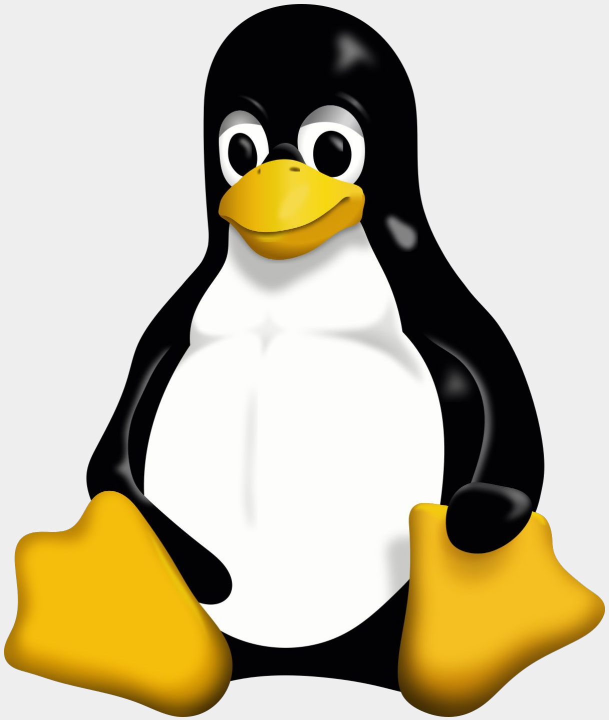
Running on ESP32-S3 (example)

Input dimensions:	32x32 px - 96x96 px
Layers:	3 - 4 layers.
Framerate:	1 - 10 FPS

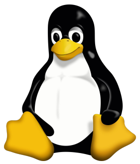
Complete example code
https://github.com/emlearn/emlearn-micropython/tree/master/examples/mnist_cnn

```
import tinymaix_cnn # from emlearn-micropython

with open('cat_classifier.tmdl', 'rb') as f:
    model_data = array.array('B', f.read())
    model = tinymaix_cnn.new(model_data)

while True:

    raw = read_camera()
    img = preprocess(raw)
    classification = model.predict(img)

    if classification == MY_CAT:
        open_door()

    machine.lightsleep(500)
```

MicroPython for Embedded Linux



Motivation: **Memory efficiency**



CPython is quite RAM hungry. Especially “standard” Python/PyData ecosystem

scikit-learn with **CPython:** **13 - 128 MB**

```
from sklearn.ensemble import RandomForestClassifier
estimator = RandomForestClassifier()
# model not even trained yet!!!
```

emlearn_trees with **MicroPython:** **0.1 - 6 MB**

100 trees, 4000 nodes per tree (max_depth=12)

```
import emlearn_trees
model = emlearn_trees.new(100, 4000, 100)
```

MicroPython attractive for Linux devices with < 512 MB RAM

Unix MicroPyton port: Limited hardware access

Not implemented:

- GPIO. machine.Pin / machine.PWM / machine.ADC
- Digital busses. machine.I2C / SPI / USART / USB
- Watchdog Timer. machine.WDT
- Power management. machine.lightsleep() /deepsleep()
- Audio input/microphone
- Camera access

C or Python modules for this. Or call external programs.
Contributions welcome!

Already very useful for unit testing

Summary

emlearn
-micropython

https://github.com/emlearn/emlearn-micropython

Take aways

1. **MicroPython productive environment (for sensor devices)**

Python familiarity and ease-of-use

Good connectivity

mip package manager

mpremote tool for device communication

2. **Can implement advanced processing of sensor data**

Accelerometer, audio, image, radar, ….

C modules a killer feature

emlearn-micropython: modules for DSP and Machine Learning

More!

FOSDEM 2025 - Low-level AI Engineering and Hacking - Sunday 16:40 (Lameere)
Milliwatt sized machine learning on microcontrollers with emlearn

FOSDEM 2025 - MicroPython & Espruino stand - AW building, level 1
See you there after this talk / later today?!

