

# Future of Benchmarking

1

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**Which one is the best?**

**Which one is the best for a pie?**

A dense, top-down view of a large pile of electronic components. The components are primarily green printed circuit boards (PCBs) of various shapes and sizes, some with multiple rows of black integrated circuits (chips) or memory modules. There are also several black cooling fans of different sizes, some with silver heat sinks. The components are scattered and overlapping, creating a complex, textured surface. The colors are dominated by the green of the PCBs, the black of the chips and fans, and the silver of the heat sinks. The lighting is bright, highlighting the intricate details of the electronics.

Which one is the best?

Which one is the best with a pi?

# Bechmarking challenges and techniques

# Benchmarking for Tiny ML systems

## Constraint environment

- Sub-mW
- 4 order of magnitude smaller than MLPerf
- Limited memory (SRAM, Flash)

## Wide range of use-cases

- Audio wake words
- Visual wake-up words
- Activity recognition for IMU
- Anomaly detection
- AR Glasses
- Etc...

## Datasets

- Open-source datasets that are large are not TinyML specific
- *Lack of large, TinyML-focused dataset*

## Models

- NN networks are largely used
- Classic ML (Decision Trees, SVMs)
- *No "MobileNet" for TinyML devices*

# TinyMLPerf Benchmark structure

| INPUT TYPE                               | USE CASES   | MODEL TYPES  | DATASETS   |
|--|---|--|--|
| AUDIO                                    | AUDIO WAKE WORDS<br>CONTEXT RECOGNITION<br>CONTROL WORDS<br>KEYWORD DETECTION   | DNN<br>CNN<br>RNN<br>LSTM                            | SPEECH COMMANDS (WARDEN, 2018A)<br>AUDIOSET (GEMMEKE ET AL., 2017)<br>EXTRASENSORY (VAIZMAN ET AL., 2017)  |
| IMAGE                                    | VISUAL WAKE WORDS<br>OBJECT DETECTION<br>IMAGE CLASSIFICATION<br>GESTURE RECOGNITION<br>OBJECT COUNTING<br>TEXT RECOGNITION | DNN<br>CNN<br>SVM<br>DECISION TREES<br>KNN<br>LINEAR | VISUAL WAKE WORDS (CHOWDHERY ET AL., 2019)<br>CIFAR10 (KRIZHEVSKY ET AL., 2009B)<br>MNIST (LECUN & CORTES, 2010)<br>IMAGENET (DENG ET AL., 2009)<br>DVS128 GESTURE (AMIR ET AL., 2017) |
| PHYSIOLOGICAL /<br>BEHAVIORAL<br>METRICS | SEGMENTATION<br>FORECASTING<br>ACTIVITY DETECTION   | DNN<br>DECISION TREE<br>SVM<br>LINEAR                | PHYSIONET (GOLDBERGER ET AL., 2000)<br>HAR (CRAMARIUC, 2019)<br>DSA (ALTUN ET AL., 2010)<br>OPPORTUNITY (ROGGEN ET AL., 2010)<br>UCI EMG (LOBOV ET AL., 2018)                          |
| INDUSTRY<br>TELEMETRY                    | SENSING (LIGHT, TEMP, ETC)<br>ANOMALY DETECTION<br>MOTOR CONTROL<br>PREDICTIVE MAINTENANCE                                  | DNN<br>DECISION TREE<br>SVM<br>LINEAR<br>NAIVE BAYES | UCI AIR QUALITY (DE VITO ET AL., 2008)<br>UCI GAS (VERGARA ET AL., 2012)<br>NASA'S PCoE (SAXENA & GOEBEL, 2008)  |

Banbury, Colby R., et al. "Benchmarking TinyML systems: Challenges and direction." *arXiv preprint arXiv:2003.04821* (2020).

# Challenges of benchmarking the devices

## Consumption variation

- Across devices
- Relative to accuracy

## Power management measurement

- Preprocessing
- Datapath
- Firmware
- Peripherals

## Limited memory:

- Benchmark might be too big to fit
- Overhead impacts power consumption
- Quantization support

## Hardware heterogeneity

- Event-based
- Memory compute
- MCU with different performance, power, capabilities
- No normalisation procedure defined yet.

