

GETTING STARTED WITH TINYML

LESSONS LEARNED FROM BUILDING AN ARTIFICIAL NOSE

Benjamin Cabé @kartben

LEARNING OBJECTIVES

What is TinyML anyway?

Sensor data $+ AI = \bigcirc$

TinyML + IoT =



BENJAMIN CABÉ

- Principal Program Manager
 Azure IoT Microsoft
- Open Source & Community Advocate
 - Amateur Potter
 - @kartben

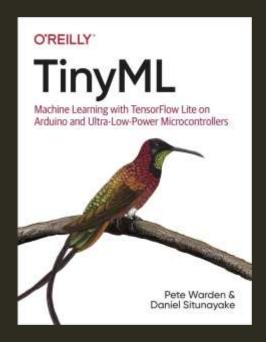


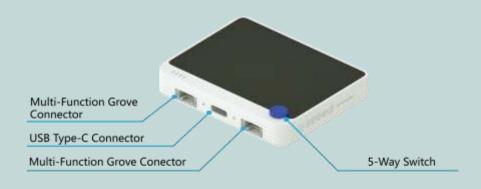


TINYML?

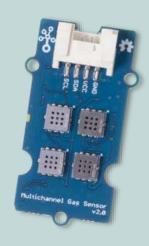


The ability to run a neural network model at an energy cost of below 1 mW.









COST CONSIDERATIONS



Wio Terminal ∼\$38

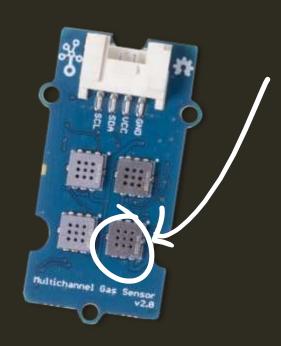
Arm Cortex-M4 512K of Flash 192K of RAM



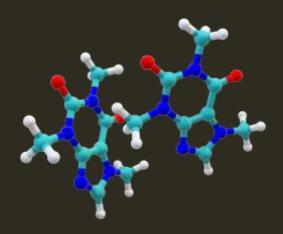
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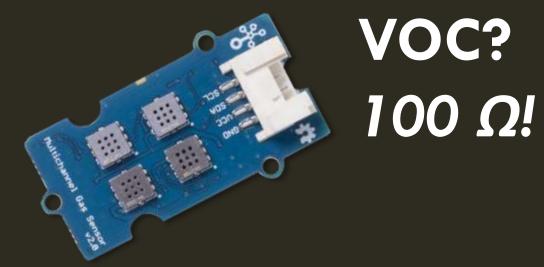
 \sim \$5 (when ordering 3000+ units)

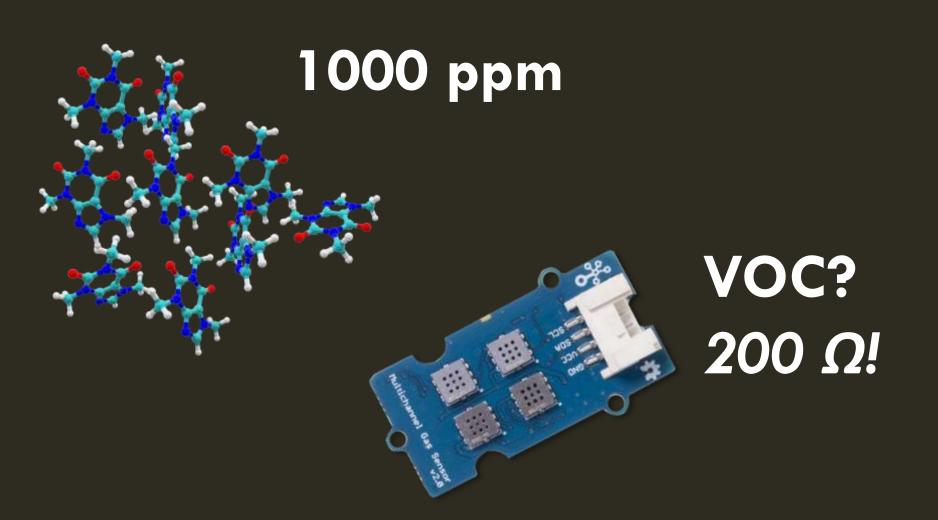
Arm Cortex-M4F 512K of Flash 192K of RAM



10 ppm







AI MODEL FOR SMELLS?