Official documentation
https://micropython.org/ https://emlearn-micropython.readthedocs.io

PyCon Berlin 2024: *Machine Learning on microcontrollers using MicroPython and emlearn*
https://www.youtube.com/watch?v=S3GjLr0ZIE0

TinyML EMEA 2024: *emlearn - scikit-learn for microcontrollers and embedded systems*
https://www.youtube.com/watch?v=LyO5k1VMdOQ

PyData ZA 2024: *Sensor data processing on microcontrollers with MicroPython (video soon)*
https://za.pycon.org/talks/31-sensor-data-processing-on-microcontrollers-with-micropython/

MicroPython - Python for microcontrollers and Embedded Linux

with focus on sensor-oriented applications

https://github.com/emlearn/emlearn-micropython

FOSDEM 2025, Brussels
Embedded devroom

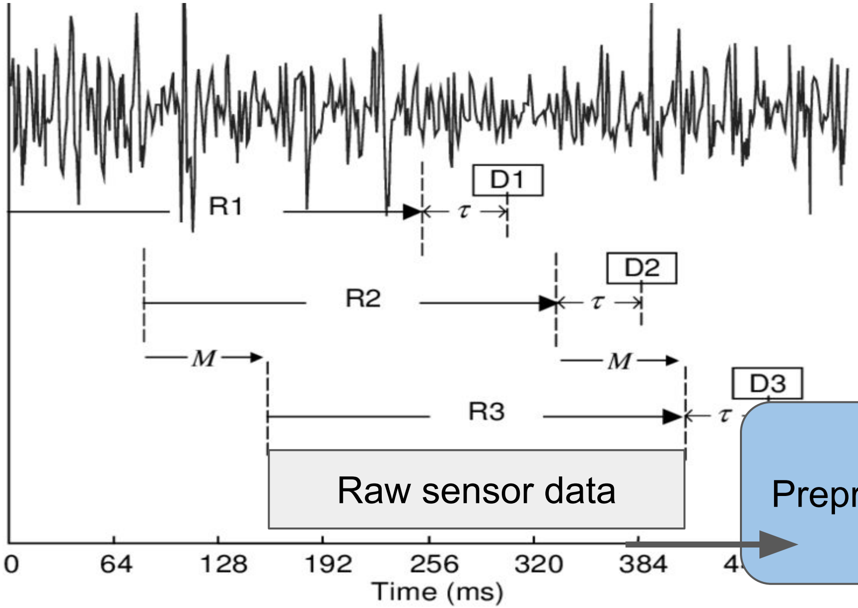
Jon Nordby jononor@gmail.com

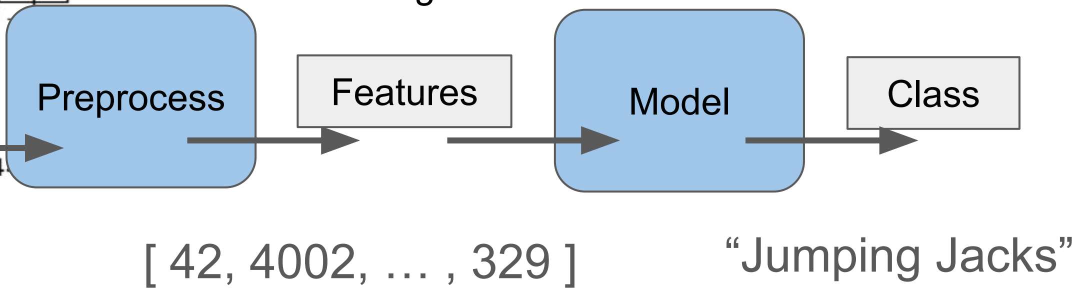
Bonus

ML on streams: Continuous classification

The sensor data stream
is sliced into overlapping windows.
Each window processed independently

Exercise activity detection:
- 4 second window, every 1 second
- 100 Hz samplerate
- Processing time 200 ms



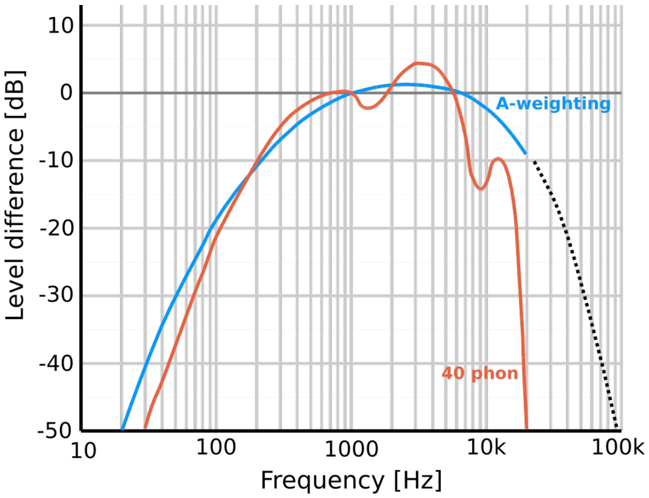


Implementing an IMU/accelerometer/gyro driver? Use the FIFO!
https://github.com/orgs/micropython/discussions/15512

Sound sensor - IIR filter

Standard sound level measurements are **A-weighted**. To approximate human hearing.