## Software heterogeneity

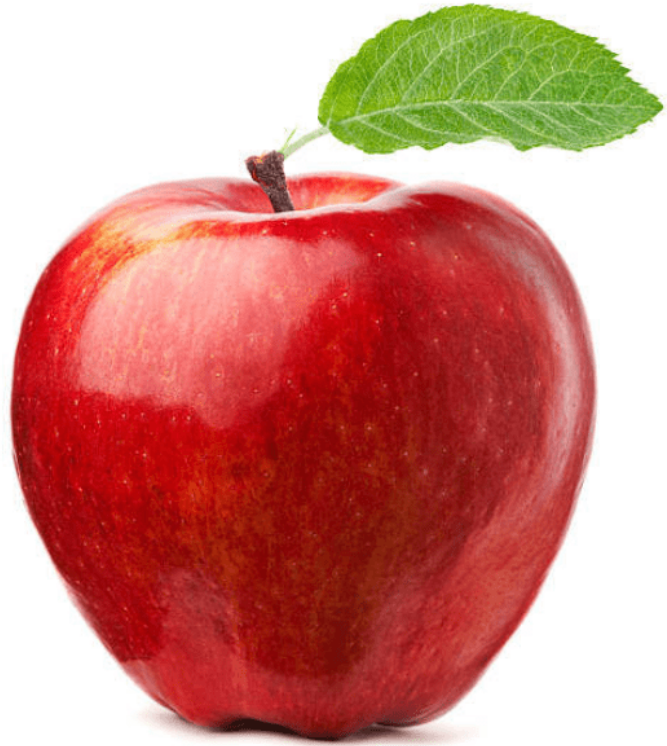
- Hand-coding
- Code generation
- ML interpreter (TensorflowLite), uPython, PyTorchMobile, ...

