

Opening the Stack: An Open-Source Journey from Wearable Biosignal Acquisition Platforms to Edge Intelligence

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PULP Platform

Open Source Hardware, the way it should be!



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- **Connecting the Humans, PULP-based Wearable interfaces for Advance HMIs**
- **Building Open Wearables with AI Capabilities**
- **Democratizing Wearable Ultrasound: the WULPUS story**

15 minutes break

- **Accelerating Innovation in Myoelectric Control through Open Software and Standardized Benchmarking**
- **Open-Source Neuromorphic Chips and Simulation Libraries for Biomedical Applications**
- **An Open Source, Device-Agnostic GUI for Bio-Signal Acquisition and Processing**

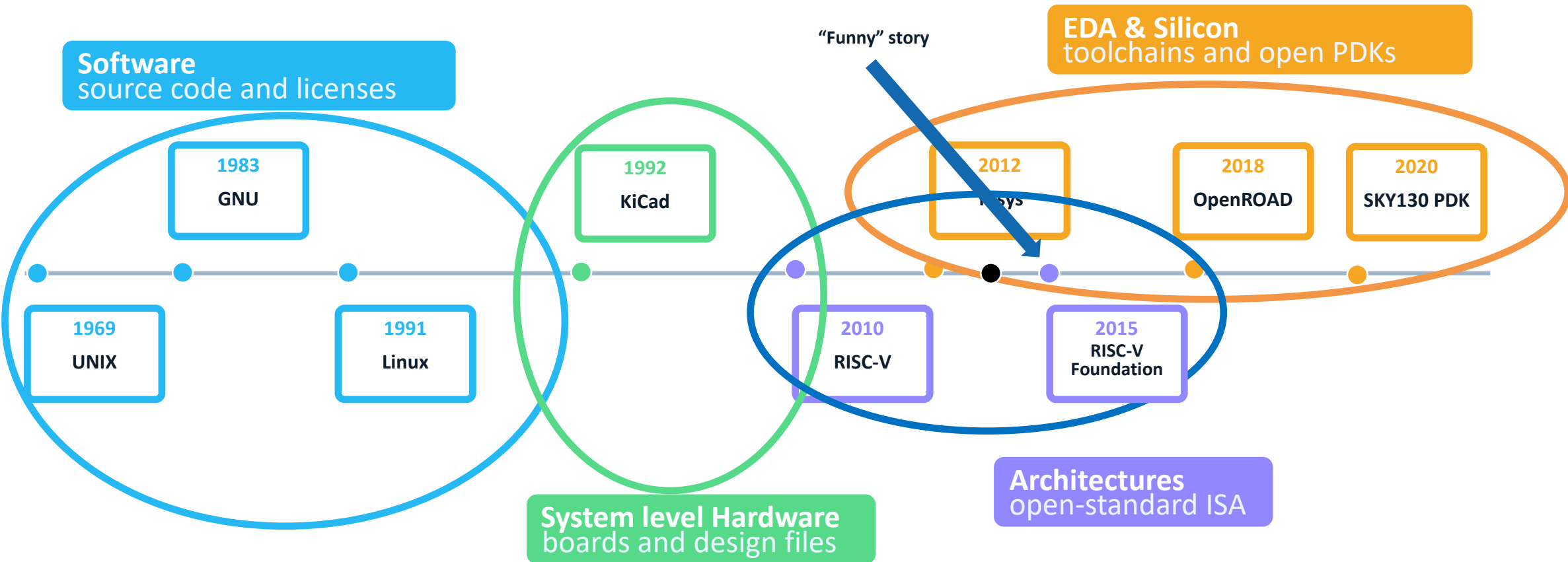
Final discussion and hands on

Your background?



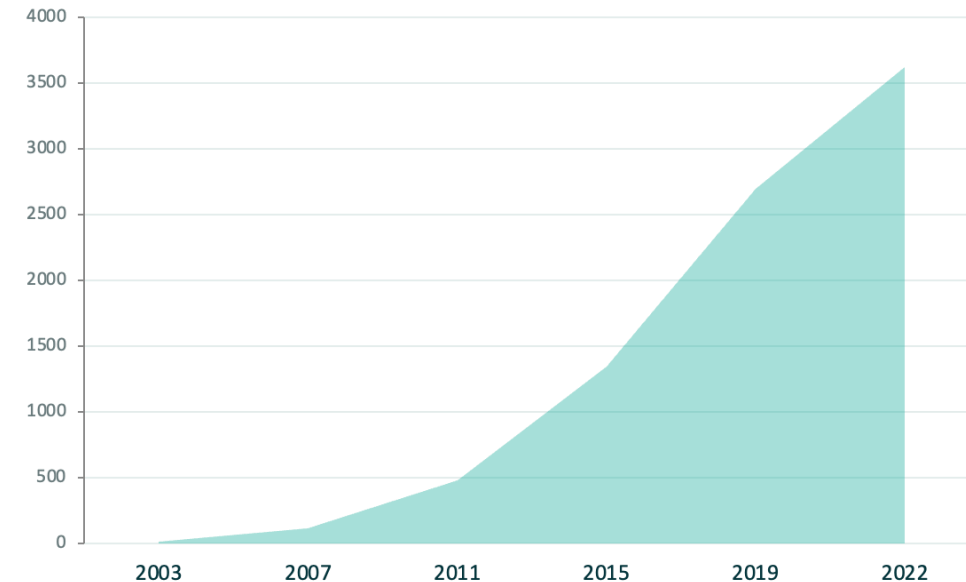
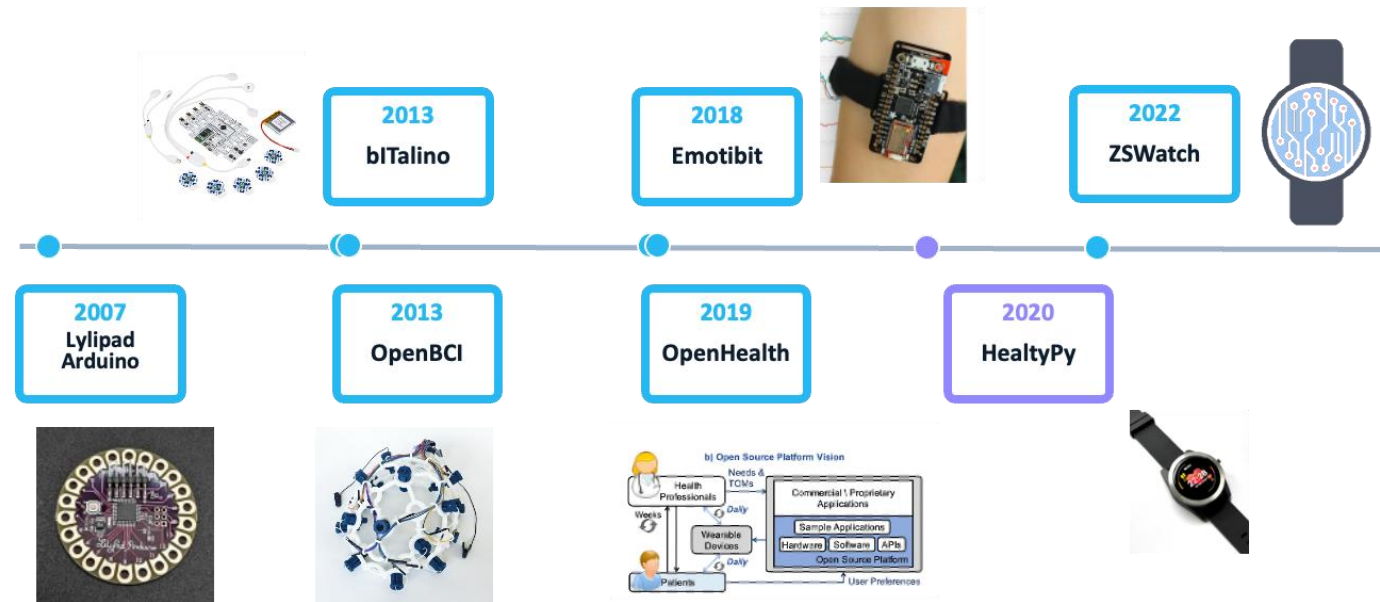
- Technical/research
- Commercial
- Biomedical
- Medical/Rehabilitation

