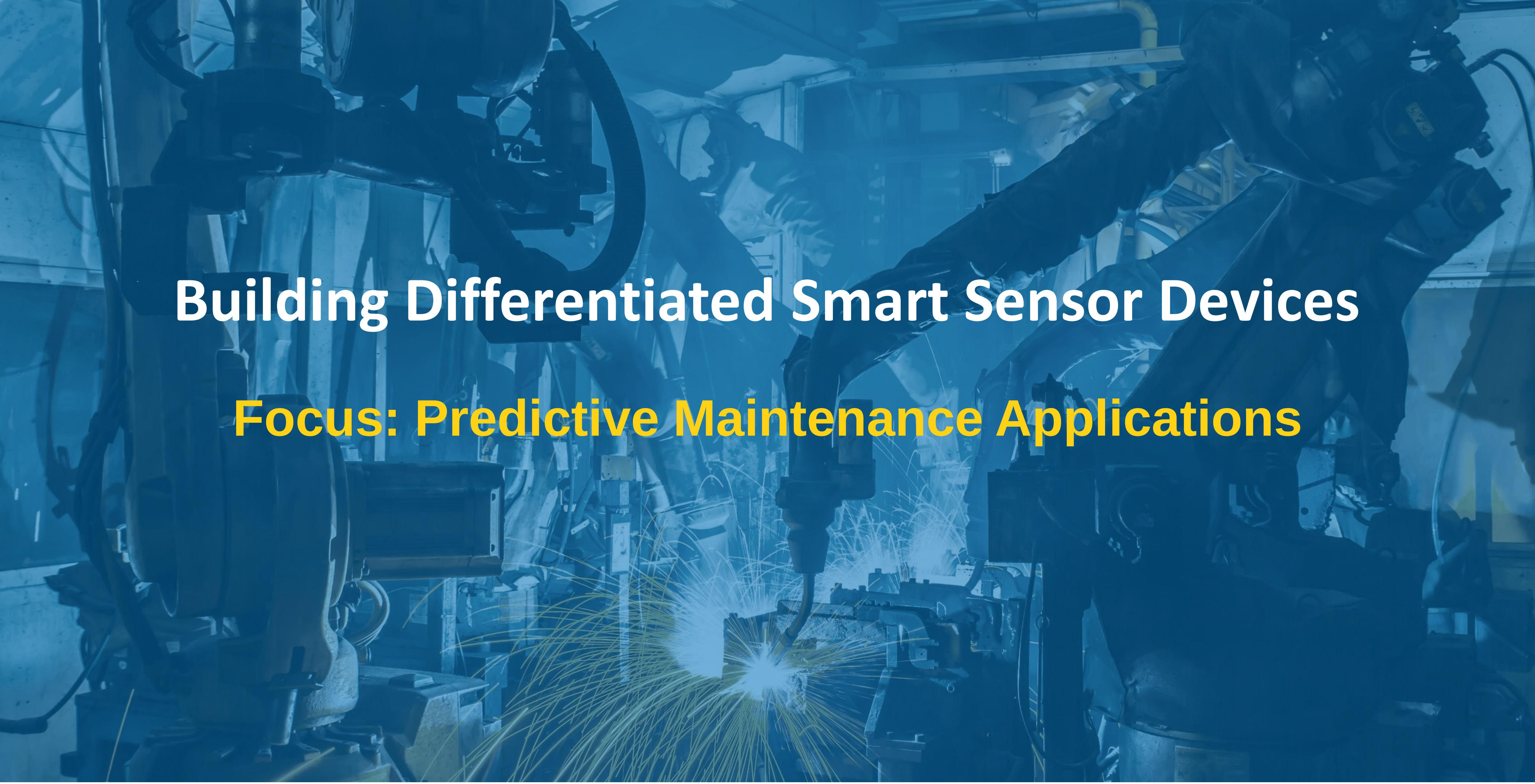
QuickLogic/SensiML: Predictive Maintenance Applications

Chris Rogers, CEO SensiML
Robert Dawson, QuickLogic Applications Manager

Agenda

- **Building Differentiated Smart Sensor Devices for PdM** (Chris Rogers 20 minutes)
  - Key IoT Sensor Requirements of Predictive Maintenance Systems
  - Common AI Issues/Solutions for Intelligent PdM Sensor Applications

- **A Brief Survey of AI/ML Algorithms Appropriate for PdM** (Chris Rogers 15 minutes)
  - AI Taxonomy and Highlight of Key Classifiers
  - Generalized Pros/Cons Amongst Various Algorithms
  - Comparative Suitability of Algorithms for Time-Series Datasets
- **SensiML Toolkit Endpoint AI Demonstration** (Chris Rogers 20 minutes)
- **QuickLogic QuickAI solution** (Robert Dawson 10 minutes)
  - EOS S3AI Architecture
  - Development environment
- **Q & A** (10 minutes)



Building Differentiated Smart Sensor Devices

Focus: Predictive Maintenance Applications

SensiML™

MAKING SENSOR DATA SENSIBLE

PREDICTIVE MAINTENANCE APPLICATIONS

MAY 2019

Requirements: Industrial IoT PdM Smart Sensors

Vision: Distill maintenance expertise into an intelligent system capable of 24x7 monitoring of ALL critical plant

From Manual Periodic Inspection…

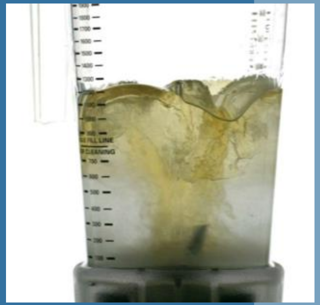
- Accurate
- Always on
- Low cost/node
- Minimal commissioning
- User manageable
- Reliable
- Secure

To Automated Continuous Plant Monitoring

Key Benefits: Avoiding Downtime, Optimizing Equipment Efficiency, Lowering OpEx

Requirements: Intelligent Sensing PdM for Consumer IoT Devices

Vision: Transform product experience & services for existing products via embedded sensor intelligence



- Accurate
- Low cost/node
- Zero commissioning
- Reliable
- Secure

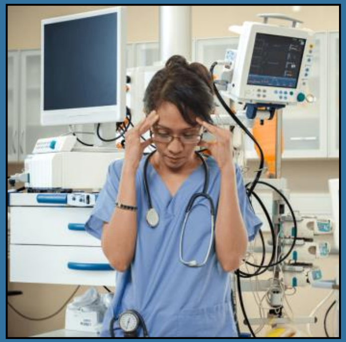
Sensor: Audio + Vibration
Event: Popcorn popping has slowed
Action: Stop cooking

Sensor: Audio + Vibration
Event: Impeller is cavitating
Action: Slow motor

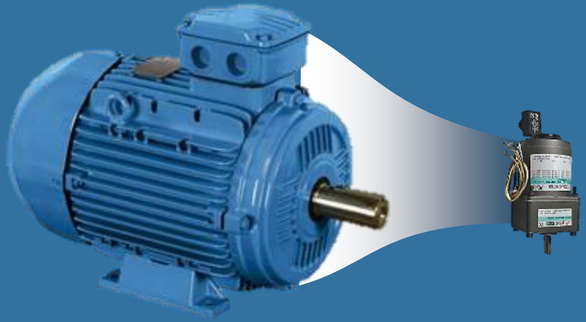
Sensor: Vibration
Event: Unbalanced load is damaging machine
Action: Slow/brake drum to rebalance
Alert service dept if continues

Many Development Similarities to PdM

Predictive Maintenance System Requirements



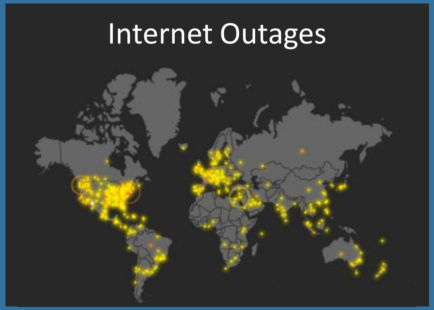
- **Accurate**
  - High Sensitivity – Minimize Missed Events, High Specificity – Minimize False Alarms
  - High performance algorithms that achieve the accuracy needed to trust the system
- **Always On**
  - Real-time reaction to critical events; involvement of operators/users in feedback loop
  - Wired sensors or ultra low power wireless devices with high level of data compression
- **Low Cost/Node**
  - Key to pervasive monitoring across all operationally important equipment
  - Wireless sensors that substantially reduce wired sensor install costs



- **Minimal Commissioning**
  - Separate wireless sensor network minimizes operational impact
  - Simple configuration and training of sensors minimizes labor cost and machine scheduling conflicts

Predictive Maintenance System Requirements

- **Reliable**
  - Independence from network/cloud improves reliability
  - Wireless sensor endpoints need battery life measurable in years