# Challenges

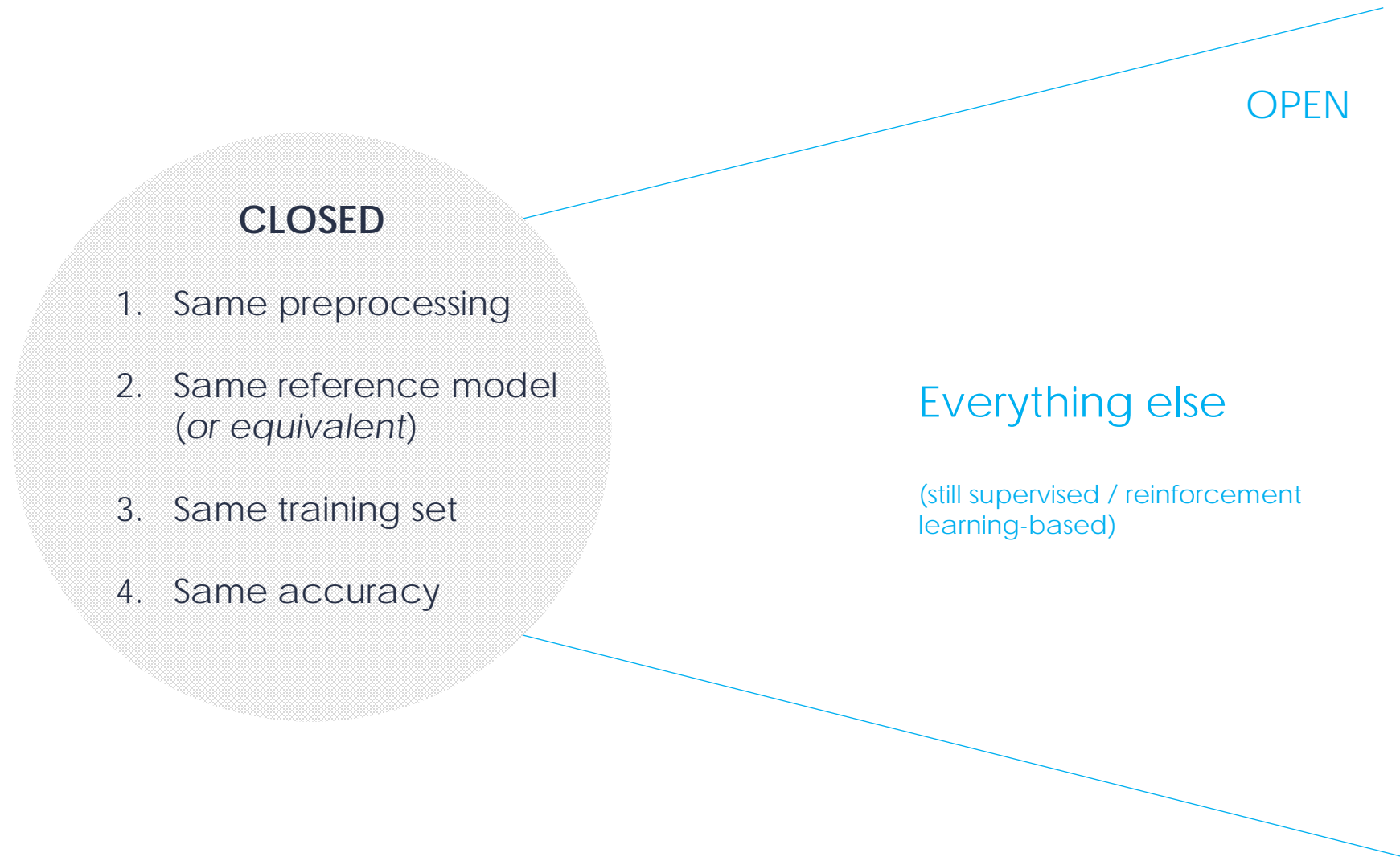
**Benchmarks should balance between:**

1. Portability
2. Comparability
3. Representativeness
4. Many options for model deployment



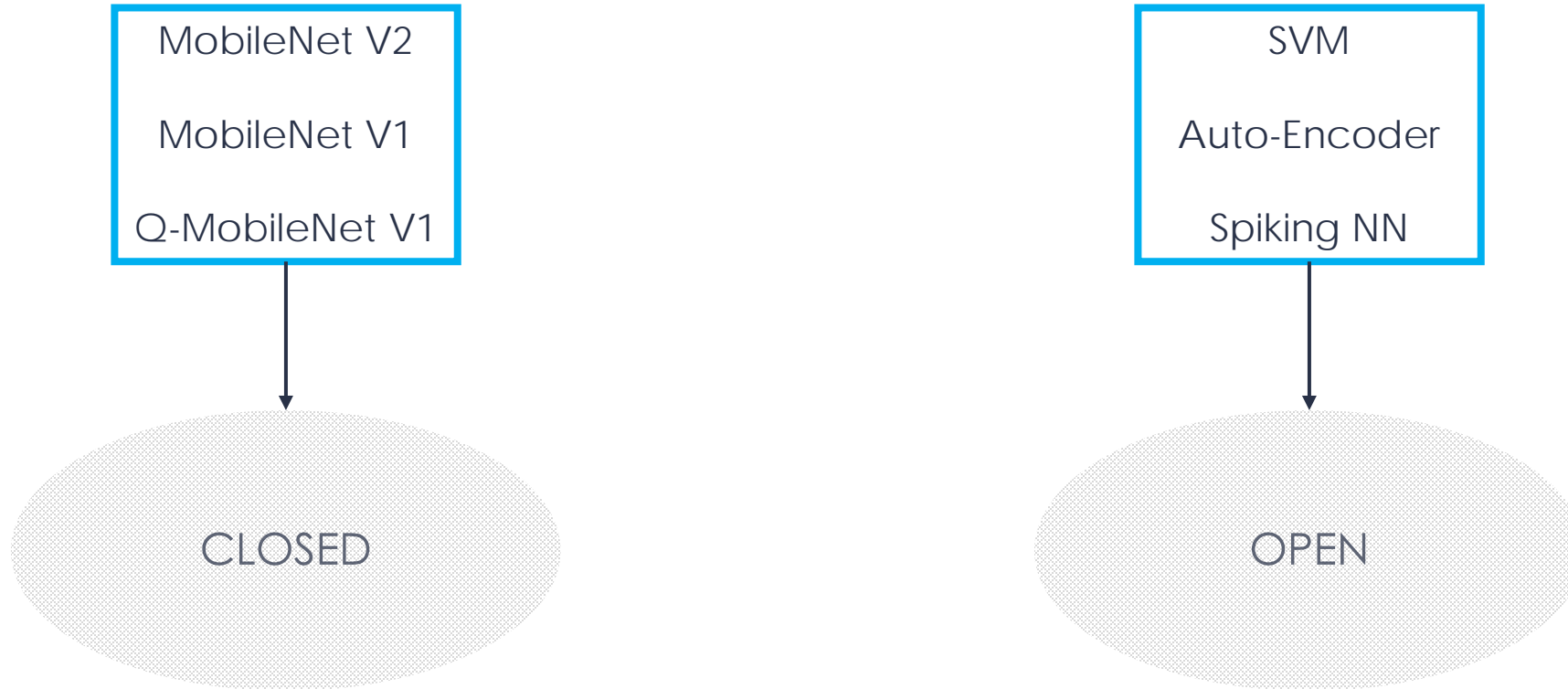


# Open-Closed divisions (from MLPerf)



# Open-closed Division : Example

**TASK** : Visual Wake-up Words / ref: [MobileNet](#)



# Overview of other potential approaches

## Unanswered questions from benchmarks

1. *Given a hardware, what is the best model I can get?*
2. *Given a model, what is the best ASIC design I can get?*
3. *Given a model, what will be its performance on hardware platforms?*

