Presentation Will Begin Shortly

4:00

WIRELESS COMPUTE

FEB 22ND | Choosing the Best MCU Platform for Your IoT Devices

MAR 28TH | EFR and EFM: An Optimized Platform for AI/ML at the Edge

MAY 2ND | Unboxing our New 32-bit Microcontroller

JUN 6TH | Introducing Simplicity Studio 6: A New Approach to IoT Development

SILICON LABS

Welcome

EFR and EFM: An optimized platform for AI/ML at the (Tiny) Edge

Andrew Halstead

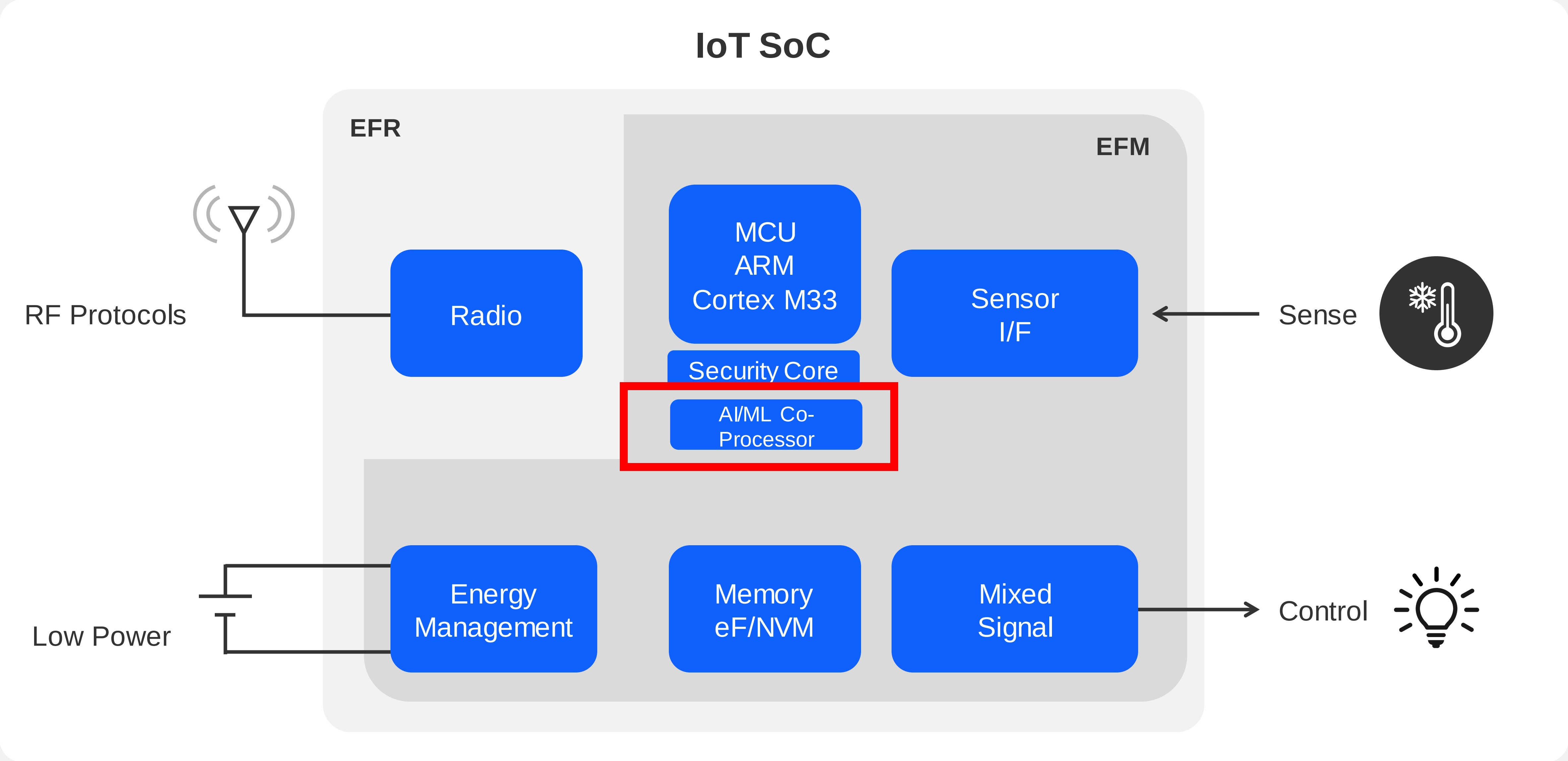
techtalks

WIRELESS COMPUTE

Agenda

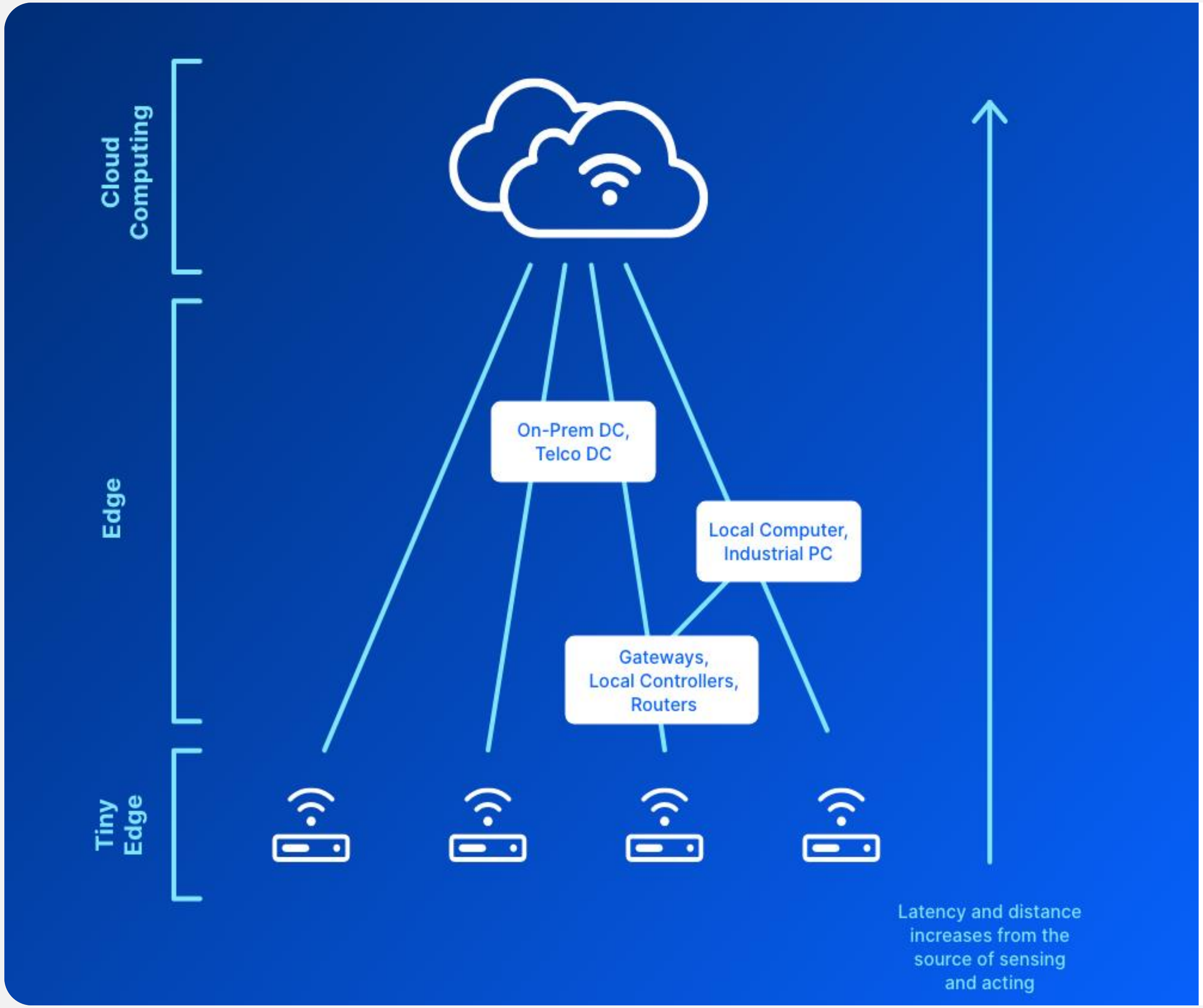
Introduction

100% IoT Focused Company



What is AI/ML at the Edge? And Why has it become Important?