Gas sensor "It smells like X!"

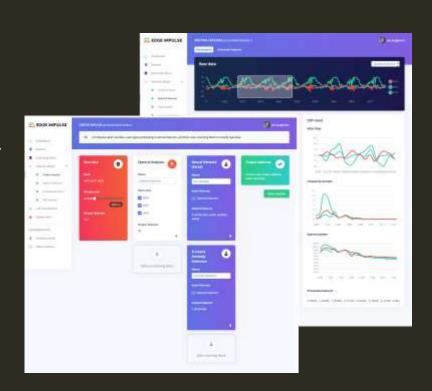


Super simple data acquisition and labelling workflow

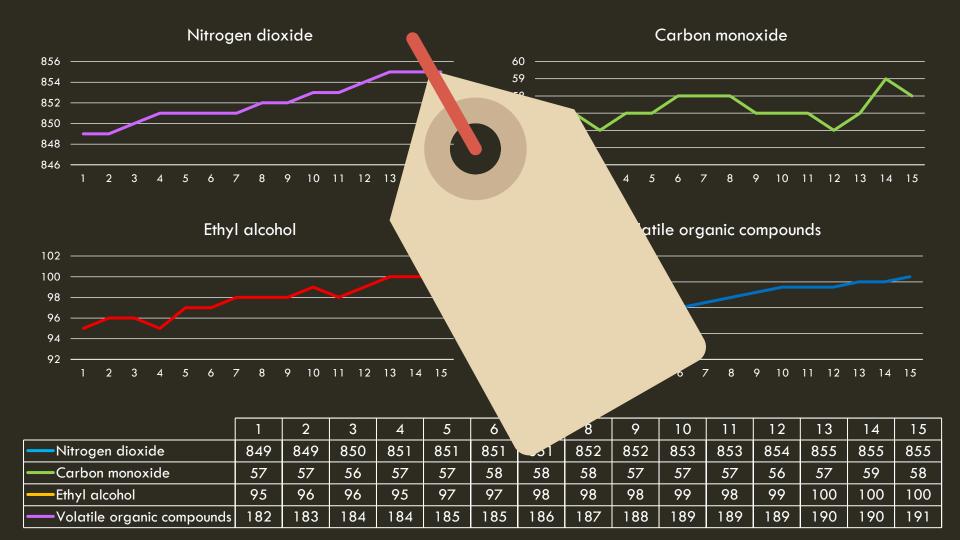
Pre-defined common NN layers, DSP, and anomaly detection "blocks"

Model training in the cloud

Runtime based on TensorFlow Lite



edgeimpulse.com



Raw features (whiskey) – 1.5 s of sensor data, 10 Hz

```
[ 849, 57, 95, 182, 849, 57, 96, 183, 850, 56, 96, 184, 851, 57, 95, 184, 851, 57, 97, 185, 851, 58, 97, 185, 851, 58, 98, 186, 852, 58, 98, 187, 852, 57, 98, 188, 853, 57, 99, 189, 853, 57, 98, 189, 854, 56, 99, 189, 855, 57, 100, 190, 855, 59, 100, 191 ]
```

Flattened features (whiskey) - step 1:

```
[ 849, 57, 95, 182 ],
[ 849, 57, 96, 183 ],
...
[ 855, 58, 100, 191 ]
```

Flattened features (whiskey) – step 2 (scale axes):

```
[0.849, 0.057, 0.095, 0.182],
[0.849, 0.057, 0.096, 0.183],
[ 0.855, 0.058, 0.100, 0.191 ]
```

Flattened features (whiskey) - step 3 (DSP):

```
[ 0.8520, 0.849, 0.855, 0.8250, 0.0019, 0.0572, 0.056, 0.059, 0.0554, 0.0007, 0.0977, 0.095, 0.100, 0.0946, 0.0016, 0.1868, 0.182, 0.191, 0.1808, 0.0027 ] VOC
```









AI MODEL FOR SMELLS?



AI MODEL FOR SMELLS?



