tinyML® Talks

Enabling Ultra-low Power Machine Learning at the Edge

“Speech-to-intent model deployment to low-power low-footprint devices”

Dmitry Maslov - Seeed Studio

August 31, 2021

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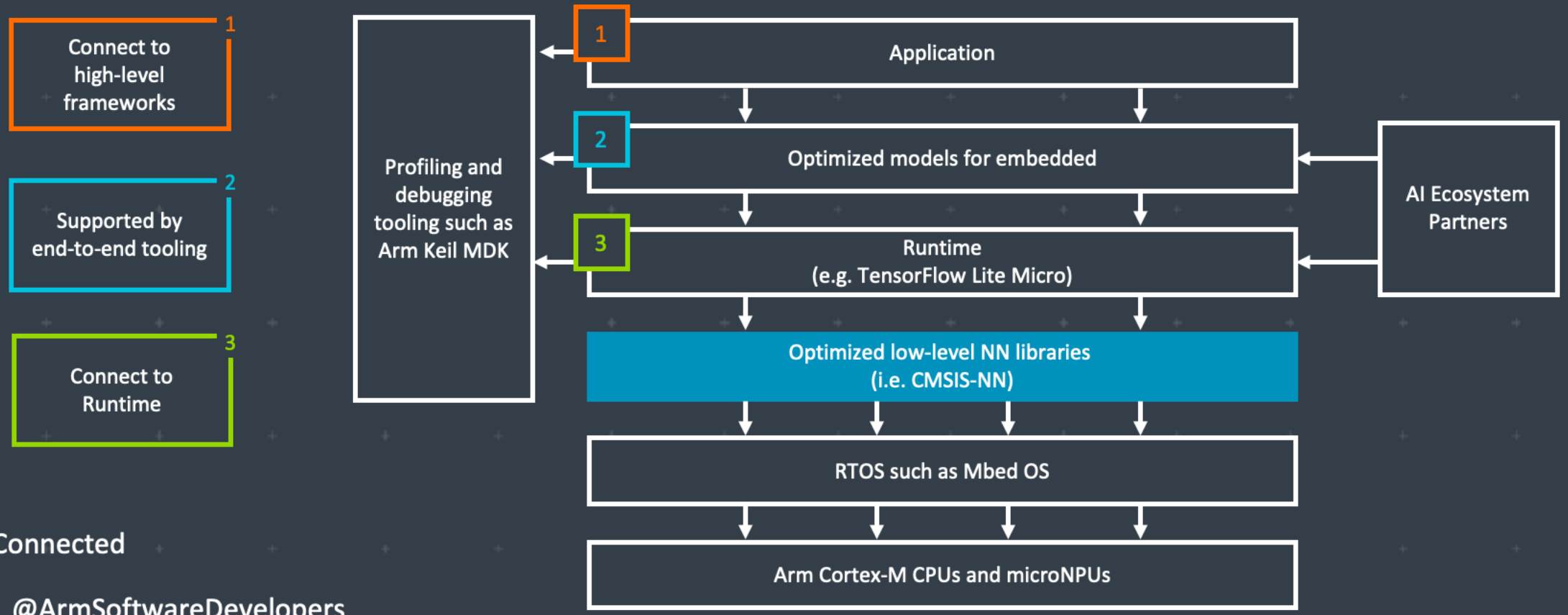

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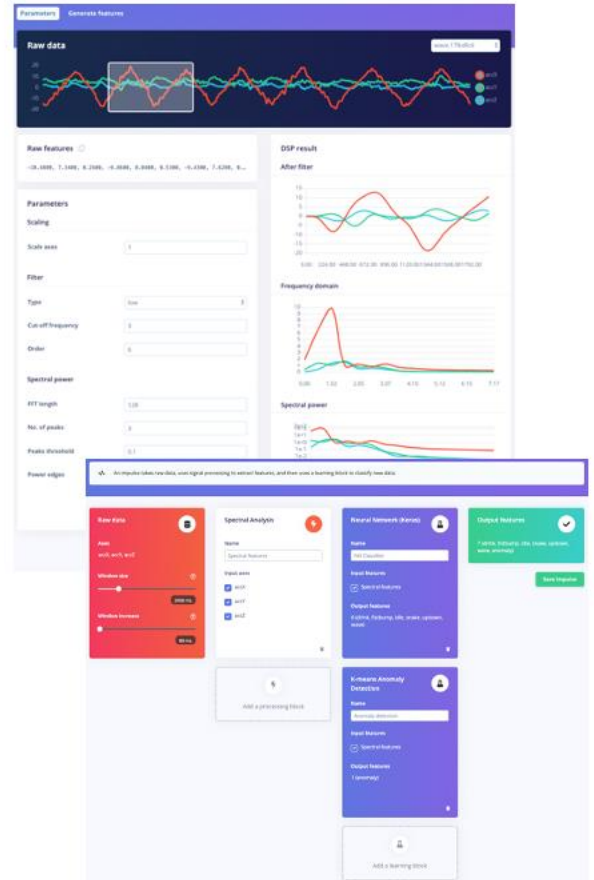

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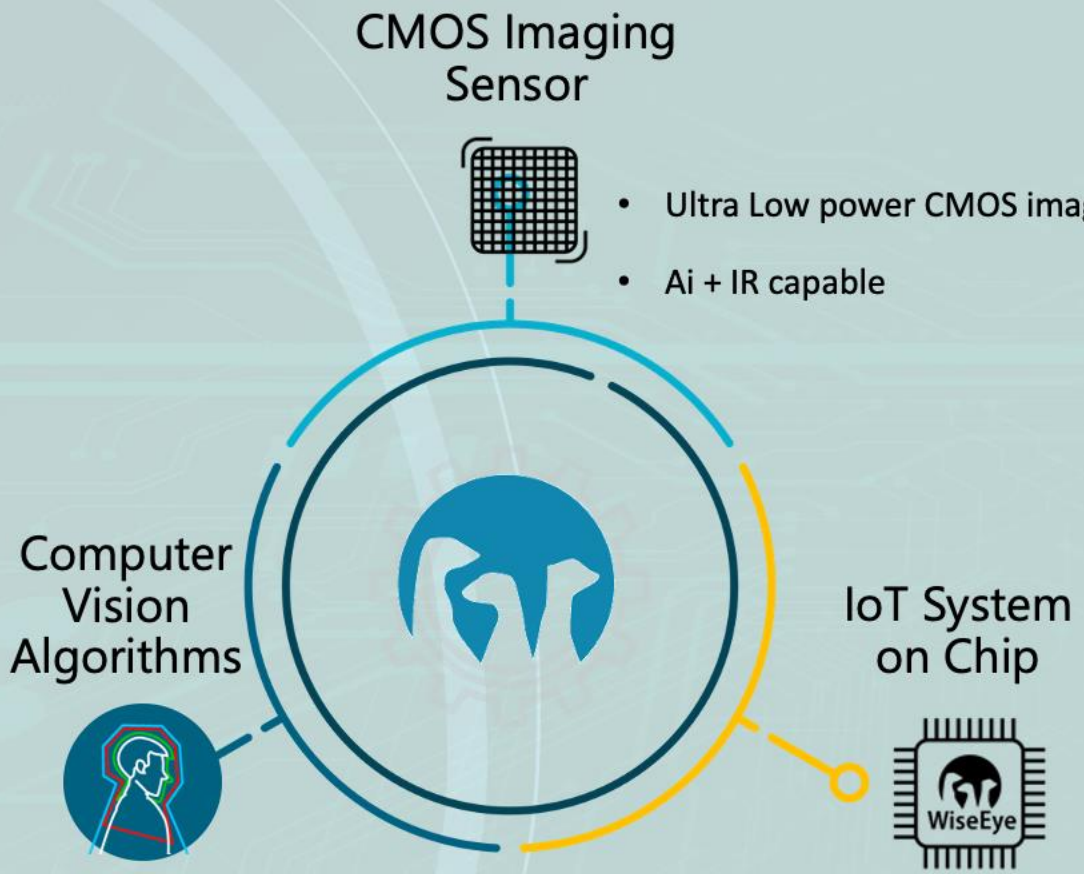

