Zephyr® Project
Developer Summit

Beefy ML

Ultra low-power algorithms on cattle

Jordan Yates, Embeint

Quick Disclaimers

- I am no longer a CSIRO employee
- I am presenting this work in a personal capacity with the permission of CSIRO
- All work in this presentation was funded by CSIRO
- Different slides can refer to different algorithms

Acknowledgements

Greg Bishop-Hurley - PhD

- CSIRO
- Project Leader
- Principal Research Scientist
- Cattle Wrangler

Reza Arablouei - PhD

- CSIRO
- Research Scientist
- ML & Data Wrangler

EMBEDDED OPEN SOURCE SUMMIT

Problem Overview

What are we trying to solve?

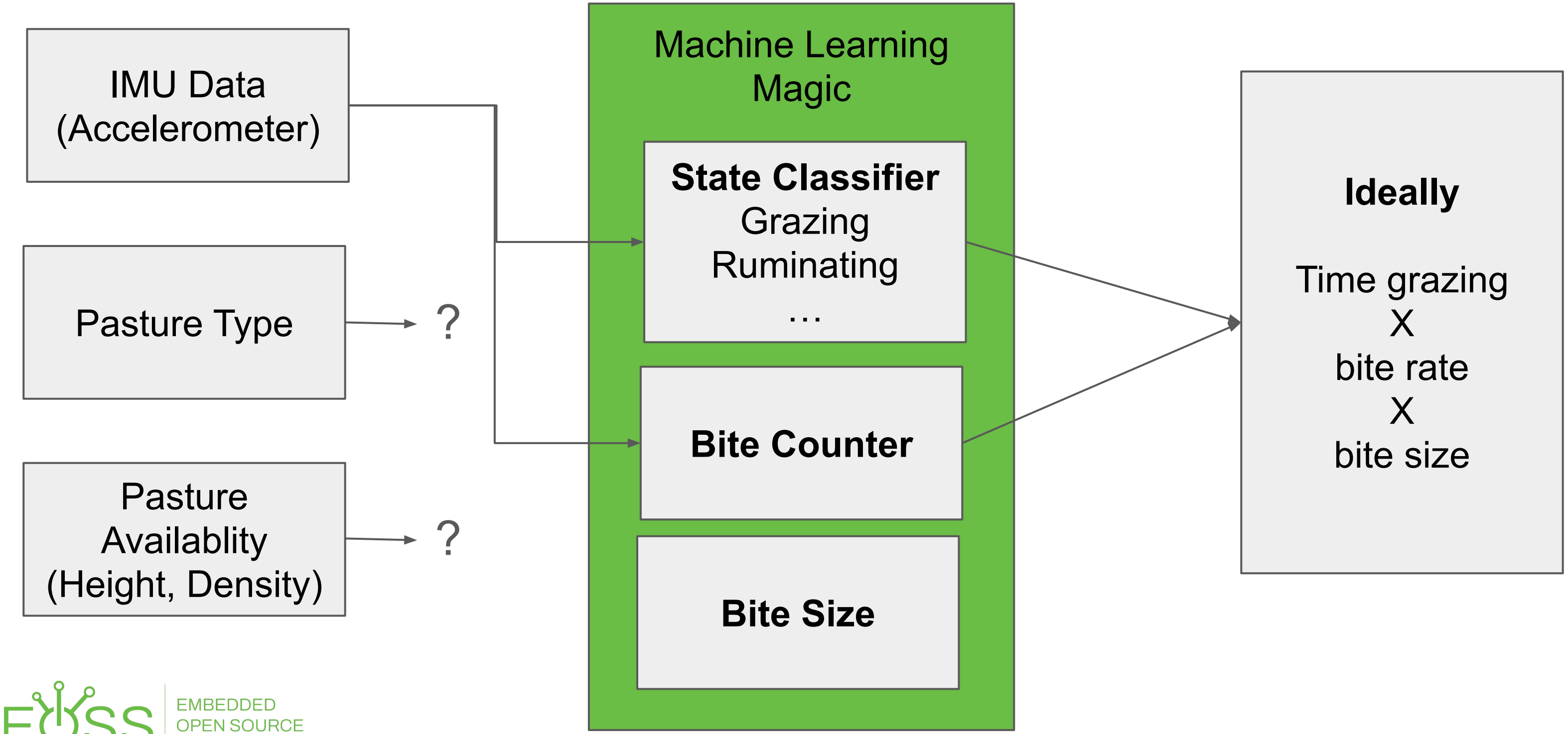
- Cattle are an emissions intensive protein source