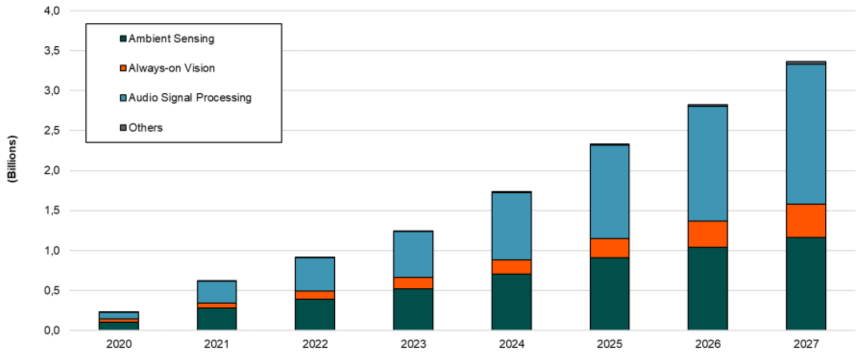
Artificial Intelligence(AI) and Machine Learning(ML) at the Tiny Edge



Key Benefits

- Low Latency
- Privacy, IP Protection, Security
- Bandwidth Constraints
- Offline Mode Operation
- Cost Reduction

>3B Devices sold with TinyML in 2027



**Source: ABI Research, Artificial Intelligence and Machine Learning, 2 QTR 2022*

SILICON LABS

Why Machine Learning on Microcontrollers?

Low Latency Required

- Mission or safety-critical applications require real-time reactions
- Large data to process - typically at vision use cases - no time to upload to anywhere to process

Privacy and IP Protection, Security

- Data never leaves the sensing device, only inference result/metadata is transferred
- Less sensitive data to transmit, less chance to be hacked
- Protecting IP

Bandwidth Constraints

- Long range, low power, and slow networks can't transfer all TimeSeries data to process somewhere else
- Overloading of mesh network is an issue
- Large data to chunk e.g. hi-res images

Offline Mode Operation

- Local system keeps operating standalone in case of any network issue
- Connectivity is occasional or blocked by admin

Cost Reduction

- Network and infrastructure costs
- Data ingestion costs
- Data storage costs
- Cloud services
- Ops, maintenance
- Compact edge with ML solutions integrated to wireless SoC
- Cheaper devices

Power constraints

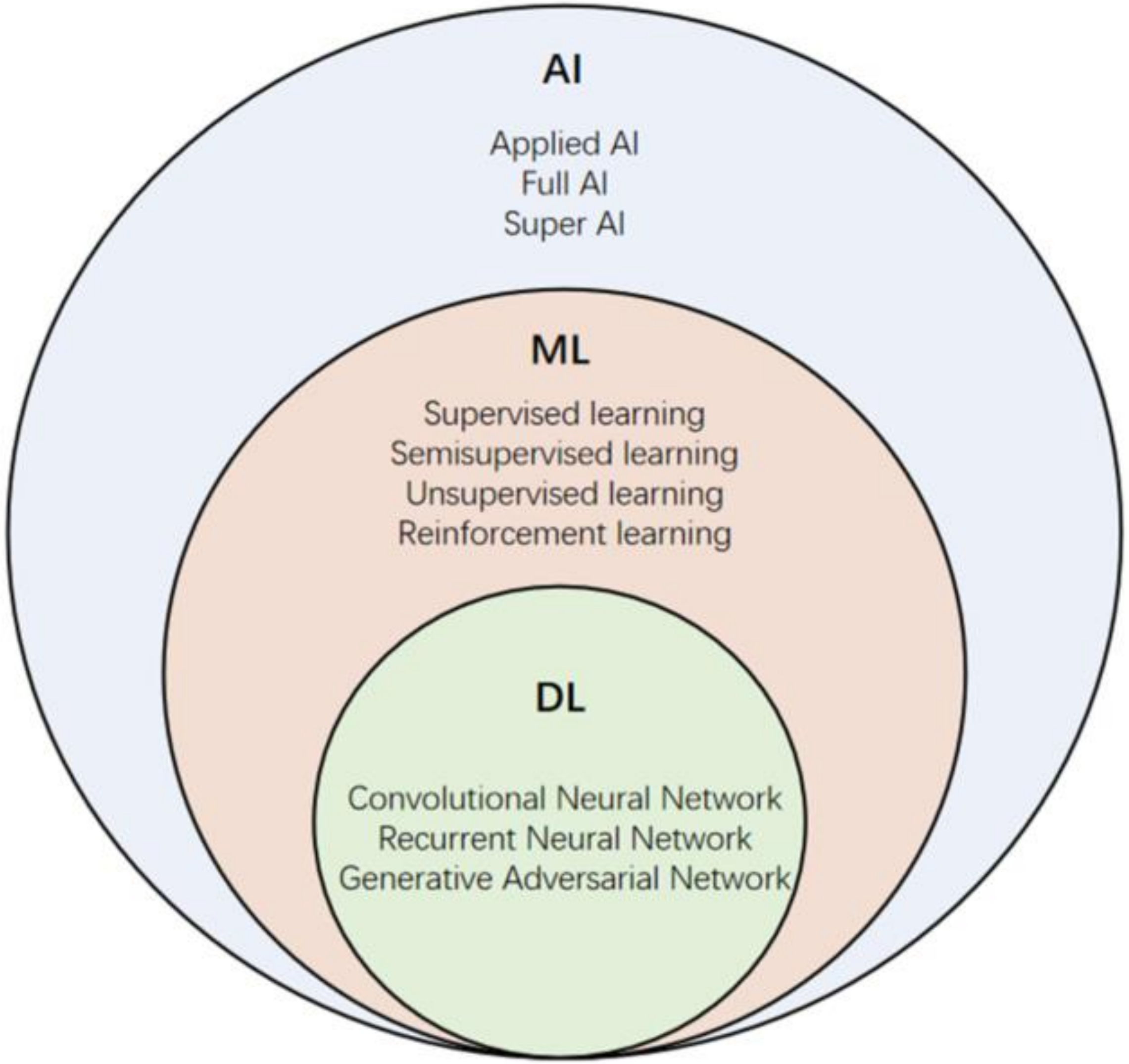
- Ultra-low power applications
- Always-on systems
- Healthy tradeoff in transmit to higher level compute vs. locally process

Data processing is more efficient with Machine Learning at the sensor level

SILICON LABS

What is Machine Learning in an Embedded Context?

The Terms…


AI
Applied AI
Full AI
Super AI
ML
Supervised learning
Semisupervised learning
Unsupervised learning
Reinforcement learning
DL
Convolutional Neural Network
Recurrent Neural Network
Generative Adversarial Network

Where is the drivable lane?