Open-source has a long impactful trajectory



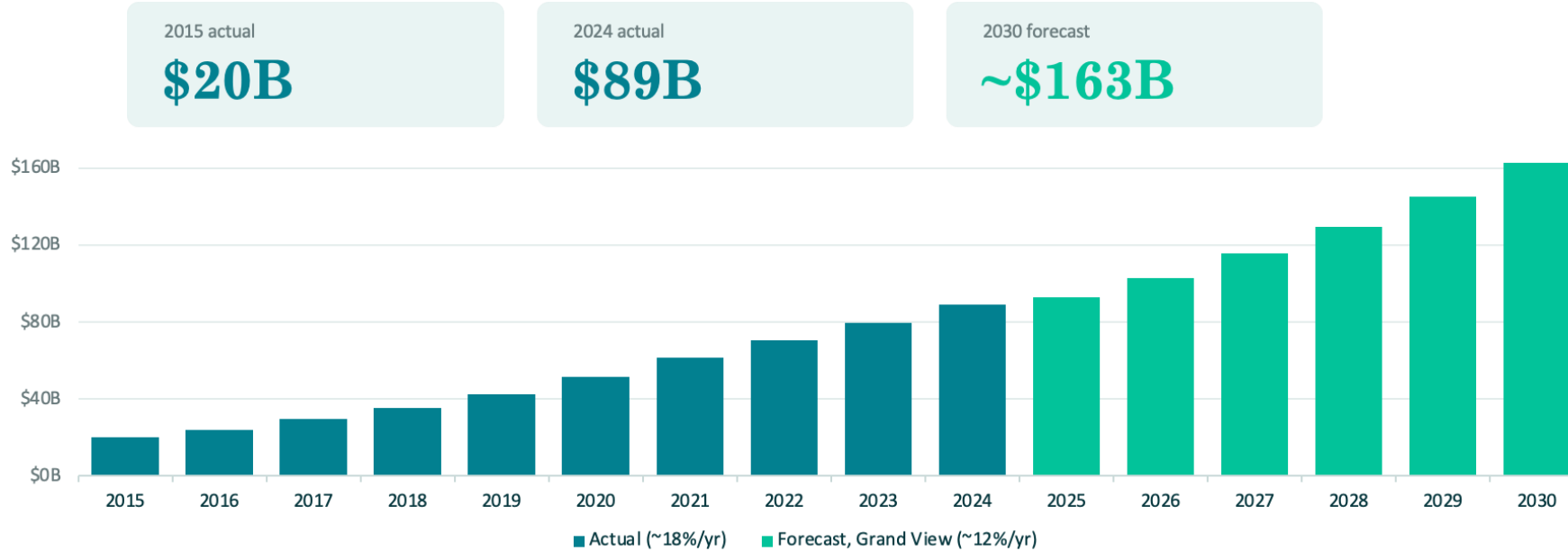
Open-source has a growing hype also in wearables

- Wearables were gaining traction both in academic research and as commercial devices
- So far, we have a growing ecosystem of devices-repositories-datasets-tools



16400+ papers on wearable tech (2003-2022)

Big Techs are investing a lot of effort for wearables



Smartwatches: Apple, Samsung, Garmin, Huawei, Xiaomi, **Fitbit (Google)**

Smart Glasses: Google, Meta-Luxottica, Snap Inc, Vuzix, **North (Google)**

Armbands: **Meta**, Myo, Scosche, Wahoo

Smart rings: Oura, Motiv, McLearn, Go2Sleep

New ways of interaction

A huge amount of data
Information

End of story? Not yet!



Commercial devices

- High performance
- Broad availability



- Closed by design



innovation (in wearable devices) greatly benefit from:

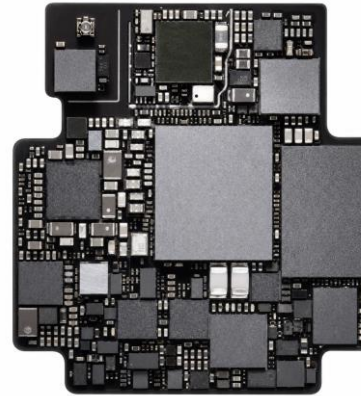
- prototype new sensing modalities,
- explore alternative acquisition settings,
- implement custom processing pipelines,
- investigate new interaction paradigms beyond vendor-defined workflows

We have 2 great news!

1- Open-source designs are industry-level



Garmin FENIX 7



APPLEWATCH



GAPWATCH



BIOGAP ULTRA

Fully open-source

From the design perspective, we can exploit the same complexity:

- Multilayer board
- BGA components (high level of integration)
- Blind
- Advanced communication stacks
- Libraries for deployment of NNs on embedded processors

2- We have a full open-source stack



Platforms

- HW
- FW
- Mechanical design files

Algorithms

- Libraries (C, Python, Matlab)
- Implementations (target platforms)

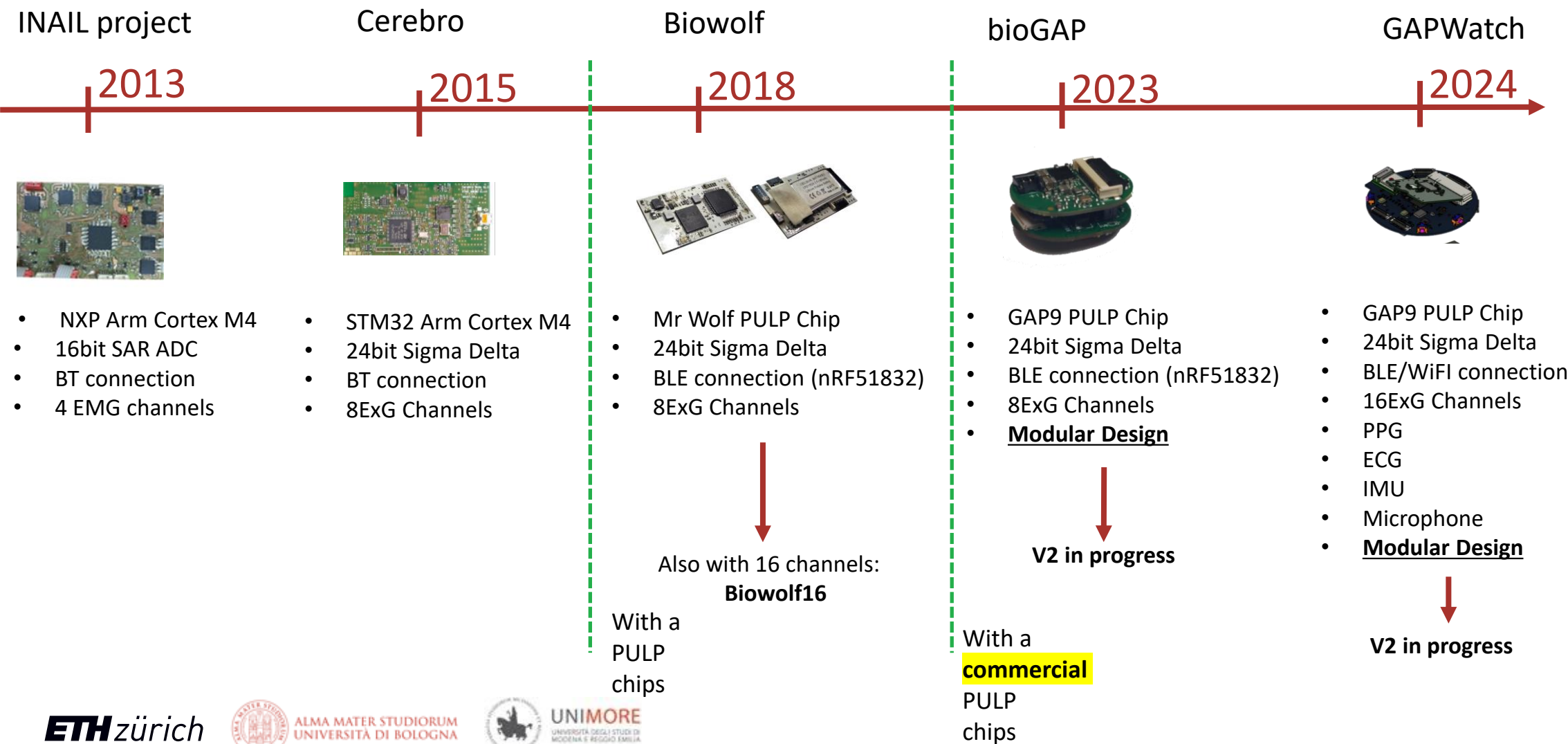
Frameworks

- Interfaces for connecting devices
- Standardized pipelines
- Benchmarking tools