- Selective breeding can be used to improve “Feed Efficiency” (or other traits)
  - Ratio of dry matter ingested to weight gain

- Weight gain is relatively easy to measure
  - Walk-over weighers are common equipment

- Dry matter ingested is harder to quantify
  - Farmers don’t want to stand in the sun all day watching their cows

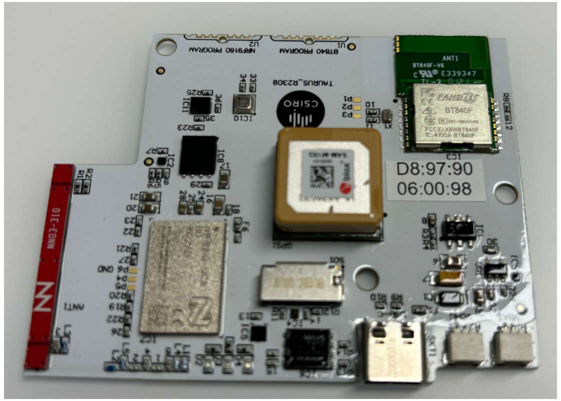
How do we get to dry matter ingested?



Hardware Platforms

Research Collar (Ground Truth)

- Many iterations over the years:
  - Loci2: TI MSP430 + LoRa + Ublox M8 GNSS
  - Loci3: Nordic nRF52840 + LoRaWAN + Ublox M8 GNSS
  - Loci4: Nordic nRF9160 (Builtin LTE & GNSS)
  - Taurus: Nordic nRF9160 (Builtin LTE) + Ublox M10 GNSS
- Indefinitely solar powered
- 14 AHr LiPo battery
- 1Hz GNSS trace (~15mA average current)
- Low power IMU
- Periodic environmental
- Contact logging via Bluetooth
- SD card logging (~1GB/month)



1MB FLASH
256KB RAM

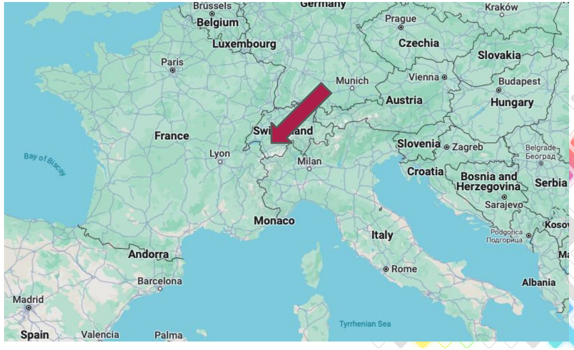
CERES Tag (Commercial Product)

- nRF52840 + GNSS + Globalstar MEO Satellite
- 1 MB Flash, 256 KB RAM
- Indefinitely solar powered
- Rechargable LiFePO4 battery
- Low power accelerometer
- Periodic environmental
- Minimal onboard flash
- <30 grams
- Originally designed for cattle

Data Collection

Ground Truth Data Collection

- ~100 multi-month deployments of research collars
  - ~10 informing current models
- Data annotation
  - 24/7 video recording in restricted fields
  - In-field annotation by researchers & farm staff
  - Automated data recording (walk over weighers, etc)
- Ear tags don’t have sufficient storage for raw data
  - Collars connect to paired ear tag
  - Ear tags stream sensor readings over Bluetooth GATT
  - Collars store readings on local SD card



