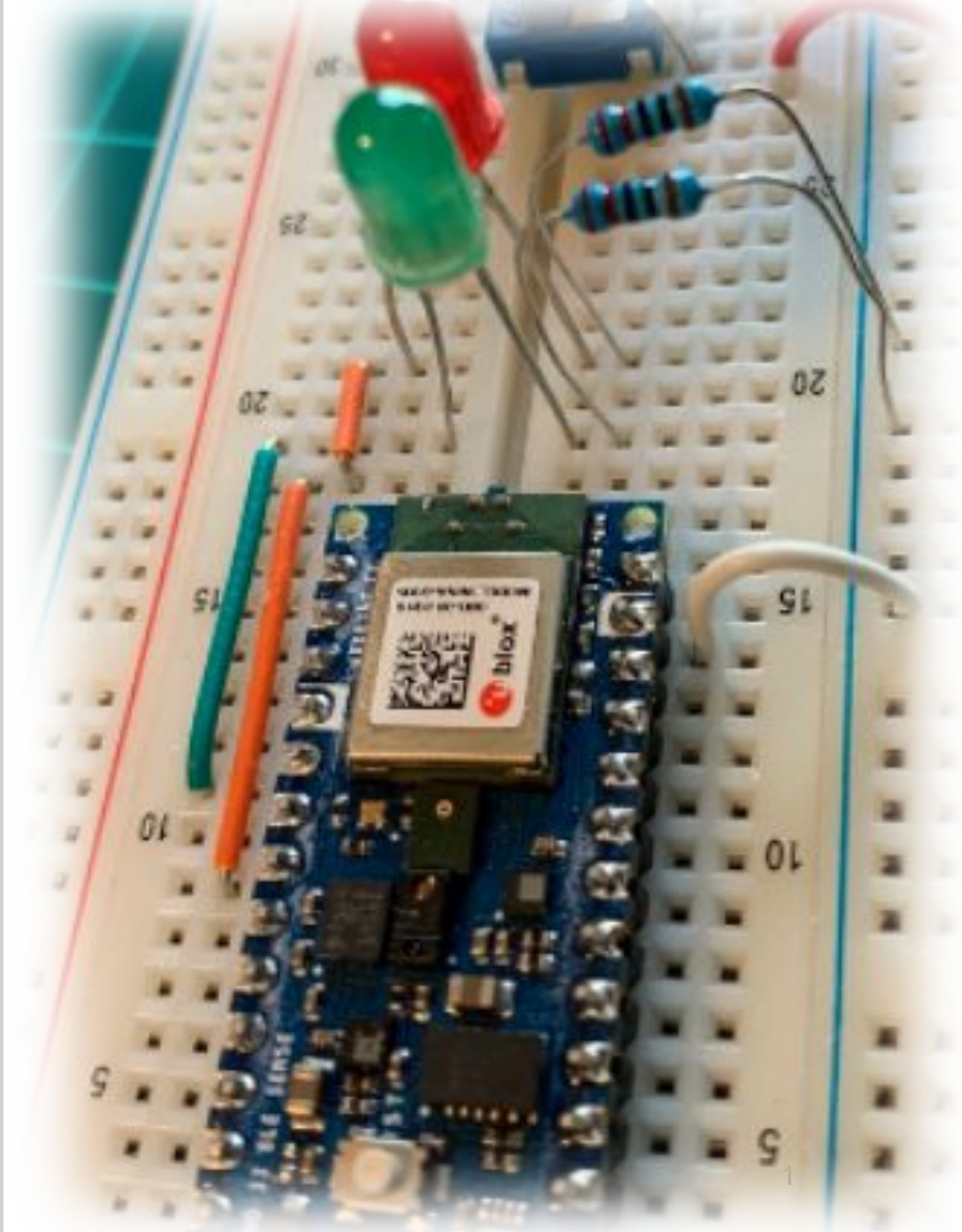
IESTI01 – TinyML

Embedded Machine Learning

2. Introduction to TinyML

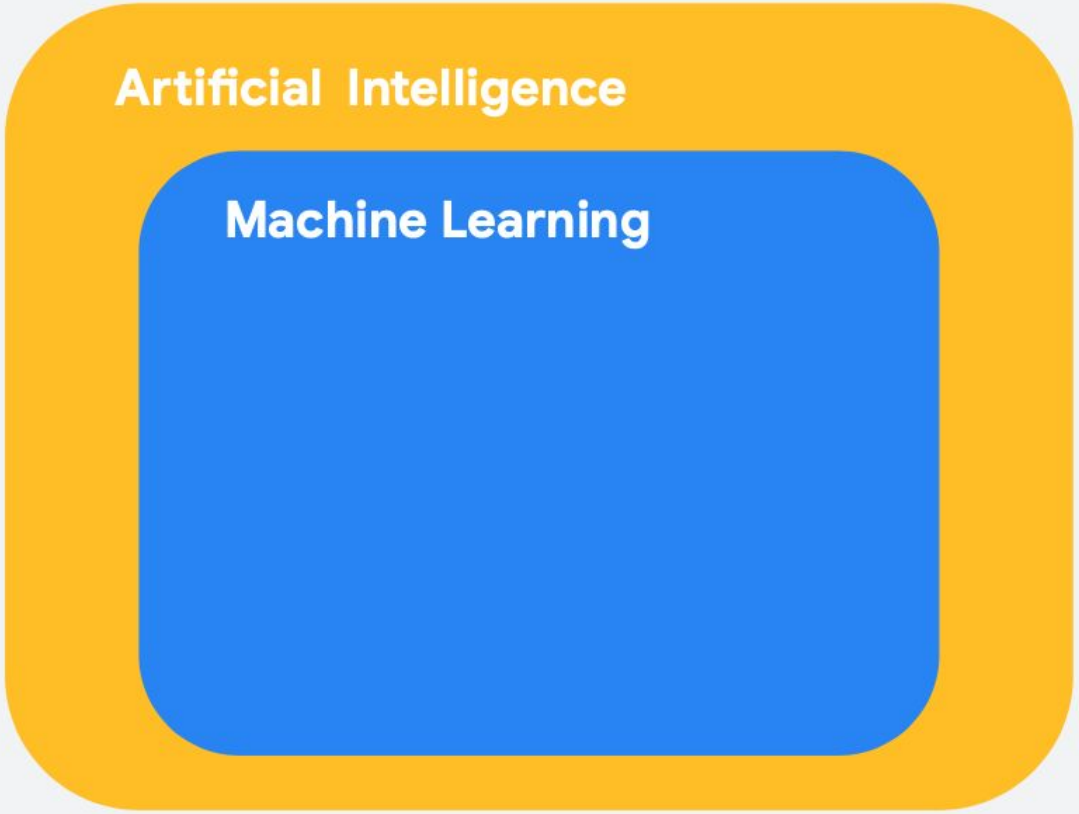


Prof. Marcelo Rovai
UNIFEI

What is Machine Learning?