All of these elements help drive an open-source project forward



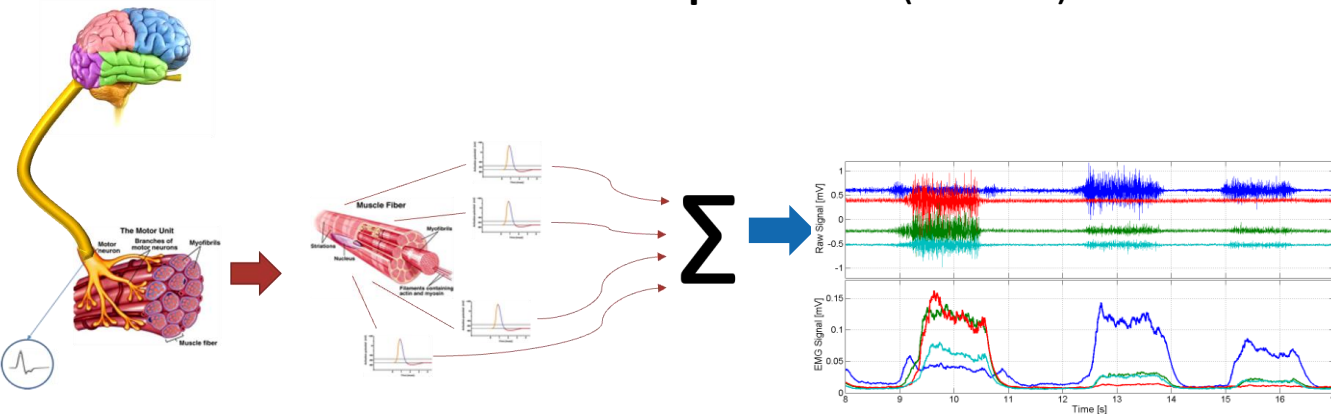
Connecting the Humans, PULP-based Wearable interfaces for Advance HMIs



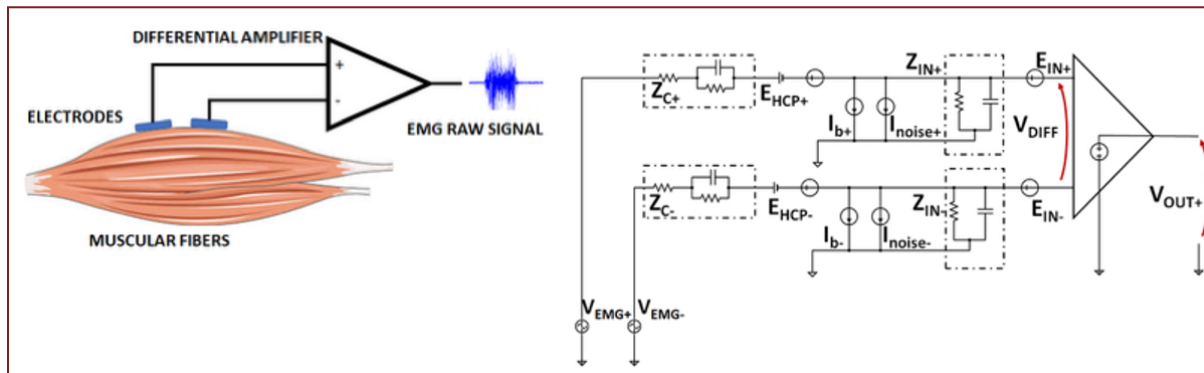
A modular device to acquire biopotentials

EMG Signal

- EMG signal measures the electrical activity generated by motor units in muscles
- **Motor Unit (MU)** → motor neuron and the muscle fibers it innervates
- **Motor Unit Action potentials (MUAPs)** → the electrical stimulus propagating through the muscular cells



MEASURING EMG



- Wide bandwidth content 20-2kHz
- Low Spatial resolution



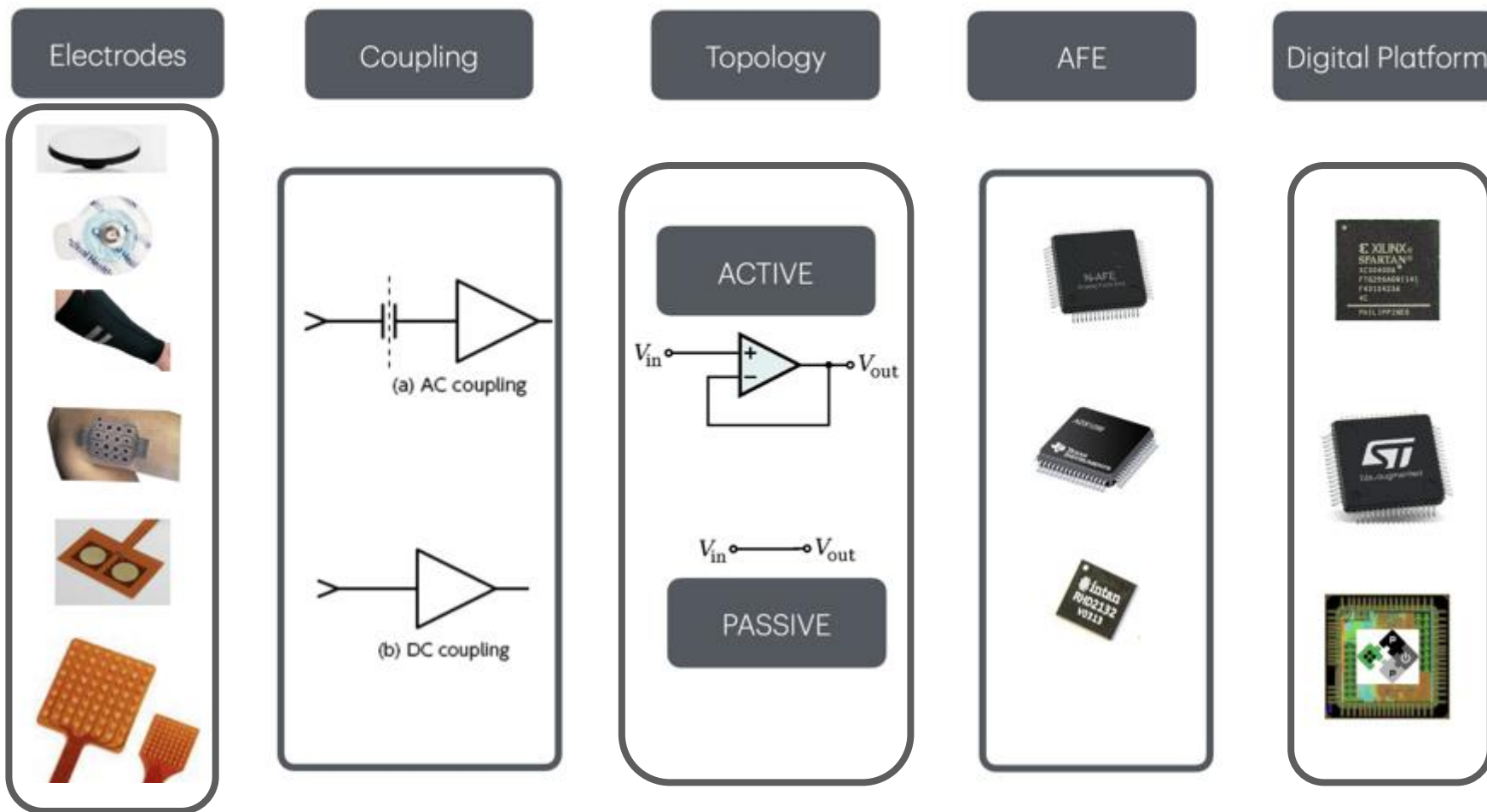
- Area of the sensors
- Integrating effects of the skin

EMG noise sources:

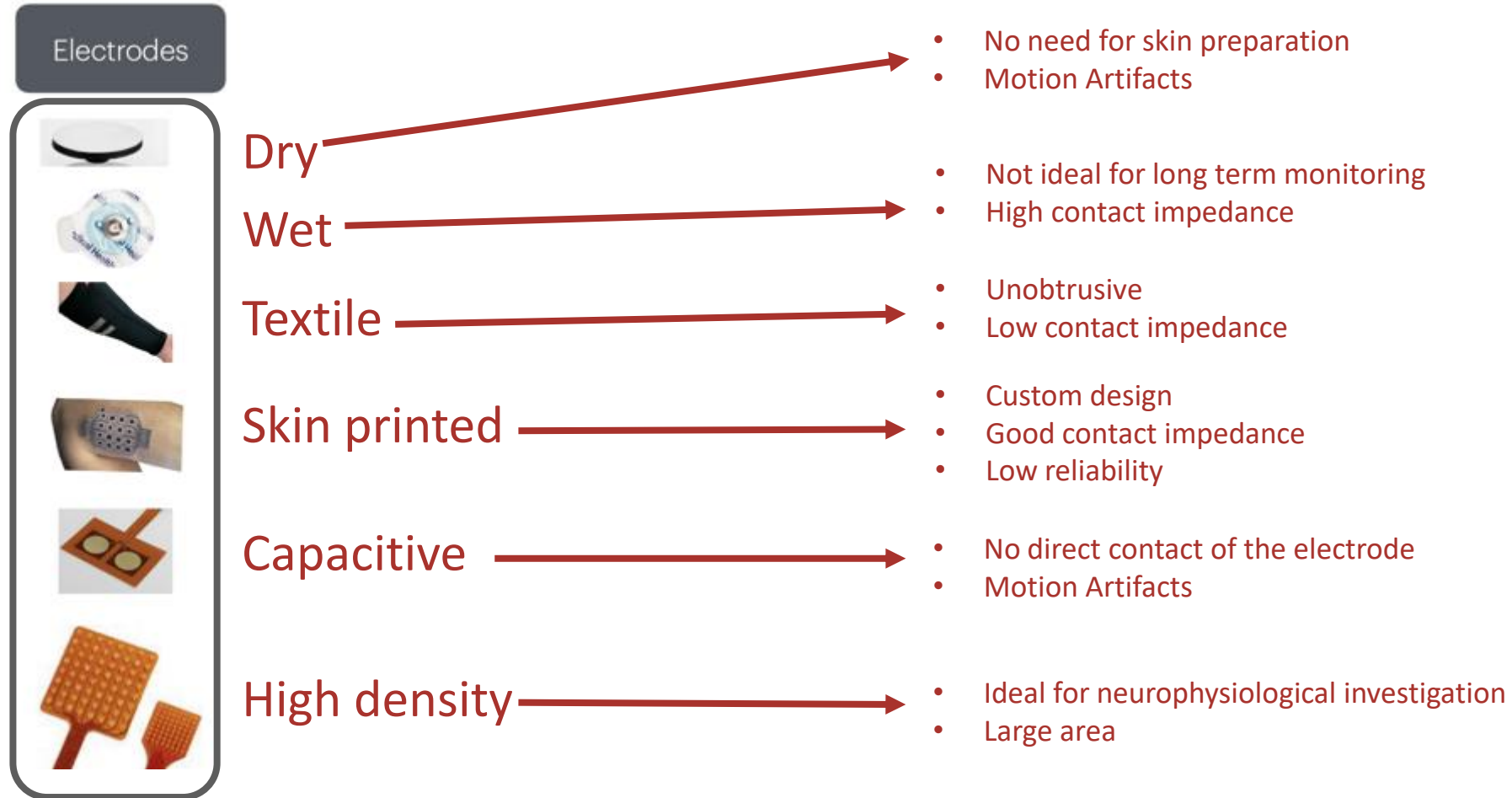
- Crosstalk
- Electrode-Skin interface Variability
- Perspiration



Architecture and connection schemes



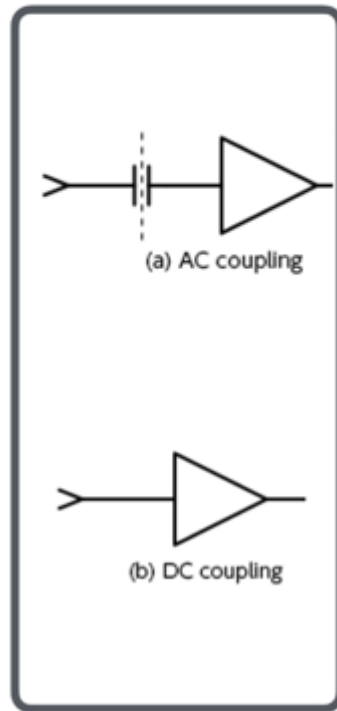
Electrodes



Signal coupling



Coupling



AC coupling removes the DC offset by using a decoupling cap.

- Signal normalized to a mean of zero.
- May unbalance the common-mode input impedance, degrading the CMRR value

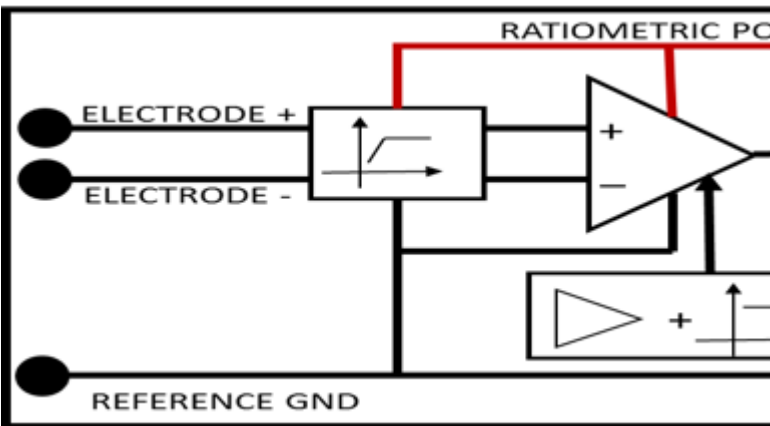
DC coupling allows AC and DC components to pass through

- Signal drifts → larger dynamic range (higher power consumption).
- Higher CMRR value → no phase distortion

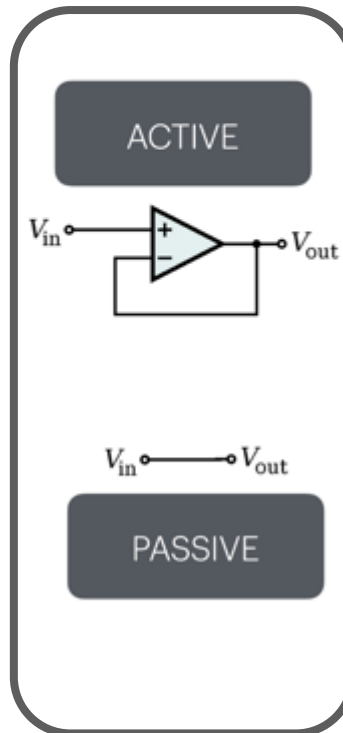
Active-passive sensors

Active sensors : pre-amplified electrodes

- A preamplification stage ensures higher impedance
- Reduces PLI noise



Topology



Passive Sensors : Direct connection with the ADC

- A direct connection grants a simpler design.
- Last generation AFEs feature ultra low noise

Analog Front-End



AFE

AD7177-2

- 4 channels **32-bit delta-sigma**.
- Power consumption (40mW ADC)
- Programmable data rates up to **250 kSPS**
- Good noise performance for accurate signal acquisition (2 μVPP @150 Hz, CMRR -116 dB)

ADS1298

- 8 channels 24-bit delta-sigma.
- **Low Power (0.7mW x channel)**
- Programmable data rates up to 32 kSPS
- Good noise performance for accurate signal acquisition (4 μV_{PP} @150 Hz, CMRR -115 dB).

RHD2032

- 32 channels 16-bit delta-sigma.
- **Low Power (5uW x channel)**
- Programmable data rates up to 30 kSPS
- Excellent noise performance for neural recording (2.4 μV RMS @(0.1 Hz - 10 kHz), CMRR -90 dB)..