- **A rules-based approach: intractable problem**

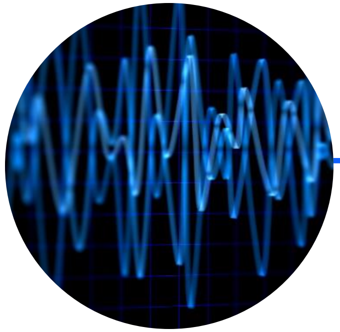





Use Case for ML in an Embedded Context

Sensors
- Acceleration, Temperature, Current/Voltage
- Time-series data on ADC or GPIO

ML methods based on Time-series Data
- Data anomaly detection
- Data pattern matching



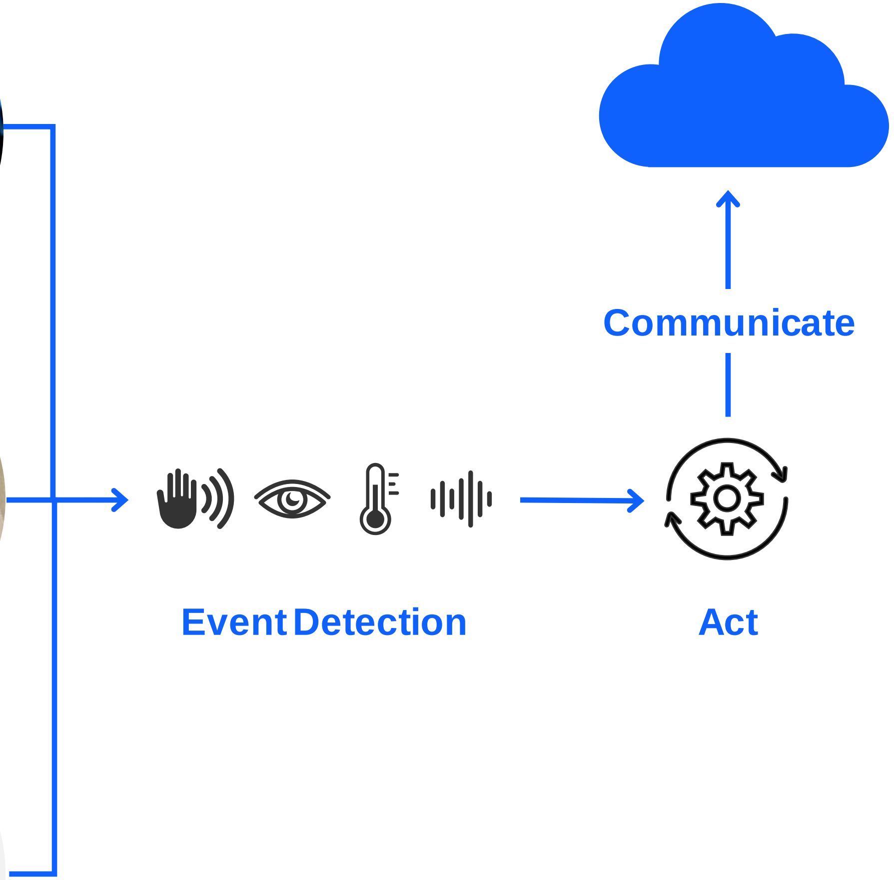
Microphones
Analog or Digital
- Audio mic array with beamforming
- Audio mic input with Audio Front End, DSP

ML methods based on Audio
- Audio pattern matching (ex. glass break)

ML methods based on Voice
- Wake word/command word detection

Camera
Low resolution imaging
- Image capture (including fingerprint reader)

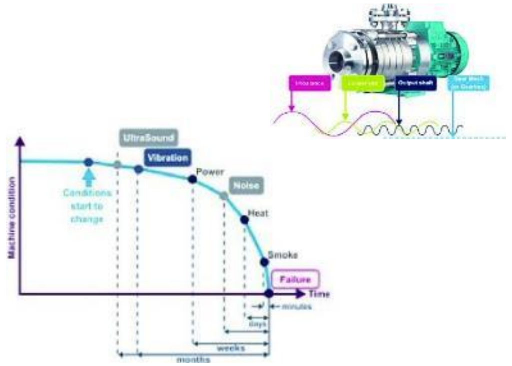
ML methods based on Vision
- Fingerprint reading
- Always-on vision – object detection
- Image classification and detection



Application Examples and Model Sizes

Wireless SoC's typical/recommended Resource needs with ML applications in Order of Magnitudes

RAM: 64kB
Ops/s: 5M-40M



SENSOR

Signal Processing
(time series, low-rate data)

- Predictive/Preventative Maintenance
- Anomaly detection (e.g. air quality, abnormal usage, leak detection)
- Condition based monitoring – machine health, Cold chain monitoring, Battery monitoring
- Bio-signal analysis -healthcare and medical (e.g., pulse detection, EKG)
- Accelerometer use-cases e.g., fall detection, pedometer, step counting
- Agricultural use-cases (e.g. cow health)

RAM: 128kB
Ops/s: 40M-100M

AUDIO

Audio Pattern Matching

- Security applications e.g., Glass break, scream, shot detection
- Cough detection
- Machine malfunction detection
- Breath monitoring

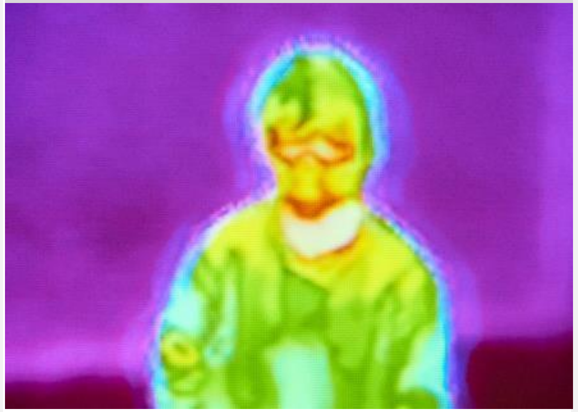
RAM: 256kB
Ops/s: 50M-500M

VOICE

Voice Commands

- 10 words command set for smart appliance
- Wake-word detection (Always-On voice)
- Smart device voice control
- Voice assistant

RAM: 256kB
Ops/s: 200M-1.5G w /hardware accelerator



VISION

Low-resolution vision

- Wake-up on object detection (always-on)
- Presence detection
- People counting, people-flow counting
- Movement detection
- Smart city monitoring (e.g. Parking spot)
- Fingerprint matching

SILICON LABS

How Silicon Labs is enabling AI/ML through Hardware.

Silicon Labs Machine Learning Solution Benefits

- Industry's widest portfolio of wireless solutions combined with ML for Tiny Edge devices
  - Bluetooth, 802.15.4/ZigBee/Thread, Matter, Z-Wave, Prop, Wi-Sun, Sidewalk, WiFi
- Integrated ML hardware accelerator (xG24, xG28) provides up to 8X faster ML inferencing with 1/6th of energy
  - Reduces BOM, footprint and design complexity while minimizing latency
- ML development tools and solutions for explorers to experts for faster application development
  - TensorFlow Lite Micro supported in GSDK
  - Partnerships with Edge Impulse, SensiML and MicroAI accelerate embedded ML development
  - Silicon Labs' ML Tool Kit on GitHub provides complete control & flexibility for the expert developers
- Wide range of use cases including low data rate sensors, audio/voice and low-res images

End-to-End Machine Learning Solution for Wireless IoT Edge Devices

  SILICON LABS

BG24 and MG24: Optimized for Battery Powered IoT Mesh Devices

SOCS AND MODULES

SOC DEVICE SPECIFICATIONS

High Performance Radio
- Up to +19.5 dBm TX
- -97.6 dBm RX @ BLE 1 Mbps
- -105.4 dBm RX @ 802.15.4

Efficient ARM® Cortex®-M33
- 78 MHz (FPU and DSP)
- Up to 1536kB of Flash
- Up to 256kB of RAM

Matrix Vector Processor
- AI/ML Accelerator

Low Power
- 5.0 mA TX @ 0 dBm
- 19.1 mA TX @ +10 dBm
- 4.4 mA RX (BLE 1 Mbps)
- 5.1 mA RX (802.15.4)
- 33.4 µA/MHz
- 1.3 µA EM2 with 16 kB RAM

Security
- Secure Vault Mid/High
- ARM® TrustZone®

SOC DEVICE SPECIFICATIONS

Low-power Peripherals
- EUSART, USART, I2C
- 20-bit ADC, 12-bit VDAC, ACMP
- Temperature sensor +/- 1.5°C
- 32kHz, 500ppm PLFRCO

