

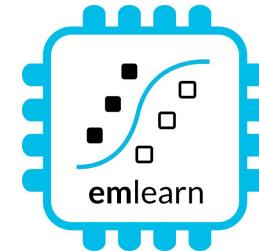
Sensor data processing on microcontrollers

with MicroPython and emlearn

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



Jon Nordby jononor@gmail.com
PyCon ZA 2024





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

 **sound sensing**

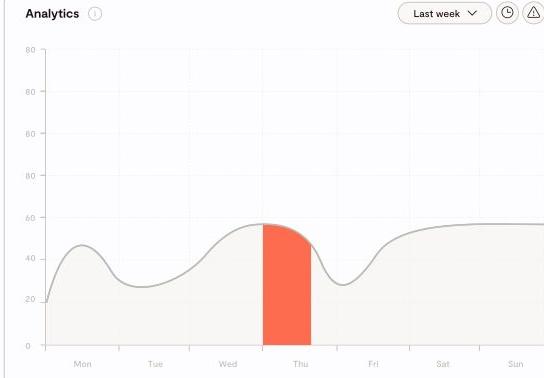
Condition Monitoring

Devices overview Search Filter by Organization Hotel Manana

Location	Room	Status
Sandstuvein...	Island 04	Green
Storgata 25...	TBJ 291	Yellow
Chr. Krohgs...	Tech 275	Red
Møllergata 12...	Ohio 3	Green
Ruseløkkveien...	HKM 261	Green
Kristian IVs...	Freeway 273	Yellow
C. J. Hambro...	Oxaca2	Green
Akersgata 65...	Storage_3	Green

Tech 275

Analytics Last week More Less



Mon Tue Wed Thu Fri Sat Sun

Trusted by Nordic market leaders

Goal

Purpose of this presentation

You, as a Python developer,
can build an IoT sensor
on a microcontroller
using MicroPython

Background

Microcontrollers &
MicroPython



MicroPython



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

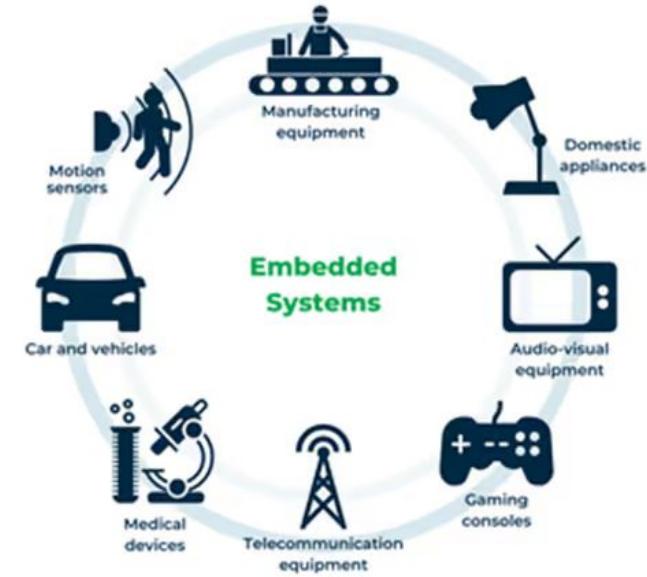
Over 20 *billions* shipped per year!