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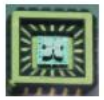
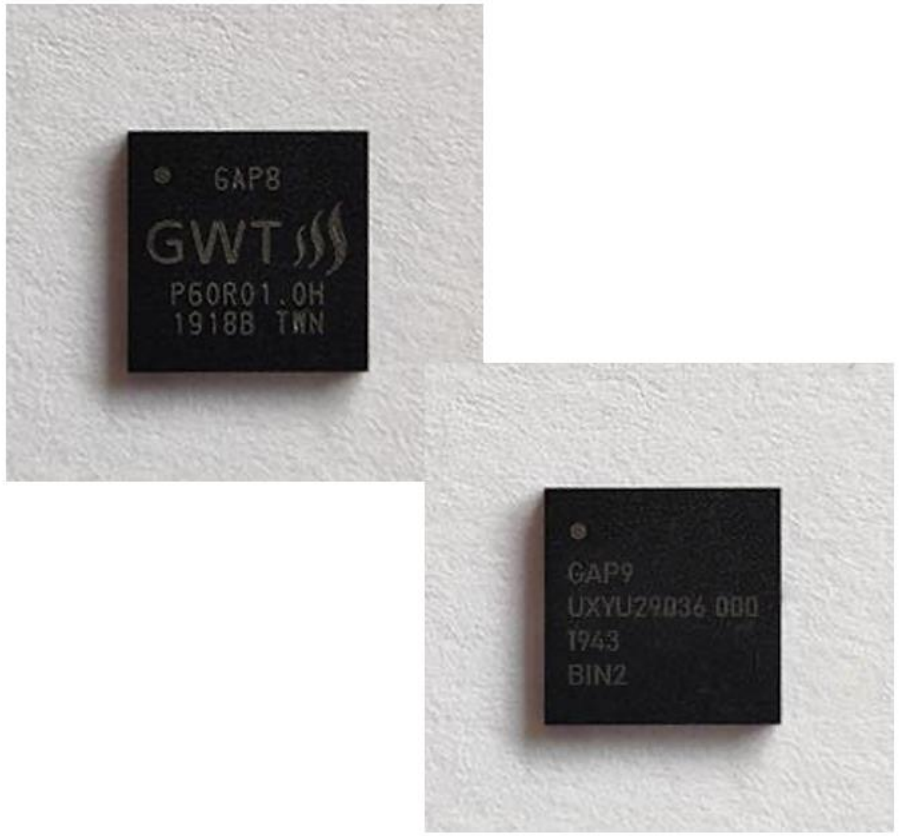
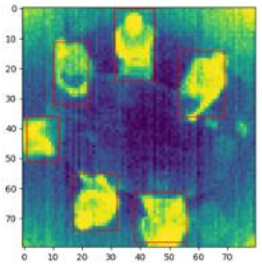




Wearables / Hearables

Battery-powered consumer electronics

IoT Sensors



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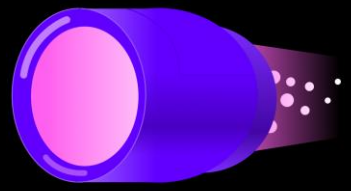
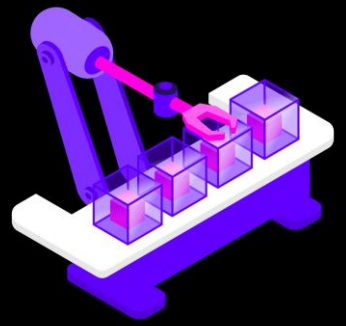
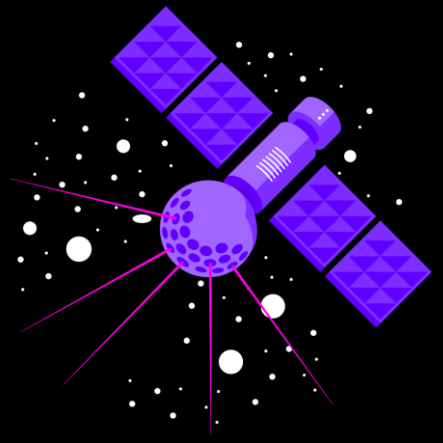
Distributed infrastructure for TinyML apps

HOTG
Decoupling intelligence







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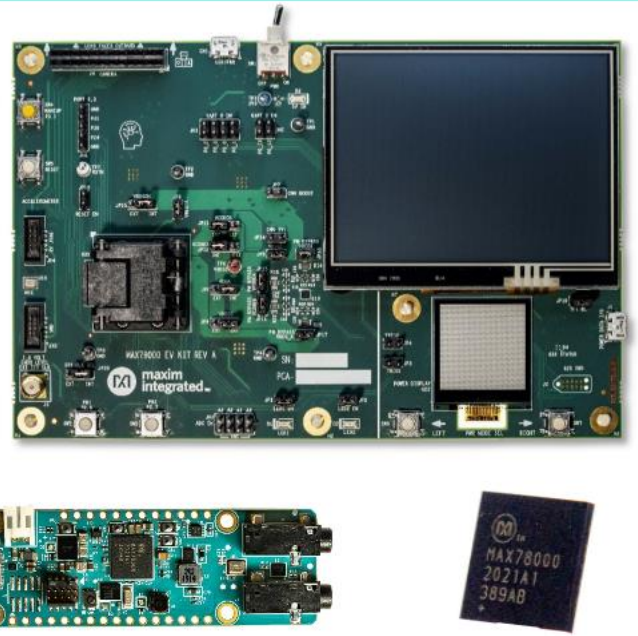