# 1

*Given a hardware, what is the best model I can get ?*

*Brute force? NO!*

*Reinforcement learning optimizing Neural  
Network Architecture*

# Network architecture search for ultra-low power design

Search space

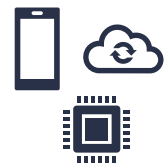
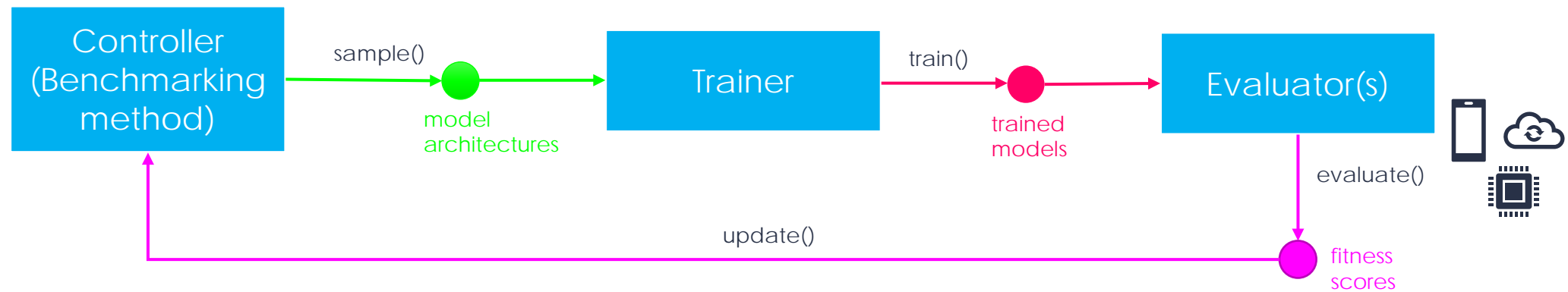
[conv3x3, conv7x7, dense, sepconv,...]

Training constraints

ex: L1, loss, etc...

Deployment

ex: simulation / emulation / real-world deployment



# 2

*Given a model, what is the best design I can get ?*

*Brute force? NO!*

*Reinforcement learning optimizing ASIC  
design for neural network*



# Hyper-parameters search for ASIC design

Search space

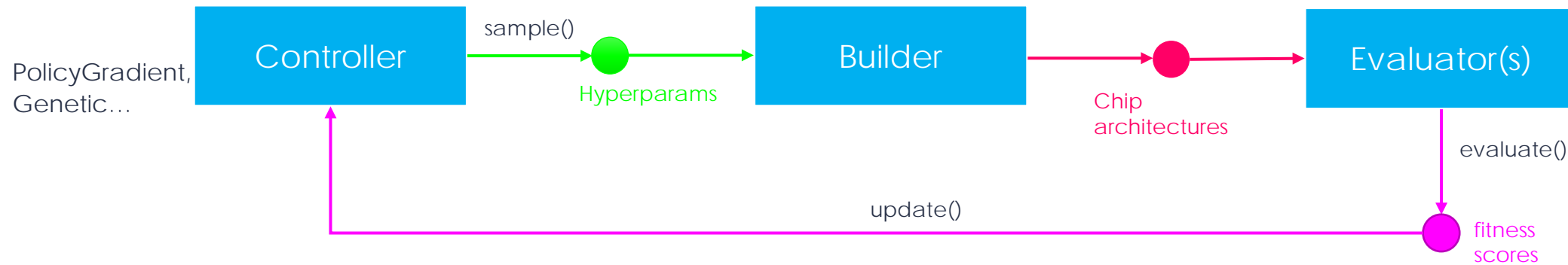
[Memory, CMOS technology...]

Constraints

E.g. Size, fill-factor...

Deployment and fitness score

E.g. penalty for slow processing, etc..