Increasingly accessible for hobbyists

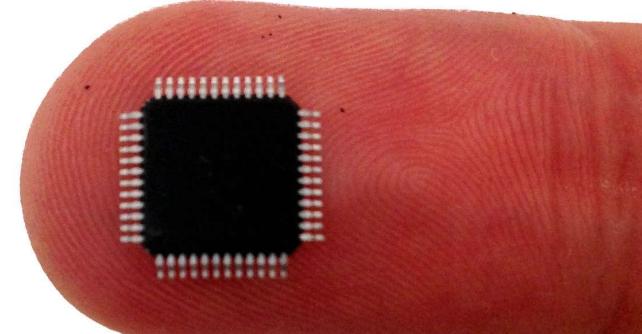
2010: Arduino Uno

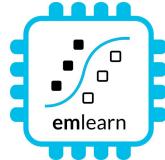
2014: MicroPython

2019: MicroPython 1.10 - ESP32 PSRAM



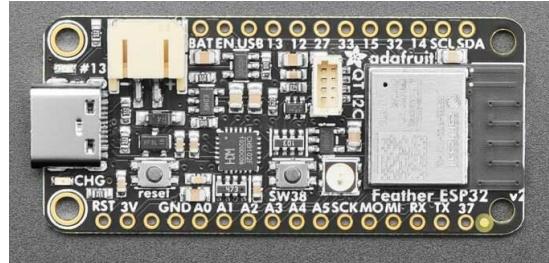
Efficiency is key !
Memory, compute, power





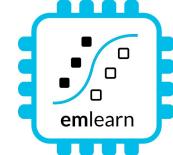
Hardware recommendation

- start with a **ESP32** device



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

MicroPython introduction



Implements a subset of Python 3.x for devices with 16 kB+ RAM
Supports 8+ microcontroller families

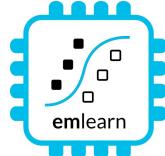
Tries to be as compatible with CPython as possible, within constraints.
Python 3.6 mostly implemented, partial after that.

No CFFI or C module compatibility!

TLDR: Small scripts will mostly work with minor mods. But not PyData stack

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

More info: <https://micropython.org>



Installing MicroPython

Download prebuilt firmware

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

Flash firmware to device

pip install esptool

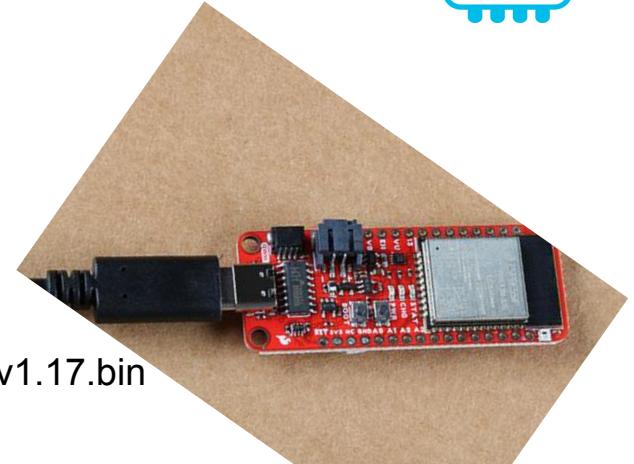
esptool.py --chip esp32 --port ... erase_flash

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

Connect to device

pip install mpremote

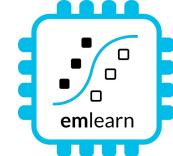
mpremote repl



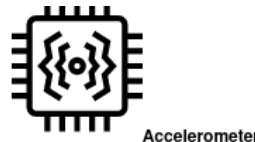
```
MicroPython v1.8.3-24-g095e43a on 2016-08-16; ESP module
Type "help()" for more information.
>>> print('Hello world!')
Hello world!
>>> █
```

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

Sensor node systems



Including on-sensor data processing
with Digital Signal Processing (DSP) and Machine Learning (ML)