EOSS EMBEDDED OPEN SOURCE SUMMIT

Example Trial Setup

EMBEDDED
OPEN SOURCE
SUMMIT

Example Trial Setup

EMBEDDED
OPEN SOURCE
SUMMIT

Deployment Monitoring

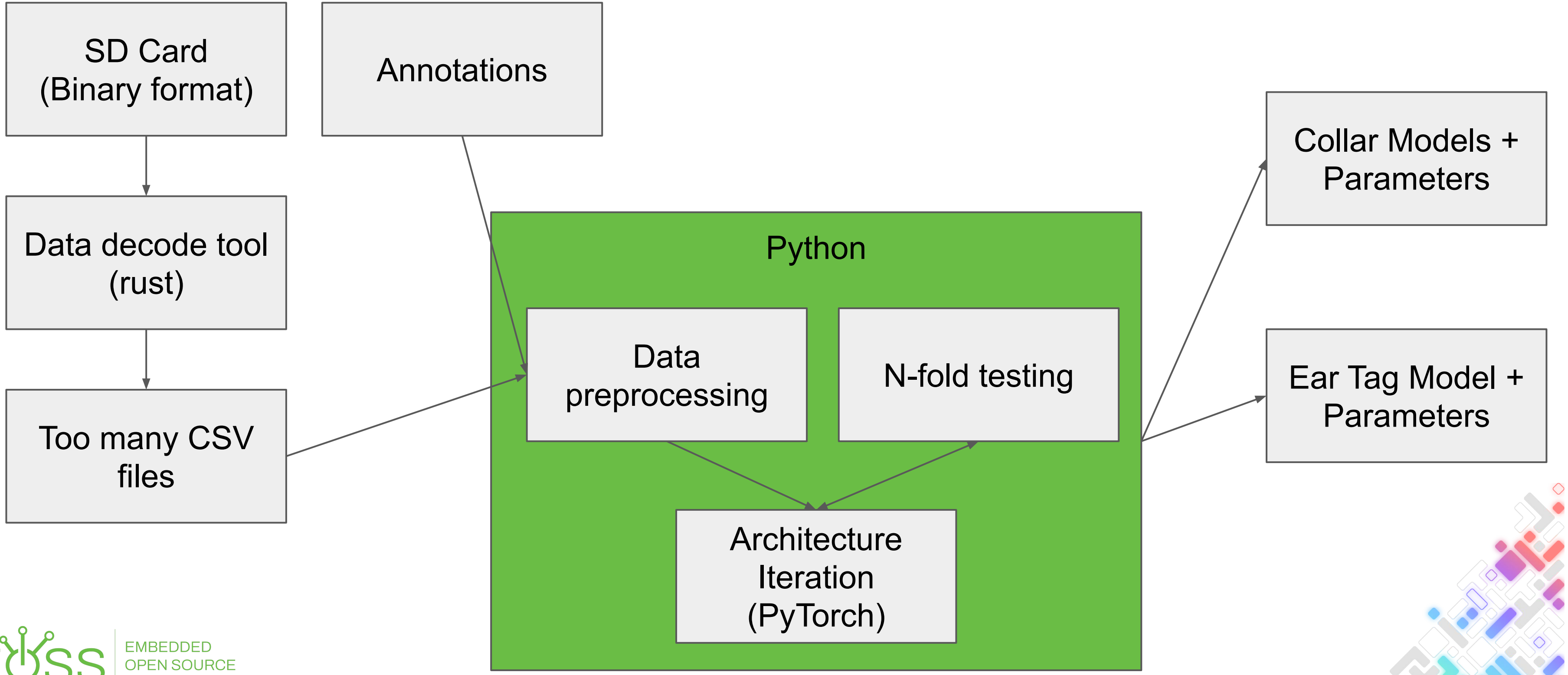
Device Table

UUID	Timestamp	Route	Battery Voltage	Battery Current	Battery SOC	Temperature	Humidity	Latitude	Longitude	Height	GPS Acc	SD Card	Graze	Walk	Ruminate	Rest	Drink	Other	GATT Thru	GATT Up	Algorithm ID	Algorithm Version
d89790060 06d	28 Mar 2024, 09:36:51	UDP	3590mV	4072mA	28%	35.440°C	47.000RH	-27.55639330	152.34448680	134.784	1.09 m								328	1		
d897900600 65	28 Mar 2024, 09:36:49	UDP	3787mV	8322mA	65%	33.690°C	76.000RH	-27.55662040	152.34437230	138.001	1.18 m		2	0	13	104	0	1	330	1	3203399426	1
d89790060 05a	28 Mar 2024, 09:36:44	UDP	3688mV	9596mA	53%	33.410°C	88.000RH	-27.55612350	152.34375140	139.841	1.13 m	4442294							333	1		
d89790060067	28 Mar 2024, 09:36:42	UDP	3759mV	1177mA	62%	31.800°C	64.000RH	-27.55615200	152.34372270	125.878	1.19 m								0	0		