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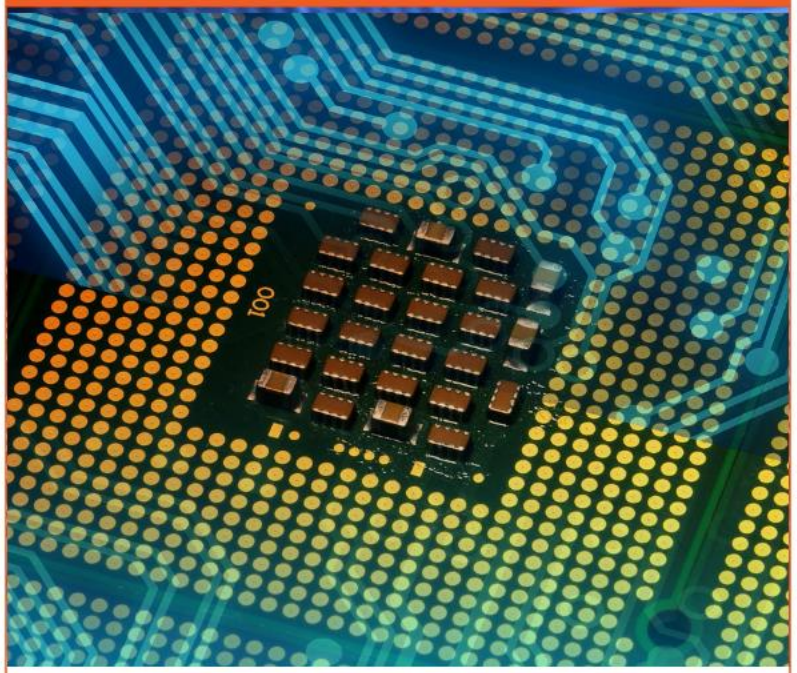

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  - Single-class algorithms: Local Outlier Factor, One Class SVM, One Class Random Forest, Isolation Forest
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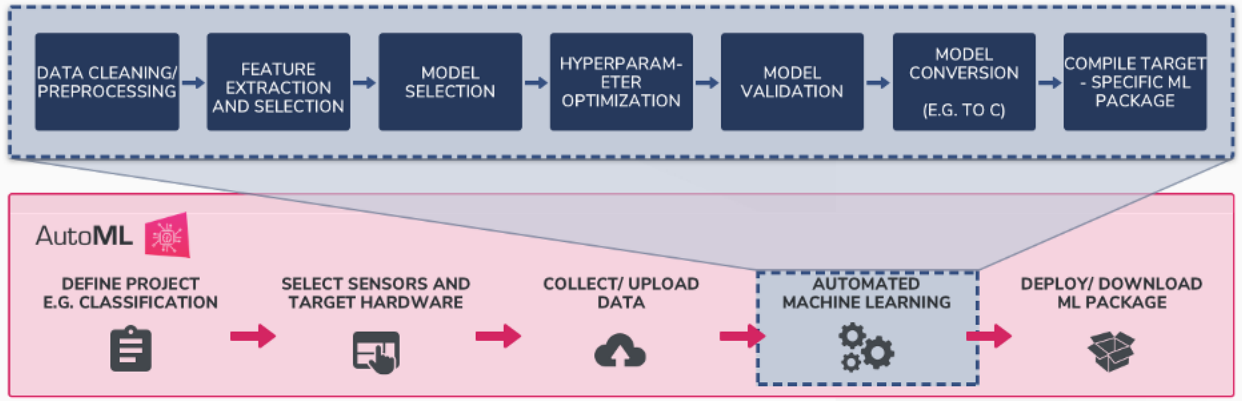
- On-device inference optimized for low latency, low power consumption, and small memory footprint applications
- Supports Arm® Cortex™- M0 to M4 class MCUs

End-to-End Machine Learning Platform



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Target Markets/Applications

- Industrial Predictive Maintenance
- Smart Home
- Wearables
- Automotive
- Mobile
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Cloud

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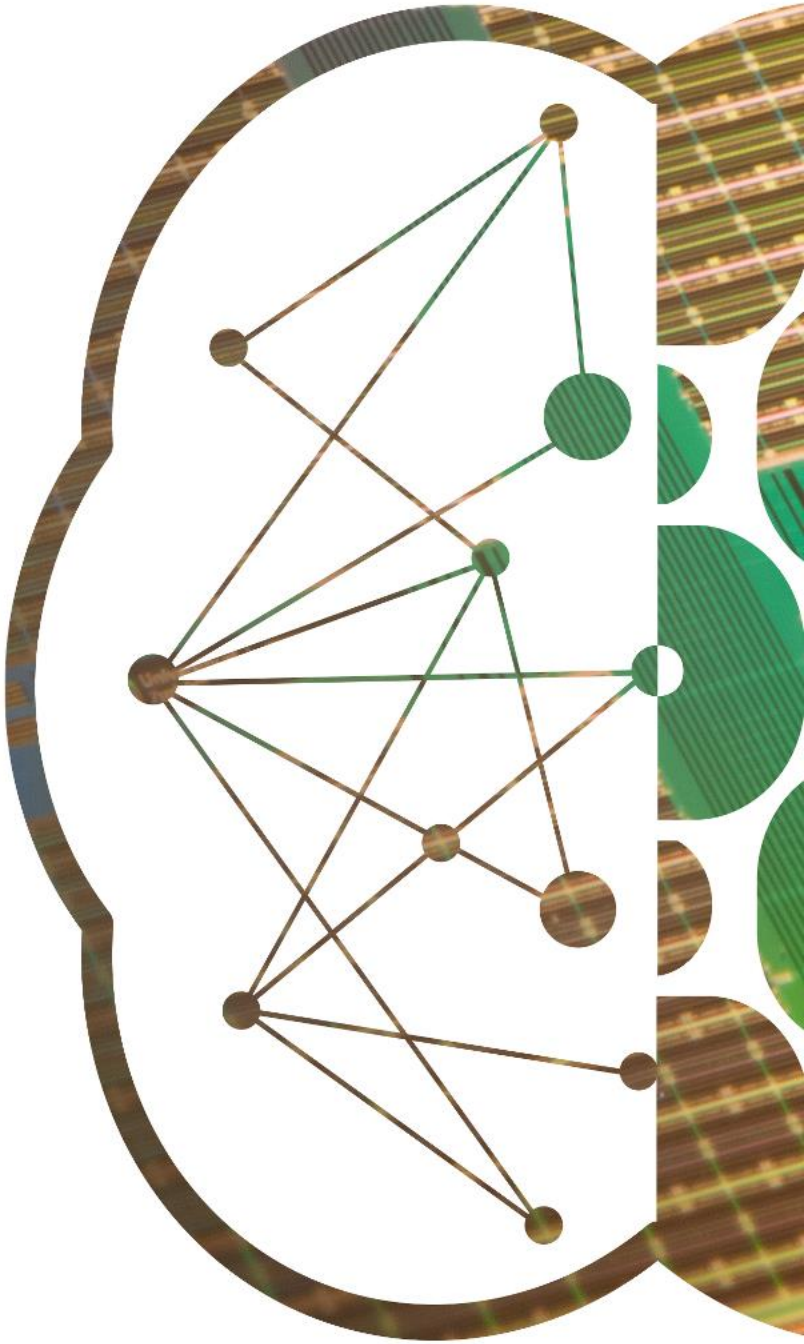

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Successful tinyML EMEA 2021

TINY ML EMEA Virtual JUNE 7-10,2021

- Videos are available on www.youtube.com/tinyML

- **4** days of tinyML excitement
  - **2** tutorials
  - **5** keynotes
  - **15** tinyTalks
  - **7** lightning talks
  - **3** panel discussions & networking
  - **16** papers in the Student Forum
  - **4** partner sessions
  - **16** sponsoring companies

- **58** speakers, **1687** registered attendees!