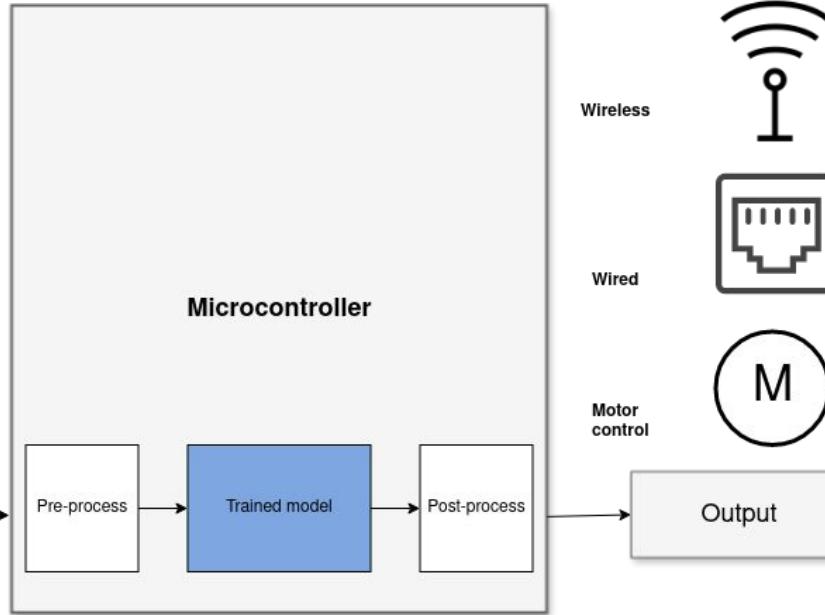
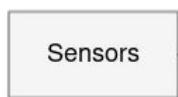
Accelerometer



Microphone



Camera



“Internet of Things”



“Wearable devices”



**Robotics,
Industrial automation**

Sensor data processing

What can be done on an ESP32
microcontroller with MicroPython
and how to make it work

Temperature logger

Temperature
0.1 Hz



Activity tracker

Accelerometer
100 Hz



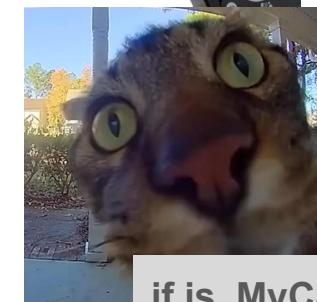
Noise monitor

Microphone
16000 Hz

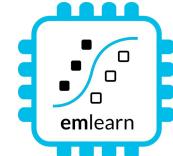


Cat Detector

Camera
27000 bytes/s



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



**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

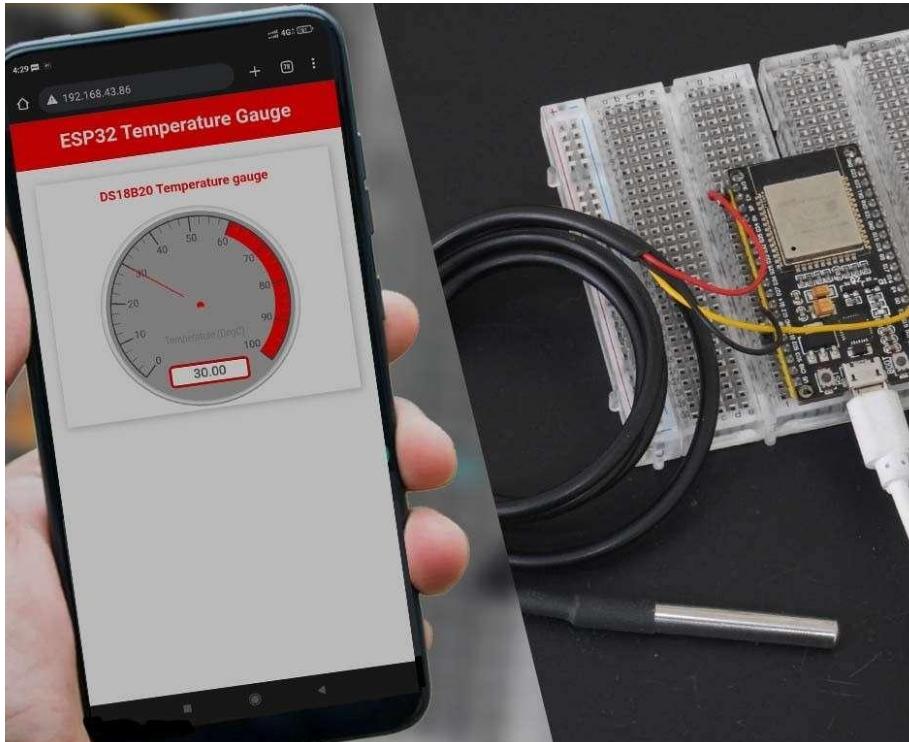
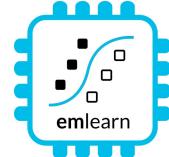
```
import time

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)
```