AI MODEL FOR SMELLS? DSP block Output layer here w/3 smells Hidden layer Hidden layer #1 #2

Input layer

TENSORFLOW LITE FOR MICROCONTROLLERS

Optimized for on-device machine learning

- latency there's no round-trip to a server
- privacy no personal data leaves the device
- connectivity Internet connectivity is not required
- size reduced model and binary size
- power consumption efficient inference & a lack of network connections

High performance (hardware acceleration and model optimization)

Available as **Arduino library**



RE: PERFORMANCE AND CODE SIZE

Classifying 3-5 smells:

- ~4KB of RAM, ~27KB of ROM (the actual TFLite model is ~3KB)
- Inference is ~1ms on an 80MHz 32-bit MCU

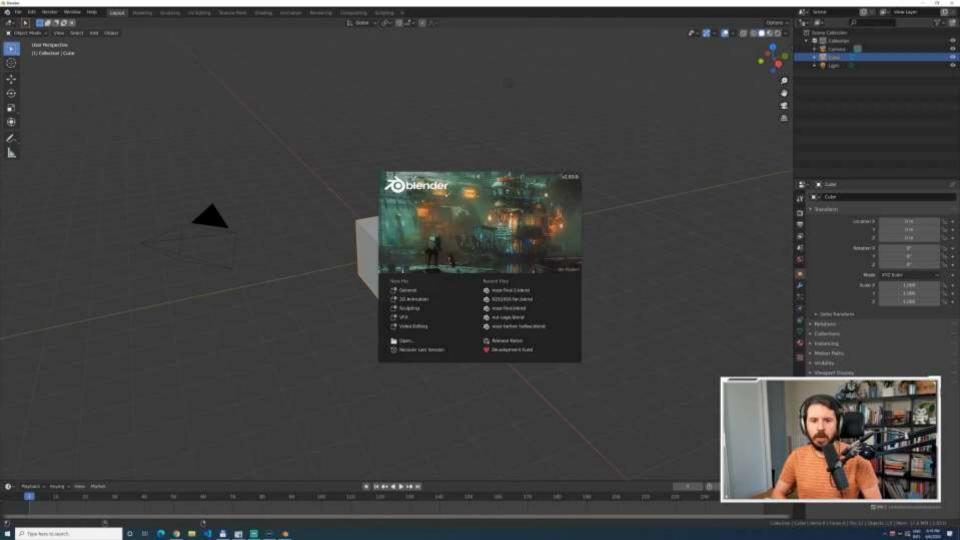
IMPROVING ACCURACY?

Better model (ex. RNN)
Better gas sensors

More gas sensors
Sensor fusion

- Humidity
- Temperature
- Color
- ...









I realized I **never quite published** the instructions to replicate my **#TinyML** and **#IoT** artificial **nose** project, powered by awesome tech from **@EdgeImpulse** and hardware from **@seeedstudio**. Working on getting this

fixed asap while sipping my espresso! 👃 🥞





Pascal BORNET

Intelligent Automation Global Expert | Chief Data Officer | Author | Forbes Tech Council | Ex-McKinsey | Top Voice in Tech | 300K+ followers



View full profile



Identifying smells with machine learning!

Built by Benjamin Cabé, this artificial nose has been trained to recognize accurately hundreds of smells. Read more here: https://lnkd.in/gdPKx9Z

This could power so many wonderful use cases: cooking assistant, alerts in case of dangerous gases, perfumes design, support to people who can't smell well... What else would you think of?

Code available here: https://lnkd.in/gSXdiah

If you like my posts, you will enjoy my new book: https://lnkd.in/g4uCcg4

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Reactions









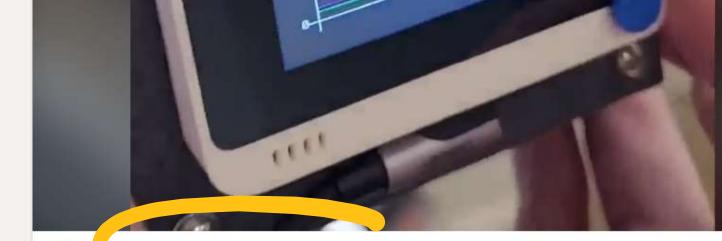












3,935 • 255 comments • 225,379 Views

Reactions

































If we satisfy weekend of May 2520 Like many of the human is bir greated, at home with time or their hands the tran organizanderso, I was have tripred to perfect my bread recipe. In fact, part a fee days before, I had proleted a gas sensor Figure () that I thought served by day, to help red framelov representatively startar and toke try bread of part the right insurant.

And them throught about it some more. Through the is the perfect extrate for the toburie start teaming this exactly a training thangthat more your a taking about that ... do I mady word to been dazens of inquestes before I have a training set large proughts teach an Alife relationance between the adaptory (vigoryers) of The seasonagh starter and the parenterings of the how last? Play Age is profly warre those days?