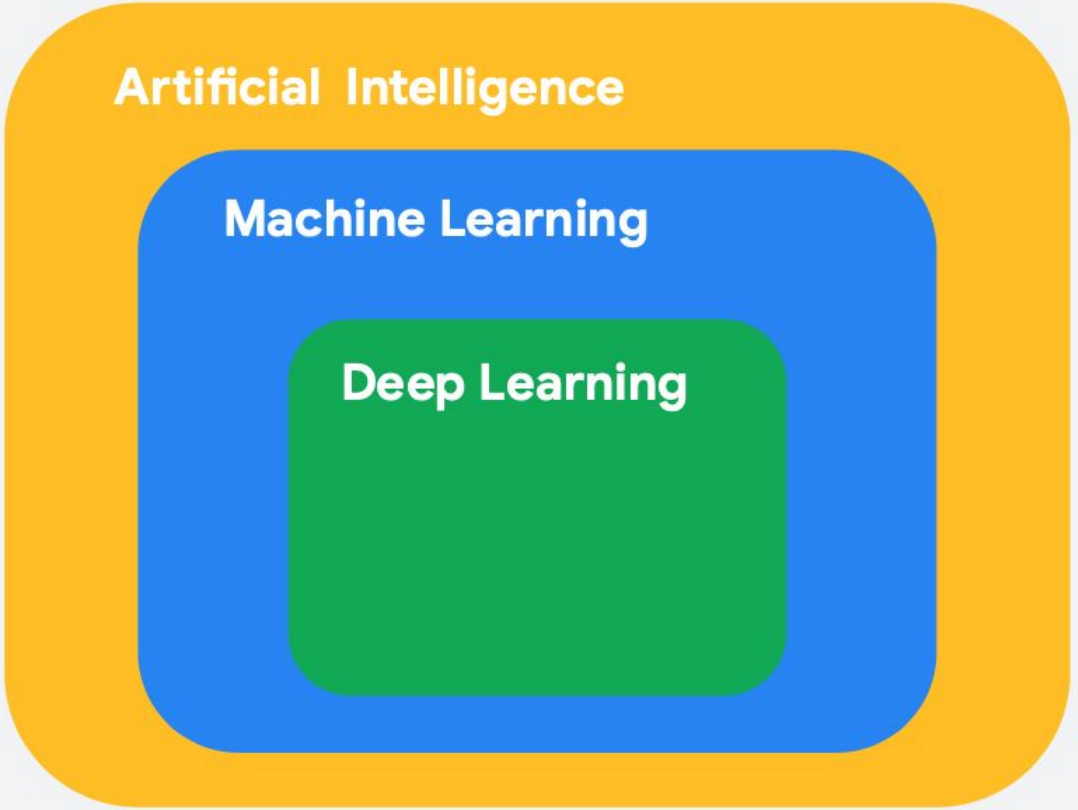
What is Machine Learning?

1. **Machine Learning** is a subfield of **Artificial Intelligence** focused on developing algorithms that learn to **solve problems by analyzing data for patterns**



What is (Deep) Machine Learning?

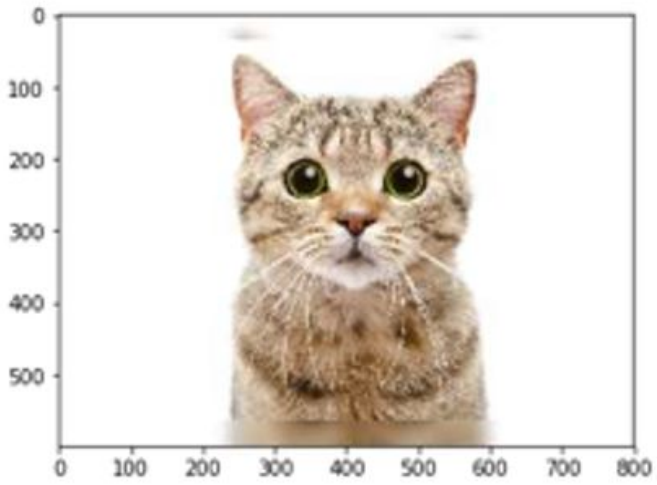
1. Machine Learning is a subfield of Artificial Intelligence focused on developing algorithms that learn to solve problems by analyzing data for patterns
2. **Deep Learning** is a type of Machine Learning that leverages **Neural Networks** and **Big Data**



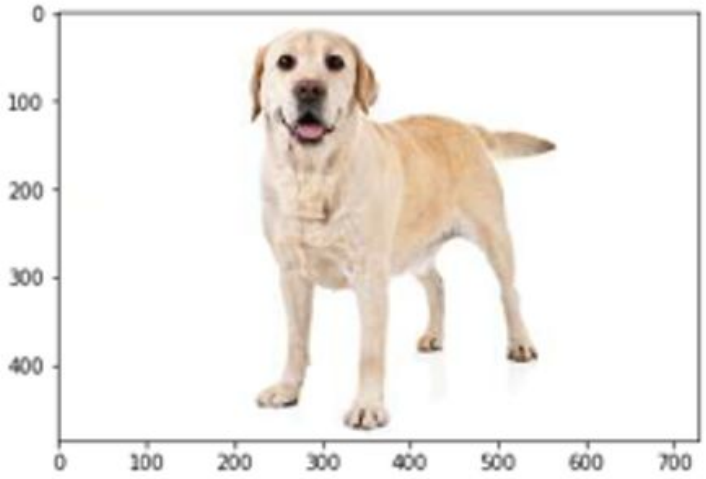
Applications of Machine Learning

Image Classification

```
[PREDICTION]        [Prob]

Egyptian cat        : 64%
tabby               : 14%
bucket              : 3%
```

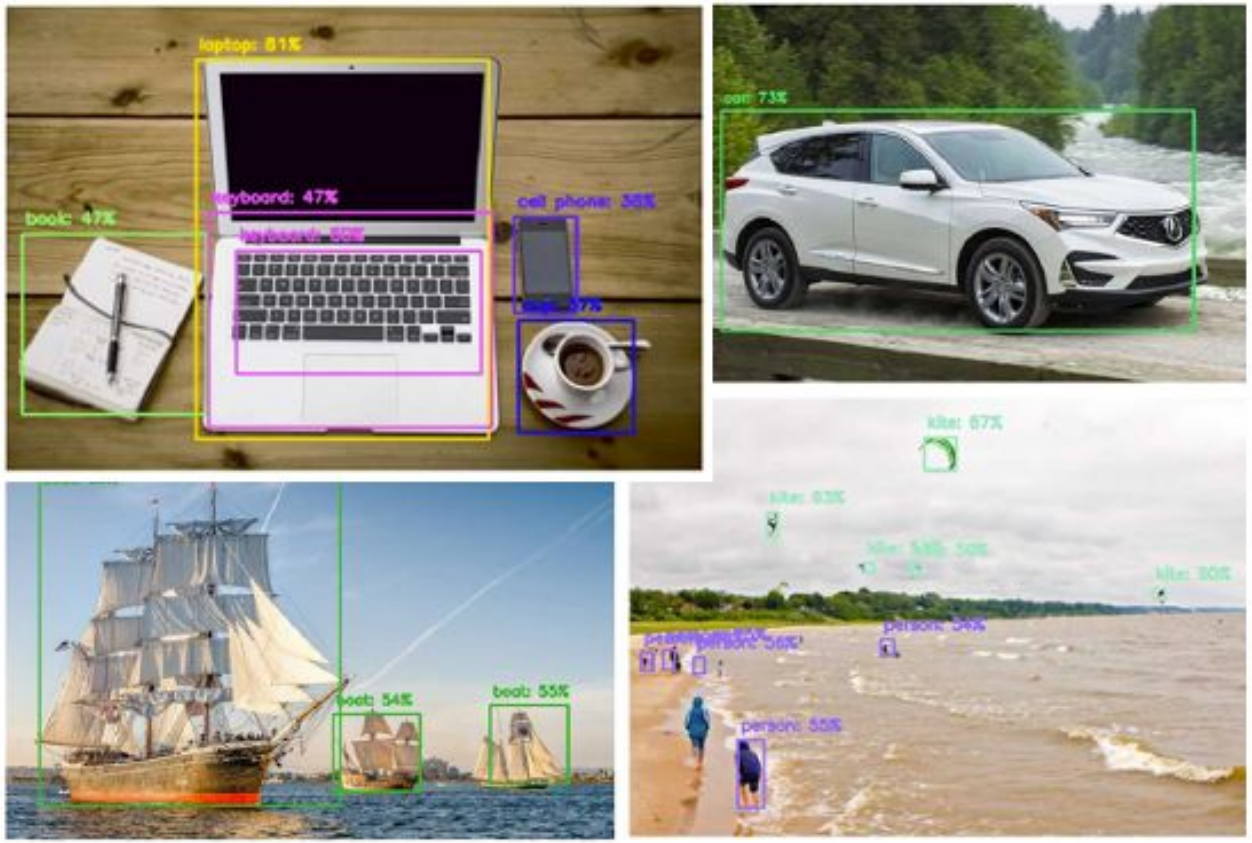


```
[PREDICTION]        [Prob]

Labrador retriever  : 83%
golden retriever    : 13%
bloodhound          : 0%
```