Typically, implemented using **Infinite Impulse Response (IIR) filters**.




```
class IIRFilter():
    def __init__(self, coefficients : array.array):
        stages = len(coefficients)//6
        self.sos = coefficients
        self.state = array.array('f', [0.0]*(2*stages))

    @micropython.native
    def process(self, samples : array.array):
        stages = len(self.sos)//6
        for i in range(len(samples)):
            x = samples[i]
            for s in range(stages):
                b0, b1, b2, a0, a1, a2 = self.sos[s*6:(s*6)+6]
                # compute difference equations of transposed direct form II
                y = b0*x + self.state[(s*2)+0]
                self.state[(s*2)+0] = b1*x - a1*y + self.state[(s*2)+1]
                self.state[(s*2)+1] = b2*x - a2*y
                x = y
            samples[i] = x
```

1100 ms 900% CPU
Native emitter
Float

Too slow by ~10x

```
# 6th order filter. 3x Second Order Sections "biquad"
a_filter_16k = [
    1.0383002230320646, 0.0, 0.0, 1.0, -0.016647242439959593, 6.928267
    1.0, -2.0, 1.0, 1.0, -1.7070508390293027, 0.7174637059318595,
    1.0, -2.0, 1.0, 1.0, -1.9838868447331497, 0.9839517531763131
]
self.frequency_filter = IIRFilter(a_filter_16k)
...
self.frequency_filter.process(samples)
```

emlearn

Sound sensor - IIR filter

Using **emliir.mpy** native module helps a lot.

BUT - conversion from float/int16 too slow

Also needs a native module

```
import emliir

class IIRFilterEmlearn:

    def __init__(self, coefficients):
        c = array.array('f', coefficients)
        self.iir = emliir.new(c)
    def process(self, samples):
        self.iir.run(samples)
```

IIR filter only
Using emliir.mpy
native module
30 ms 20% CPU - OK

```
@micropython.native
def float_to_int16(inp, out):
    for i in range(len(inp)):
        out[i] = int(inp[i]*32768)

@micropython.native
def int16_to_float(inp, out):
    for i in range(len(inp)):
        out[i] = inp[i]/32768.0

int16_to_float(samples, self.float_array)
self.frequency_filter.process(self.float_array)
float_to_int16(self.float_array, samples)
```

But need to convert data types
Adds 70ms+ with micropython.native
Too slow! Total > 100 ms
Must create native module

emliir.mpy from emlearm-micropython
https://github.com/emlearn/emlearn-micropython/

TinyML for MicroPython - comparisons

Project	**Deployment**	**Models**	**Program size**	**Compute time**
emlearn	Easy. Native mod .mpy	DT, RF, KNN, CNN	Good	Good
everywhereml	Easy. Pure Python .py	DT, RF, SVM, KNN,	High with large models	Poor
m2cgen	Easy. Pure Python .py	DT, RF, SVM, KNN, MLP	High with large models	Poor
OpenMV.tf	Hard. Custom Fork	CNN	High initial size	Good
ulab	Hard. User C module	(build-your-own) Using ndarray primitives	High initial size	Unknown (assume good)

Make it Work,
Make it Right,
Make it Fast

- Ken Beck

→ Write simple automated tests,
Code in straightforward Python,
Measure performance with benchmarks

Optimize *if needed*

- Start with simple techniques
- Go more advanced *if needed*

time.time and **assert**
for benchmark and tests

```
import time

repeats = 100
expect = 18965.39
input = ....

start = time.ticks_us()
for r in range(repeats):
    out = rms_python(input)
    assert p == expect, (out, expect)
t = time.ticks_diff(time.ticks_us(), start) / repeats
print('python', t)

start = time.ticks_us()
for r in range(repeats):
    out = rms_micropython_native(input)
    assert out == expect, (out, expect)
t = time.ticks_diff(time.ticks_us(), start) / repeats
print('native', t)
```

Inline Assembly

MicroPython can expose Assembler opcodes as Python statements.