250+ videos with 133k views

YouTube

Next tinyML Talks

Date	Presenter	Topic / Title
Thursday, September 9	**Pete Warden,** Technical lead of the TensorFlow Lite, Google	TinyML and the Developing World

Webcast start time is 8 am Pacific time

Please contact talks@tinyml.org if you are interested in presenting

TINY ML TALKS webcast

Reminders

Slides & Videos will be posted tomorrow

tinyml.org/forums

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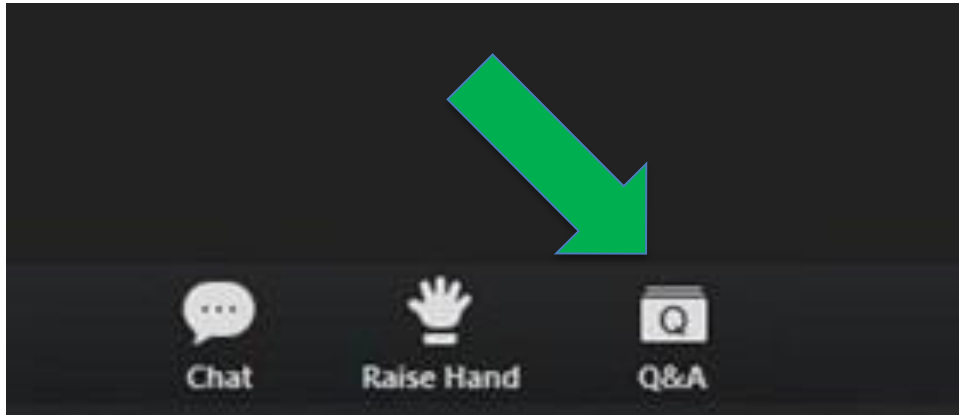
Please use the Q&A window for your questions



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Dmitry Maslov

Dmitry Maslov is a Machine Learning engineer, working at Seeed Studio on applications for embedded devices, both MCUs and SBCs. Recently he published a series of TinyML projects combined into a course, where he utilizes Edge Impulse/Tensorflow Lite for Microcontrollers to tackle challenging sensor data analysis tasks using Seeed Studio's Wio Terminal as a reference hardware. He also runs the Hardware.ai YouTube channel that is focused on embedded ML and robotics.

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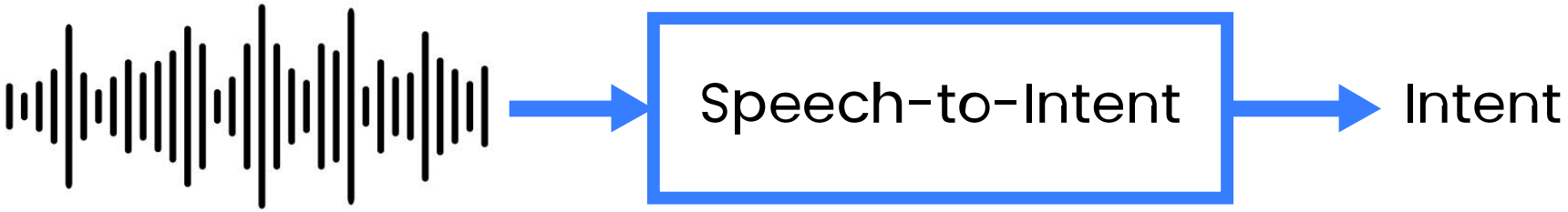
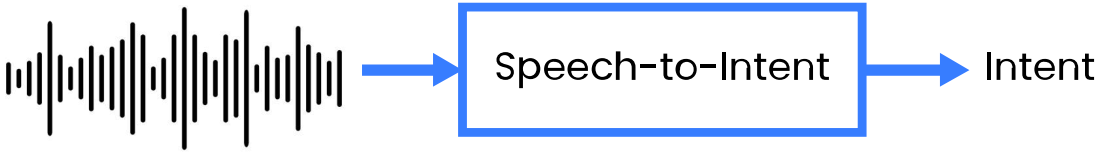
Speech-to-intent models on low-power and low-footprint devices



TensorFlow Lite

Different types of speech processing

- Open domain speech transcription, aka STT
- Keyword spotting
- Speech-to-Intent



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Keyword spotting

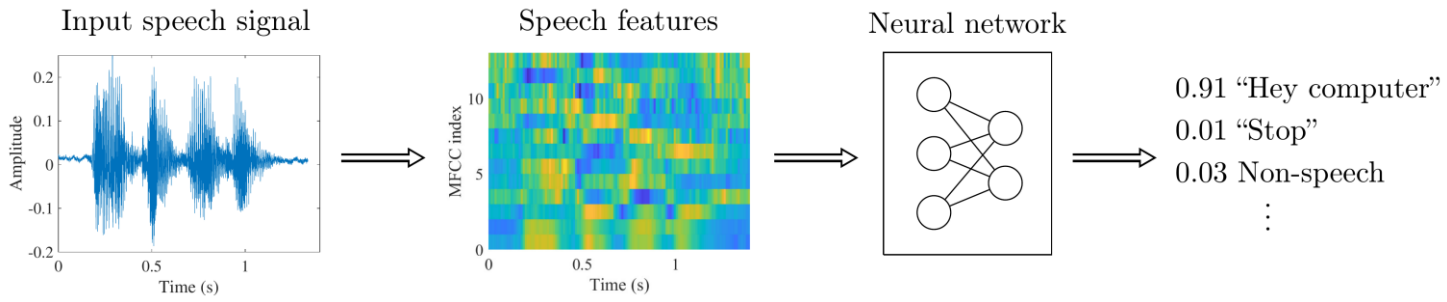
Keyword spotting is a task of detecting a key phrase within a stream of audio.

Benefits:

- very small models, fit even to very constrained resources devices
- normally faster than real time

Drawbacks:

- Recognizing single separate words becoming more difficult as vocabulary size increases
- Needs complete retraining for a new task