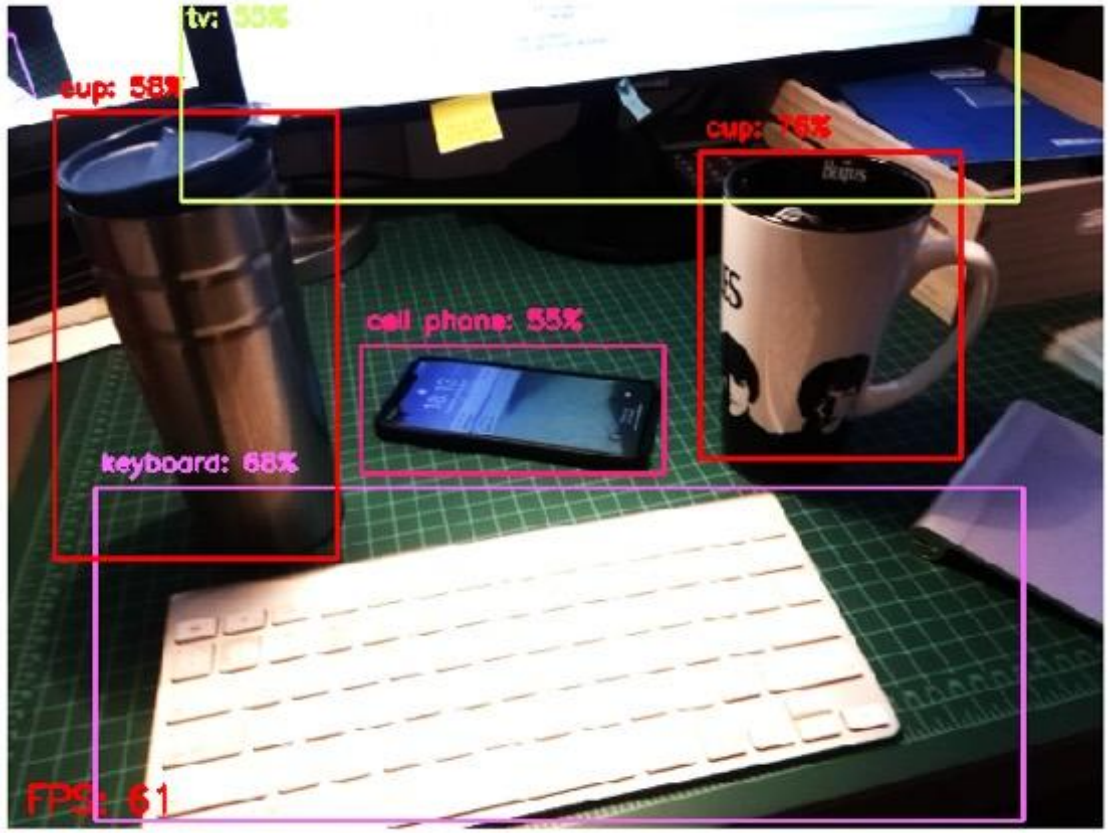


```
[PREDICTION]        [Prob]

German shepherd     : 60%
dhole               : 16%
malinois            : 7%
```