World Class Software
- Matter[1]
- Thread[1]
- Zigbee[1]
- Bluetooth (1M/2M/LR)
- Bluetooth mesh
- Dynamic multiprotocol[1]
- Proprietary

Wide Operating Range
- 1.71 to 3.8 volts
- +125ºC operating temperature

Multiple Package Options
- 5x5 QFN40 (26 GPIO)
- 6x6 QFN48 (28/32 GPIO)

DIFFERENTIATED FEATURES

Integrated Power Amplifier
- +19.5 dBm output power

AI/ML accelerator
- Accelerates inferencing while reducing power consumption

Secure Vault High
- Protects data and device from local and remote attacks

20-bit ADC
- 16-bit ENOB for advance sensing

PLFRCO
- Eliminates need for 32 KHz crystal

xG28: Single or Dual Band SoC for the Next Generation of IoT

Single or Dual Band

More GPIOs

DEVICE SPECIFICATIONS

High Performance Dual Band Radio
- Up to +20 dBm Sub-GHz Output Power
- -125.8 dBm Rx Sensitivity @ 915 MHz 4.8 kbps O-QPSK
- Up to +10 dBm 2.4 GHz Output Power
- -94.2 dBm Rx Sensitivity @ BLE 1 Mbps

Efficient ARM® Cortex®-M33
- Up to 78 MHz
- Up to 1024kB Flash, 256kB RAM

Low Power
- 82.8 mA TX Current (915 MHz, +20 dBm)
- 26.2 mA Tx Current (915 MHz, +14 dBm)
- 4.6 mA RX (915 MHz 4.8 kbps O-QPSK)
- 22.5 mA TX Current (2.4 GHz +10 dBm)
- 5.2 mA RX (BLE 1 Mbps)
- Active Current: 33 µA/MHz @39 MHz
- 1.3 µA EM2 (16 kB Retained) / 2.8 µA EM2 (256 kB Retained)

Protocol support
- Wi-SUN
- Amazon Sidewalk
- CONNECT
- Wireless M-BUS
- Proprietary
- Bluetooth LE

Package Options
- 6x6 QFN48 (31 GPIO)
- 8x8 QFN68 (49 GPIO)

DIFFERENTIATED FEATURES

Single and Dual Band Support
- Supports Sub-GHz and Sub-GHz + Bluetooth LE

Large memory footprint
- Support larger stacks or applications in a single chip

AI/ML accelerator
- Faster inferencing with lower power

Secure Vault™ Mid and High options
- Flexible platform for evolving security needs

+20 dBm output power
- Eliminates the need for an external power amplifier

16-bit ADC
- Up to 14-bit ENOB for better analog resolution

Preamble Sense
- Ultra low power receive mode

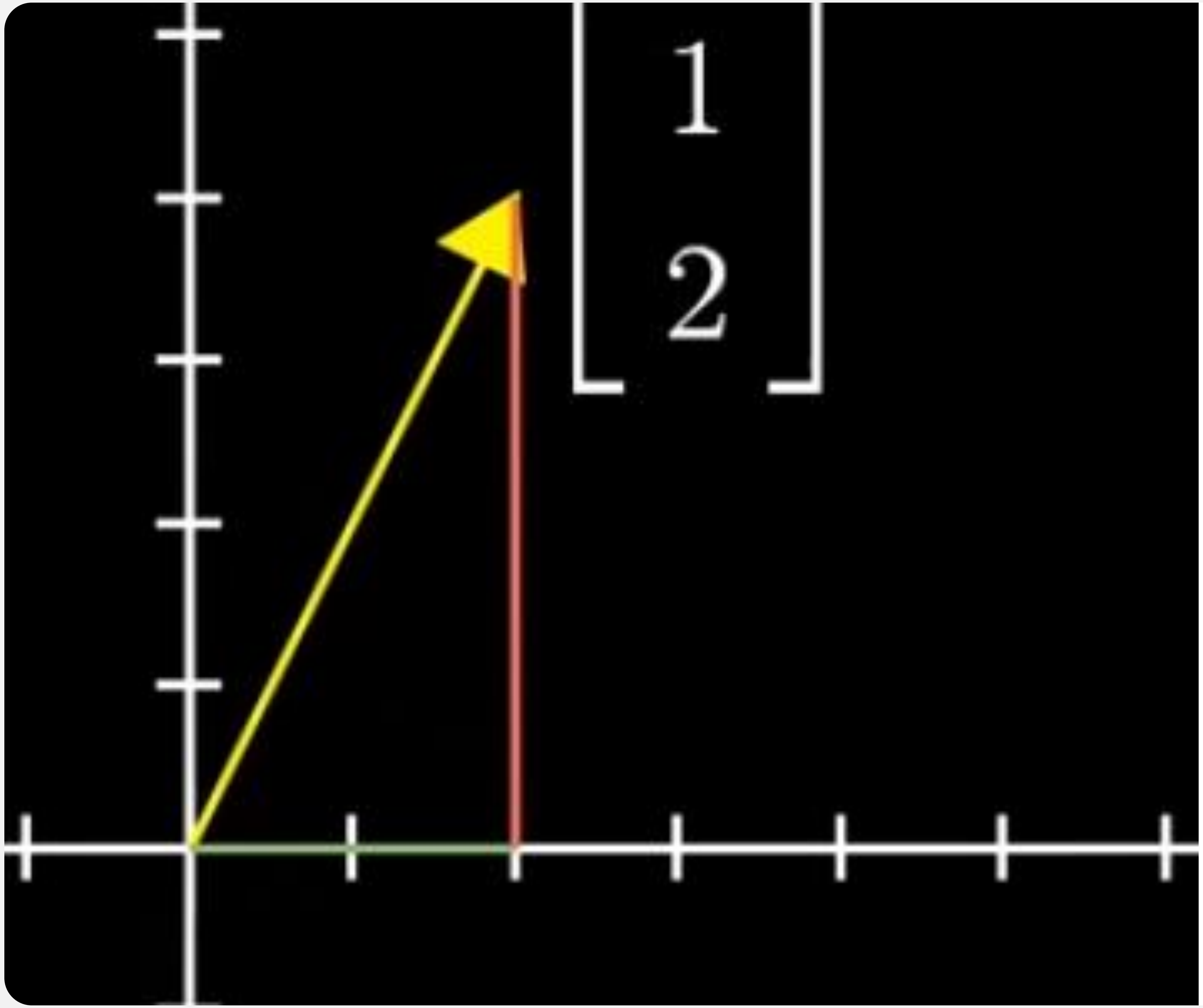
Antenna Diversity
- 6-8 dBm better link budget (Sub-GHz only)

Segment LCD
- 4x48 segment LCD

High GPIO count
- Support up to 49 GPIO

Introducing the MVP

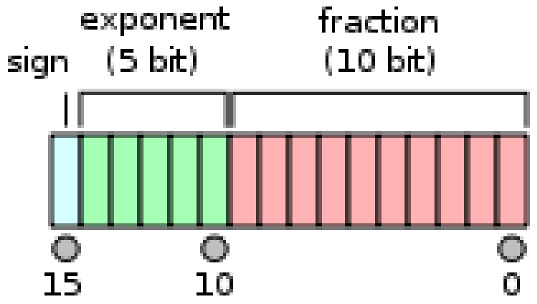
Some Terms…



- **MVP – stands for Matrix-Vector Processor**
- **What is a 'Vector'?**
- **What is a 'Matrix'?**
  - Why are these relevant in Machine Learning?
- **What is Matrix-Vector multiplication**
  - Why are these relevant in Machine Learning?

What is the MVP? When is it useful?