EMBEDDED
OPEN SOURCE
SUMMIT

Data Processing

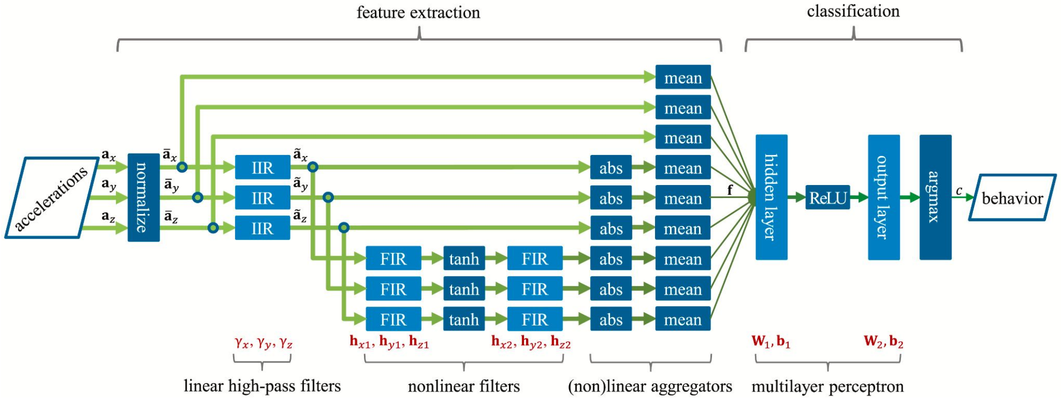
Data Processing Pipeline



Algorithm Design

Architecture tweaking points:

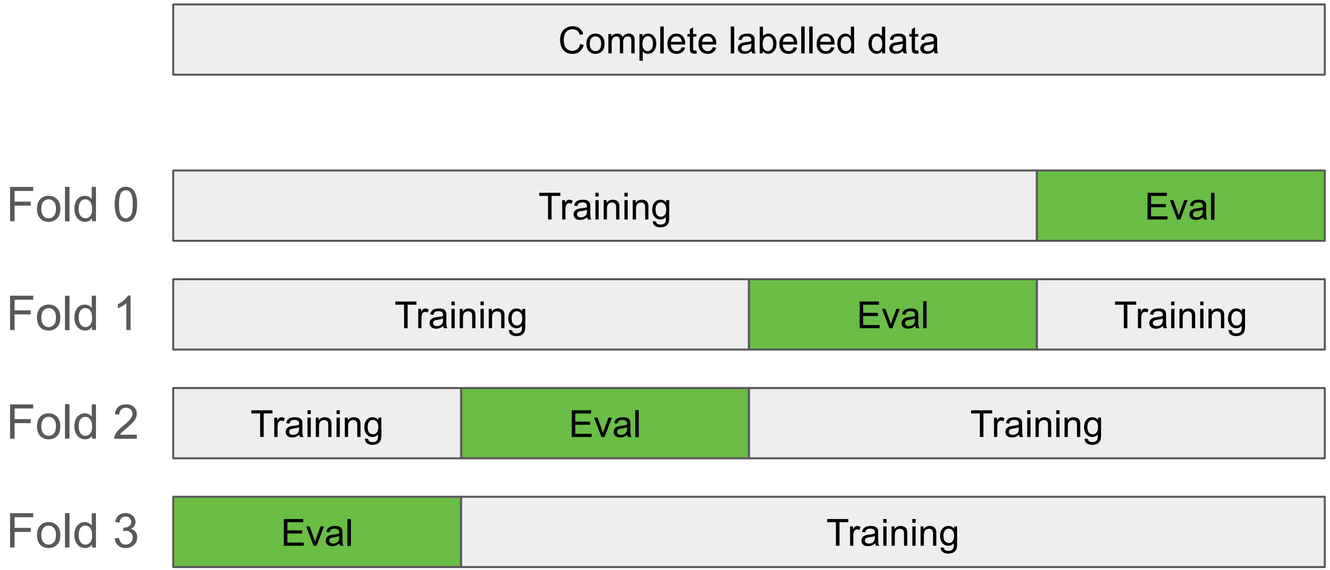
- Number of features
- Feature width
- Number of layers
- Activation functions



Iteration is a heuristic process:

- Combinatorial optimisation
- Evaluating both architecture and model parameters

Algorithm Evaluation (N-fold testing)



Algorithm Challenges

Cattle are not co-operative test subjects:

- Collars move around on the neck
- Ear tags move around in the ear

Unbalanced data sets:

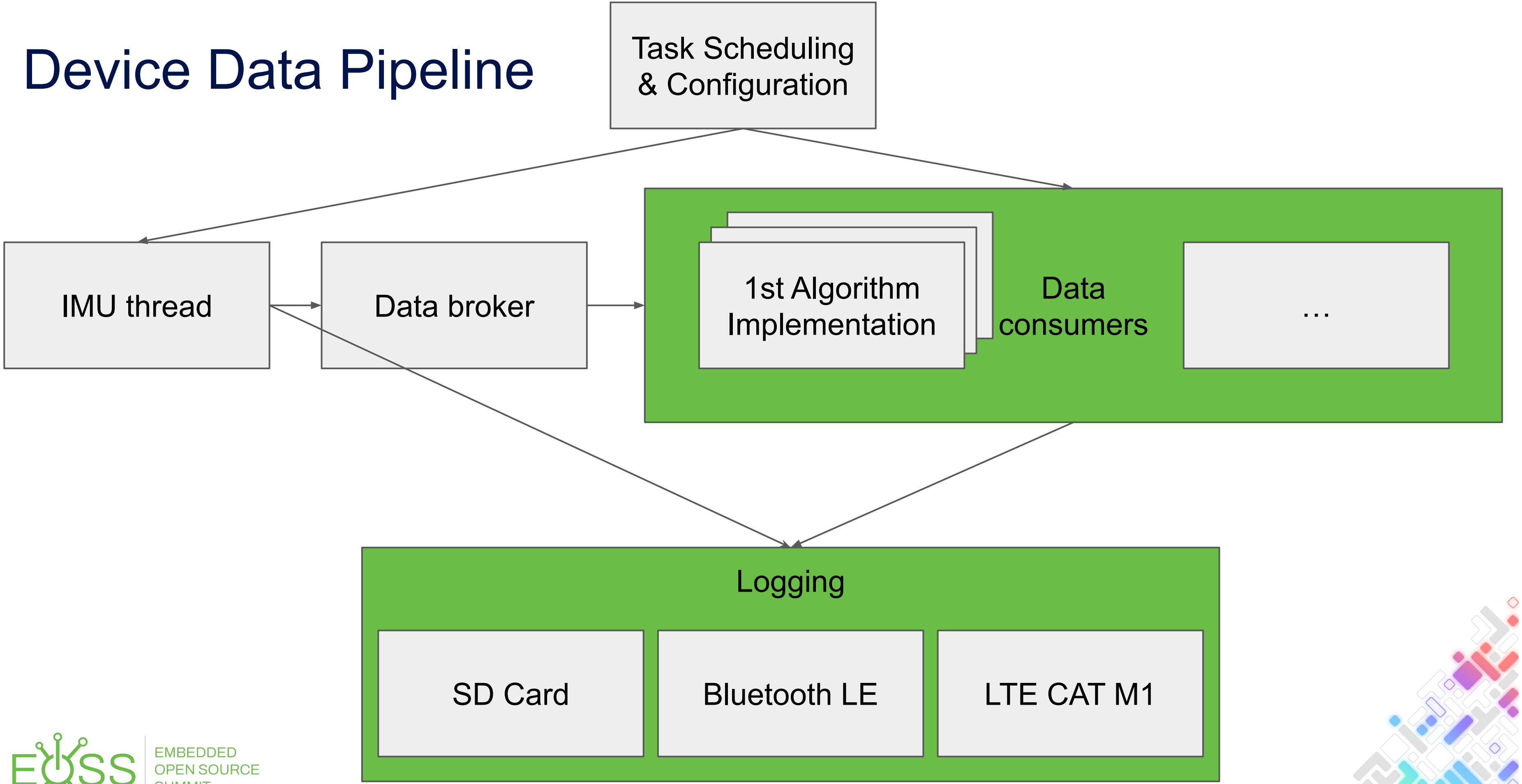
- Cattle behaviour is not a uniform distribution (Grazing >>>>> Drinking)

MEMS accelerometers are non-ideal:

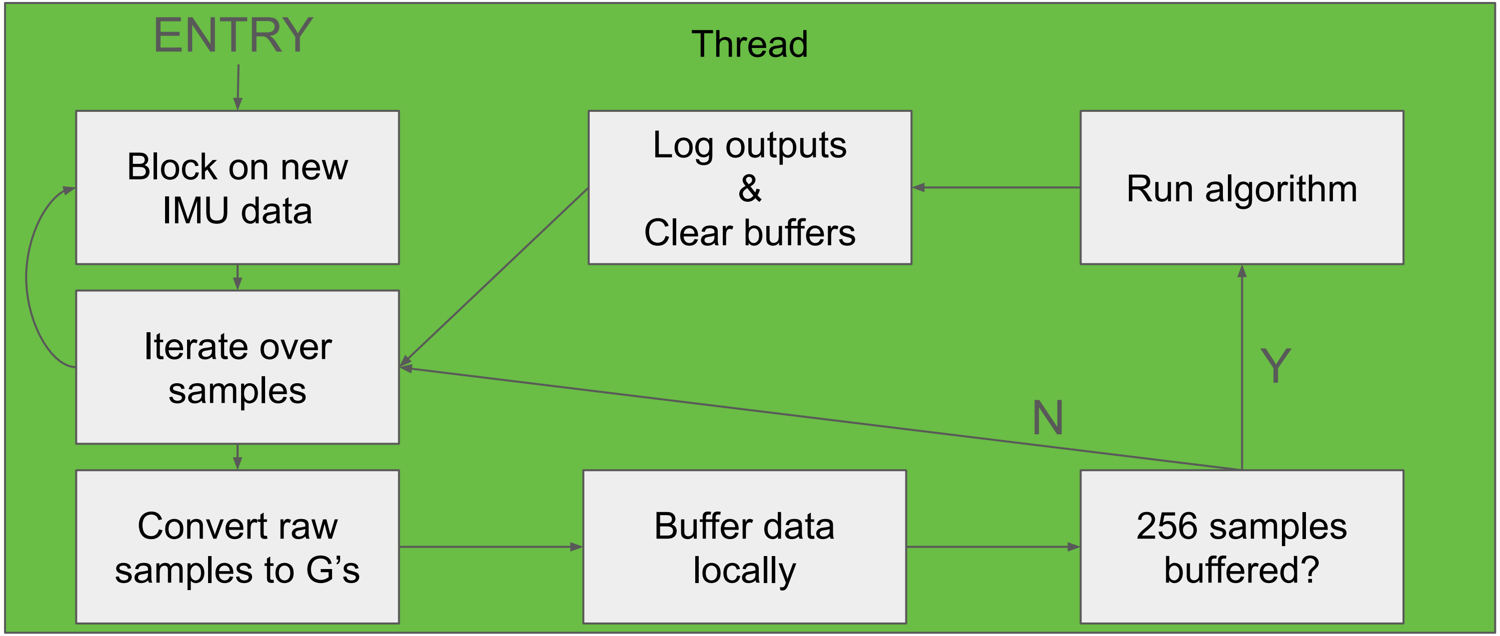
- Host of confounding factors
  - Temperature variation
  - Non-linearities
  - Inherent noise
  - Cross-axis sensitivity
  - etc
- Requires statistical properties, not individual samples
- Gyroscopes are even worse

On-Device Implementation

Device Data Pipeline



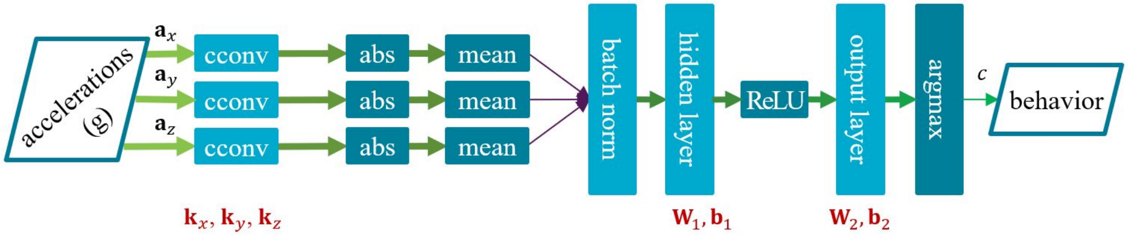
Algorithm Thread



Algorithm Implementation - CMSIS DSP

Various operations required:

● FIR filters	arm_fir_f32
● Convolution	arm_conv_f32
● Matrix multiplication	arm_mat_mult_f32
● Hyperbolic tangent	tanhf (math.h)
● Absolute value	arm_abs_f32
● Mean	arm_mean_f32