Object Detection

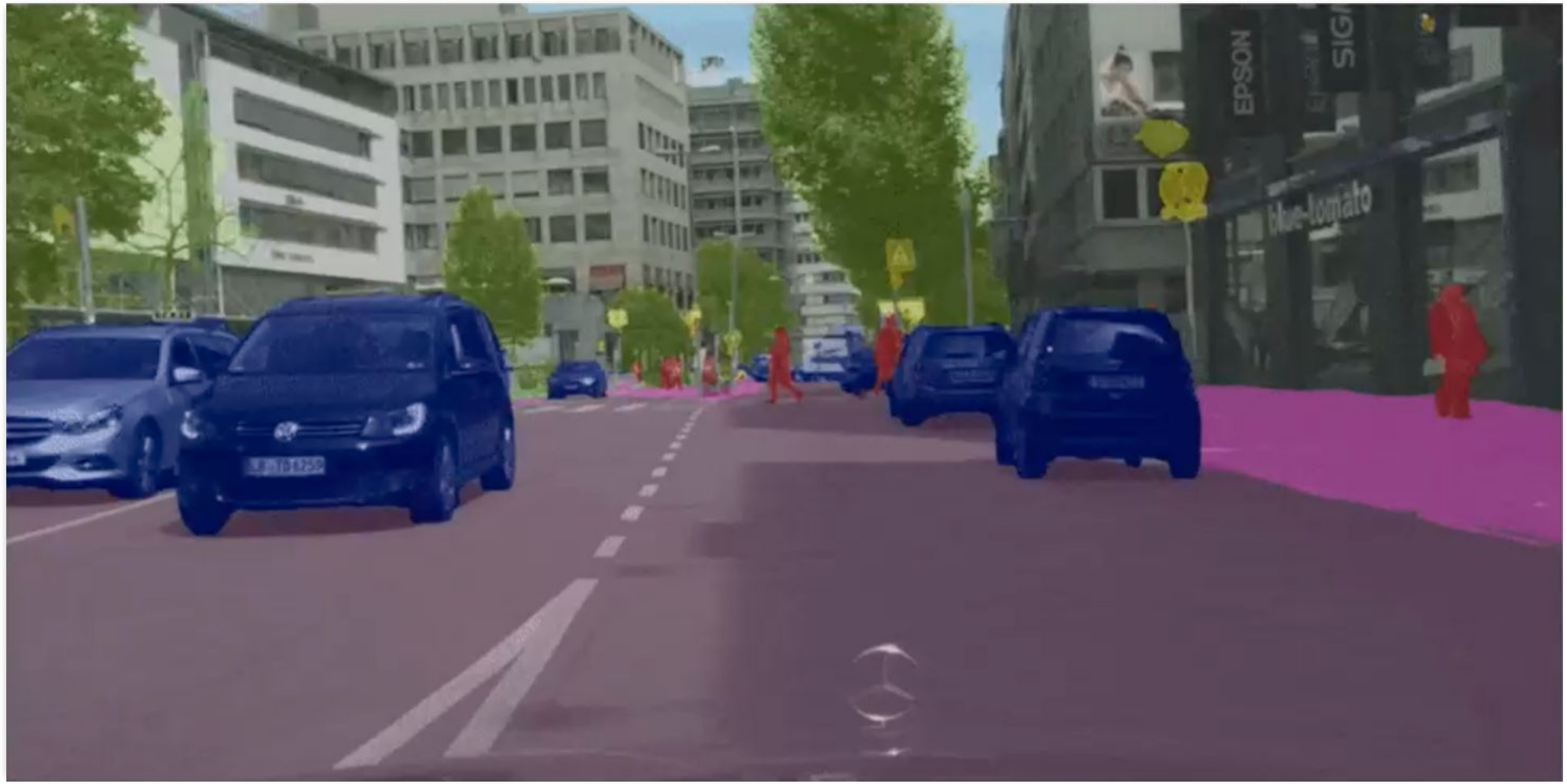


Photos



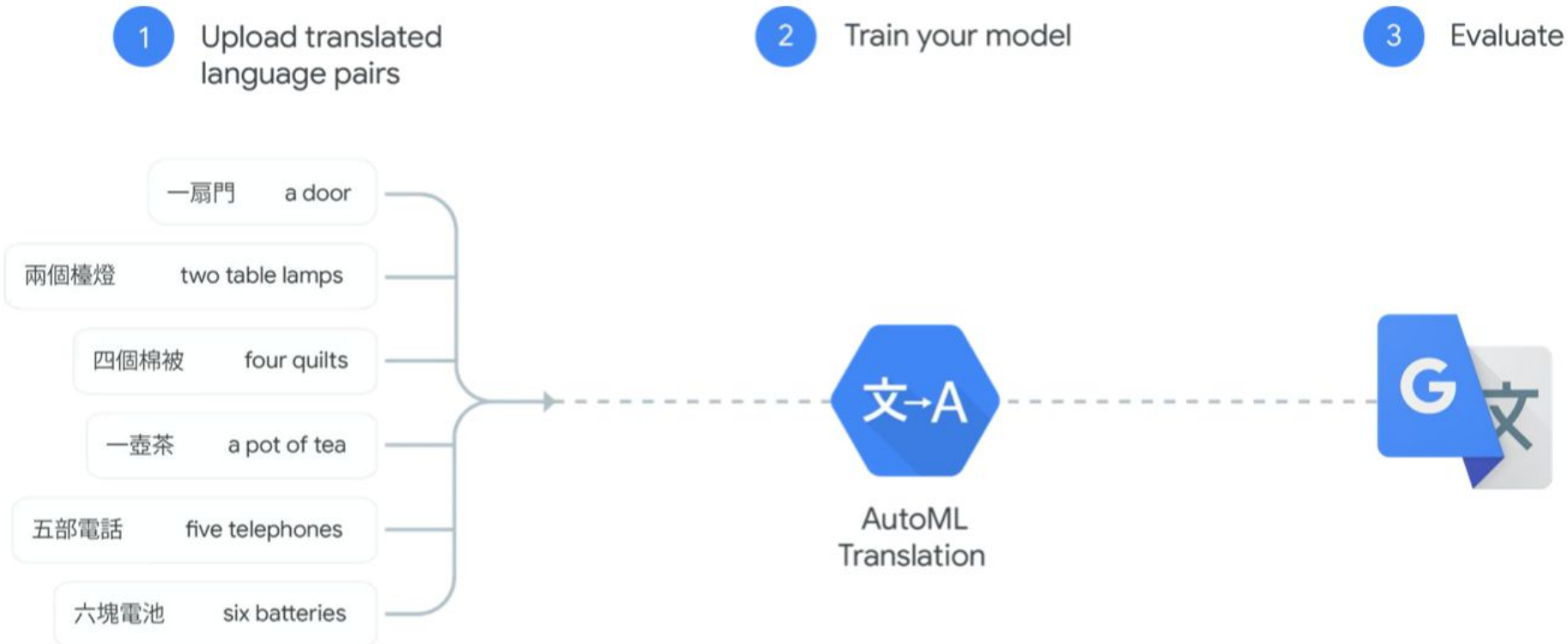
Live Video

Segmentation

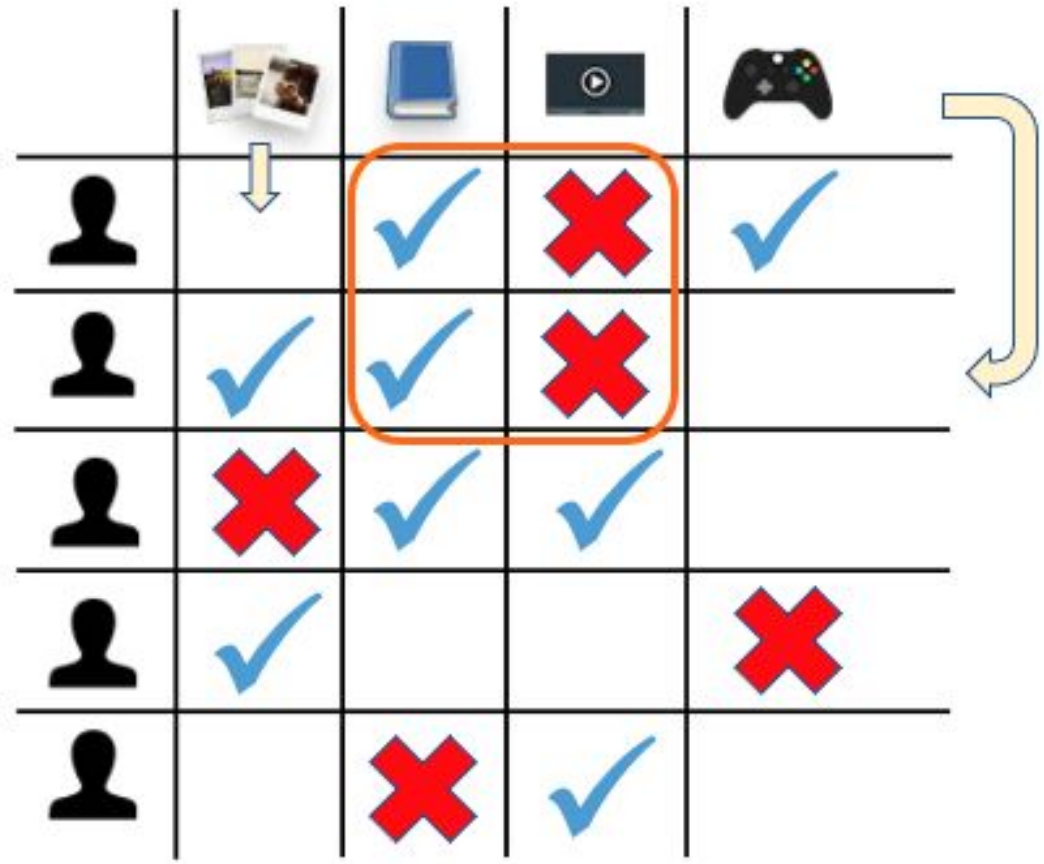


Pose Estimation

Machine Translation



Recommendations



General AI does not exist (yet)