- **Fundamentally, the MVP performs floating point operations very efficiently in hardware.**
- **It's native processing numeric format is IEEE 745-2008 half-precision (16-bit) floating point numbers.**
- **How is this format different from integer format?**
- **What types of applications benefit from the MVP?**



Technical Details of the MVP

Resource	Cortex-M33	MVPv1
Data Buses	1x32-bit read/write bus	2x32-bit read buses 1x32-bit write bus
I/O data type	8, 16, and 32-bit integers 16/32-bit floating point	8-bit integers 16-bit floating point
Computation types supported by hardware	8, 16, 32-bit integers 32-bit floating point	16-bit floating point
Instruction Location	Sequenced instructions	8 macro instruction records
Data Organization Restrictions	Data can be organized in highly complex ways, where software defines the access pattern through instructions	Data is defined in a flexible matrix/array/tensor format requiring a regular pattern of storage that can be specified in terms of independent per- dimension strides
Single Instruction, Multiple Data (SIMD)	4 bytes	2x16-bit floating point numbers (or 2 converted int8 integers)

The MVP Math library

- Accelerate and do more efficiently linear algebra operations with internal MVP subsystem
- Math APIs (alternative to CMSIS_DSP) available in GSDK Alpha, GA release in 23Q2

VECTOR OPERATIONS

- Vector Add
- Vector Absolute Value
- Vector Clip
- Vector Dot Product
- Vector Multiply
- Vector Negate
- Vector Offset
- Vector Scale
- Vector Sub
- Complex Vector Conjugate
- Complex Vector Dot Product
- Complex Vector Magnitude
- Complex Vector Magnitude Squared
- Complex Vector Multiply
- Complex Vector Multiply Real
- Vector Copy
- Vector Fill

MATRIX OPERATIONS

- Matrix Initialize
- Matrix Multiply
- Matrix Scale
- Matrix Sub
- Matrix Transpose
- Matrix Multiply Vector
- Matrix Add
- Complex Matrix Multiply
- Complex Matrix Transpose

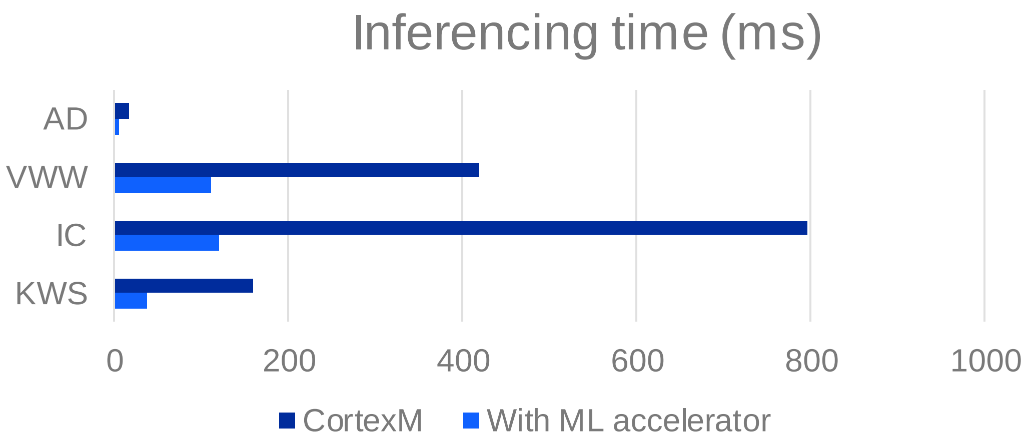
Matrix dims.		CMSIS f32 cpu-cycles	CMSIS f16 cpu-cycles	MVP cpu-cycles	instr	stalls
2x2	2x2	226	304	403	8	0
4x2	2x4	602	913	424	32	0
6x2	2x6	1210	1921	464	72	0
8x2	2x8	2050	3321	516	128	0
10x2	2x10	3122	5113	592	200	0
12x2	2x12	4426	7297	676	288	0
14x2	2x14	5962	9873	784	392	0
16x2	2x16	7730	12841	904	512	0
18x2	2x18	9730	16201	1036	648	0
20x2	2x20	11962	19953	1192	800	0
20x4	4x20	17962	27956	1593	1200	1
20x6	6x20	23742	39956	2193	1600	201
20x8	8x20	27562	47556	2793	2000	400
20x10	10x20	33162	59556	3393	2400	601
20x12	12x20	37162	67156	3993	2800	801
20x14	14x20	42762	79156	4593	3200	1000
20x16	16x20	46762	86756	5193	3600	1201
20x18	18x20	52362	98756	5793	4000	1401
20x20	20x20	56362	106356	6393	4400	1600

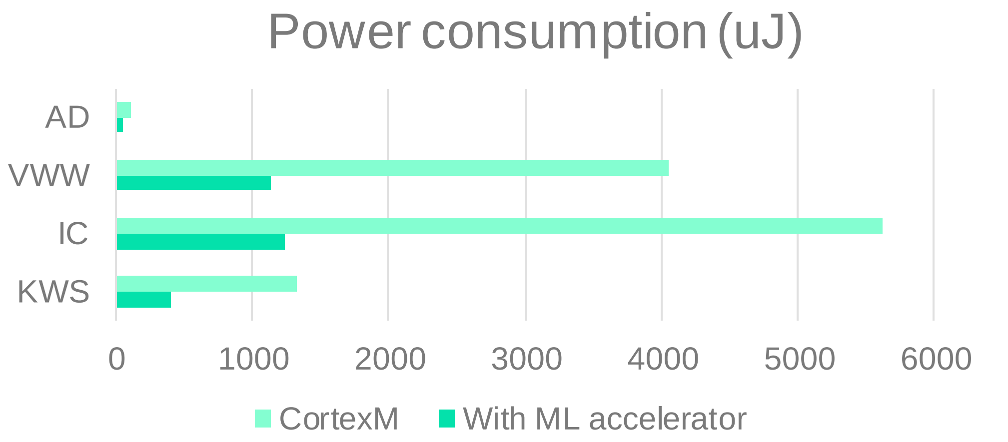
- ✓ **Faster and more efficient execution of many algorithms with large data for example filtering algorithms**
- ✓ **Saving CPU cycles, saving power, resulting longer battery life**
- ✓ **Option to win sockets against faster CPUs**

The Benefits…

- Dedicated **ML computing subsystem** next to the CPU: Matrix Vector Processor (MVP)
- Optimized MVP to accelerate ML inferencing with a lot of processing power **offloading the CPU**
- **Up to 8x faster** inferencing over Cortex-M (see below perf. benchmark)
- Up to **6x lower power** for inferencing (see below perf. benchmark)
- Dedicated OPNs for MVP accelerated parts → EFR32MG24B[2]… or [3]