Digital Platform



The digital processing of the biopotentials can be executed on

- commercial low-power / high performance programmable systems
- FPGAs
- Custom ICs

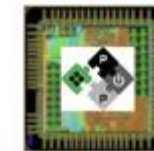
Digital Platform



High end FPGA

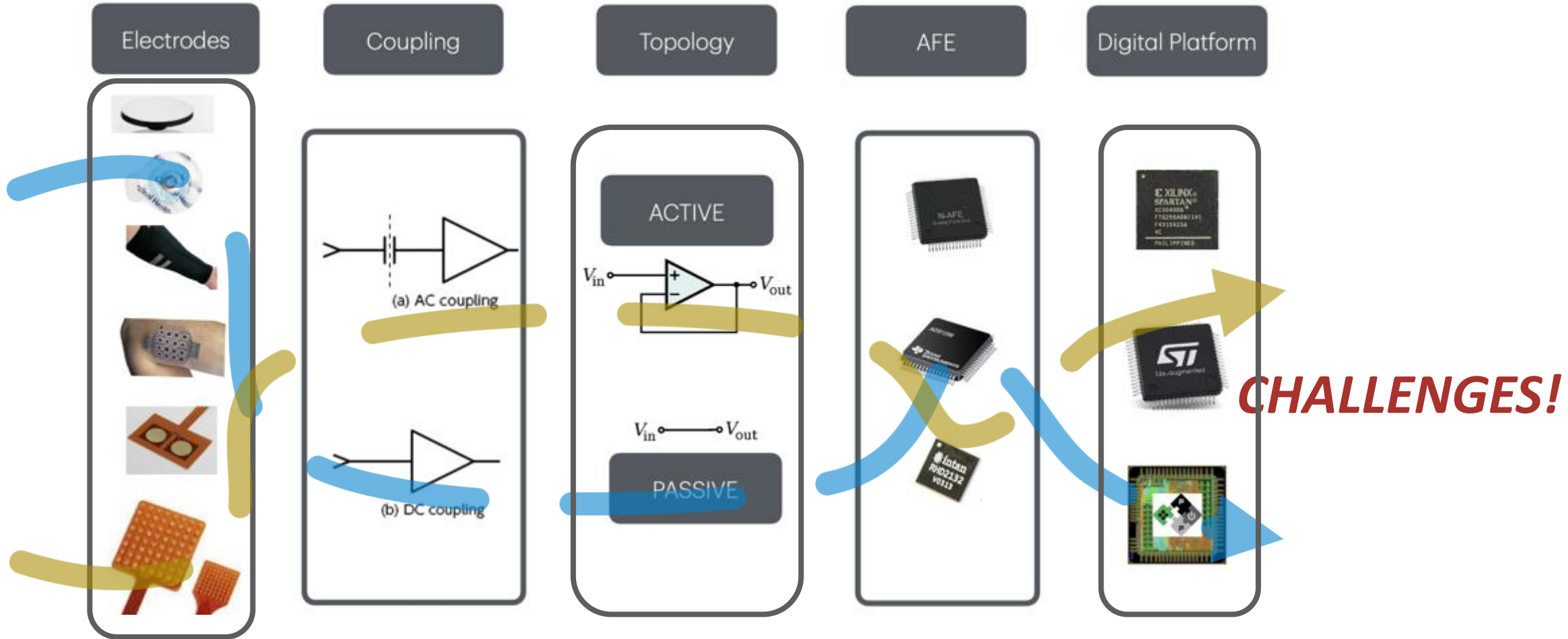


Microcontrollers



PULP / ASICS

Where do we stand ?



GAPwatch: a modular wristband-armband wearable computing platform



- PULP-based computing platform: **GAP9**
 - TOPS capabilities, 10 RISC-V cores, 128 kB L1 memory, 1.5 MB RAM, 370 MHz operation (state-of-the-art performance for tinyML)
- ESP32 WiFi + BLE connectivity
- 16 ExG channels AFE based on ADS1298 for biopotential measurement
- 9 Axis UMU
- EDA-PPG-ECG acquisition IC
- Microphone

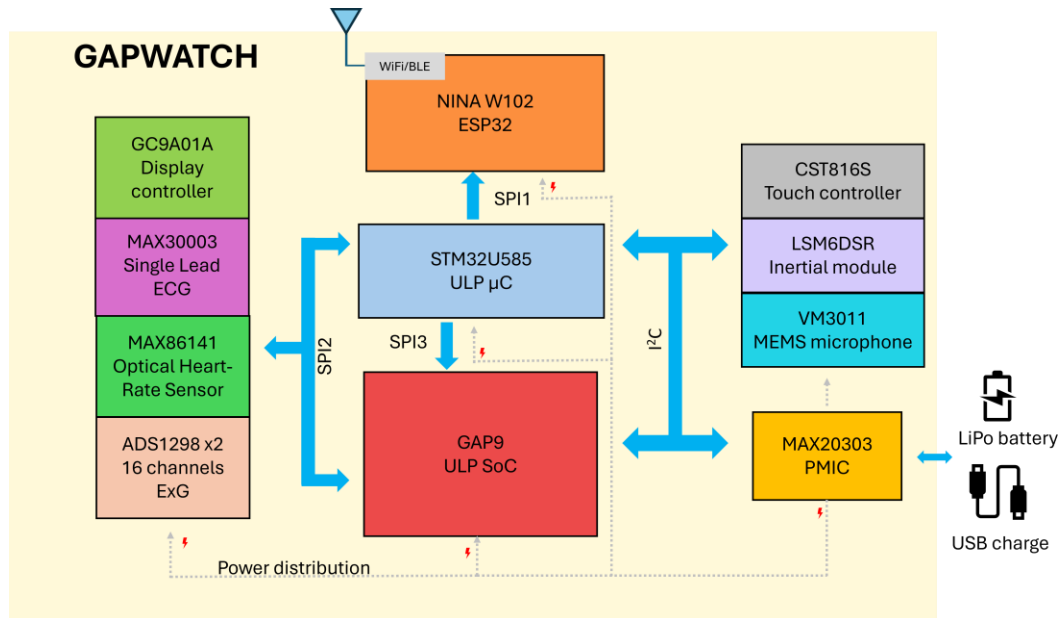
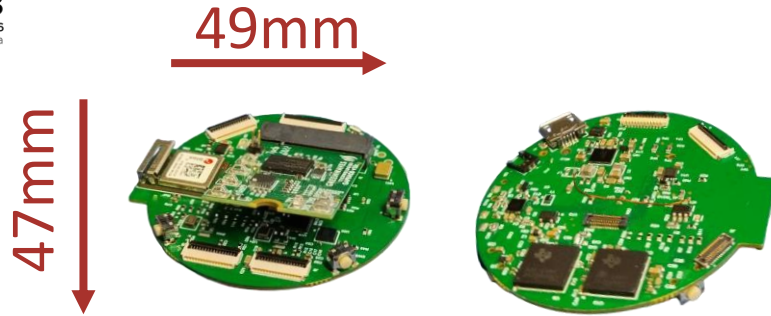


GAPWatch: Main Components



- **Compute:**
 - GAP9 SoC
 - μ C (STM32U585)
- **Sensors:**
 - PPG dual channel (MAX86140)
 - ECG single lead (MAX3003)
 - 16 channels ExG (two ADS1298)
 - 3D ACC (LSM6DSX)
 - Expansion flex connectors
- **Radio:**
 - BLE + WiFi (ESP32)
- **UI:**
 - 240x240 display with touch interface

GAPWatch: System Diagram



- **Data Flow**

- STM32 microcontroller acts as the central gateway, managing all data routing so the GAP9