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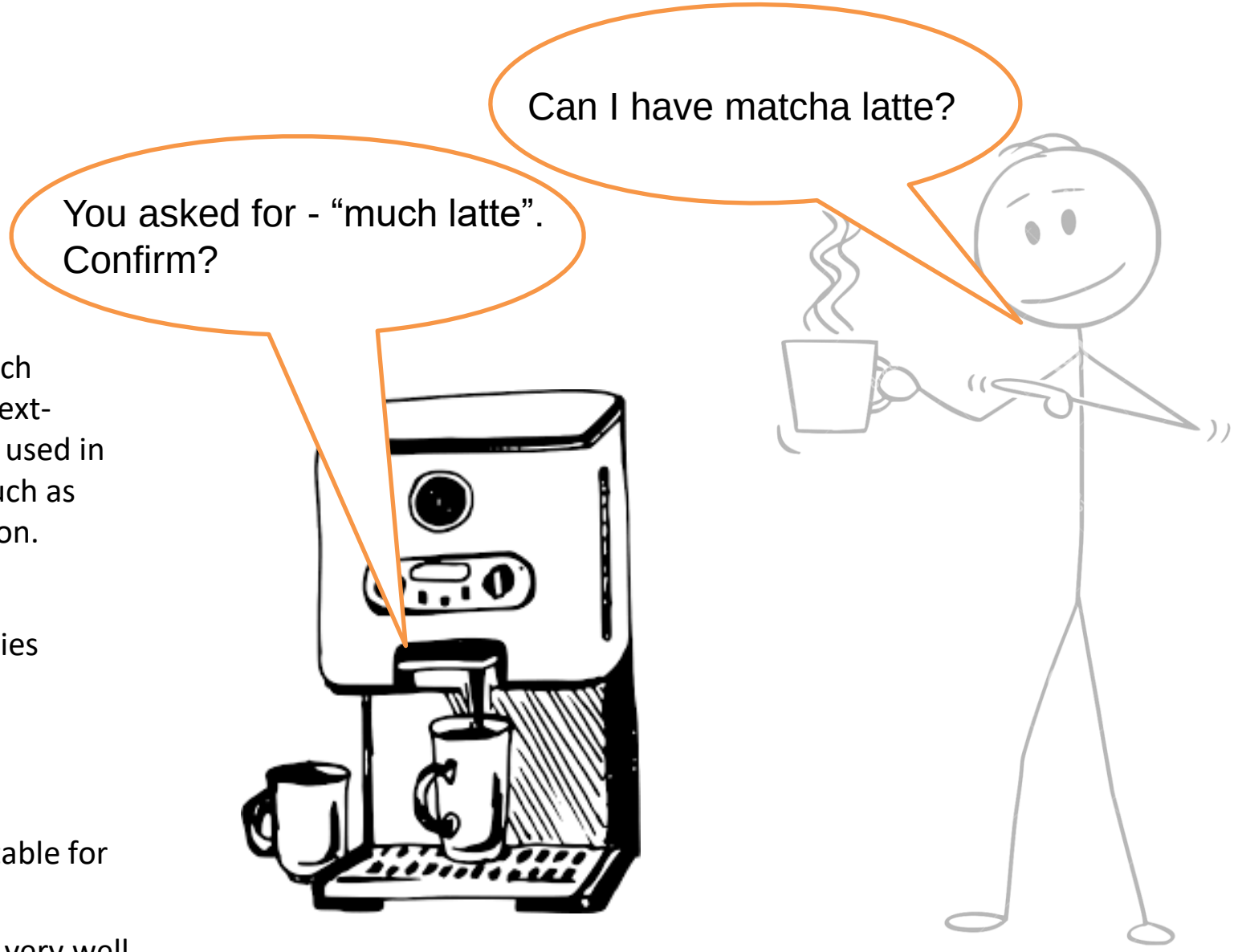


Large-vocabulary continuous speech recognition (LVCSR) models + Text-based Natural language parser, used in mostly Cloud-based systems, such as Alexa, Google Assistant and so on.

Benefits:

- Can react to wide variety of queries
- Robust to environmental noises

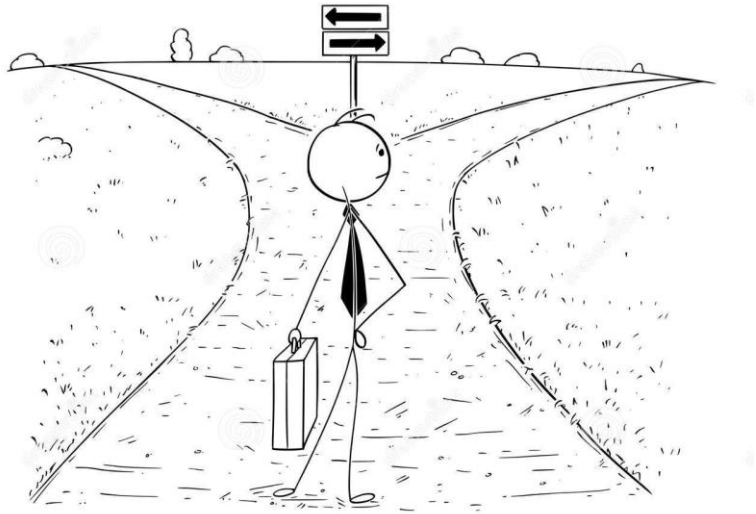
Drawbacks:

- demanding a lot of resource and computing power, not very suitable for the Edge computing
- Struggle with specific words, not very well represented in common use-case scenarios

Open-domain transcription + NLU

Comparison

Keyword spotting works well on microcontrollers, fairly easy to train with variety of no-code open-source tools available, e.g. Edge Impulse, but cannot handle large(er) vocabularies well



LVCSR models + Text-based Natural language parser approach is robust and somewhat easier to implement, given abundance of publicly available ASR engines, but is not suitable for running even on SBCs, let alone microcontrollers

Enter the better way

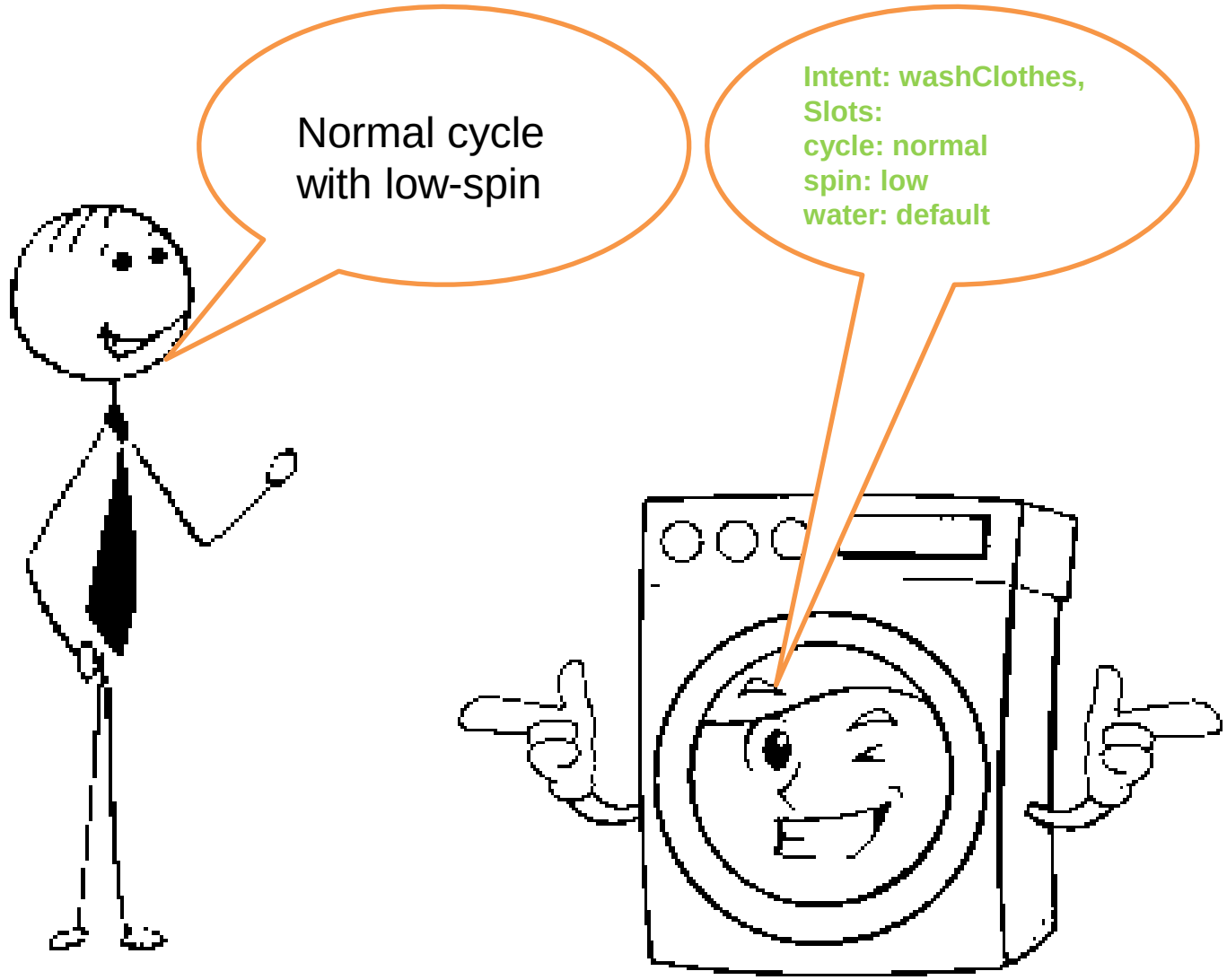
Well represented in research, but lacking widely available open-source implementations suitable for microcontrollers.