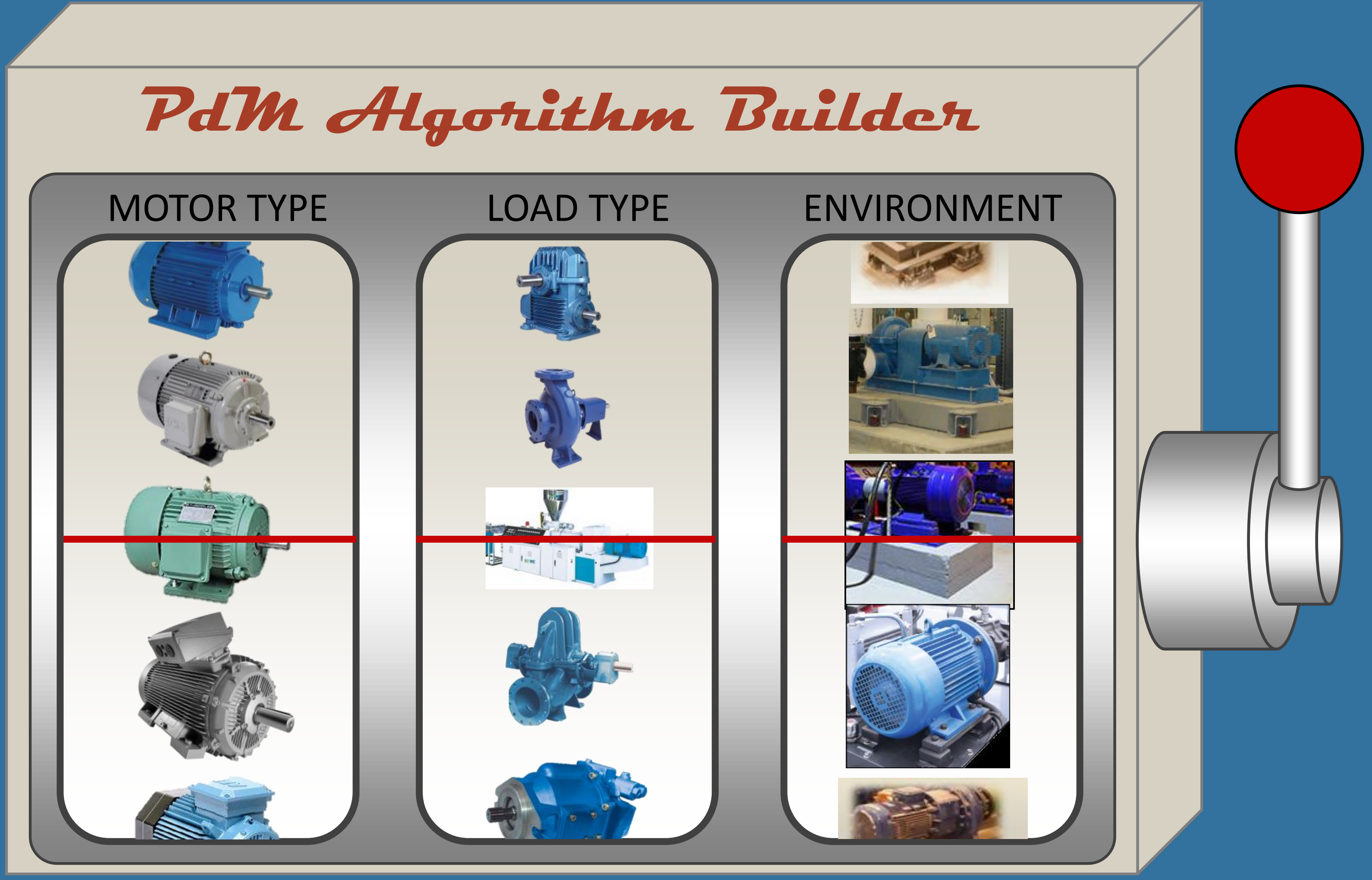
- **User manageable**
  - Configurable by end use technicians and operators w/o data science and programming expertise
  - Adaptive edge learning capability to accommodate site-specific conditions

- **Secure**
  - Many end-user IT depts will not allow operational data outside their network
  - Distributed partitioning of analytics processing adds data security/privacy

Real World Issue: Gathering Sufficient Data for AI Training

Consider building a high-quality predictive maintenance model for an industrial motor

- Is there a pre-existing accurate model for the actual motor type in service?
- Does the customer only care about just the motor itself?
- Can we anticipate the impact of countless site-specific environmental differences?
- Is it even practical to empirically collect data for anticipated physical failure states?



Pre-canned algorithms practically address only a few monitoring conditions

Common Solutions to the Data Sufficiency Problem

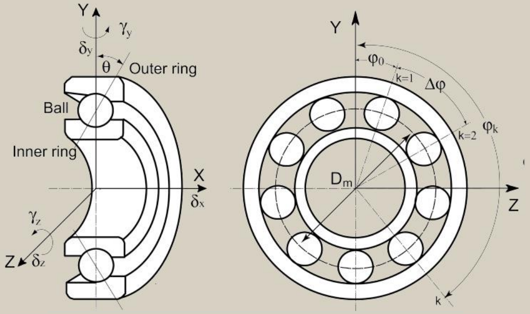
Favor Analytic Insight At Cost Of PdM Scope

A Priori PdM Inference Models

- Motor Speed

  +
- 3-Axis Vibration Sensor Data

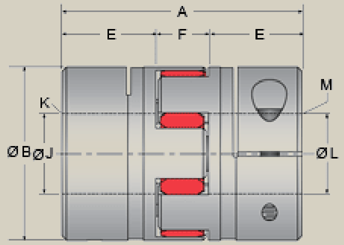
  +
- Physical Component Metadata



Known Rotating Vibration Fault Modes

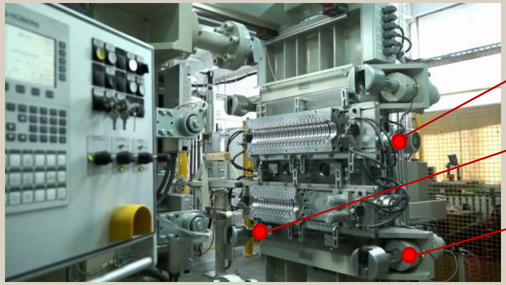
FFT

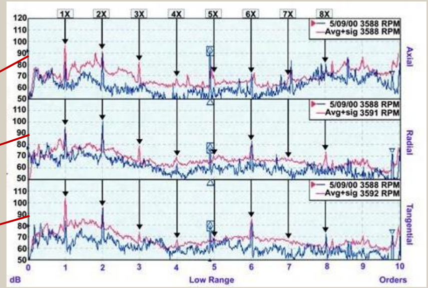
- Rolling Element Faults
- Inner/Outer Bearing Race Defects
- Shaft Misalignment



Cast Wider Net But With Limited Insight

Anomaly Detection





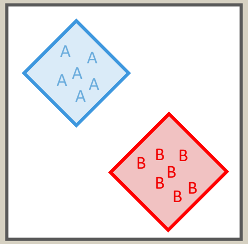
- Collect Empirical Data on Actual Machine
- Known Normal Operating Condition Cycles
- Define Thresholds for Excursions Beyond
- Live with False Positives and Lack of Insight

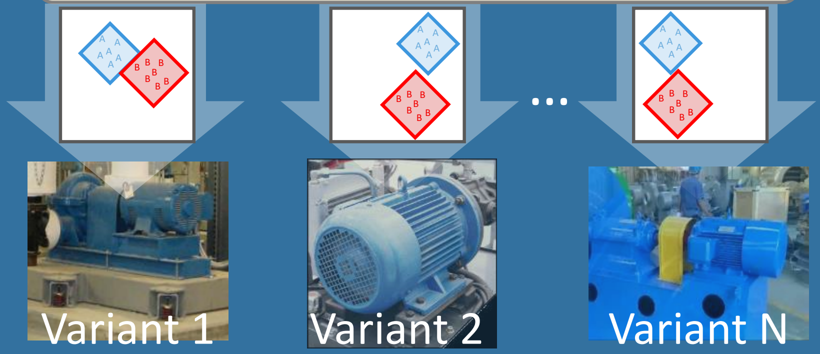
A Differentiated Approach: Simplified Runtime Adaptation

Customizable Edge Model Tuning

Baseline PdM Inference Model

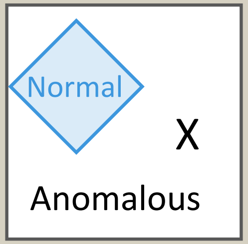
<u>Common Algorithm Elements</u>
- Raw Inputs
- Pre-processing
- Classifier