- **Segmented SPI Topology:**

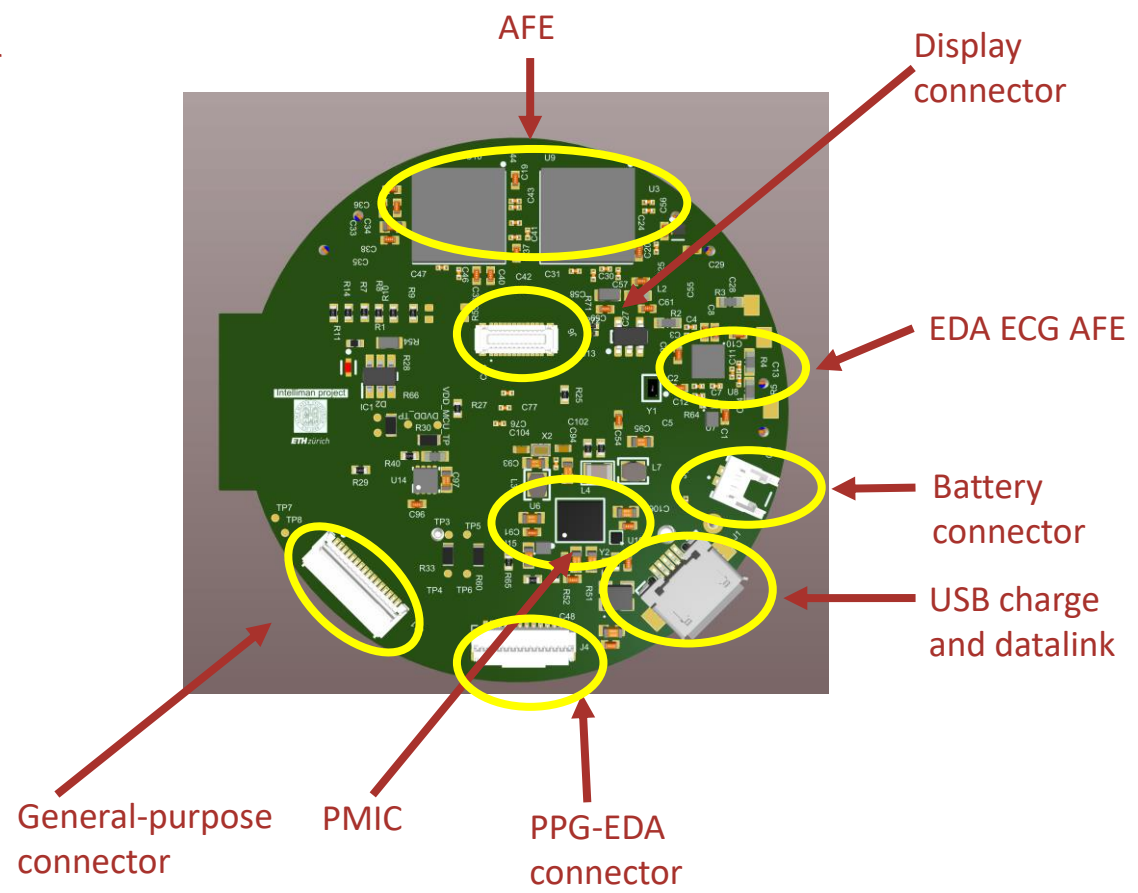
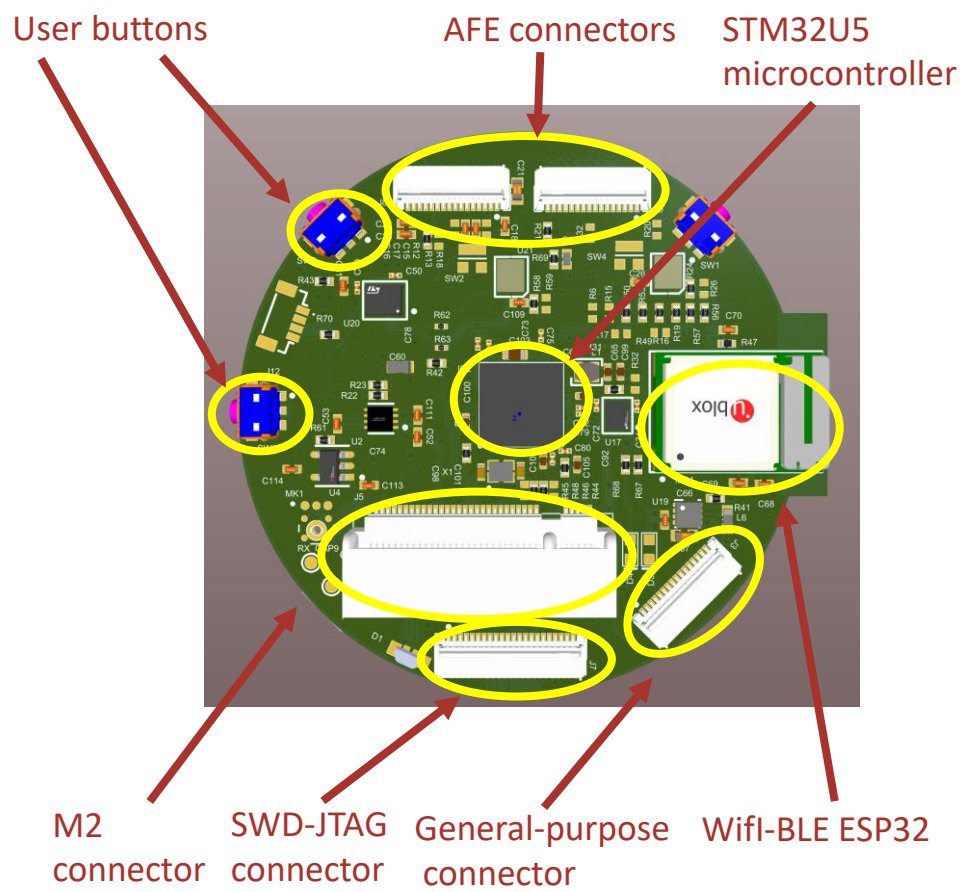
- Isolation of the communication lines: μC - GAP9, μC - Radio. μC - Sensors

- **Centralized PMIC:**

- The MAX20303 handles all battery management and generates the main digital power rails.
- Separate 3.3V rail using low-noise LDOs for analog