Production-ready, not open-source:

- Picovoice
- Fluent.ai

Production-ready, FOSS, not suitable for microcontrollers:

- Speechbrain.io



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The device

ARM Cortex M4F-based 120 Mhz, overclock to 200 MHz

320x240 LCD screen

Built-in sensors: microphone, light sensor, accelerometer

Wi-Fi + Bluetooth

Highly compatible with variety of ML training and deployment platforms: easy to set up and use TFLite Micro and Edge Impulse (code and no-code solutions available)

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The dataset

FLUENT SPEECH COMMANDS DATASET

Dataset contains 97 speakers saying 248 different phrases. The 248 utterances map to 31 unique intents, that are divided into three slots: action, object, and location. The goal in preparing this dataset was to provide a benchmark for end-to-end spoken language understanding models.

Trained on Fluent Speech Commands dataset, tested on 160 phrases recorded with Wio Terminal microphone.

No samples from Wio Terminal were used in training, although the training samples were augmented with audiomentations library, since Fluent Speech Commands dataset recordings all have very clean, noise-free sound.

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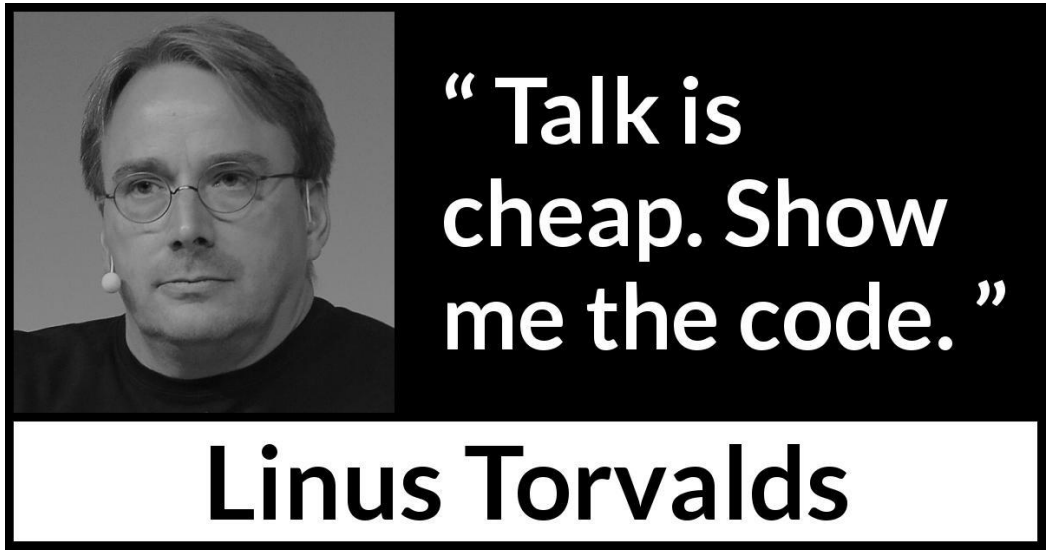

One of the main motivations behind my work on this project was to create an open-source easily accessible package for training and deploying Speech-to-Intent models on Microcontrollers and SBCs. While it may not be fancy or SOTA at this point, it can (and will) be extended with more advanced model architectures and training techniques (more on that in improvement section).

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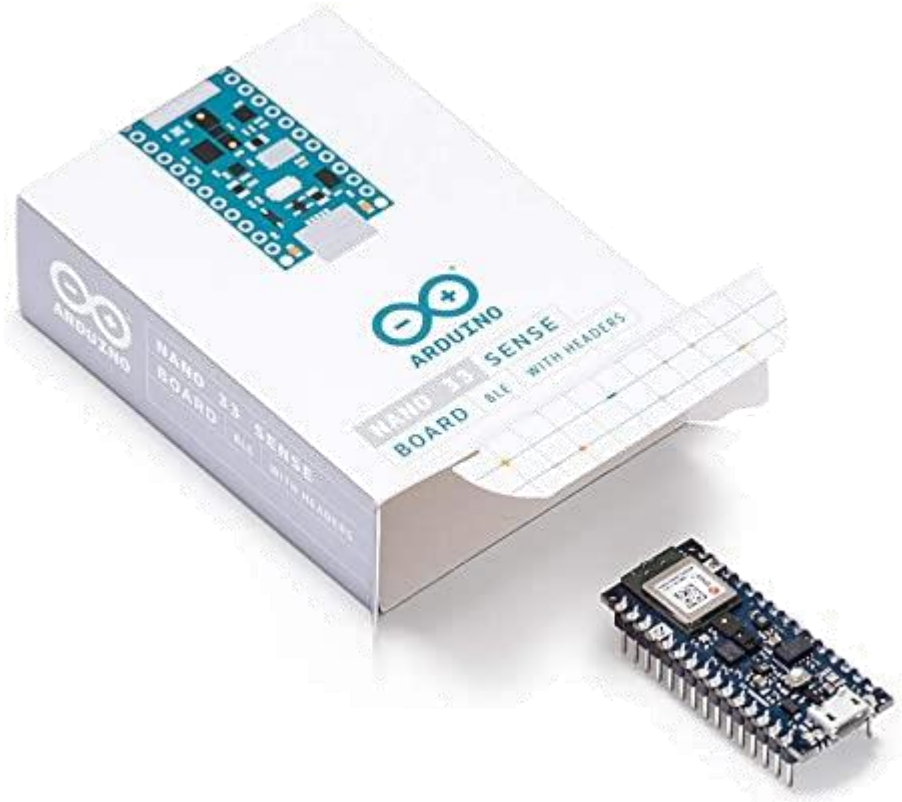
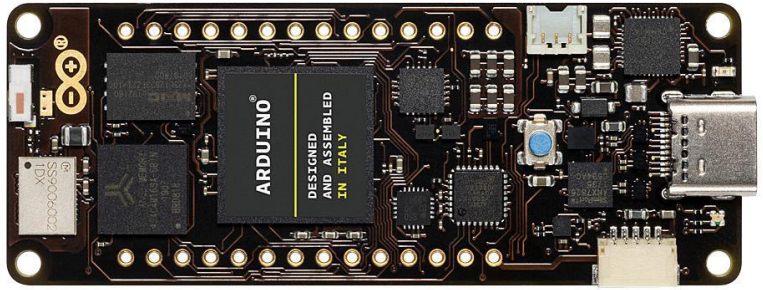
Other devices?