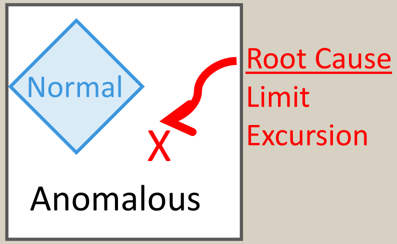
MRO Driven Learning

Baseline Anomaly Detection

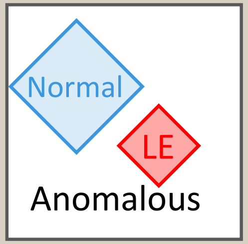


<u>Common Algorithm Elements</u>
- Raw Inputs
- Pre-processing
- Classifier

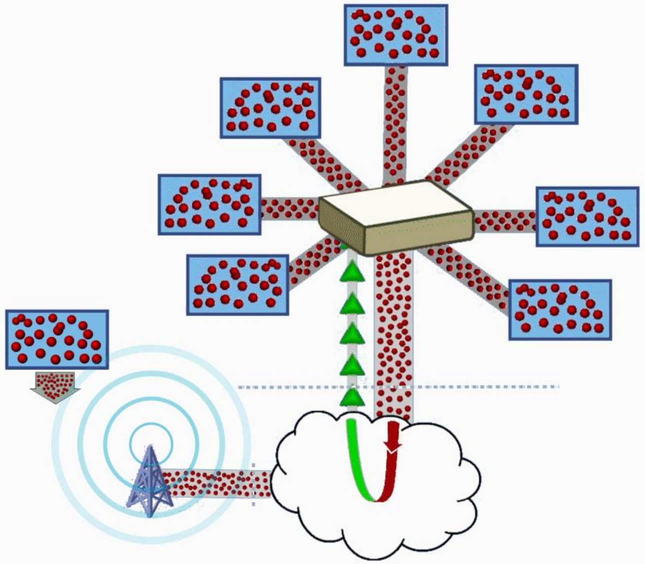
MRO Analysis



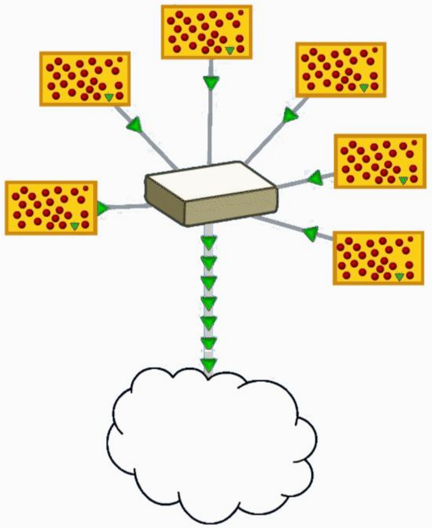
Model Update



Real World Issue: Centralized Cloud Analytics Do Not Scale



Cloud-Centric Analytics



Distributed Analytics Involving
IoT Endpoint Processing

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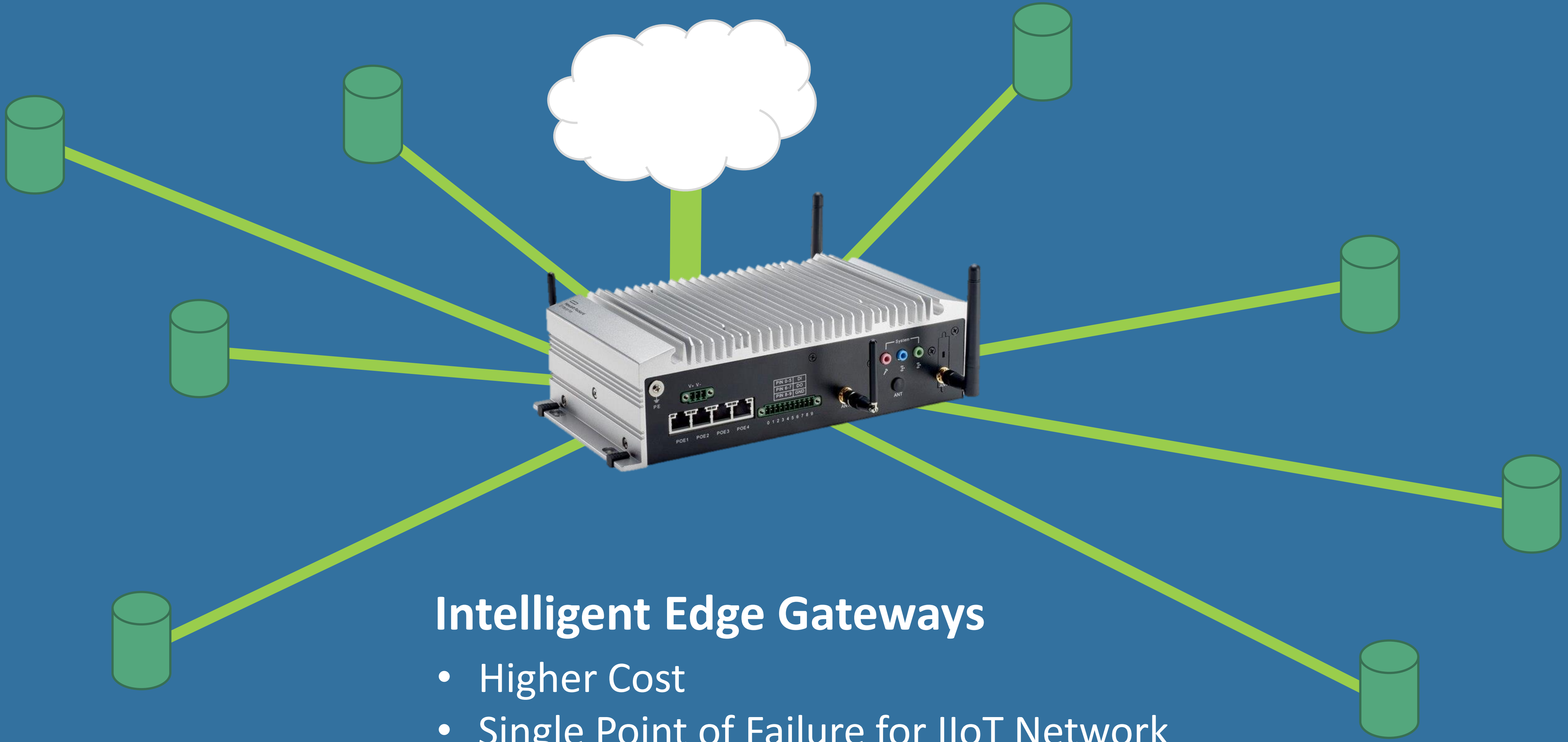
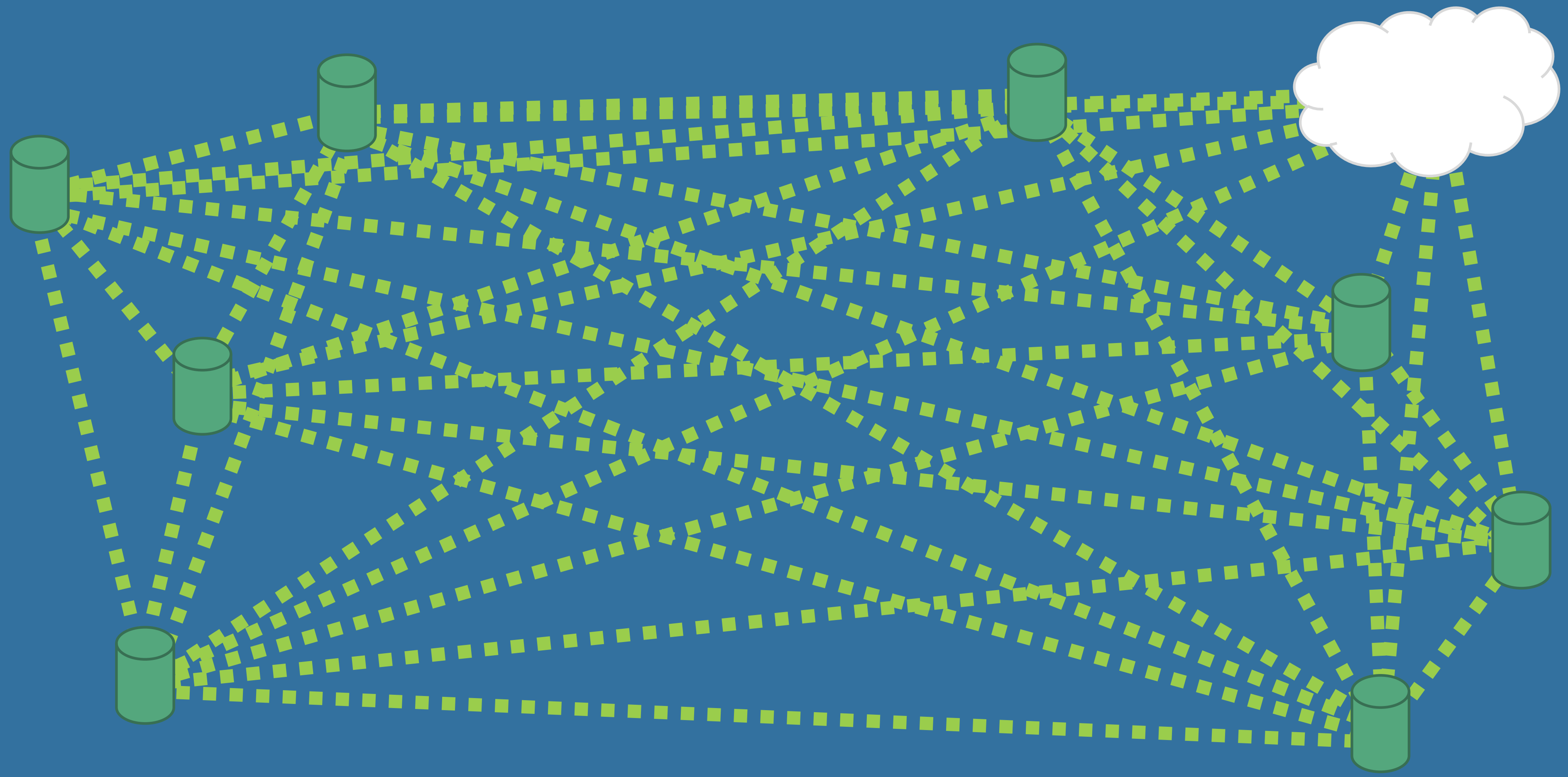
Existing Solution to Cloud Computing Limitations