Temperature sensor



Temperature is a **slow changing phenomena**.
Want: **1 value for longish time interval**
(ex: 5 min)

! Sensor can be noisy. Filtering advised

Will show **analog sensor** example.
Same approach can be used for a **digital sensor**.
And for **other slow-changing phenomena**.

Temperature sensor

Solution: Read the sensor in a loop

Filter noise using use a median filter.

= Trivially doable in straightforward Python

Efficiency techniques (non-critical)

- Using *lightsleep()* to conserve power.
- Pre-allocate fixed **array.array**,
instead of over mutating a **list** (append)
- to reduce allocations

Sending data as Bluetooth Low Energy advertisements, see
<https://github.com/orgs/micropython/discussions/15926>

```
import machine

N_SAMPLES = 10
SAMPLE_INTERVAL = 1.0
SLEEP_INTERVAL = 60.0

analog_input = machine.ADC(machine.Pin(22))
samples = array.array('H') # raw values from ADC, as uint16
measurement_no = 0

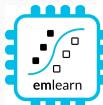
while True:

    # collect data for measurement
    for i in range(N_SAMPLES):
        samples[i] = adc.read_u16()
        time.sleep(SAMPLE_INTERVAL)

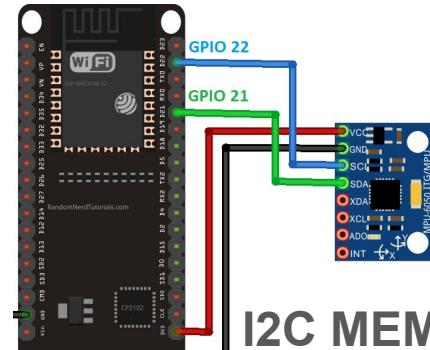
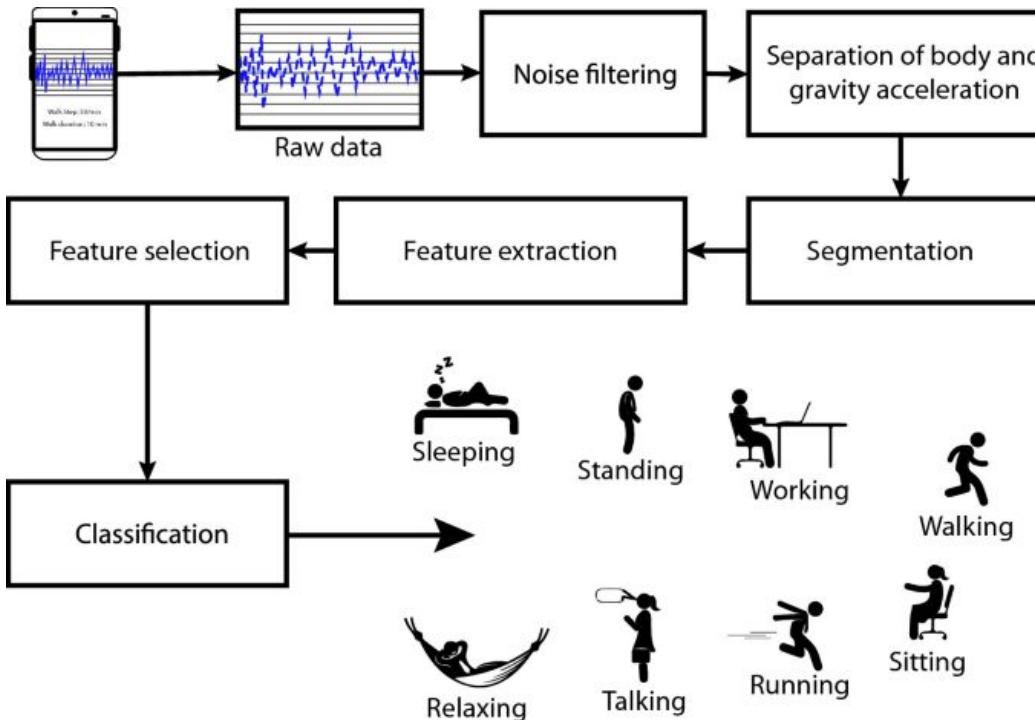
    # aggregate samples, convert to temperature
    raw = median(samples)
    temperature = (raw * 0.323) - 50.0 # calculation depends on

    # Do something with the measurement
    send_bluetooth_le(measurement_no, temperature)

    # sleep until next time to collect new measurement
    machine.lightsleep(int(SLEEP_INTERVAL*1000))
    measurement_no += 1
```