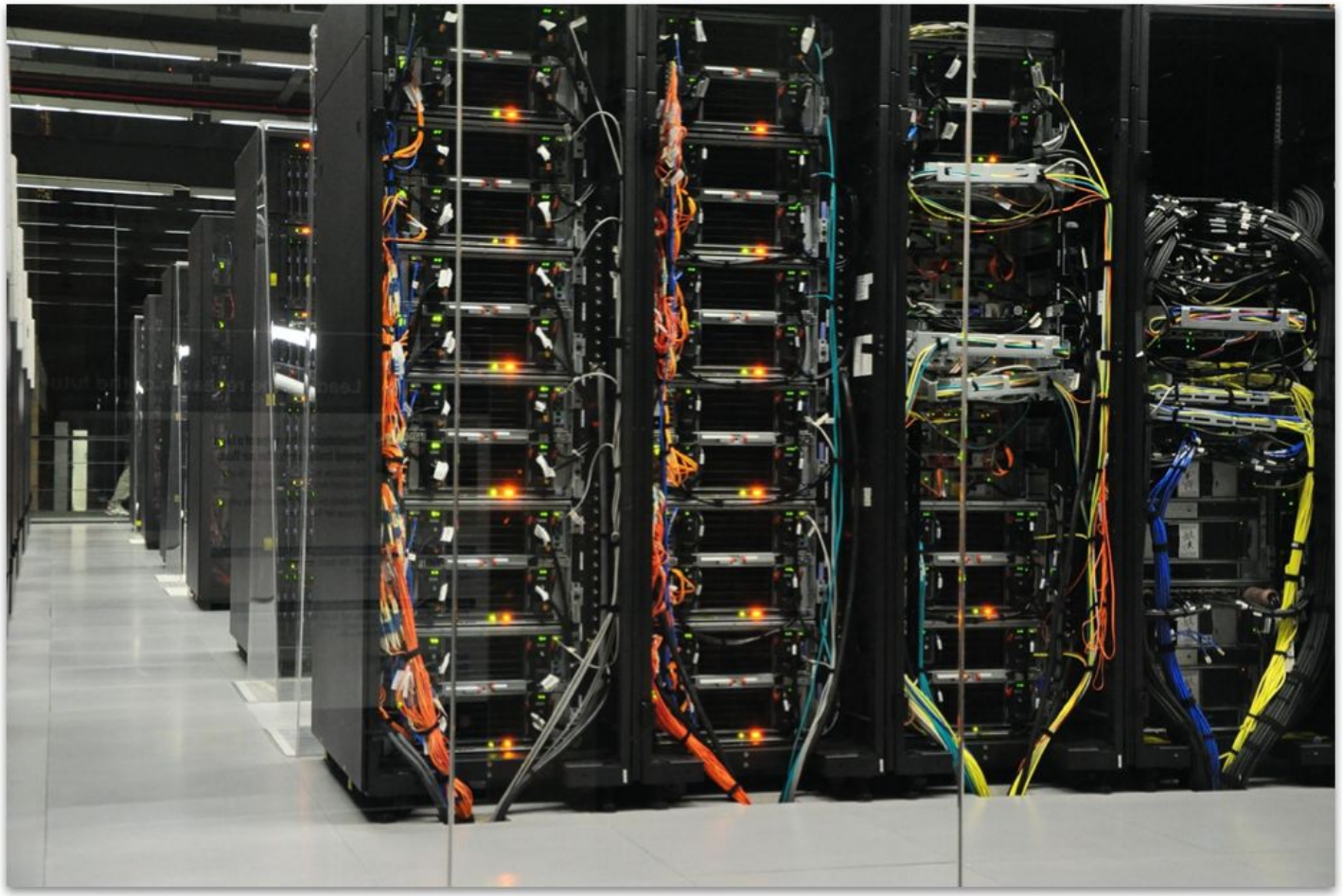
Dedicated ML Application examples

- Image Classification
- Object Detection
- Pose Estimation
- Voice Recognition
- Gesture Recognition
- Anomaly Detection
- Natural Language Processing (NLP)

Dedicated TinyML Application Examples

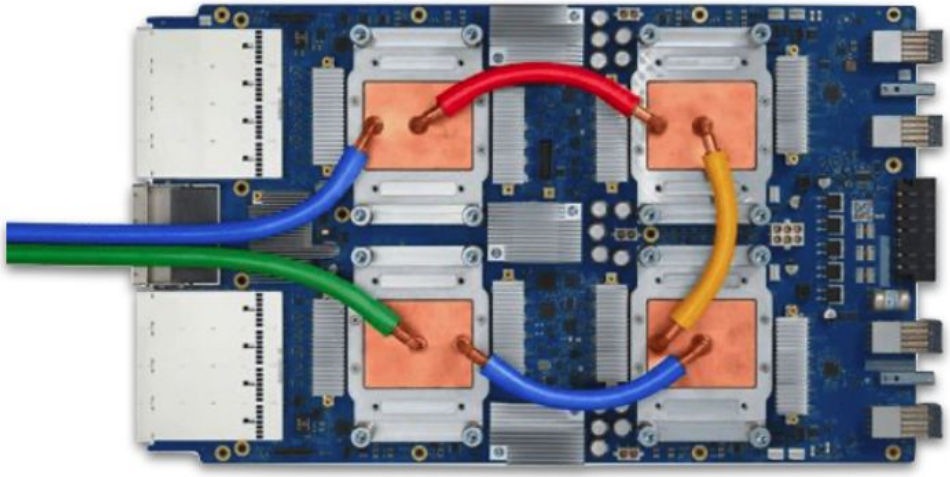
- Image Classification (Camera)
- Object Detection (‖)
  - Pose Estimation
- Voice Recognition (Microphone)
- Gesture Recognition (Accelerometer)
- Anomaly Detection (‖)
  - Natural Language Processing (NLP)

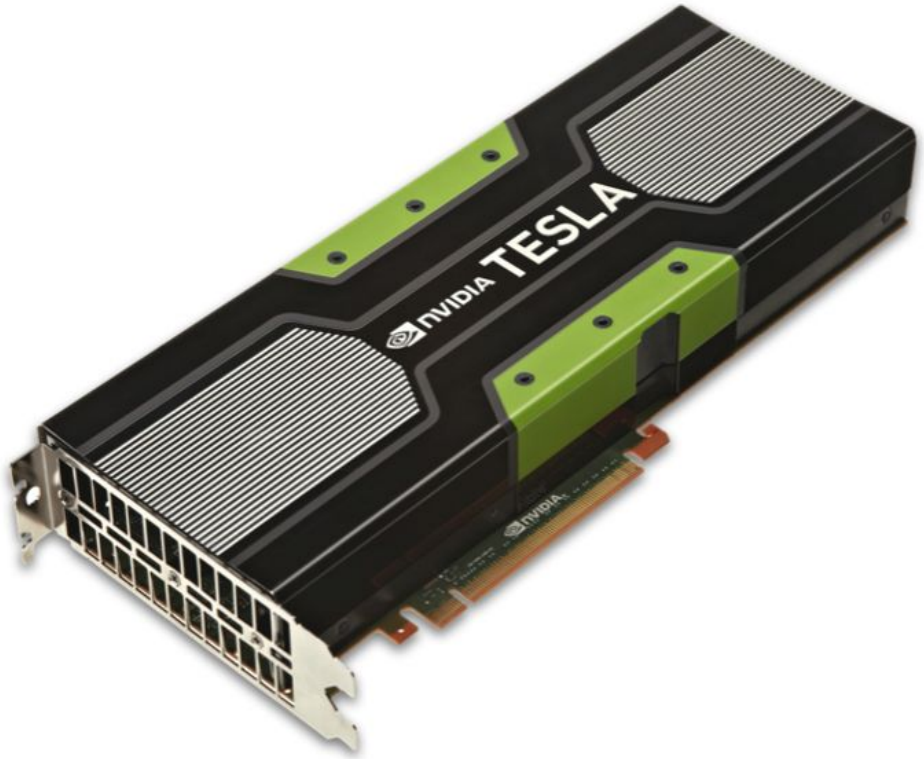
Datacenter



All the capabilities on previous examples, required a **remarkable amount of horsepower and computing capabilities**, so what companies are doing, they are taking all these computers and jam packing them into **data centers**, that are all just being dedicated in order to provide **machine learning** capabilities today.