Intelligent Edge Gateways

- Higher Cost
- Single Point of Failure for IIoT Network

A Differentiated Approach: Distributed Intelligent Endpoints

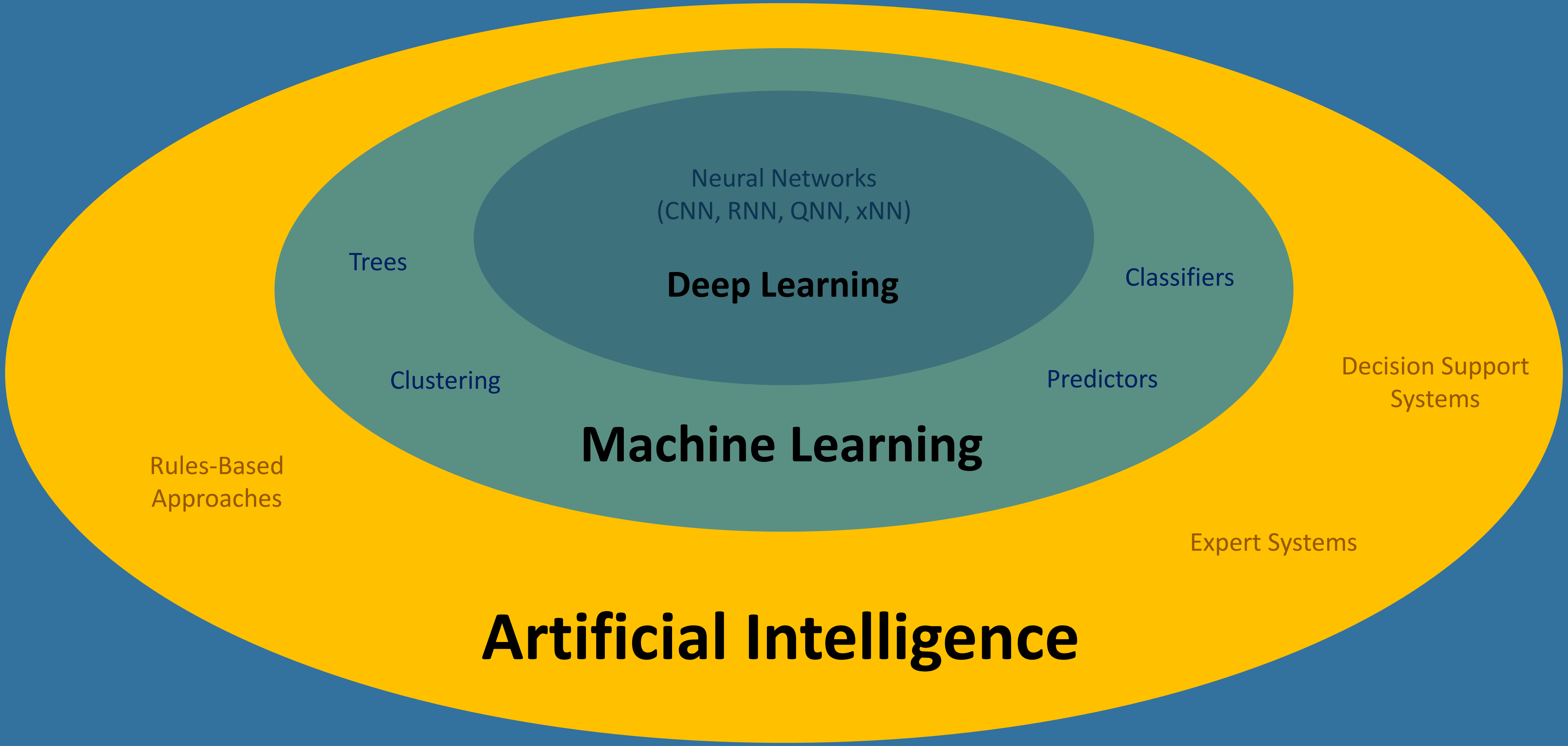


An Interconnected Wireless Mesh of Intelligent Sensor Endpoints

A Brief Survey of AI/ML Algorithms

Focus: Predictive Maintenance Applications

A High-Level Taxonomy of AI



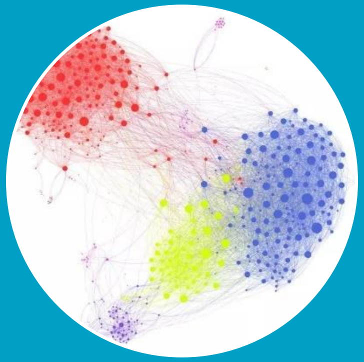
Means for Automated Learning

Teach Device To Recognize Insights From Prior Sensor Data and Insights

Supervised Learning

Uses labeled training data to
“teach” desired insights

Mine Available Data to Spot Trends and Gain New Insights



Unsupervised Learning

No labels used during learning,
algorithm discovers similarities itself

Optimize an Unknown Process Through Reward-Based Learning

Reinforcement Learning

No training data or labels,
learning through maximizing outcomes

Nearly all smart IoT endpoints rely on supervised learning where <u>labeled training data is vitally important</u>

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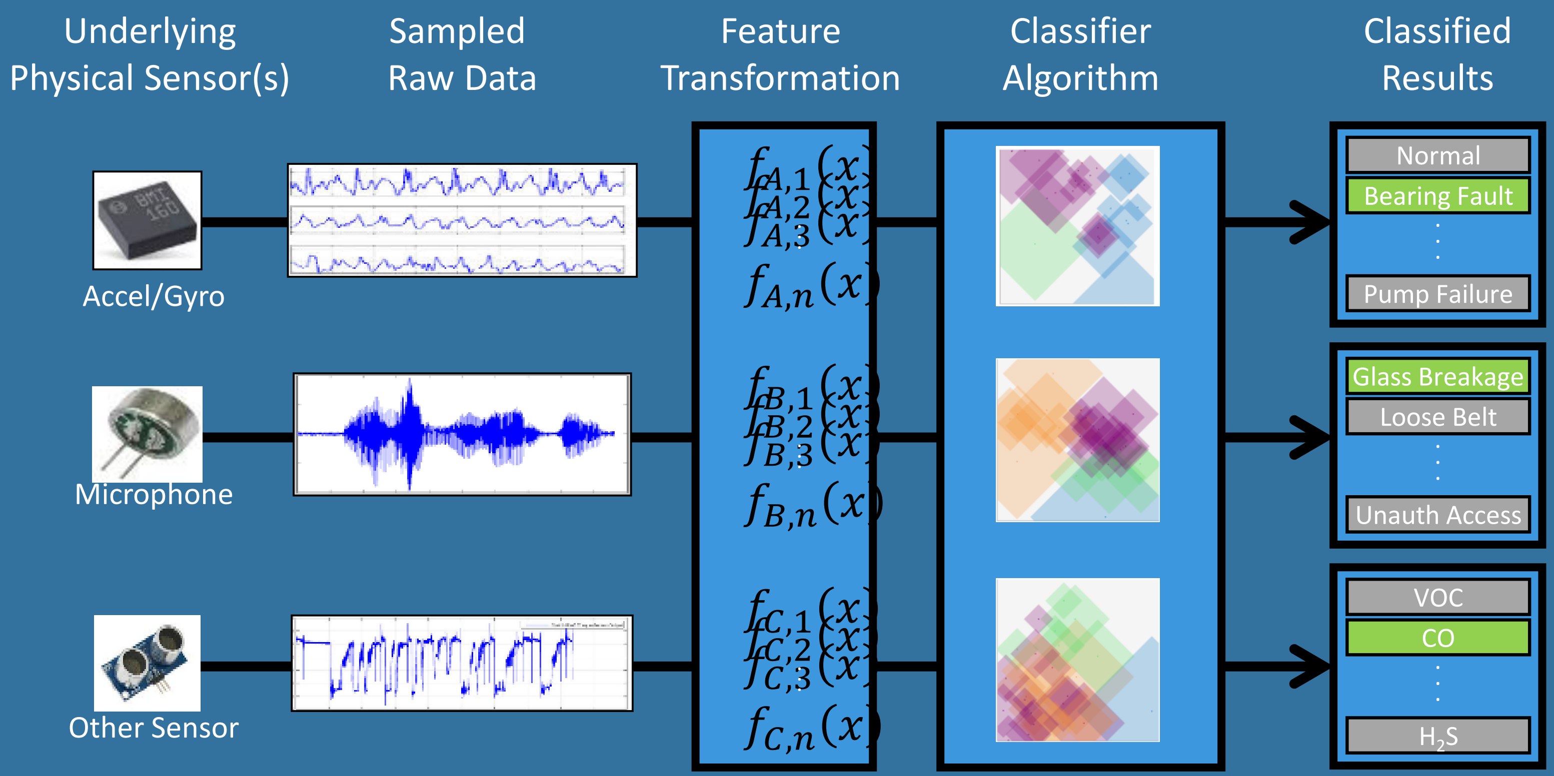
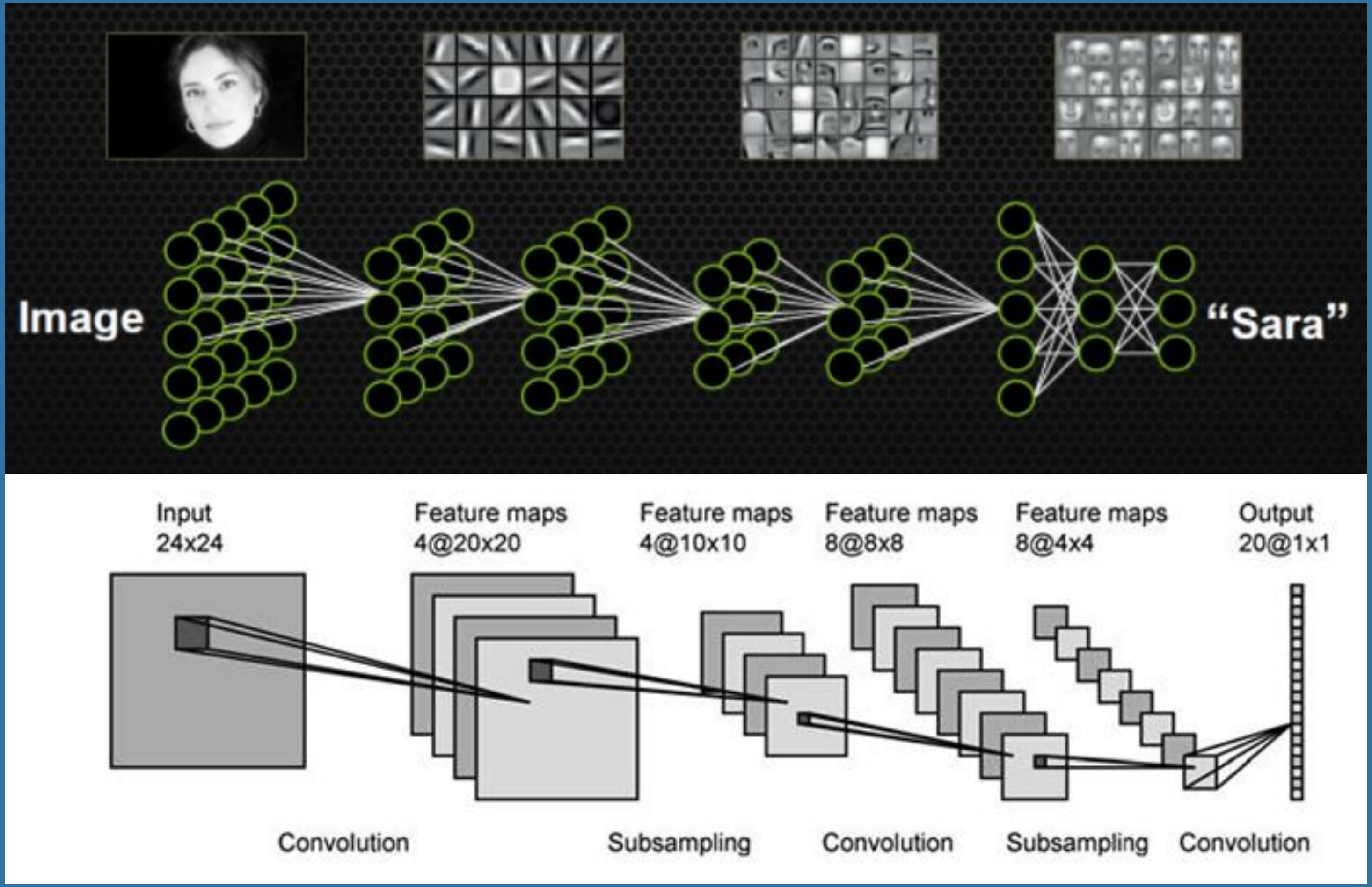
ML Classifiers: Time-Series Sensor Data