Activity tracker - concept



I2C MEMS IMU
accelerometer/gyro
(Example wiring)



Complete
hardware unit
LilyGo
T-Watch S3

Activity Tracker - data acquisition

Want data chunks of 1 second.

25 Hz sample rate.

4 ms between samples

OK for basic Human Activity Detection

Might for some tasks want 100+ Hz.

Efficiency techniques (recommended)

- Utilizing FIFO buffer in sensor
- Using *lightsleep()* to conserve power.

```
THRESHOLD = 25
sensor = SomeIMU(i2c=...)
samples = []
while True:
    t = time.ticks_ms()
    samples.append(sensor.get_xyz())

    if len(samples) == THRESHOLD:
        process_samples(samples)
        samples = []

# Try compensate for execution time data sampling time
time_spent = time.ticks_diff(time.ticks_ms(), t)
wait_time = max(1000/SAMPLERATE - time_spent, 0)
time.sleep_ms(wait_time)

THRESHOLD = 25 # NOTE: max 75% of FIFO capacity
imu = SuperIMU2k(i2c=..., odr=SAMPLERATE)

while True:
    level = imu.get_fifo_level()
    if level >= THRESHOLD:
        samples = imu.read_fifo_data(THRESHOLD)

        process_samples(samples)

        machine.lightsleep(100)
```

Polling individual samples

Must always use < 4 ms,
otherwise will drop sample

Limits what *process_samples()* can do

! GC can easily take 10-100 ms

Using sensor FIFO buffer

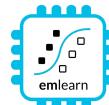
Can spend 100 ms+ on processing

Can sleep 90%+ of the time

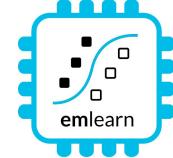
Perfectly spaced samples, always

Implementing an IMU/accelerometer/gyro driver? Use the FIFO!

<https://github.com/orgs/micropython/discussions/15512>



Activity Tracker - Feature Extraction



Basic statistical summarizations are useful.

Can be sufficient for Human Activity Recognition

At 25 Hz, 3 channels, every 1 second.

Doable in pure Python

Estimated processing time 10-100 ms

Can be optimized using specialized code emitters.

More later...

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>

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

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

energy = ((sqsum / len(l2)) ** 0.5) # rms
std = ((sqsum - avg * avg) ** 0.5)
```

Activity Tracker

Classification using Random Forest

everywhereml / m2cgen:

Generate Python .py code module

emltrees from emlearn-micropython

Dynamic native module .mpy

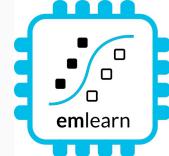
Implemented in C

Load model from .csv file

10 trees sufficient for OK performance on common HAR datasets (PAMAP2/UCI)