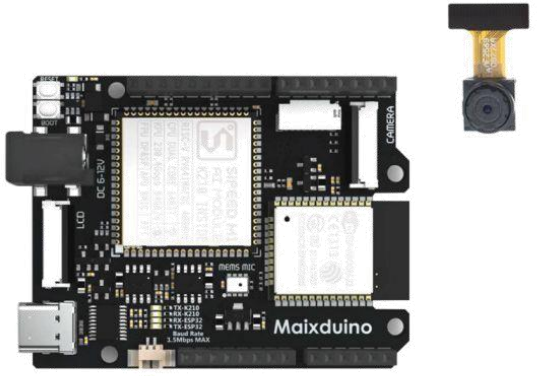


Can easily be run on:

- other Cortex M4F microcontrollers
- other ARM Cortex MCUs
- SBCs with Tensorflow Lite Interpreter

- other architecture MCUs (ESP32, K210)





Improvement

While it works as is, there are many things that can be improved:

- model pre-training
- seq2seq, LSTM, attention
- trainable filters
- AutoML, synthetic data

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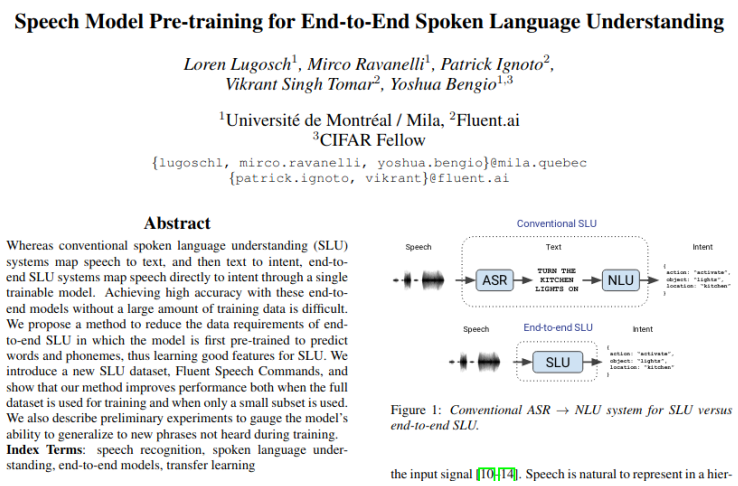
Model pre-training



Speech Model Pre-training for End-to-End Spoken Language Understanding

Loren Lugosch[1], *Mirco Ravanelli*[1], *Patrick Ignoto*[2], *Vikrant Singh Tomar*[2], *Yoshua Bengio*[1,3]

[1]Université de Montréal / Mila, [2]Fluent.ai
[3]CIFAR Fellow
{lugoschl, mirco.ravanelli, yoshua.bengio}@mila.quebec
{patrick.ignoto, vikrant}@fluent.ai

Abstract

Whereas conventional spoken language understanding (SLU) systems map speech to text, and then text to intent, end-to-end SLU systems map speech directly to intent through a single trainable model. Achieving high accuracy with these end-to-end models without a large amount of training data is difficult. We propose a method to reduce the data requirements of end-to-end SLU in which the model is first pre-trained to predict words and phonemes, thus learning good features for SLU. We introduce a new SLU dataset, Fluent Speech Commands, and show that our method improves performance both when the full dataset is used for training and when only a small subset is used. We also describe preliminary experiments to gauge the model's ability to generalize to new phrases not heard during training.

Index Terms: speech recognition, spoken language understanding, end-to-end models, transfer learning

Figure 1: *Conventional ASR → NLU system for SLU versus end-to-end SLU.*

the input signal [T0,T4]. Speech is natural to represent in a hier-

arXiv:1904.03670 [eess.AS]

It is intuitive, that as long as language is the same, transfer learning can be leveraged to improve model accuracy and decrease training time.

General idea is to pre-train the model on phoneme classification task and then transfer this knowledge to classifying intents and slot, which are words consisting of phonemes.

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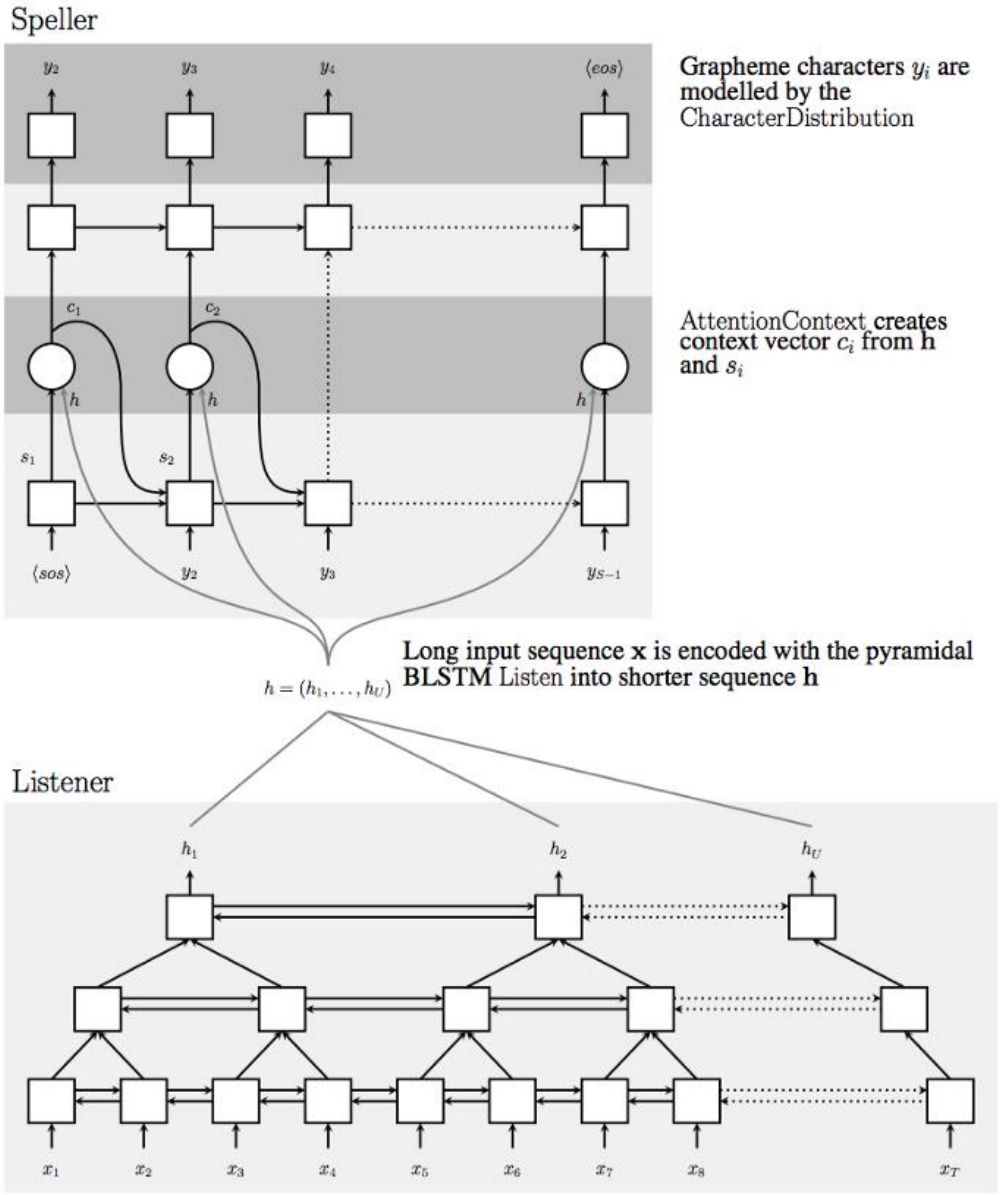
Seq2seq, LSTM, attention

All of the model architectures present in Speech-to-Intent package at the moment only utilize Convolutional and Fully Connected layers with Global Max Pooling after feature extractor. That hinders model ability to process time-domain information and also limits it to fixed-length inputs and outputs.