EOSS EMBEDDED OPEN SOURCE SUMMIT

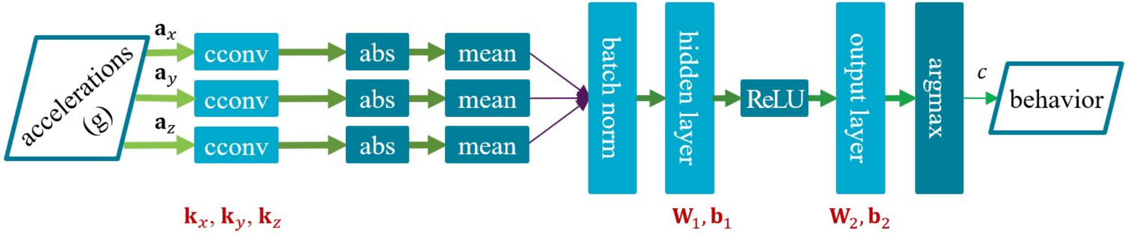
Algorithm Implementation

Implemented as two separate functions:

- Feature Extraction
- Classification

Unit tested against example outputs from PyTorch (via ztest)

- CMSIS DSP implementation matches to at least 5 decimal places



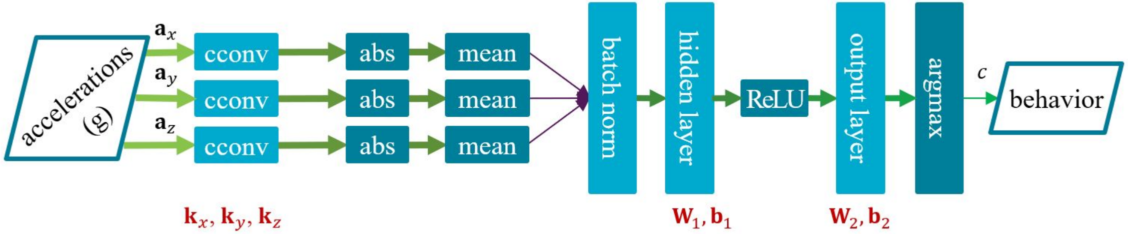
Algorithm Implementation

Implemented on 32 bit floating point numbers:

- Nordic chipsets have hardware FPU

Quantized implementations (Q7) were tested:

- Faster runtime (~2x)
- Significantly smaller weights (11kB vs 41kB)
- Slightly lower accuracy (0.874 vs 0.881)
- Significantly more painful to implement

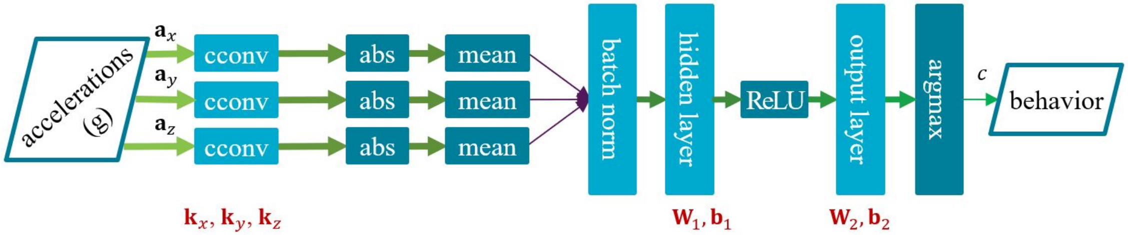


Algorithm Implementation

Algorithm implementation can be ROM heavy. Driven by the following:

- Number of feature vector elements
- Dimensions of weight matricies

RAM usage is minimised through intelligent re-use of buffers.



Implementation performance

Algorithm runs over 5.12 seconds worth of data (256 samples).

Feature extraction and classification runs in 20ms (0.4% CPU utilization).

Weights for each algorithm are approximately 2kB ROM.

```
|       |   └── egrazor                                        5232   1.76%
|       |       ├── lib                                        4060   1.37%
|       |       |   ├── egrazor_collar_angus_v2.c              2104   0.71%
|       |       |   └── egrazor_collar_brahman_v1.c            1956   0.66%
```

DSP functions use < 1kB ROM.

```
│    └──lib                     17436  5.87%
       ├──cmsis-dsp               746  0.25%
```

Algorithm Accuracy

Confusion Matricies:

true \ predicted	grazing	walking	ruminating	resting	drinking	other
grazing	6551	3	3	9	7	15
walking	8	39	0	11	0	7
ruminating	2	0	2254	242	0	4
resting	8	3	172	2908	16	19
drinking	12	0	0	32	57	3
other	57	4	12	48	7	50

(a) The Arm18 dataset with 6 classes.