```
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)
```



```
from everywhere_digits import RandomForestClassifier
model = RandomForestClassifier()
out = model.predict(x)
```

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

10x faster

10x more space efficient

C modules

Written in C.

Defines a Python module with API.
functions/classes etc.

Can be implemented by users,
libraries or be part of MicroPython
core.

Can be portable or specific to one
hardware/platform

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

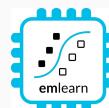
// Helper C function to compute factorial
static mp_int_t factorial_helper(mp_int_t x) {
    if (x == 0) {
        return 1;
    }
    return x * factorial_helper(x - 1);
}

// 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
}
```

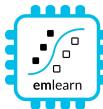


Native module (.mpy) VS External C module

	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

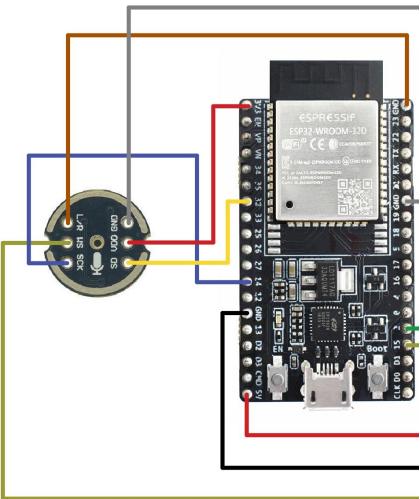
* Improved greatly in upcoming MicroPython (1.24+).

Contributions by Volodymyr Shymanskyy, Alessandro Gatti, Damien George, and others



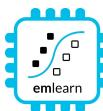
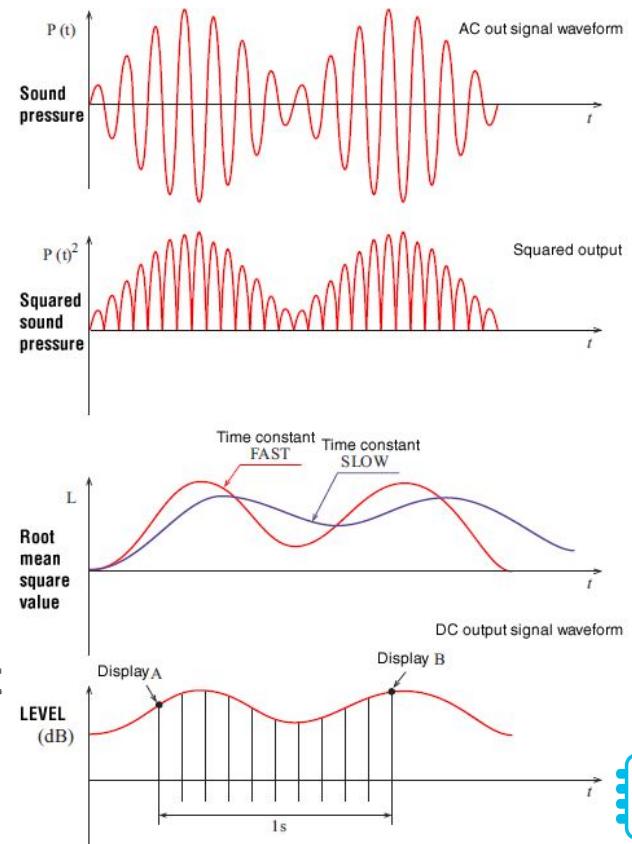
Sound sensor

I2S digital microphone (Example wiring)



Complete hardware unit
LilyGo TTGO
T-Camera Mic v1.6

Soundlevel calculation Processing steps



Sound sensor - Data Acquisition

16 kHz samplerate - no problem to read
48 kHz would probably also read fine
- but 3x the load for processing.