Listen, Attend and Spell (LAS) model consists of two sub-modules: the listener and the speller. The listener is an acoustic model encoder, whose key operation is Listen. The speller is an attention-based character decoder, whose key operation is AttendAndSpell. The Listen function transforms the original signal x into a high level representation h = (h1,...,hU) with U ≤ T, while the AttendAndSpell function consumes h and produces a probability distribution over character sequences.



arXiv:1508.01211 [cs.CL]

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Trainable filters

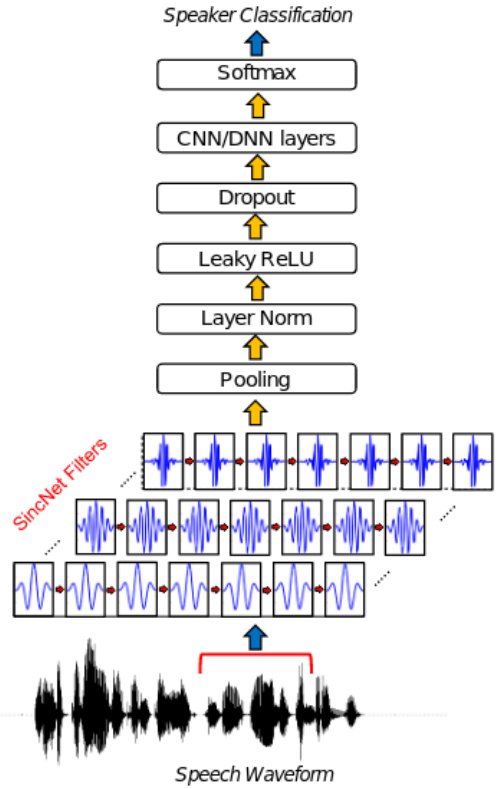

Fig. 1: Architecture of SincNet.

arXiv:1808.00158 [eess.AS]

While a lot of the times we rely on computing input features for speech recognition model with hand-written algorithms (FFT, MFCC, MFE) it is possible to allow the network to learn the discriminatory filters during training process.

"SincNet is based on parametrized sinc functions, which implement band-pass filters. In contrast to standard CNNs, that learn all elements of each filter, only low and high cutoff frequencies are directly learned from data with the proposed method. This offers a very compact and efficient way to derive a customized filter bank specifically tuned for the desired application."

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- Listen, Attend and Spell William Chan, Navdeep Jaitly, Quoc V. Le, Oriol Vinyals https://arxiv.org/abs/1508.01211
- Speech Model Pre-training for End-to-End Spoken Language Understanding Loren Lugosch, Mirco Ravanelli, Patrick Ignoto, Vikrant Singh Tomar, Yoshua Bengio https://arxiv.org/abs/1904.03670
- Speaker Recognition from Raw Waveform with SincNet Mirco Ravanelli, Yoshua Bengio https://arxiv.org/abs/1808.00158
- FLUENT SPEECH COMMANDS DATASET https://www.kaggle.com/tommyngx/fluent-speech-corpus
- Small-Footprint Open-Vocabulary Keyword Spotting

with Quantized LSTM Networks Th´eodore Bluche, Ma¨el Primet, Thibault Gisselbrecht https://arxiv.org/pdf/2002.10851.pdf

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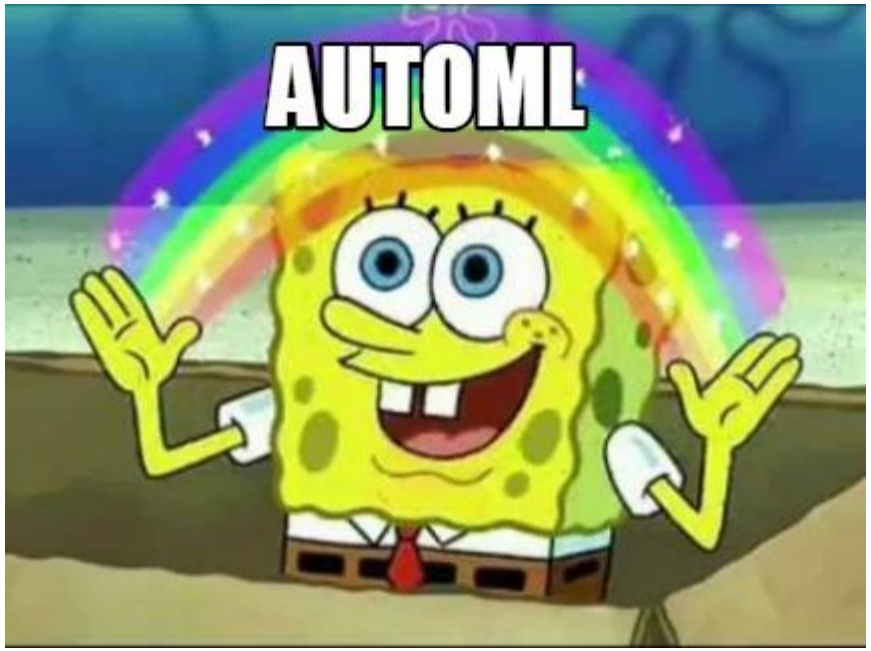
Project repository https://github.com/AIWintermuteAI/Speech-to-Intent-Micro

TinyML Course with Wio Terminal https://wiki.seeedstudio.com/Wio-Terminal-TinyML/

TinyML Course Playlist https://www.youtube.com/playlist?list=PL5efXgSvwk9UCtJ6JKTyWAccSVfTXSlA3

It might not give you SOTA, but at least you can say “Well, the computer tried everything and this is the best it could come up with.”

Specifically it can be very useful for hyperparameter search and finding the right number of filters in Convolutional layers, that can produce the best model for device’s RAM and FLASH memory constraints.



TINY ML TALKS webcast

And the answer is - absolutely!

We encourage you to fork the code repository, try training on your own dataset and perhaps try implementing more advanced architectures or model training techniques.

TINY ML TALKS webcast

"hardware.ai youtube"

"seeed studio"

Hardware.ai

Workshop

Graphical Programming for TinyML, the Easiest way to Start with Embedded ML

9:30 AM - 10:30 AM

Add to Calendar

Huiying Lai
Application Engineer, Seeed

Benjamin Cabé
Principal Program Manager, Azure IoT

Panel

Inspiring the Next Generation of ML Developers

8:30 AM - 9:00 AM

Add to Calendar

Moderator: Jen Fox
Sr. Program Manager, Microsoft

Mike Senese
Executive Editor, Make Magazine

Eric Pan
Founder and CEO, Seeed Studio

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