Performance data with ML hardware accelerator vs. pure SW on CortexM*



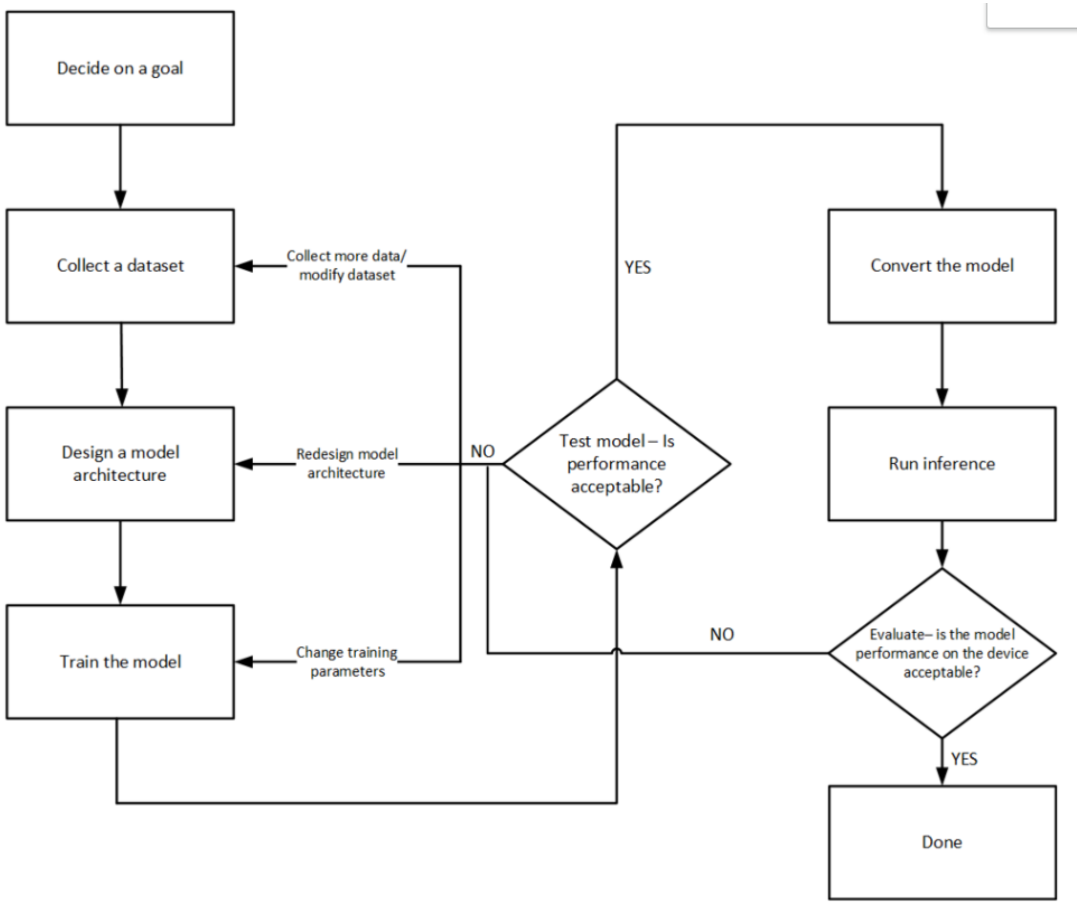


*Standardized performance benchmark validated by independent benchmarking body **MLCommons.org**. Published in MLPerf Tiny v1.0. Results are for inferencing only (not for the complete application). You can refer to MLCommons as validated results-

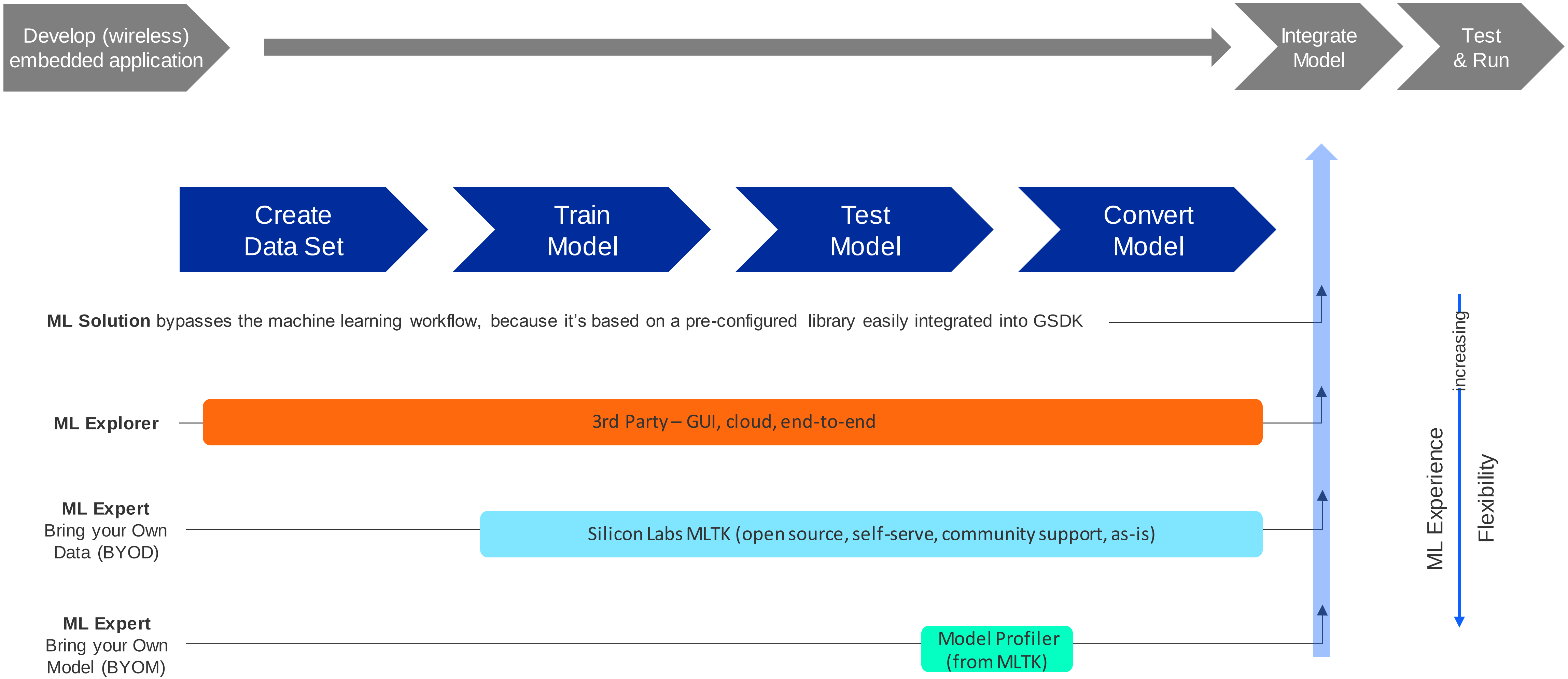
How Silicon Labs is enabling AI/ML through software?

Machine Learning Development Steps

- **Goal**
  - What are you trying to achieve?
- **Collect a dataset**
  - Construct a dataset that you will use to train the model, some will be kept aside for testing the model.
- **Design Model architecture**
  - It is not the raw data that is inputted into the model, it is the pre-processed data.
  - Therefore, we must choose a pre-processing block that is relevant for the type of data we are dealing with.
- **Train the Model**
  - About 80% of the dataset should be used at this stage.
  - the desired output is good predictions on generalized inputs.
  - Need to avoid underfitting and overfitting.
- **Test the Model**
  - check the performance of the model



Embedded Development with Machine Learning (supervised)



Software and Tool Support by customer skills: know your customer's skills

ML Expert

Python scripts and tutorials

SILICON LABS
Machine Learning Toolkit*

siliconlabs.github.io/mltk

TensorFlow

TFLite Flatbuffer

TFLite-micro Interpreter

CMSIS-NN Kernels	Silicon Labs HW-based Kernels
Cortex M	MVP (NPU)

ML Explorer

GUI Developer Tools

EDGE IMPULSE

edgeimpulse.com

SensiML™

sensiml.com

TFLite-micro Interpreter

CMSIS-NN Kernels	Silicon Labs HW-based Kernels
Cortex M	MVP (NPU)

ML Solutions

Solution Libraries

Wake Word / Voice Command — sensory

sensory.com

Anomaly Detection — Micro.ai

micro.ai

System Integrators

KLIKA TECH GLOBAL IOT SOLUTIONS, AIZIP, Capgemini, AITAD, Talent·Technology·Solutions Bellintegrator

Cortex M (& MVP)

*Machine Learning Toolkit is public but pre-alpha release

ML Partnership Overview

- HW & FW IoT Development
- Create Data Set
- Train Model
- Test Model
- Convert Model
- Integrate Model
- Test & Run

ML Explorer — 3rd Party – GUI, cloud, customers use for end-to-end development

ML Solution — bypasses the machine learning workflow, because it's based on a pre-configured library easily integrated into GSDK

Full Development Services

	Edge Impulse	SensiML	MicroAI*	Sensory	AIZIP	NeutonAI	Klika-Tech	AITAD
Low-Rate Sensors	✓	✓	✓		✓	✓	✓	✓
Audio Pattern Matching	✓	✓			✓	✓	✓	✓
Voice Commands	✓	✓		✓	✓	✓	✓	✓
Low-Resolution Vision	✓				✓			✓
Regions	AMER, EMEA, APAC	AMER, EMEA, APAC	AMER, APAC	AMER, EMEA, APAC	AMER, EMEA, APAC	AMER, EMEA, APAC	AMER, EMEA, APAC	EMEA