Efficiency techniques (critical)

- Using dedicated I2S hardware for audio input
- memoryview() to allow bytes-based API to write into our int16 array, without needing conversion

Rendering text/widgets to screen

<https://github.com/peterhinch/micropython-nano-gui>

```
# 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

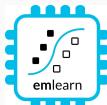
meter = SoundlevelMeter(buffer_size=chunk_samples, samplerate=16000)

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()
```



Sound sensor - RMS calculation

125ms @ 16kHz = 2000 samples

Processing deadline: 125 ms

Root Mean Square (energy calculation)

1. Plain Python = **too slow!**
2. Native emitter + trivial change
= **runs fine**
3. Viper emitter + low-level rewrite
for integer-based arithmetic
= **add 10x efficiency**

```
def rms_python(arr):  
    acc = 0.0  
    for i in range(len(arr)):  
        v = float(arr[i])  
        acc += (v * v)  
    mean = acc / len(arr)  
    out = math.sqrt(mean)  
    return out
```

1. 113 ms 95% CPU
Plain Python
All floats

```
@micropython.native  
def rms_micropython_native(arr):  
    acc = 0  
    for i in range(len(arr)):  
        v = arr[i]  
        acc += (v * v)  
    mean = acc / len(arr)  
    out = math.sqrt(mean)  
    return out
```

2. 35 ms 28% CPU
Native emitter
Integer squaring Float
accumulator

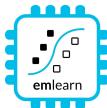
```
@micropython.viper  
def rms_micropython_viper(arr) -> object:  
    buf = ptr16(arr) # XXX: input MUST BE h/uint16 array  
    l = int(len(arr))  
    cumulated_average : int = 0  
    cumulated_remainder : int = 0  
    addendum : int = 0  
    n_values : int = 0  
    for i in range(l):  
        v = int(buf[i])  
        value = (v * v) # square it  
        n_values += 1  
        addendum = value - cumulated_average + cumulated_remainder  
        cumulated_average += addendum // n_values  
        cumulated_remainder = addendum % n_values  
    out = math.sqrt(cumulated_average)  
    return out
```

3. 2 ms 2% CPU
Viper emitter
Integer-based
Cumulative Moving Average[1]

1. CodeProject.com: Stefan Lang (2014)

Precise and safe calculation method for the average of large integer arrays

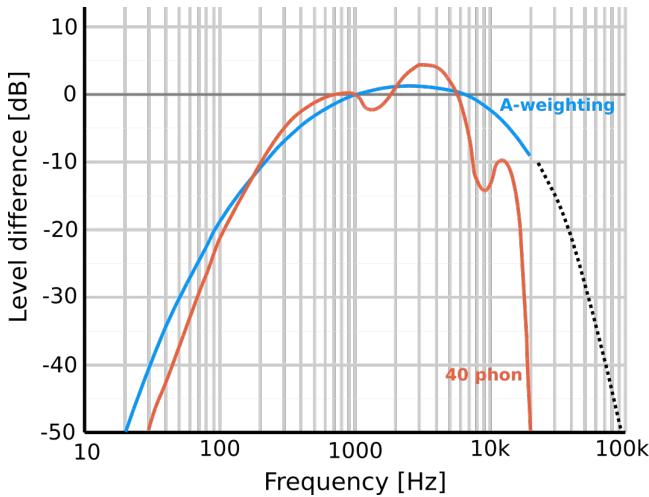
<https://www.codeproject.com/Articles/807195/Precise-and-safe-calculation-method-for-the-averag>



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, 6.9282670,
    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)
```



Sound sensor - IIR filter

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

BUT - conversion from float/int16 too slow
Also needs a native module

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

```
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)
```

```
@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



Cat Detector - Data Acquisition

Want: Classify *low-res* images, at 1 FPS+

Using mp_camera by cnadler86
[https://github.com/
cnadler86/micropython-camera-API](https://github.com/cnadler86/micropython-camera-API)

96x96 px grayscale.
Takes ~100 ms - OK



Cat Detector - Classification with CNN

Go-to solution for image classification:
Convolutional Neural Network (CNN)

tinymaix_cnn from emlearn-micropython
32x32 px input. 3 layers. Under 100 ms - OK