Allows to write a function in Assembler
inline in the Python program
Can compile and execute on device

Supported on ARM Cortex M chips
Not supported (yet) on ESP32

For the most hardcore hackers!

Official Documentation:
https://docs.micropython.org/en/latest/reference/asm_thumb2_index.html

```
@micropython.asm_thumb
def fir(r0, r1, r2):
    mov(r3, r8)          # For Pico: can't push({r8}). r0-r7 only.
    push({r3})
    ldr(r7, [r0, 0])     # Array length
    mov(r6, r7)          # Copy for filter
    mov(r3, r0)
    add(r3, 12)          # r3 points to ring buffer start
    sub(r7, 1)
    add(r7, r7, r7)
    add(r7, r7, r7)      # convert to bytes
    add(r5, r7, r3)      # r5 points to ring buffer end (last valid address)
    ldr(r4, [r0, 8])     # Current insertion point address
    cmp(r4, 0)           # If it's zero we need to initialise
    bne(INITIALISED)
    mov(r4, r3)          # Initialise: point to buffer start
    label(INITIALISED)
    str(r2, [r4, 0])     # put new data in buffer and post increment
    add(r4, 4)
    cmp(r4, r5)          # Check for buffer end
    ble(BUFOK)
    mov(r4, r3)          # Incremented past end: point to start
    label(BUFOK)
    str(r4, [r0, 8])     # Save the insertion point for next call
                         # *** Filter ***
    ldr(r0, [r0, 4])     # Bits to shift
```

Example: FIR filter implementation (cut out)
https://github.com/peterhinch/micropython-filters/blob/master/fir.py

emlearn

Training model on dataset

Using a scikit-learn based pipeline.

```
# Setup subject-based cross validation
splitter = GroupShuffleSplit(n_splits=n_splits, test_size=0.25,
    random_state=random_state)

# Random Forest classifier
clf = RandomForestClassifier(random_state = random_state,
    n_jobs=1, class_weight = "balanced")

# Hyper-parameter search
search = GridSearchCV(clf, param_grid=hyperparameters,
   scoring=metric, refit=metric, cv=splitter)
search.fit(X, Y, groups=groups)
```

```
(venv) [jon@jon-thinkpad har_trees]$ MIN_SAMPLES_LEAF=150,200,400 python har_train.py
-dataset har_exercise_1 --window-length 400 --window-hop 10
2024-12-04 12:54:52 [info     ] data-loaded                  dataset=har_exercise_1
uration=0.016095876693725586 samples=32000
2024-12-04 12:54:56 [info     ] feature-extraction-done      dataset=har_exercise_1
uration=4.534412145614624 labeled_instances=1952 total_instances=1952
Class distribution
 activity
jumpingjack    549
lunge          488
other          488
squat          427
Name: count, dtype: int64
```

```
Model written to ./har_exercise_1_trees.csv
Testdata written to ./har_exercise_1.testdata.npz
Results
    n_estimators  min_samples_leaf  mean_train_f1_micro  mean_test_f1_micro
0             10               150             0.996311            0.962705
1             10               200             0.995628            0.956557
2             10               400             0.986202            0.920902
```

har_train.py

```
import emlearn
converted = emlearn.convert(clf)
converted.save(name='gesture', format='csv', file='model.csv')
```

Activity Tracker - Feature Extraction

Statistical summarizations are useful time-series features, sufficient for basic Human Activity Recognition.

! Preprocessing *must be compatible between training* on host PC (CPython) *and device* (MicroPython)

Solution: Write preprocessor for MicroPython, re-use in Python

subprocess('micropython preprocess.py data.npy features.npy')

Alternative: (when using common MicroPython/CPython subset)

import mypreprocessor.py

Using micropython-npyfile to read/write Numpy .npy files
https://github.com/jonnor/micropython-npyfile/

```
l = sorted(list(v))
l2 = [x*x for x in l]
sm = sum(l)
sqs = sum(l2)
avg = sum(l) / len(l)

median = l[MEDIAN]
q25 = l[Q1]
q75 = l[Q3]
iqr = (l[Q3] - l[Q1])

energy = ((sqs / len(l2)) ** 0.5)
std = ((sqs - avg * avg) ** 0.5)
```

https://github.com/emlearn/emlearn-micropython/blob/master/examples/har_trees/timebased.py