TPUs/GPUs

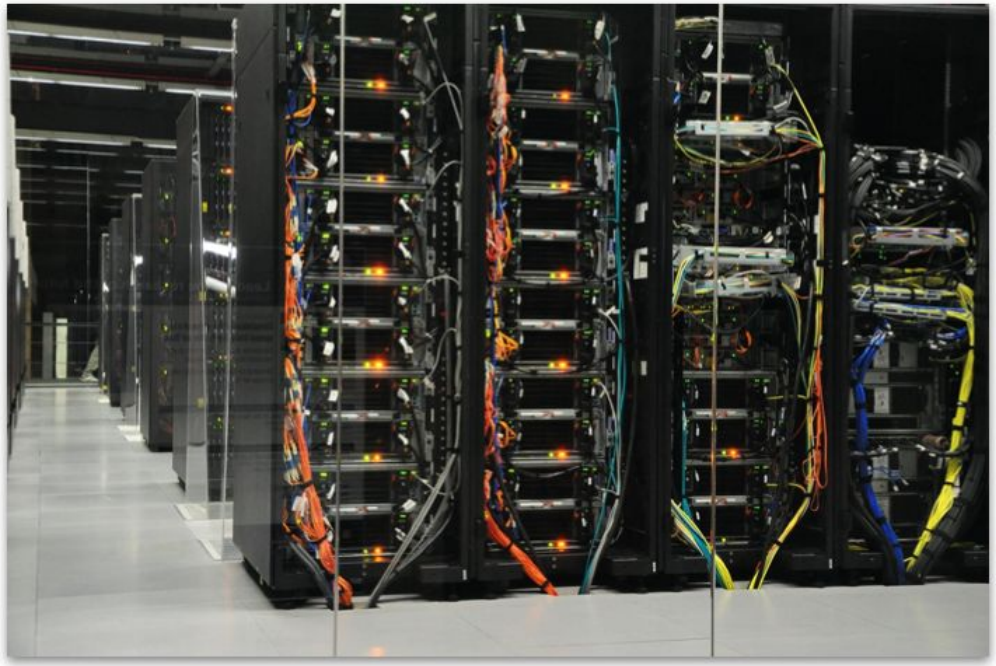




In order to be able to provide ML capability, companies like **Google are building TPUs** (Tensor Processing Units) and **NVIDIA GPUs** (Graphics Processing Units). Both of these computing systems are capable of **running machine learning extremely fast**.

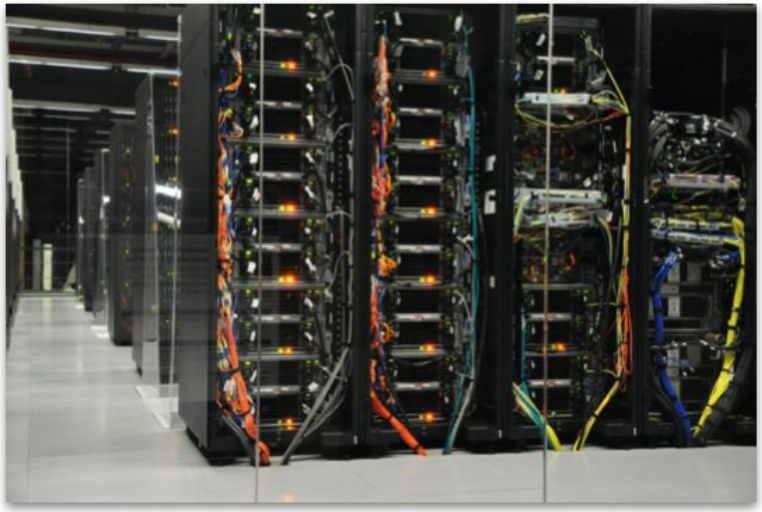
Bigger Is Not Always Better.

Why?



Because we can not have a DataCenter to do ML inside our phone, for example!

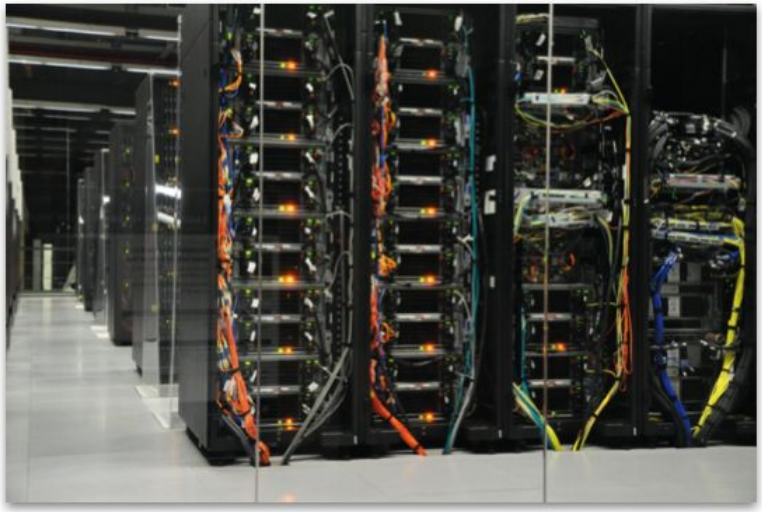
Why?



High power

Low power

Why?



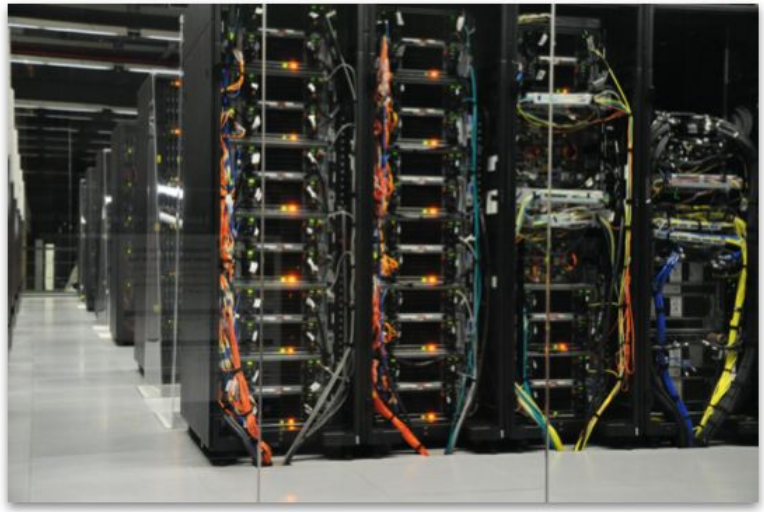
High power

High bandwidth

Low power

Low bandwidth

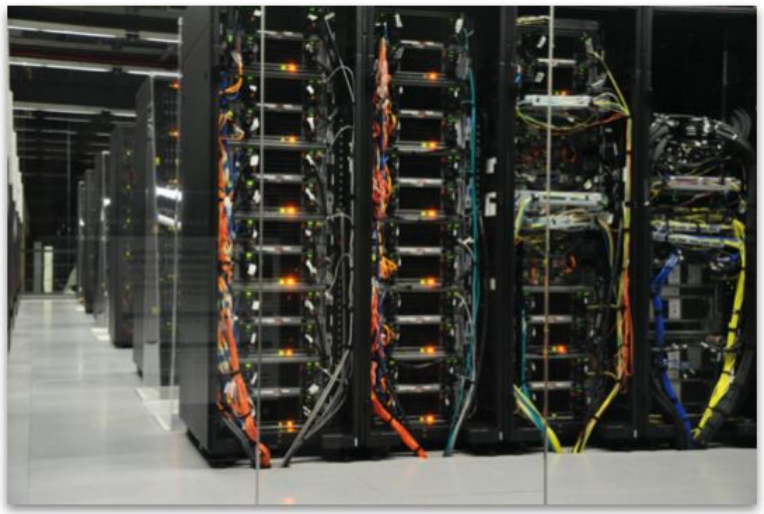
Why?