That is how, over the course of the root low disc, templed up building a (10), governor purpose, artificial rans - one that can arrest intrustry anything you bount it is recognized The artificial THE HOUSe rained evaluation of a Suphry reural network that / trained our gitter her pales that Edge (mouble and Sept uploaded and a Arguna comparate recoveration.

Harmonia to areas the way, and not just about machine harrivry. From designing my Erus 30 are bounded a functional transfer from perfect earlier flat noise is not exactly optimal. Personal transfer of Sudding Own Thing" from screen, so I've exceed to share it with the Main. continues, there are the steps for repleating the

BUILD YOUR ARTIFICIAL NOSE 1. GET YOUN PARTS READY

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TIME REGUNEED

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TOOLS

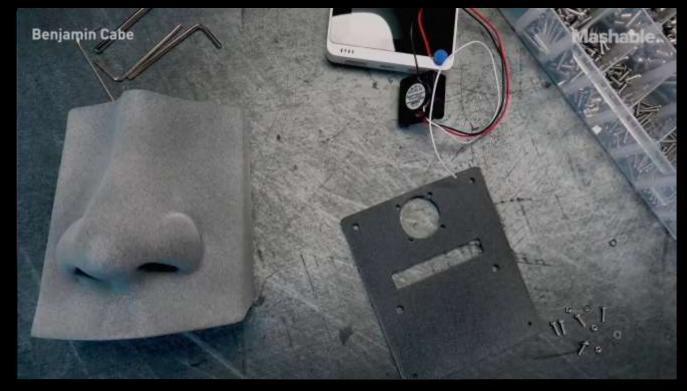
Computer with internal contraction in the last











Next Up



Sinone Gertz used to make useless inventions, then she beat Tesla to the Cybertuck



Cooksy wants to be your second per of eyes in the kitchen — Future Birrik



You don't have to water your bouseplants individually anymore — Future Blok



"The Underground Railtoad" takes an honest look at a critical part of American history

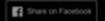


Surprise, you can actually turn anything into a smart device —



DryCycle looks like a minielectric car. but it's made to blue paths. — Future Blink

Umm, this Al tool can...smell for you — Future Blink









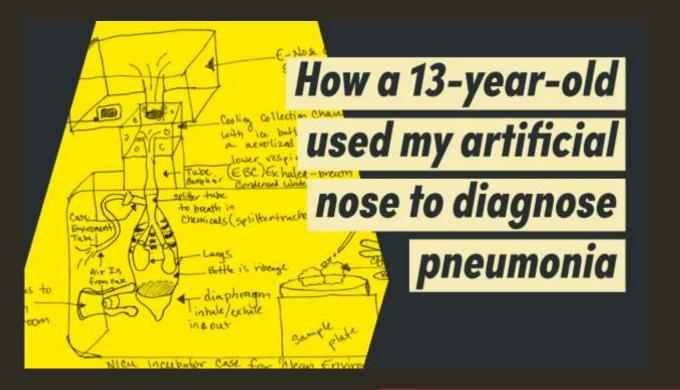




Stay cool this summer with...ii wearable Al neck fari? — Future Blink



Researchers made a robot that mimics a real, backflippin; spider — Strictly Robots



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 Y Hacker News new | threads | past | comments | ask | show | jobs | submit
 1. A 13-year-old used my artificial nose to diagnose pneumonia (benjamin-cabe.com)
 229 points by kartben_ 5 hours ago | hide | 128 comments
 - 2. My smart home 2021: A Home Assistant love story (jorisroovers.com)

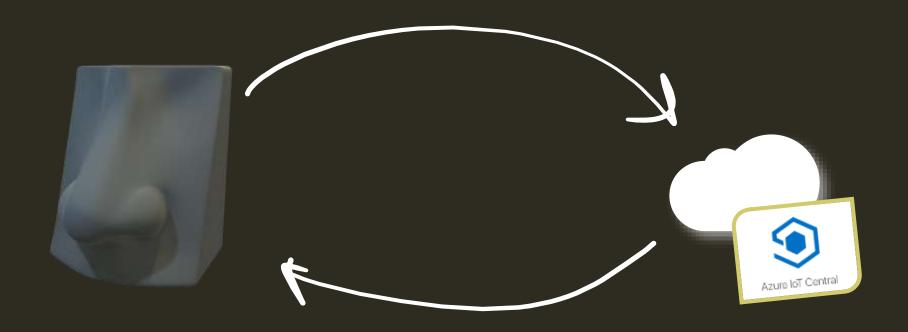
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- - Ply smalt home 2U21: A Home Assistant love story