Examples: kNN, Radial Basis Function, Support Vector Machine, Random Forest

Goal: Find right set of pre-determined features that distinguish desired classes when subject to classification

Deep Learning Neural Network



Examples: Convolutional Neural Networks, Recurrent Neural Networks, Quantized Neural Networks
Goal: Construct abstracted features that minimize classification errors during training; then apply to new data

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Algorithm Selection

Where cost and power matter…

Choose the least complex algorithm
that will achieve the accuracy desired

- Slow varying sensors can often utilize basic rules or threshold analysis
- Dynamic time series data can nearly always be addressed with ML classifiers
- Spatial (image) data typically requires neural networks

Challenges of Intelligent IoT Edge Devices

Cumbersome and Expensive Development

Resource Constrained HW

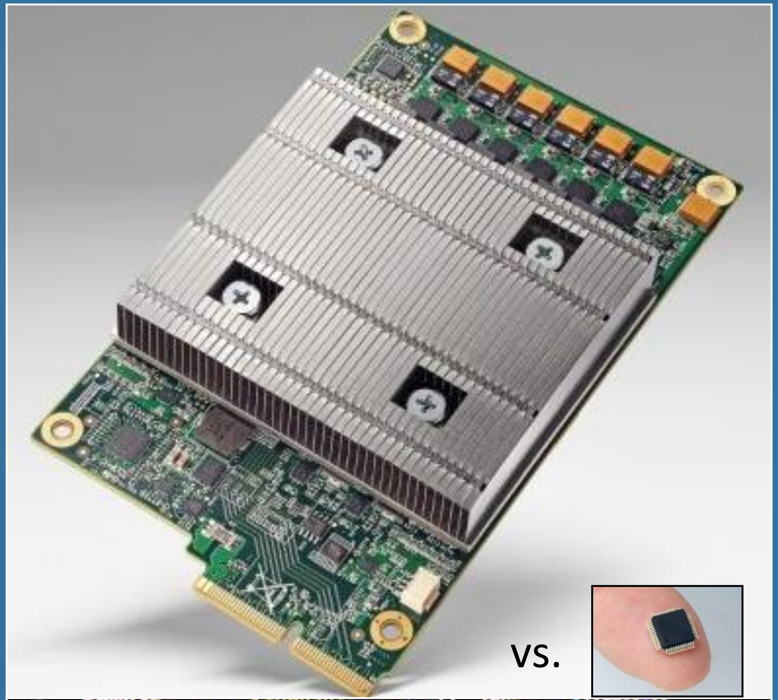
- Can't just run TensorFlow
- Limited SRAM, MIPS, FPU / GPU
- Mobile or wireless battery/power requirements
- Application<>Hardware code fit adds risk

Resource Constrained Development Teams

- Embedded coding more complicated and fragmented than cloud PaaS
- Scarcity of data scientists, DSP, FPGA, and firmware engineers
- Limited bandwidth to explore new tools / methods
- Lack of AI/ML familiarity creates QA and support friction

Lack of Automated Tools

- Typical process: MATLAB modeling followed by hand coded C/C++
- Available AI tools focus on algorithms not end-to-end workflows
- Per product algorithm cost: $$$k, 6-9 months; often far greater



Overview Of The SensiML Endpoint AI Toolkit

Time-Series AI Inferencing

SensiML Overview

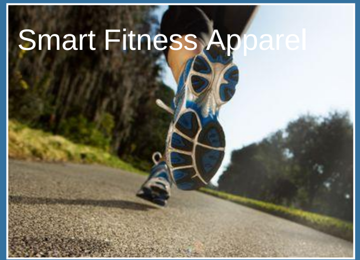
An Edge AI Software Toolkit enabling developers to build intelligent IoT sensing devices in days/weeks without data science or embedded firmware expertise