High power
High bandwidth
High latency

Low power
Low bandwidth
Low latency


Dinner with Layla in 30 min
ALWAYS
ON?



Google Assistant

Endpoint Devices

Google Assistant

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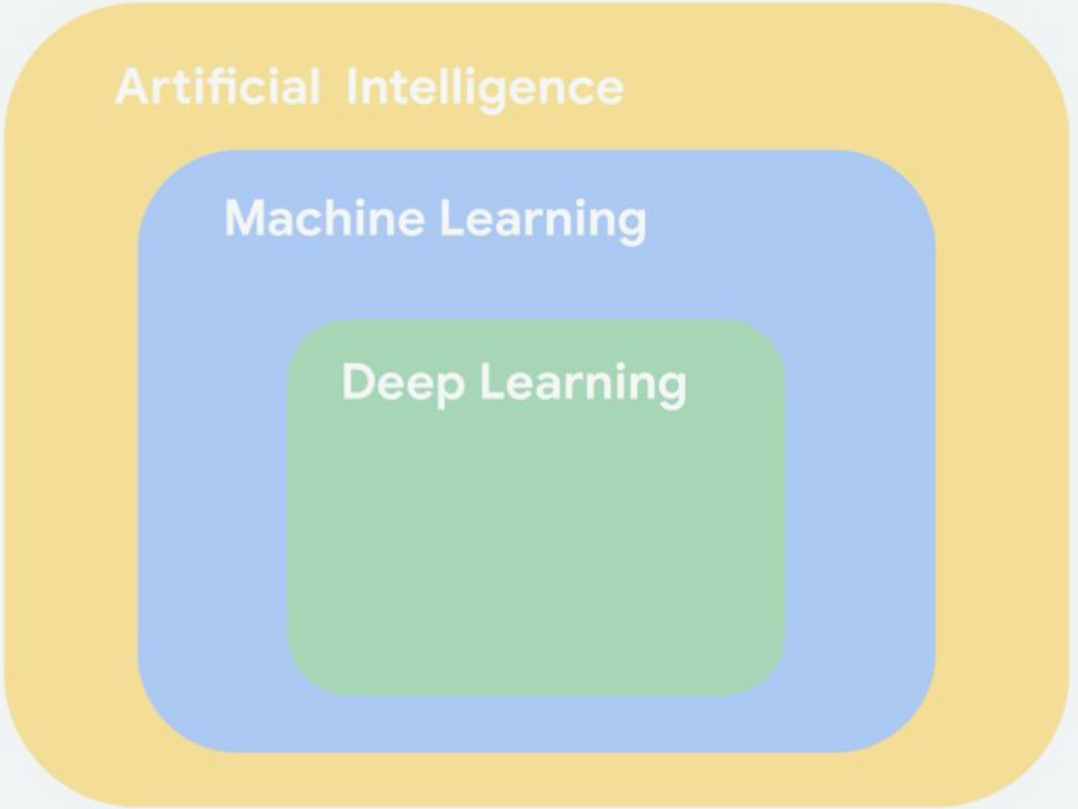
Big Data ←



No Good Data Left Behind

5 Quintillion

bytes of data produced every day by IoT

<1%

of unstructured data is analyzed or used at all

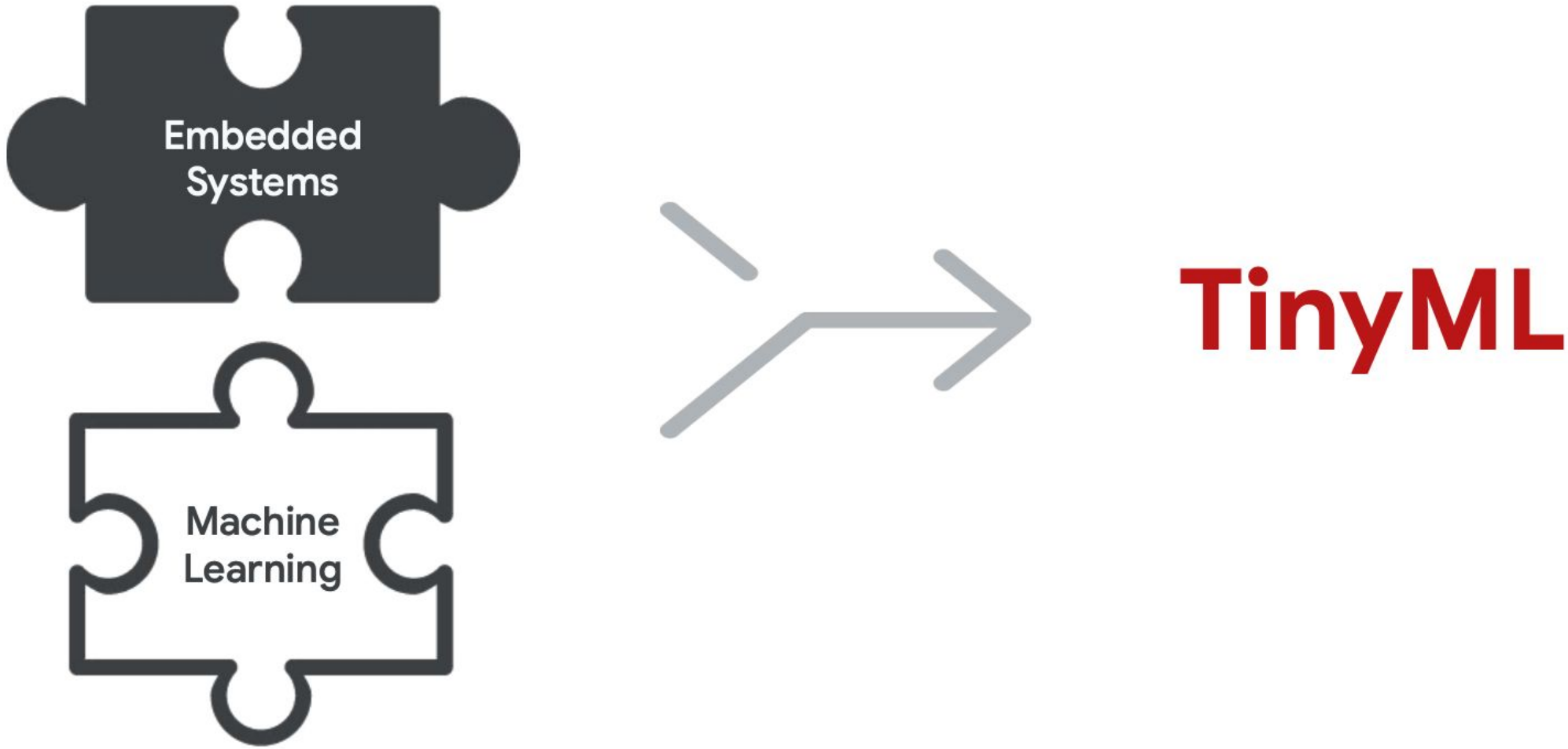
Source: Harvard Business Review, What's Your Data Strategy?, April 18, 2017
Cisco, Internet of Things (IoT) Data Continues to Explode Exponentially. Who Is Using That Data and How?, Feb 5, 2018

Summary

- ML has several diverse applications in the real-world
- ML is increasingly moving from the cloud to endpoint devices
- Endpoint devices are everywhere around us

How do we enable TinyML?