Time-based features extraction
Are Microcontrollers Ready for Deep Learning-Based Human Activity Recognition?
Atis Elsts, and Ryan McConville
https://www.mdpi.com/2079-9292/10/21/2640

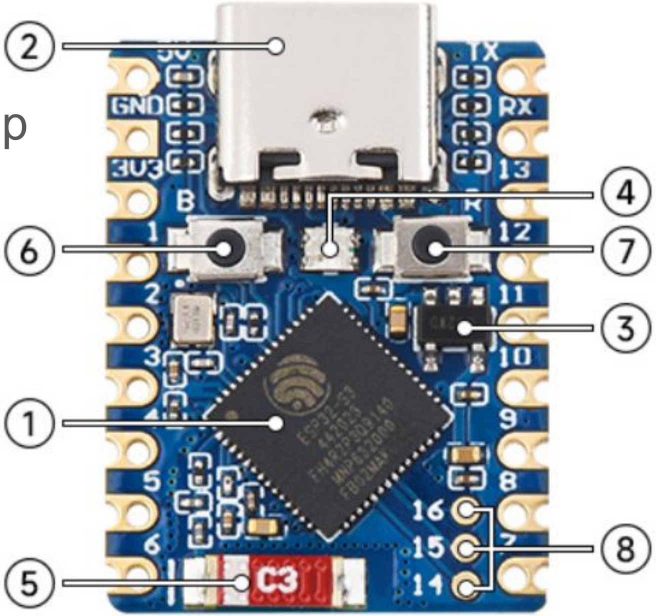
What is a microcontroller?

Modern microcontroller:
A complete programmable System-on-Chip

Example: ESP32-S3FH4R2

32 bit CPU, 240 Mhz
Floating Point Unit
2 MB RAM
4 MB FLASH

WiFi
Bluetooth Low Energy
USB-C

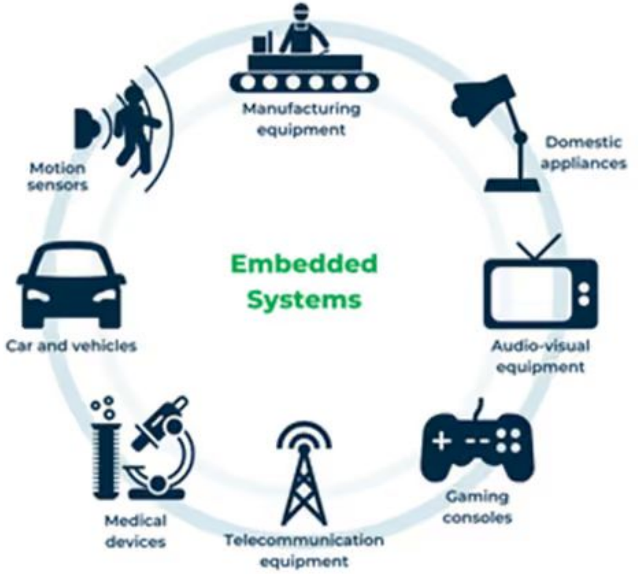


Espressif ESP32-S3FH4R2 chip:	2.5	USD
Waveshare ESP32-S3-Tiny board:	6	USD

Microcontroller - tiny programmable chip

Compute power: 1 / 1000x of a smartphone

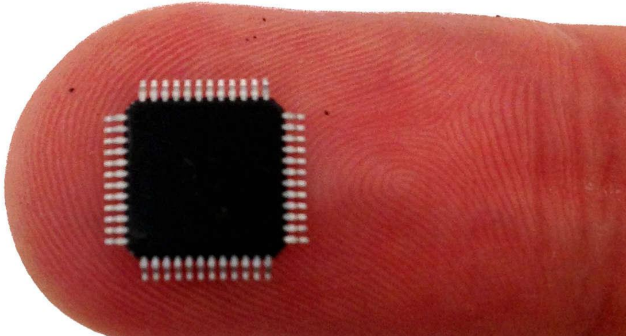
- **RAM:** **0.10 - 1 000 kB**
- **Program space:** **1.0 - 10 000 kB**
- **Compute** **10 - 1 000 DMIPS**
- **Price:** **0.10 - 10 USD**
- **Energy:** **1 - 1 000 milliWatt**



Over 20 *billions* shipped *per year*!

Efficiency is key !
Memory, compute, power

Increasingly accessible for hobbyists



2010: Arduino Uno

2014: MicroPython

2019: MicroPython 1.10 - ESP32 PSRAM