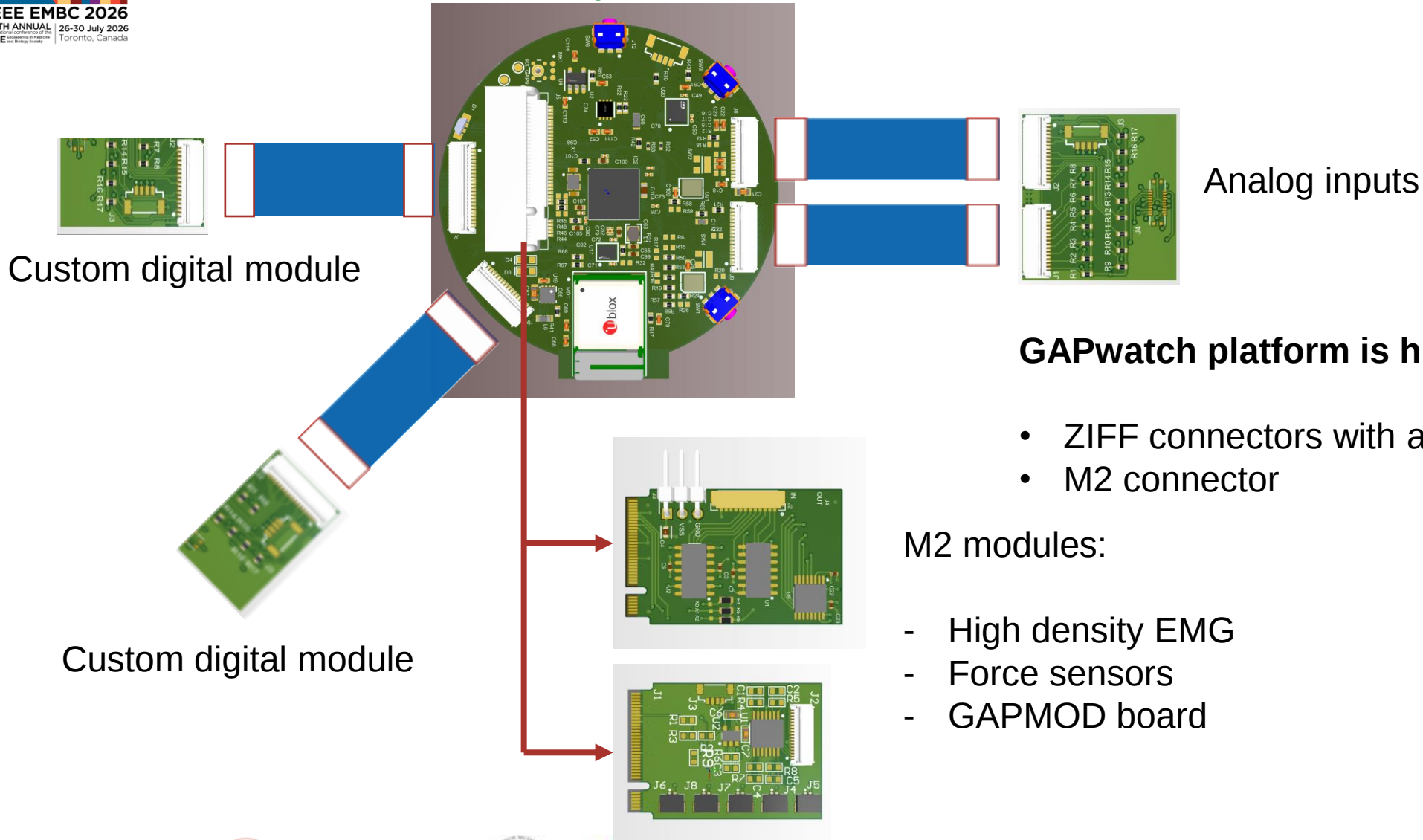


GAPWATCH: Base Board – Connectors





GAPWATCH: Expansion boards and connectors



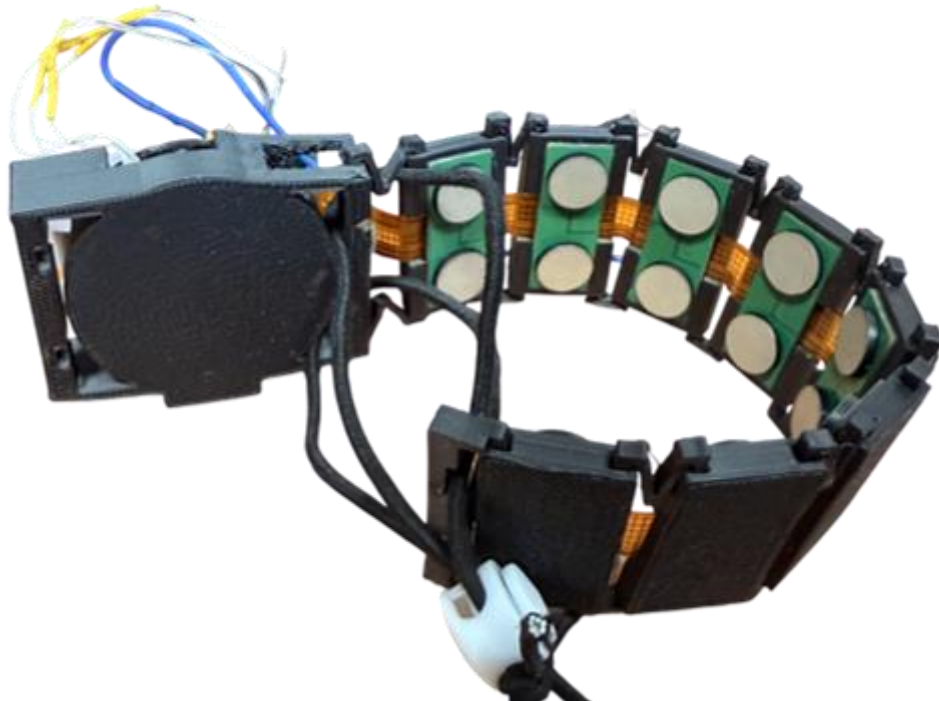
GAPwatch platform is highly configurable:

- ZIFF connectors with analog inputs
- M2 connector

M2 modules:

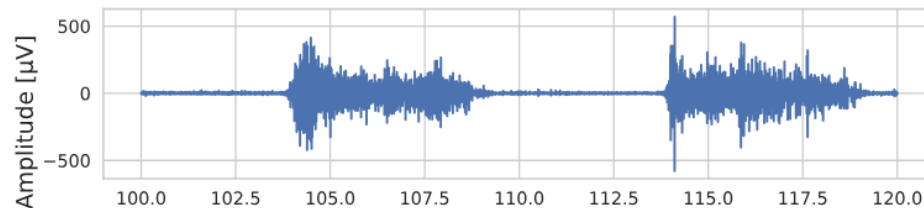
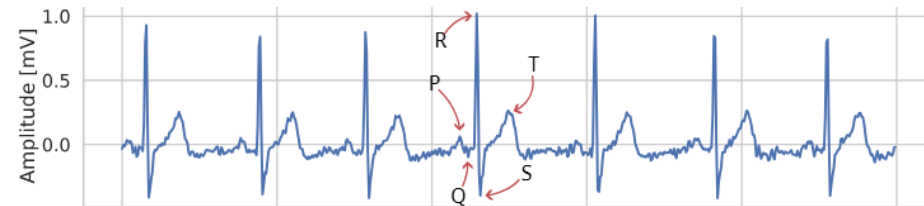
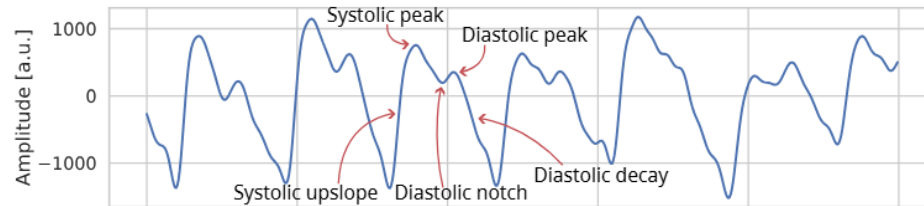
- High density EMG
- Force sensors
- GAPMOD board

sEMG Armband



- **Adaptive & Ergonomic Mechanics**
 - Fully 3D-Printed TPU Structure
 - "Accordion-Style" Segments
- **Active Sensor Nodes**
 - SoftPulse™ Dry Electrodes: Every case houses two Datwyler dry electrodes
 - Local Amplification: each node features a PCB with a unit-gain, low-noise amplifier.
- **Routing & Integration**
 - Flex-PCB Backbone: A PCB collects signals from all local boards
 - 16-Channel Monopolar Montage: Feeds into the smartwatch's dual ADS1298 front-ends (24-bit ADC).
- **Streaming capabilities:**
 - Possibility to stream 16 chs @ 4ksps using WiFi
 - ~2hrs of continuous streaming (250mAh battery)

Experimental use case



- **Photoplethysmography (PPG)**

- Origin: An optical technique using LEDs and photodiodes to measure blood volume changes
- Key Uses: Continuous Heart Rate (HR) and SpO2 monitoring

- **Electrocardiography (ECG)**

- Origin: Captures the electrical potential of the heart muscle across the skin.
- Key Uses: Clinical-grade cardiovascular diagnostics, precise Heart Rate Variability (HRV) analysis.

- **Surface Electromyography (sEMG)**

- Origin: Non-invasive recording of the biopotentials produced by skeletal muscle fibers during contraction.
- Key Uses: Muscle fatigue tracking and advanced Human-Machine Interfaces (HMI)

Onboard Processing for Heart Rate (HR) monitoring

Challenge: Extracting accurate Heart Rate (HR) from PPG corrupted by motion artifacts

Limitation: Classical methods fail to obtain robust HR estimation under heavy motion artifacts

Proposed Solution: Using a lightweight Temporal Convolutional Network (TEMPONet) on a combination of PPG and 3D ACC data

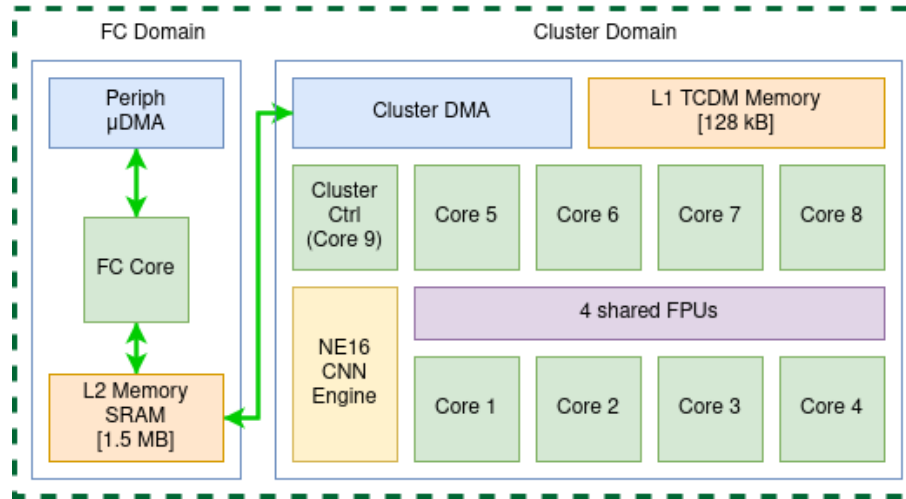
Deployment: Deploy the network directly on-board the GAPWatch, exploiting its local edge computation.