Low-Power Sensor Processors

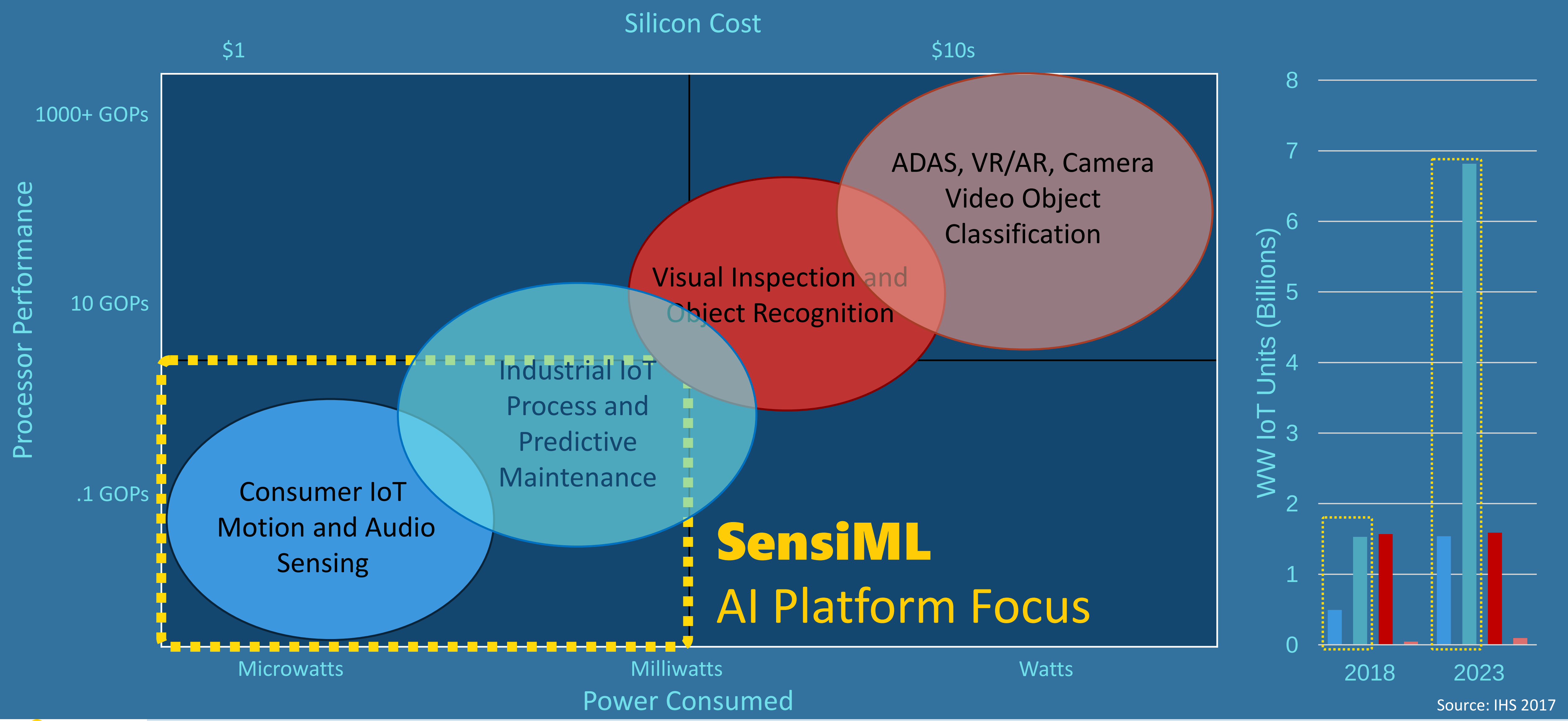
+

Endpoint AI Toolkit Software

Innovative AI Device Solutions



Edge and Endpoint AI Solutions



Example Intelligent Sensor Endpoint Applications

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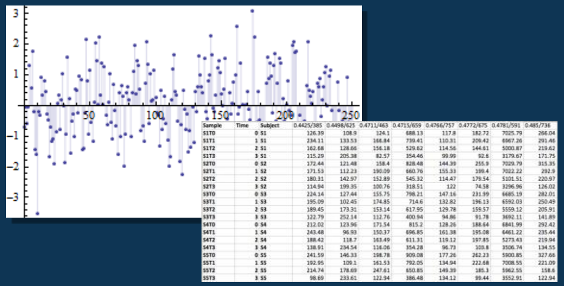
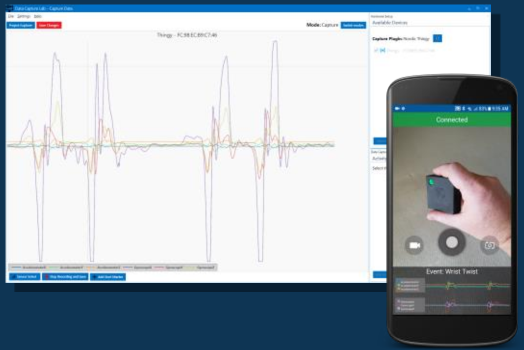
Building a Smart Sensing Device with SensiML

1 Import or Collect Sensor Data





2 Choose Preferred Smart Device Processor

Intel® Atom™ or x86

Raspberry Pi 3

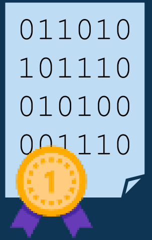
QuickLogic® QuickAI™

Nordic Semi® nRF52

ARM Cortex-M Series

3 Auto-Generate Smart Sensor Algorithm

SensiML Knowledge Pack (Optimized Algorithm Code)