*MicroAI has a platform for users to develop their own application, but it's solely for anomaly detection or system health score

ML Explorer

ML Solution

Full Dev Service

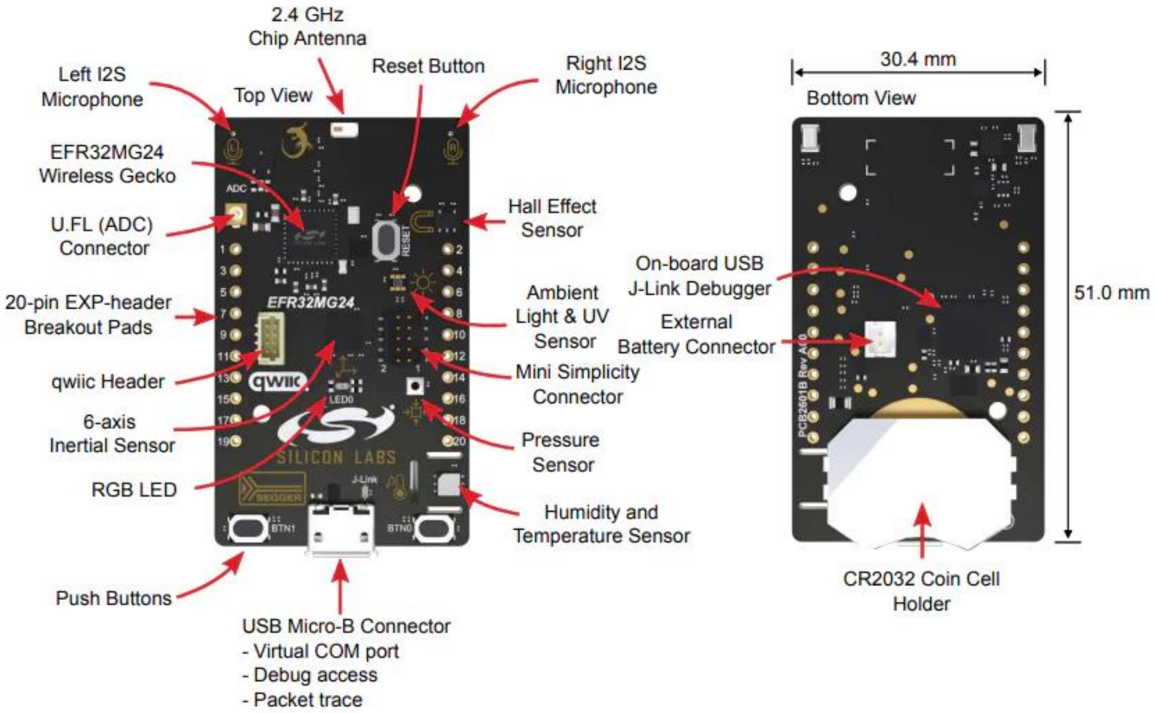
EDGE IMPULSE · SensiML · Micro.ai · sensory · AIZIP · Intelligent Agent Neuton · KLIKA·TECH GLOBAL IOT SOLUTIONS · AITAD

SILICON LABS

How to get Started?

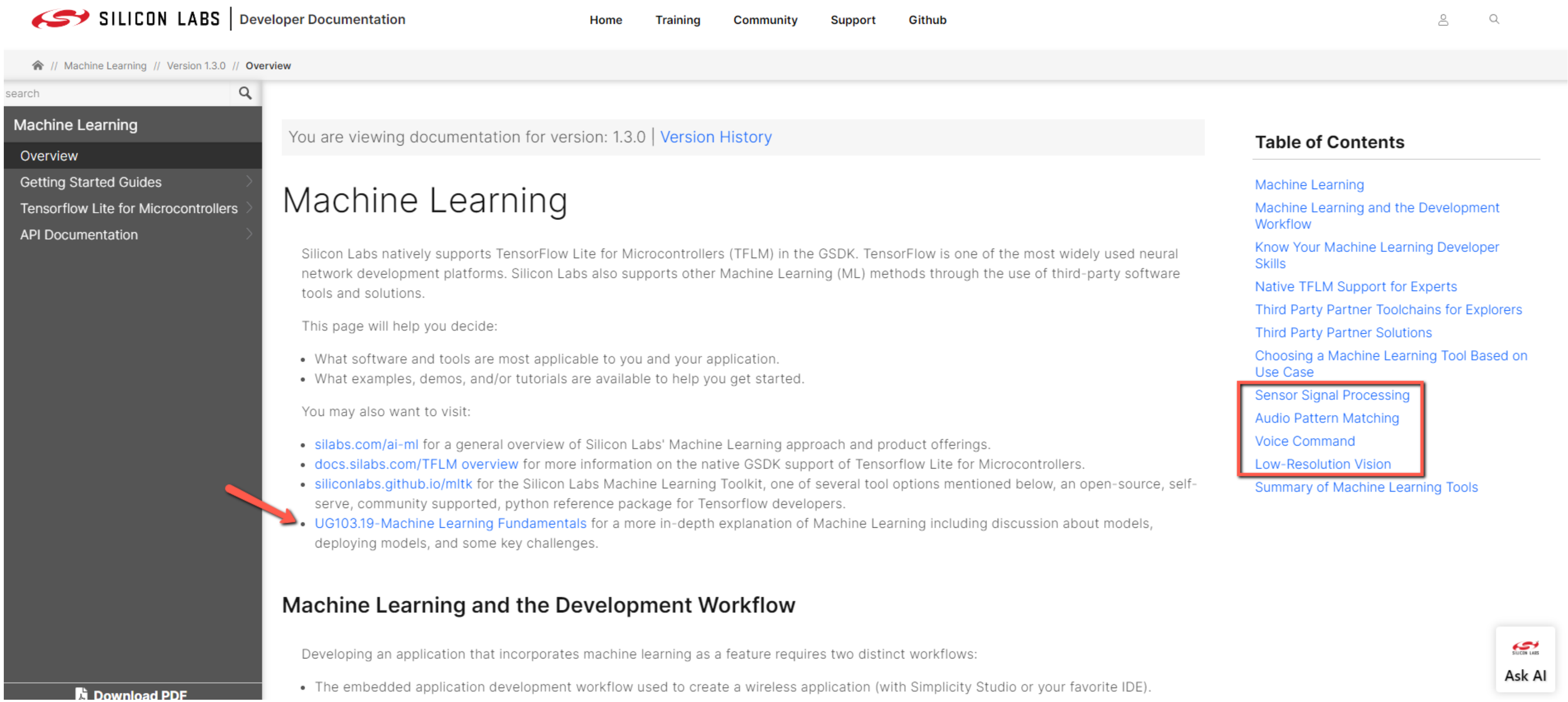
The Kit I Recommend to get Started with…

- You can pick up a xG24 Development Board here:
  - https://www.silabs.com/development-tools/wireless/efr32xg24-dev-kit?tab=overview



Visit our Machine Learning Landing Page…

https://docs.silabs.com/machine-learning/1.3.0/machine-learning-overview/


SILICON LABS | Developer Documentation

Home Training Community Support Github

// Machine Learning // Version 1.3.0 // Overview

search

Machine Learning

- Overview
- Getting Started Guides
- Tensorflow Lite for Microcontrollers
- API Documentation

Download PDF

You are viewing documentation for version: 1.3.0 | Version History

Machine Learning

Silicon Labs natively supports TensorFlow Lite for Microcontrollers (TFLM) in the GSDK. TensorFlow is one of the most widely used neural network development platforms. Silicon Labs also supports other Machine Learning (ML) methods through the use of third-party software tools and solutions.

This page will help you decide:

- What software and tools are most applicable to you and your application.
- What examples, demos, and/or tutorials are available to help you get started.