Output: Stream out the final HR estimation using the BLE link.

GAP9 SoC and deployment



GAP9 SoC



- **PULP-based SoC**
- **Single-core RISC-V controller**
- **Multi-Core RISC-V Cluster**
- **NE16 AI Accelerator**

Deployment steps



ONNX

Trained
model



Optional Post training
quantization

NNTool + Autotiler

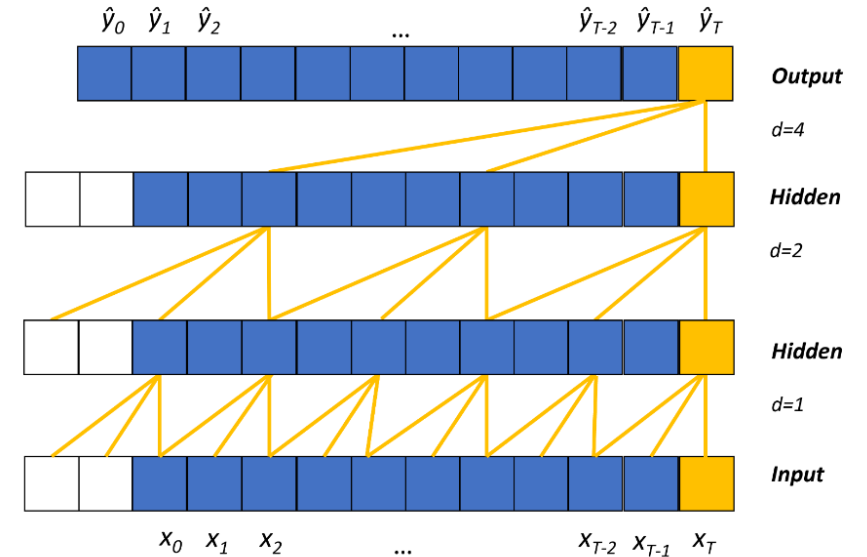


C code of
the network

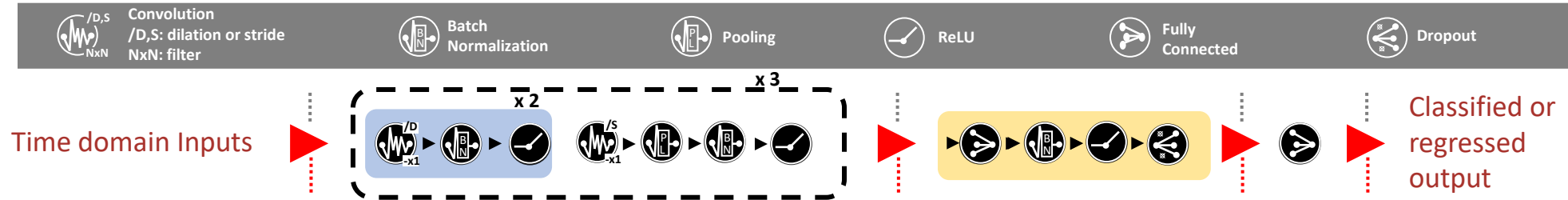
Temporal Convolutional Networks (TCNs)



- **TCNs are a specialized subclass of one-dimensional CNN that:**
 - Ensure causal convolution
 - Feature dilated convolution
 - Have an exponential growth of the receptive field with the number of layers
 - Cover long-range temporal dependencies



TEMPONet Architecture



- **Architectural Foundation**

- Developed for sEMG hand-kinematics.
- Acts as a specialized feature extractor, learning both short- and long-range temporal dependencies

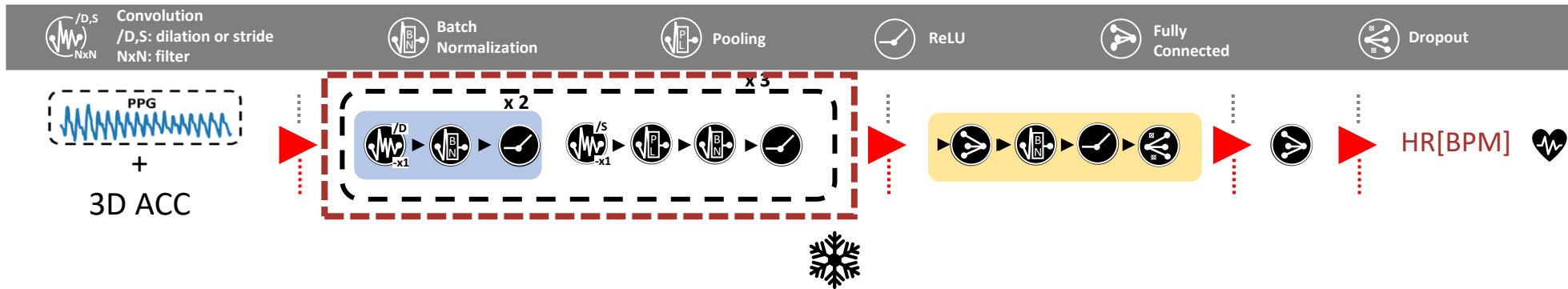
- **The Feature Extractor**

- Progressive Receptive Field: increasing dilation factors
- Temporal Downsampling: larger kernels with strides

- **Lightweight Classification/Regression Head**

- Tiny Memory Footprint: The head is constrained to two Fully Connected layers.
- Flexible Output: Classification or Regression

Onboard Processing for HR Regression



Method

- Lightweight version of TEMPONet
- PPG + 3D ACC: 8s window with 2s step
- **Custom dataset 4 subjects, ~48 min**
- Synch ECG for HR Ground truth

Pre-Training

- Initial training performed on the public PPG Dalia³ dataset to learn robust feature representations.

Fine-Tuning Strategy on custom dataset:

- Frozen convolutional blocks (first two layers); only the third block and regression MLP were fine-tuned

Experimental Results



Deployment:

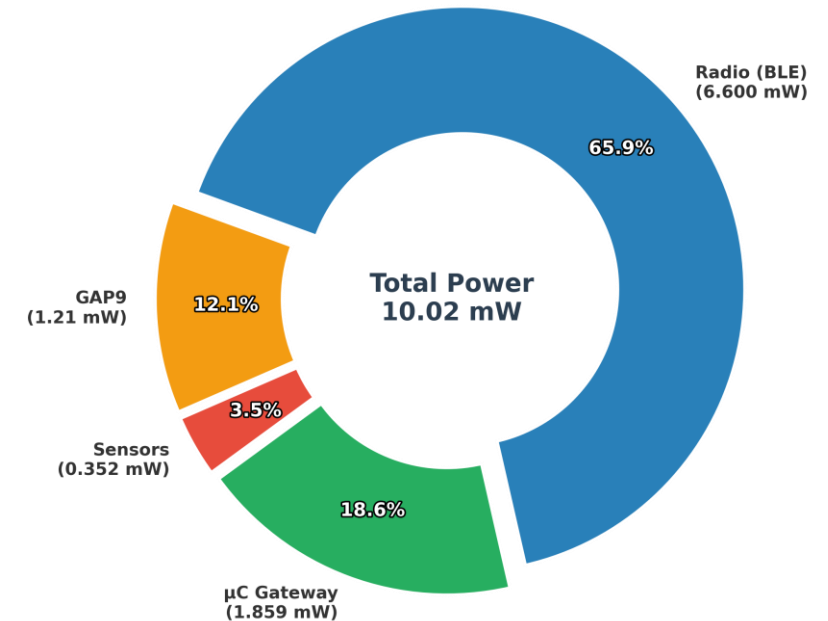
- Deployed on GAP9 using 8-bit quantization
- **162k** params
- Inference time of just **2.83ms**
- **58μJ** per inference

Accuracy:

- MAE of **3.18** $\pm$ 0.55 bpm for the finetuned network
- 2x better than frozen net

Power budget:

- Average power of the system of 10mW, >92-hours of battery life
- 13x less power than transmitting raw signals



Thank you for your attention!