"INTELLIGENCE AT THE EDGE" + INTERNET = **



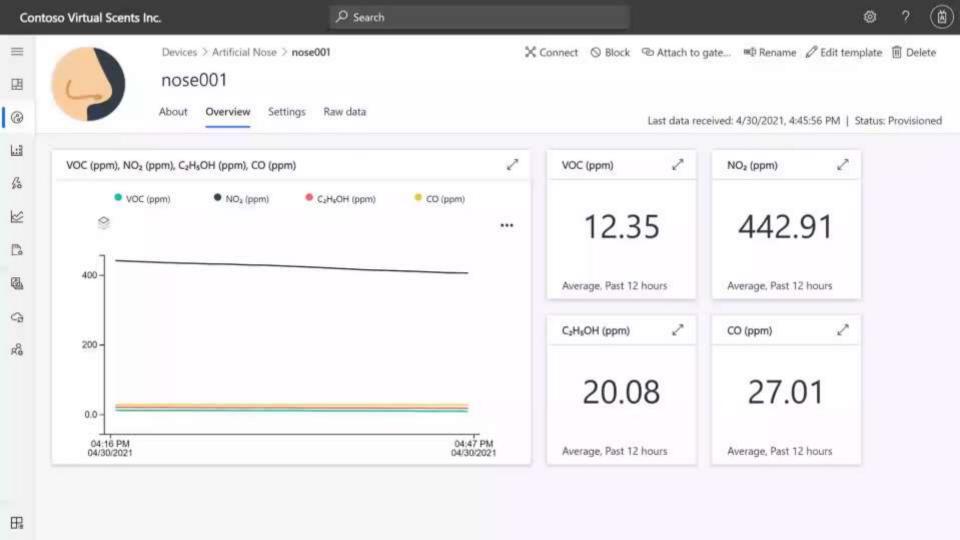
^{*} a.k.a. AloT

FROM AN "ARTIFICIAL NOSE"... TO A "CONNECTED ARTIFICIAL NOSE"









"CONNECTING" AN IOT DEVICE IS ONLY THE 1ST STEP

Visualize data in real time

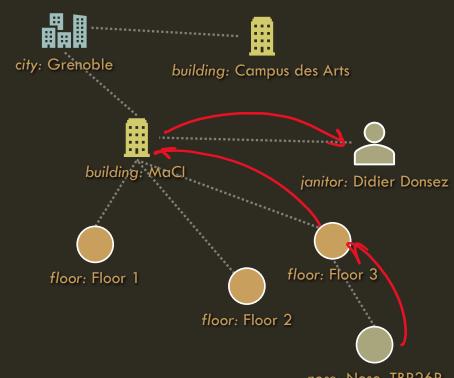
Store telemetry history

Implement rules

Integrate with enterprise systems

FROM CONNECTED THINGS TO CONNECTED ENVIRONMENTS*





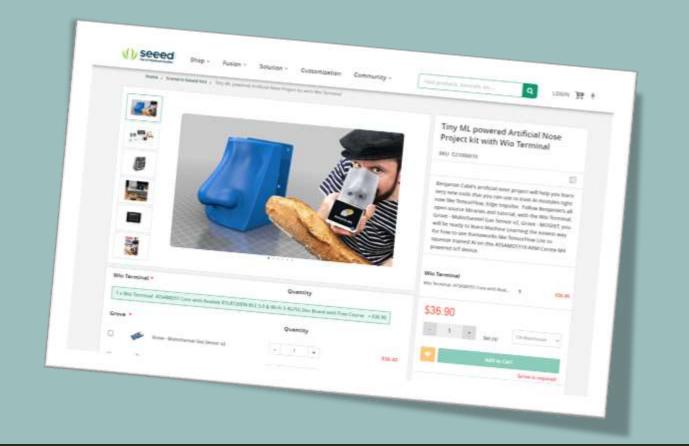
nose: Nose_TBR26P

IN A NUTSHELL

TinyML enables an Internet of Signals

(Tiny) Edge & Cloud each have their strengths









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https://blog.benjamin-cabe.com