4 Flash Result to Your Device

Custom Smart Sensing Device

SensiML™ AI Based Smart Sensor Algorithms For All

Fast

>5x faster than hand-coding

Intelligent

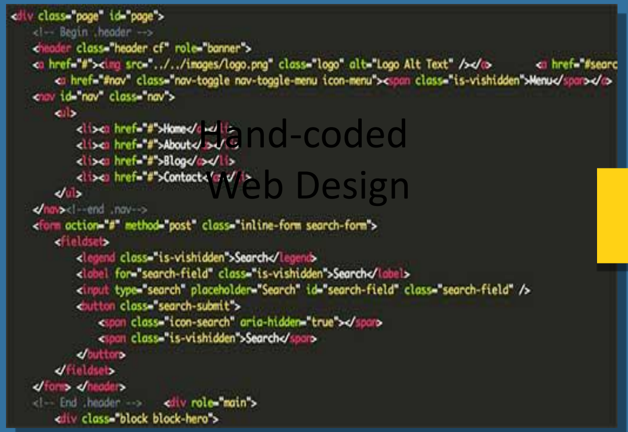
No data science required

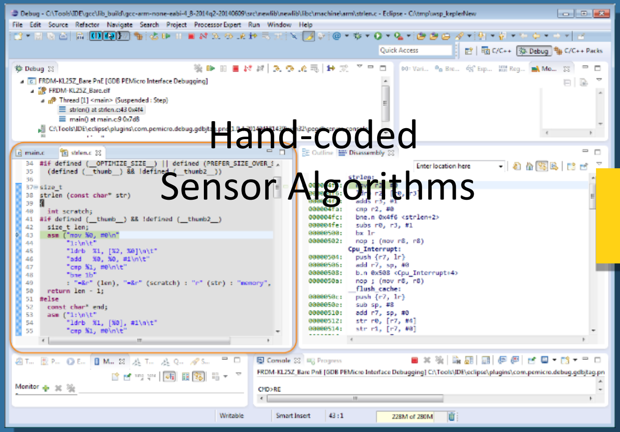
Just collect example data

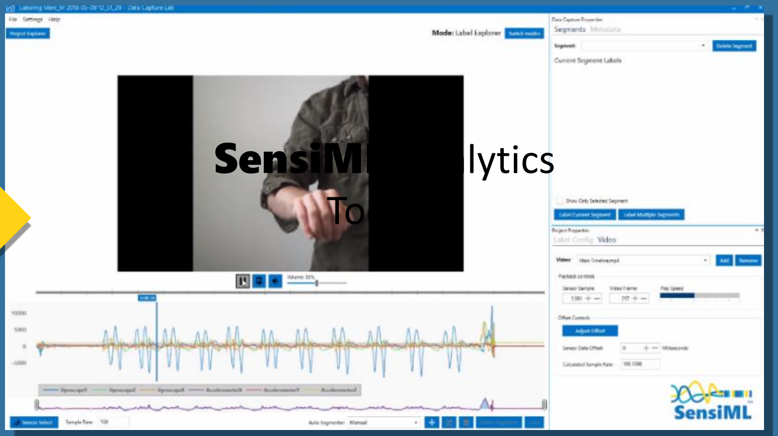
Complete

Entire algorithm dev process

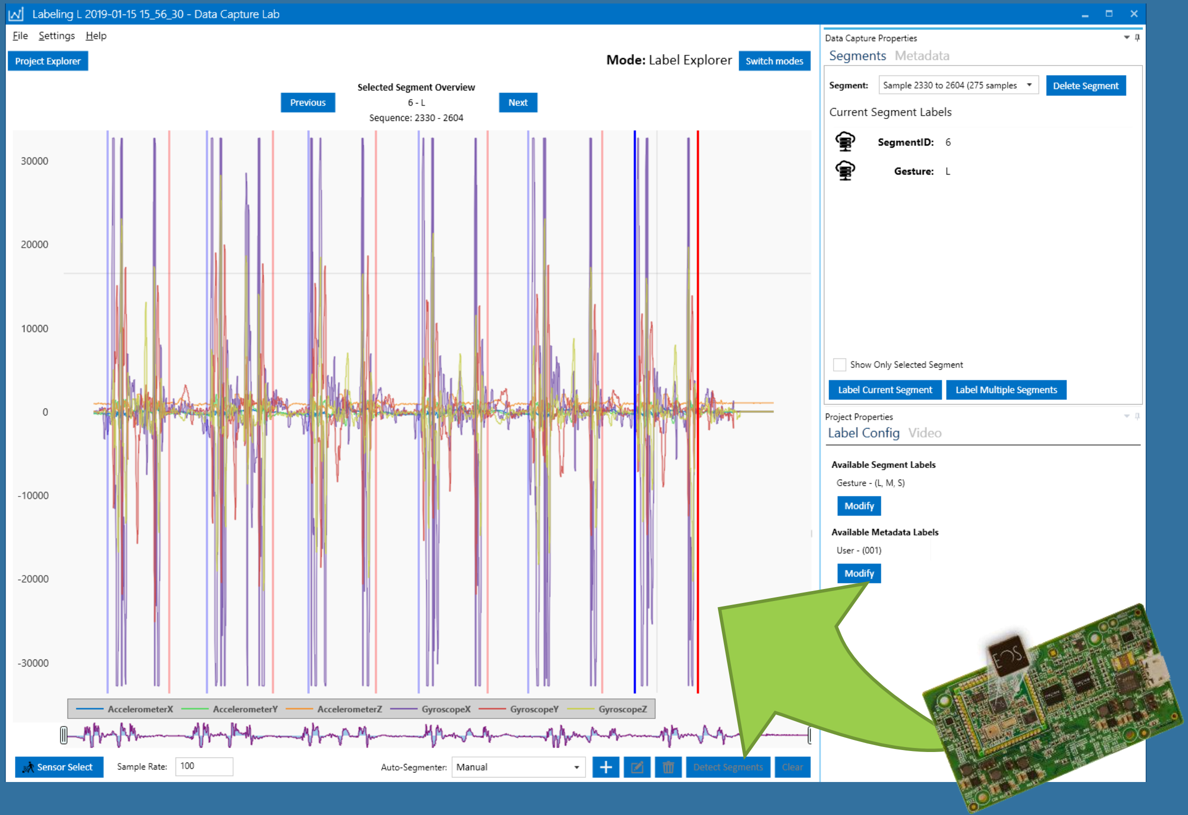
Device-ready firmware as output







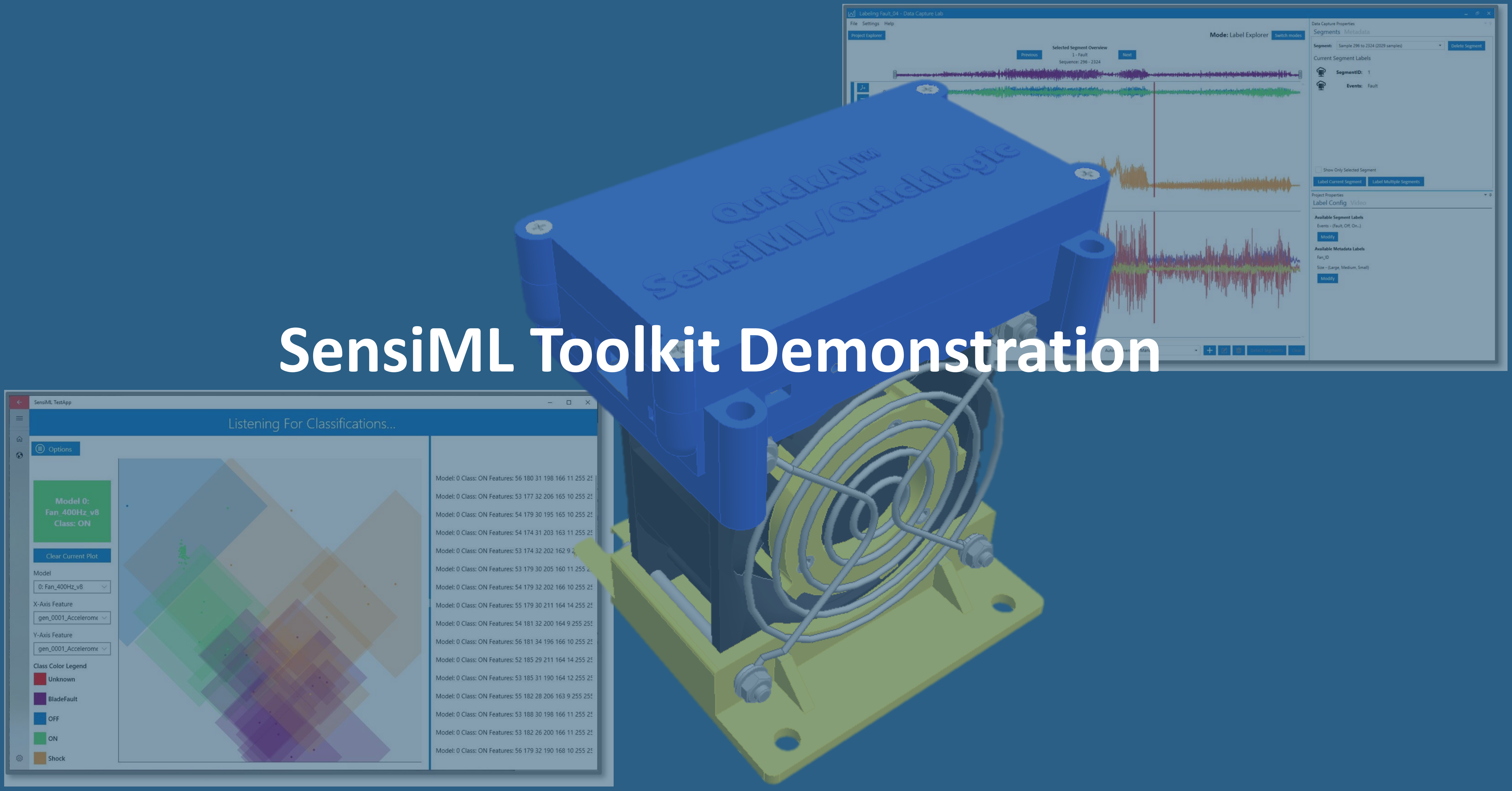
SensiML Data Capture Lab = Accurately Labeled Training Data



Encompasses 4Cs of Labeling Training Data:
Collection, Cleansing, Collaboration, Curation

Little or No Accommodation for Dataset Labeling
User left to own devices (Custom scripts, MATLAB)

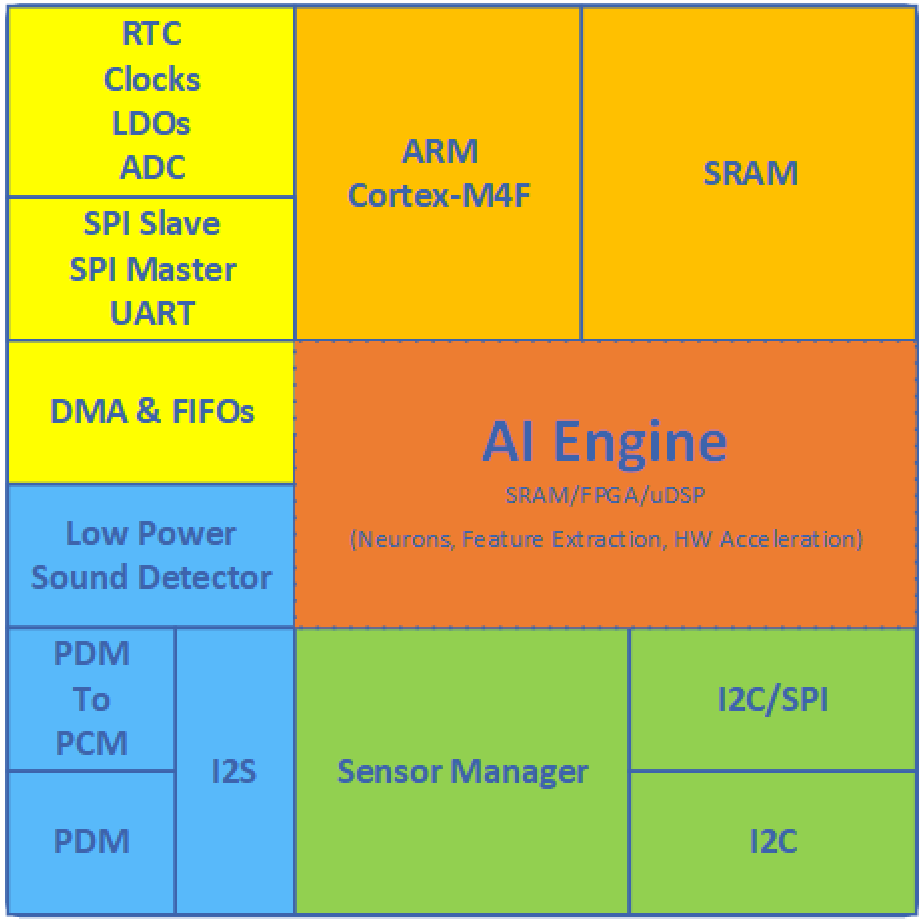
SensiML Toolkit Demonstration



QuickLogic EOS S3AI

Robert Dawson, QuickLogic Applications Manager

EOS EOSAI Multi-Core SoC



Sensor Manager — Autonomously handles management and control of all sensors

AI Engine — Programmable/Tuneable Hardware AI accelerator, implemented in

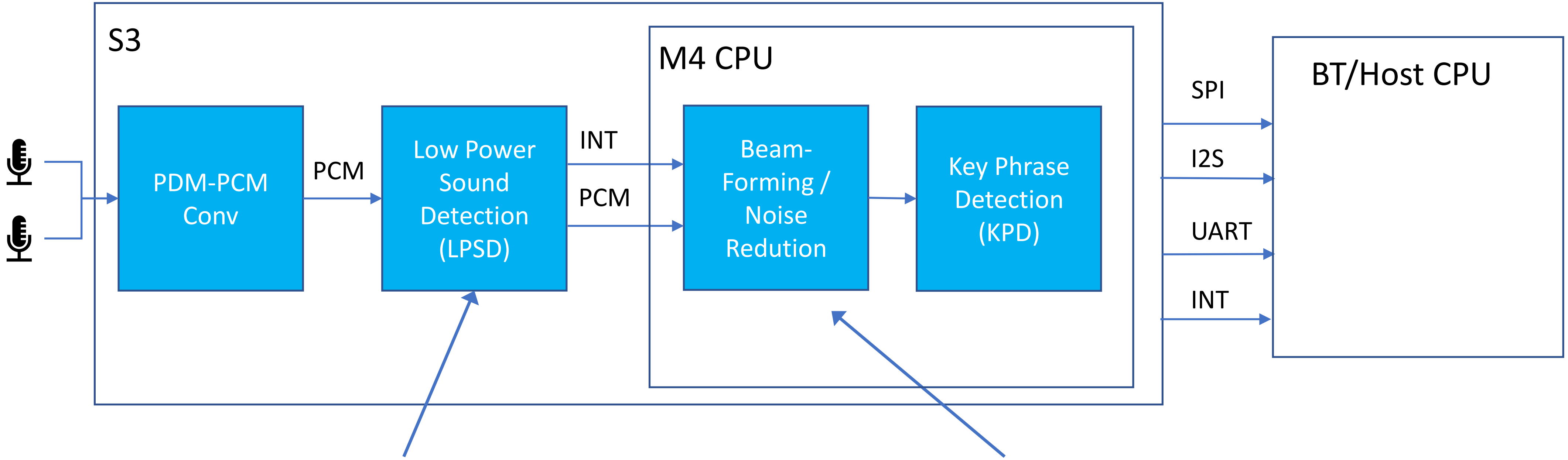
- uDSP-Like processor for low power always on real time sensor processing
- eFPGA Allows additional Feature extraction, interfaces and peripherals