true \ predicted	grazing	walking	ruminating resting	drinking	other
grazing	6548	3	16	8	13
walking	7	44	7	0	7
ruminating resting	11	3	5586	12	16
drinking	25	0	28	50	1
other	55	6	58	7	52

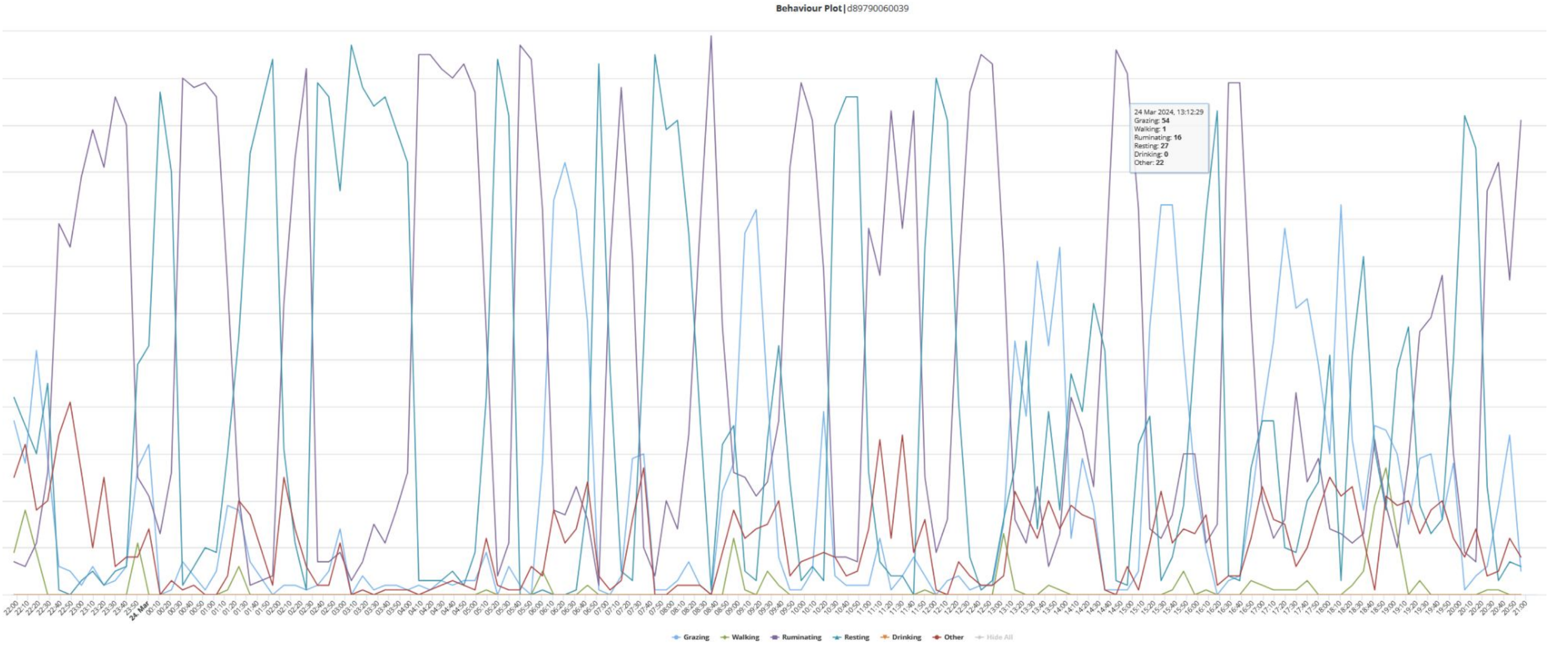
(b) The Arm18 dataset with 5 classes.

true \ predicted	grazing	walking	ruminating resting	drinking	other
grazing	5978	37	62	54	25
walking	131	751	17	1	10
ruminating resting	103	23	3833	98	23
drinking	59	0	99	434	2
other	58	28	59	7	70

(c) The Arm20 dataset.

- Imbalanced data
- Drinking looks more like grazing than walking

Algorithm Outputs



References

In-situ classification of cattle behavior using accelerometry data

https://doi.org/10.1016/j.compag.2021.106045

In-situ animal behavior classification using knowledge distillation and fixed-point quantization

https://doi.org/10.1016/j.atech.2022.100159

Animal behavior classification via deep learning on embedded systems

https://doi.org/10.1016/j.compag.2023.107707

Questions

Zephyr® Project

Developer Summit