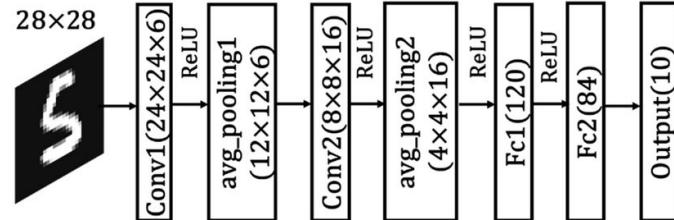
Preprocessing (untested)

Downscaling 96 px -> 32 px

Image brightness normalization

= **Image classification is doable
(with native C modules)**

See also OpenMV - MicroPython for Computer Vision- <https://docs.openmv.io/index.html>



[https://github.com/emlearn/emlearn-micropython/
tree/master/examples/mnist_cnn](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)
```



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

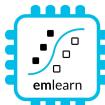
For the most hardcore hackers!

Official Documentation:

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

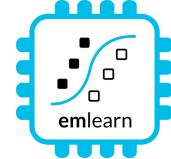
```
@micropython.asm_thumb
def fir(r0, r1, r2):
    mov(r3, r8)                      # For Pico: can't push({r8}). r0-r7 only.
    push({r3})
    ldr(r7, [r0, 0])                 # Array length
    mov(r6, r7)
    mov(r3, r0)
    add(r3, 12)                     # r3 points to ring buffer start
    sub(r7, 1)
    add(r7, r7, r7)
    add(r7, r7, r7)
    add(r5, r7, r3)
    ldr(r4, [r0, 8])
    cmp(r4, 0)
    bne(INITIALISED)
    mov(r4, r3)
    label(INITIALISED)
    str(r2, [r4, 0])
    add(r4, 4)
    cmp(r4, r5)
    ble(BUFOK)
    mov(r4, r3)
    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>



Conclusions

Feasibility and techniques for sensor data processing



Accelerometer data et.c

Up to 1000 samples/second

= doable with plain Python

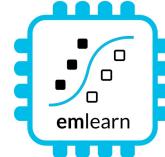
+ Benefits from @micropython.native / viper

Sound and low-res/low-rate video

Over 10'000 samples/second

= use of C modules becomes key

Other resources



MicroPython docs: Maximising MicroPython speed

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

PyConAU 2018: Writing fast and efficient MicroPython (Damien George)

<https://www.youtube.com/watch?v=hHec4qL00x0>

PyConAU 2019: Extending MicroPython: Using C for good!" (Matt Trentini)

<https://www.youtube.com/watch?v=437CZBnK8vI>

MicroPython docs: Extending MicroPython in C

<https://docs.micropython.org/en/latest/develop/extendingmicropython.html>

PyCon Berlin 2024: Machine Learning on microcontrollers

using MicroPython and emlearn

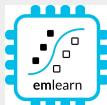
<https://www.youtube.com/@PyDataTV>

Summary

Learn more:

[https://github.com/
emlearn/emlearn-micropython](https://github.com/emlearn/emlearn-micropython)

1. **Current microcontrollers can run Python** thanks to MicroPython
2. **MicroPython is a powerful platform** for building sensor nodes
3. Wide **range of performance tools available** for creating advanced and efficient sensor nodes
4. **emlearn-micropython** is a collection of native modules for Machine Learning in MicroPython



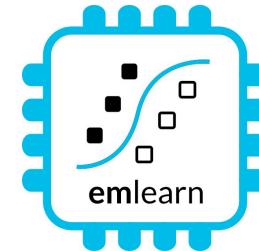
Sensor data processing on microcontrollers

with MicroPython and emlearn

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

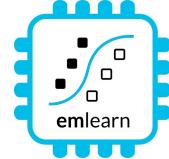


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PyCon ZA 2024



Bonus

TinyML for MicroPython - comparisons



Project	Deployment	Models	Size	Compute time
emlearn -micropython	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)