# Challenges

- How to choose the NAS algorithm?
- How to make sure this NAS does not diverge for certain hardware?
- Computational time of NAS is quite important
- Need to avoid “cold-start” -> Database of already tested models and accelerators
- Identify good emulation environments

# 3

*Given a model, what will be its performance on hardware platforms?*

*Run physical test -> takes time!*

*What if the model does not fit,  
but only because of memory?*

*Projecting the performance of  
a model by regression*

# Theoretical Baselines for ML Benchmarking

Peak performance  $PP$  [FLOPs/s]

**4 GFLOPs/s**

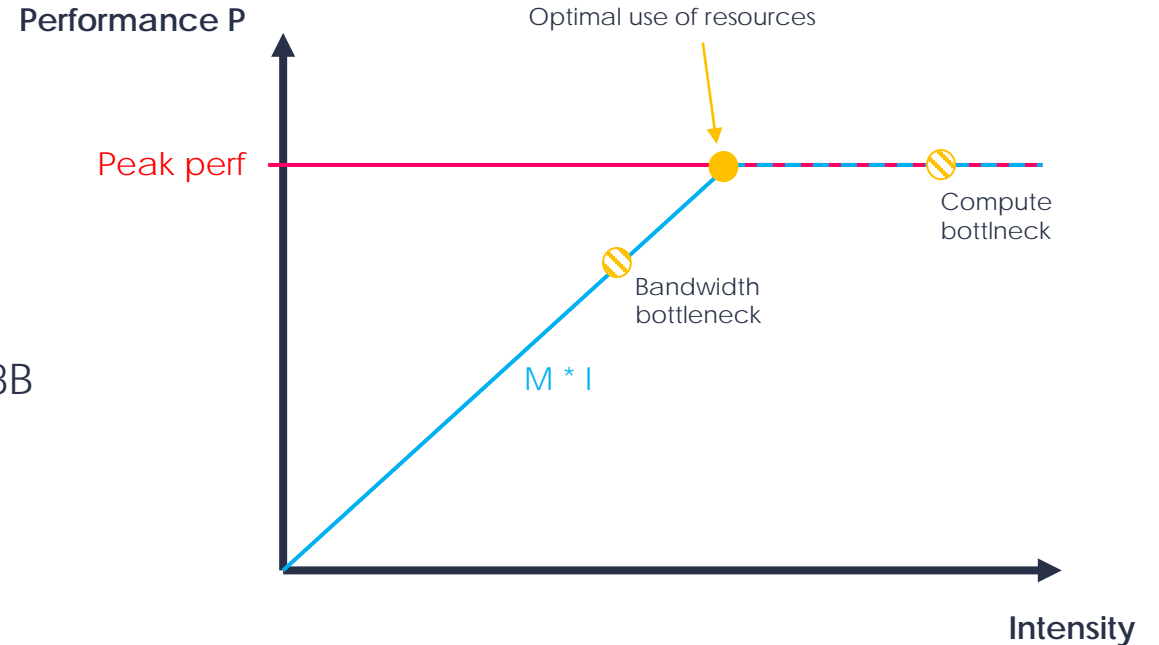
Memory bandwidth  $M$  [Byte/s]

**1 GB/s**

Intensity  $I$  [FLOPs/Byte read]

40 FLOPs / 8B  
= **5 FLOPs/B**

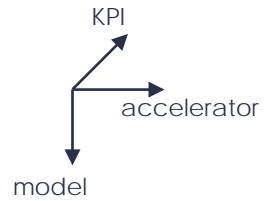
$$P = \min(PP, M * I)$$



"Roofline: An insightful visual performance model for multicore architectures", S. Williams et al., 2009

"Evaluating Theoretical Baselines for ML Benchmarking Across Different Accelerators", M. Blott et al., 2021

# Projection-based benchmarks



|        | Accelerator1 | Accelerator2 | Accelerator3 | ... | AcceleratorN |
|--------|--------------|--------------|--------------|-----|--------------|
| Model1 | 0.88         | 0.99         | 0.90         | ... | 0.99         |
| Model2 | 0.84         | 0.84         | 0.85         | ... | 0.81         |
| Model3 | 0.95         | 0.97         | 0.91         | ... | 0.89         |
| Model4 | 0.81         | 0.94         | 0.85         | ... | 0.96         |
| Model5 | 0.92         | 0.91         | 0.88         | ... | 0.98         |



# Challenges for Projection-based benchmark

- Cold start problem
- Recommendation-based system?
- How to find good embeddings to allow interpolation?
  - Embeddings for models?
  - Embeddings for accelerators?
  - What about the performance of a model, on a hardware, on a certain dataset?
- How to deal with constraints? Memory, consumption@FPS, etc...?

# Summary


Remaining challenges:

- Still no “apple-vs-orange” comparison
- Three questions not yet answered
  - What is the best hardware for my model?
  - What is the best model for my hardware?
  - What would be the performance of this model on this hardware?
- Absence of clear “comparison” website for TinyML benchmarks

# THANK YOU



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