Sound & Voice Processing — Digital Mic interfaces and Low Power Sound Detector *(LPSD) (Used with Voice or Sound)

Cortex M4-F — 80 MHz & 512KB SRAM, general purpose processing and running O/S

System & I/O — SPI M/S, I2C, UART, DMA, RTC, Oscillators, ADC & LDO

Low Power Sound Detector (LPSD)



- LPSD is “smart” VAD
- Listens for acoustic activity, but adapts to patterns
- Runs while rest of system sleeps
- Power @VDD = 150 uW

- M4 runs VR & NS software for Key Phrase Detection (KPD)
- M4 shuts down if no acoustic activity for 700mS
- Power @VDD = 2,650 uW
- Power @ VDD = 1,200uW without BF & NS

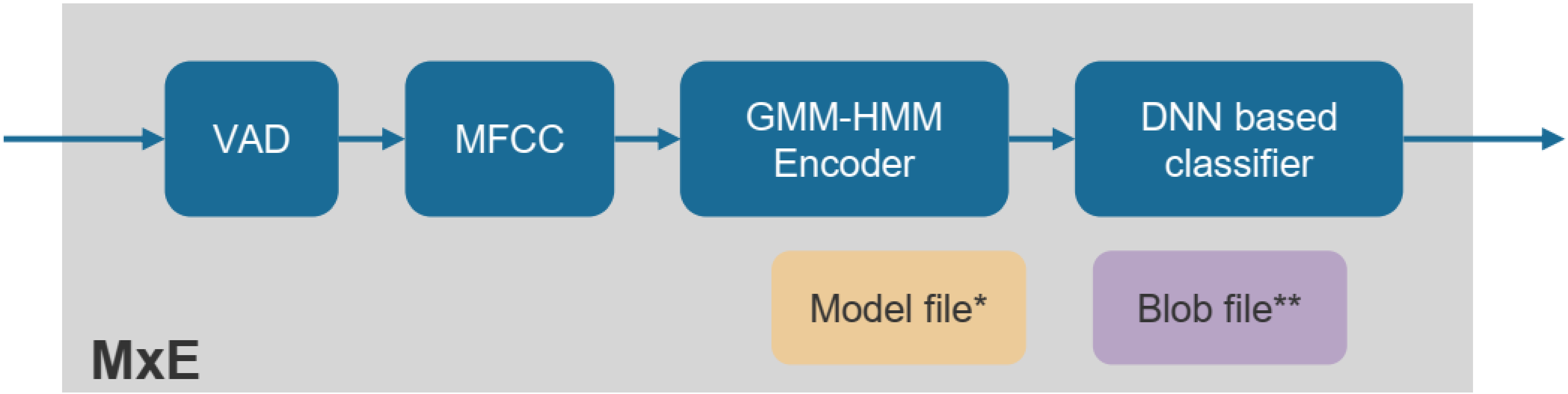
M4 asleep 70% of the time is good approx. over “average” day

M4 asleep 70% of time = 465uW - 900uW @VDD

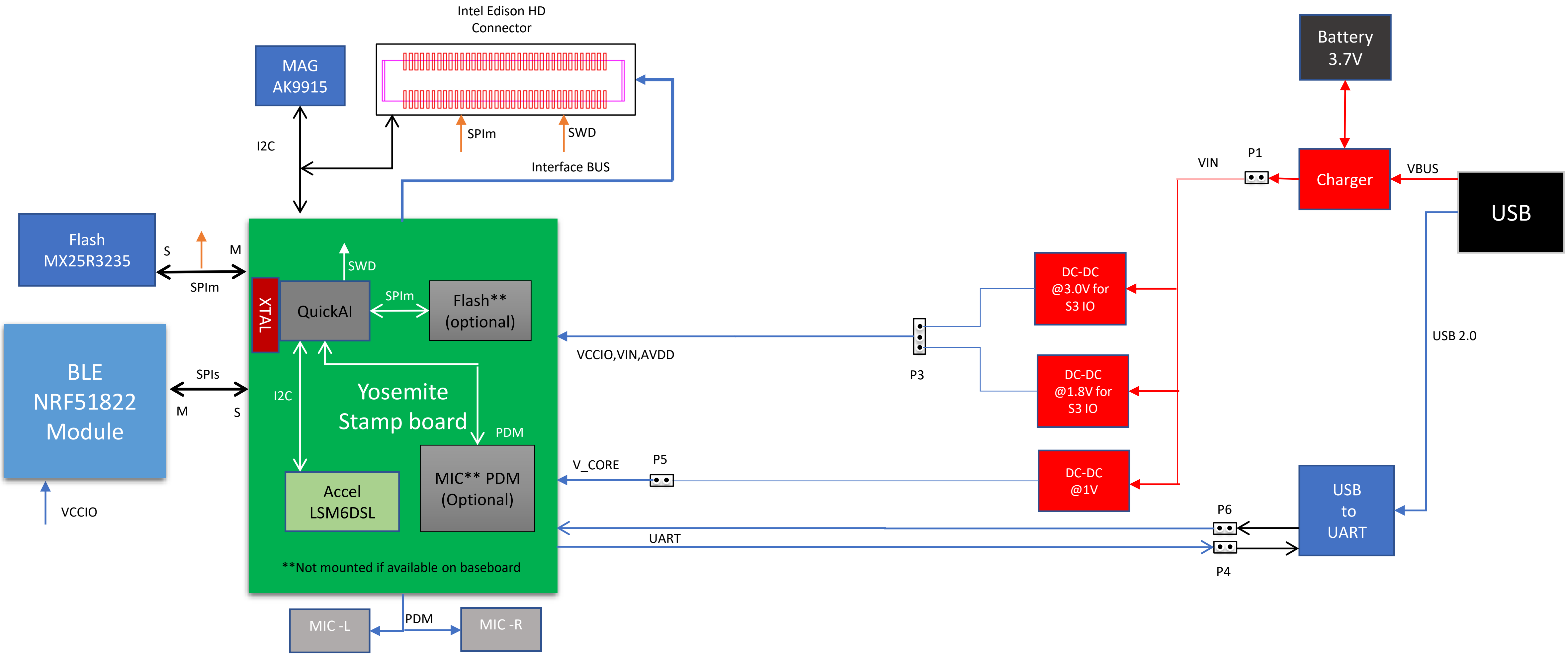
Voice Solution

- Zero risk / cost evaluation of custom voice phrases
- No Algorithm development

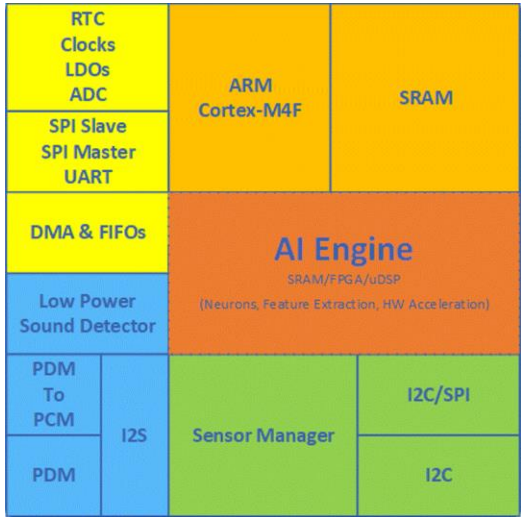
- Will be integrated into QuickAI solution in June

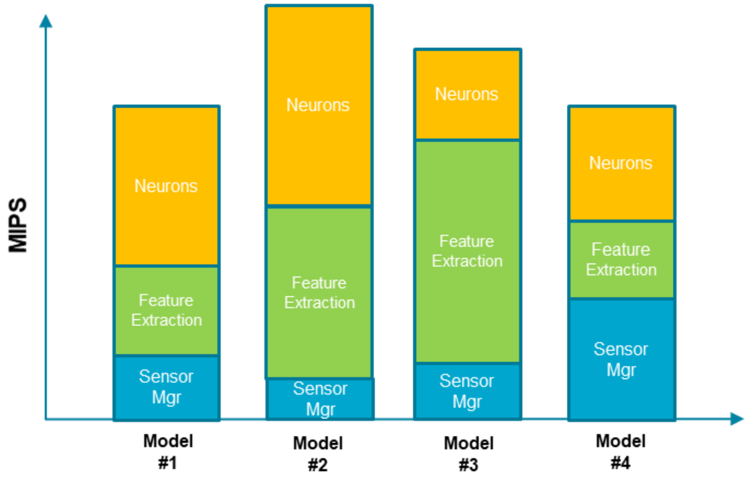


Merced HDK System Block Diagram



Quicklogic + SensiML The Total AI Endpoint Solution





- Multi-Core Processing
  - AI Engine
    - FPGA – Feature Extraction Algos lower power
      - Math intensive code like FFT can be accelerated in eFPGA
      - Accelerator in eFPGA will typically run at 1/5 to 1/8 the clock rate of M4 to achieve the same result
    - Flex Fusion Engine – Low power Sensor processing
  - M4 – Sand box for customer Algos

- Data Collection:
  - Automated collection and labeling of training data
- Data Analytics
  - Selects the optimal feature extraction & classifier combinations to meet stated accuracy and resource constraints
- HW Platform Programming
  - Generates the selected algorithm employing optimal HW accelerated libraries available for the QuickLogic HW

Q & A

Thank You

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