You may also want to visit:

- silabs.com/ai-ml for a general overview of Silicon Labs' Machine Learning approach and product offerings.
- docs.silabs.com/TFLM overview for more information on the native GSDK support of Tensorflow Lite for Microcontrollers.
- siliconlabs.github.io/mltk for the Silicon Labs Machine Learning Toolkit, one of several tool options mentioned below, an open-source, self-serve, community supported, python reference package for Tensorflow developers.
- UG103.19-Machine Learning Fundamentals for a more in-depth explanation of Machine Learning including discussion about models, deploying models, and some key challenges.

Machine Learning and the Development Workflow

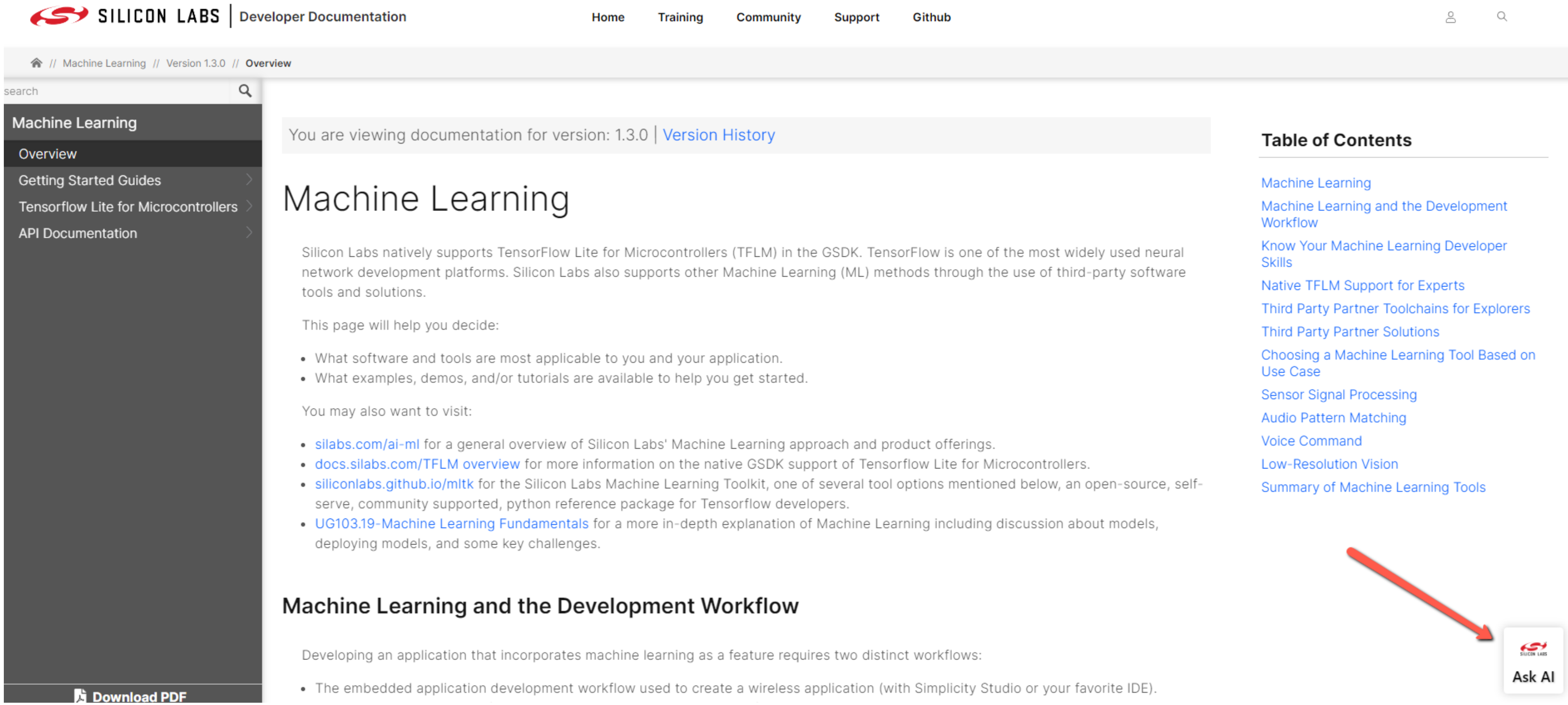
Developing an application that incorporates machine learning as a feature requires two distinct workflows:

- The embedded application development workflow used to create a wireless application (with Simplicity Studio or your favorite IDE).

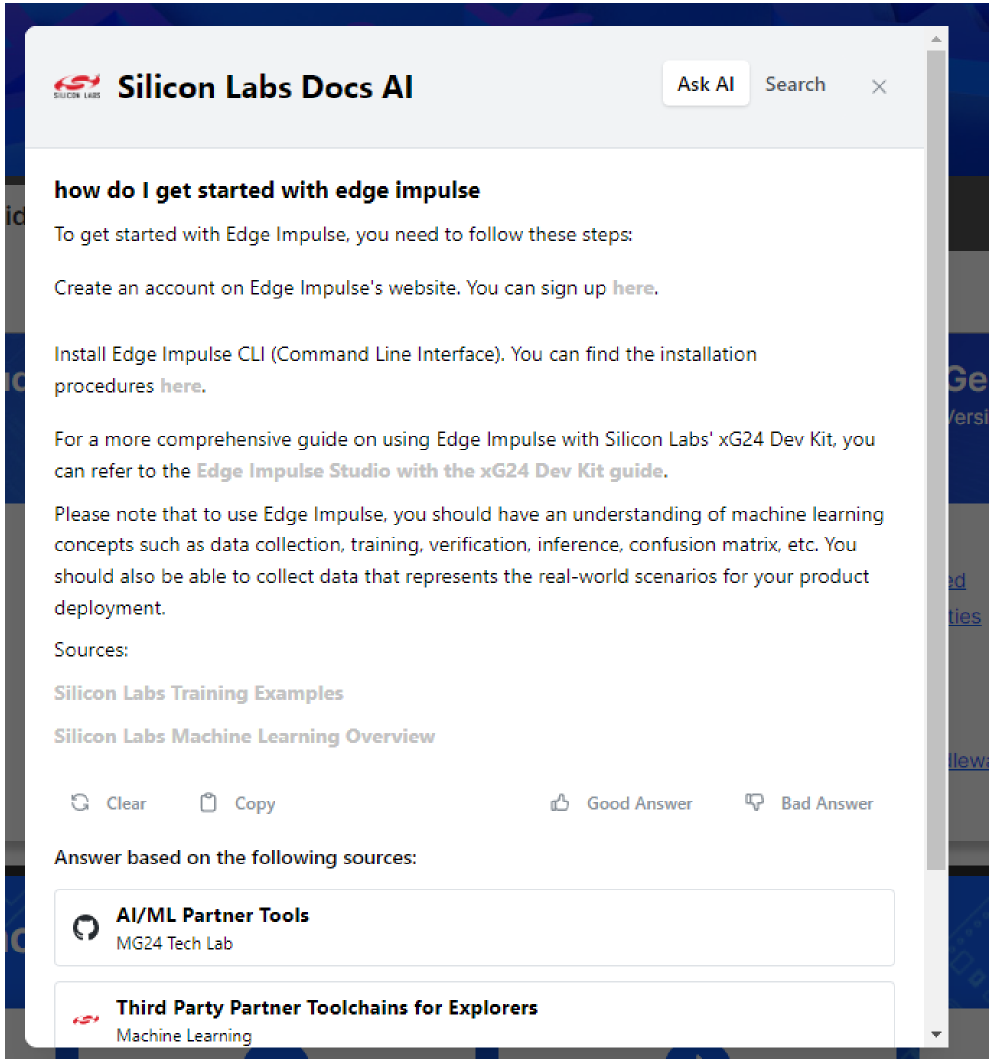
Table of Contents

Ask AI

Check Out our Partner Tools…



It's Response…



Q&A

WIRELESS COMPUTE

Thank You

Watch ON DEMAND

techtalks

WIRELESS COMPUTE