What Makes TinyML?

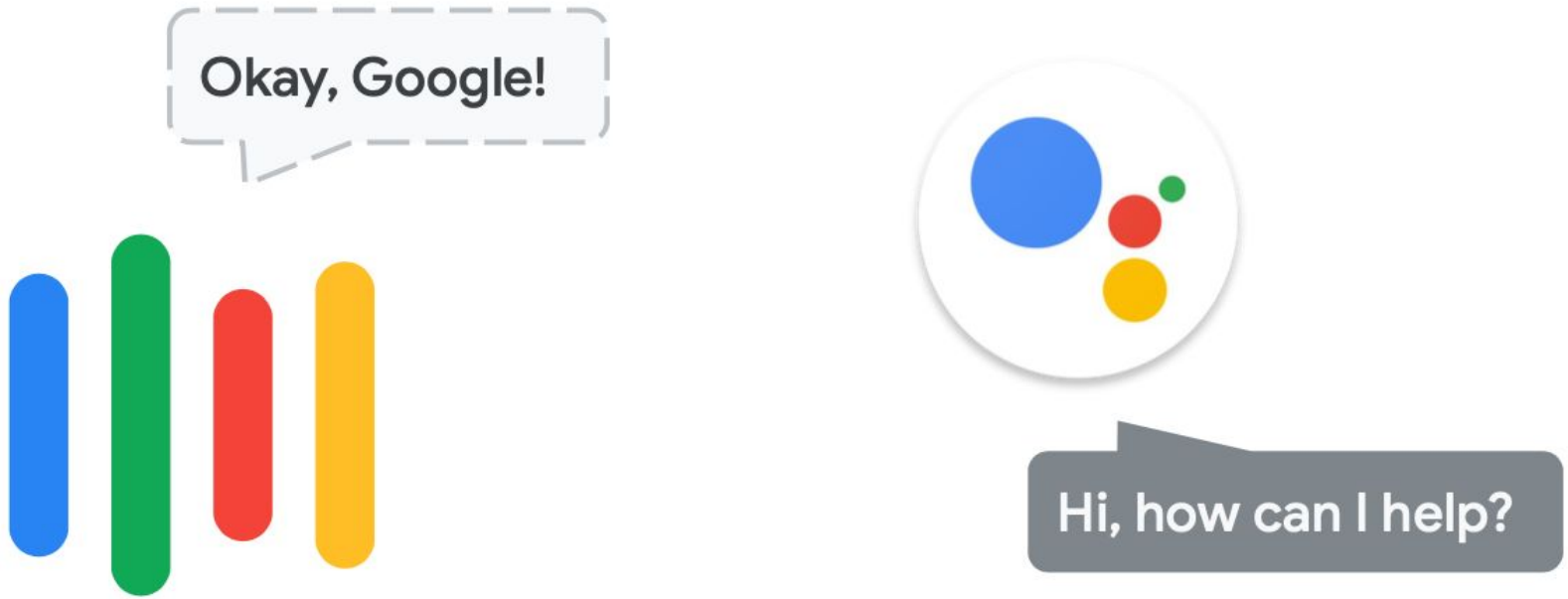


Let’s Take an Example

+

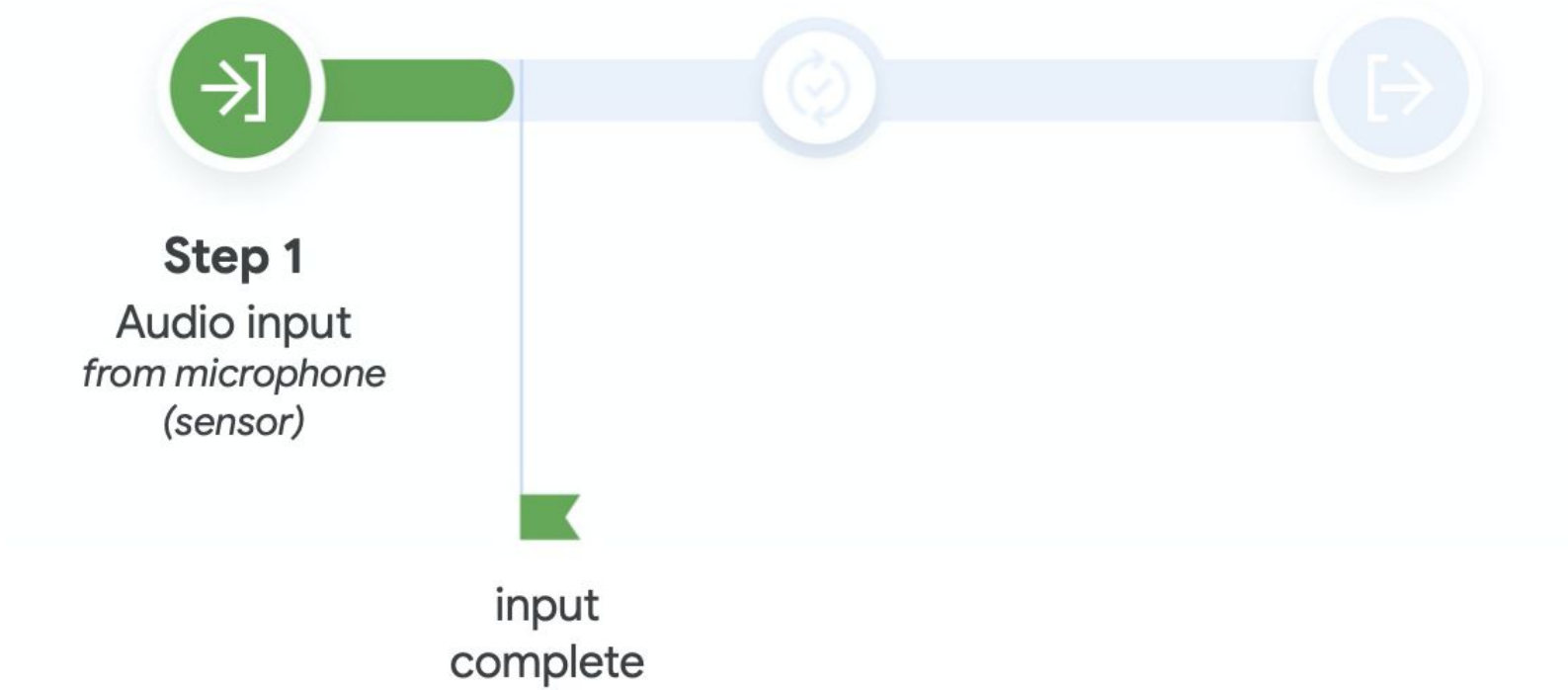
Google Assistant

Let’s Take an Example

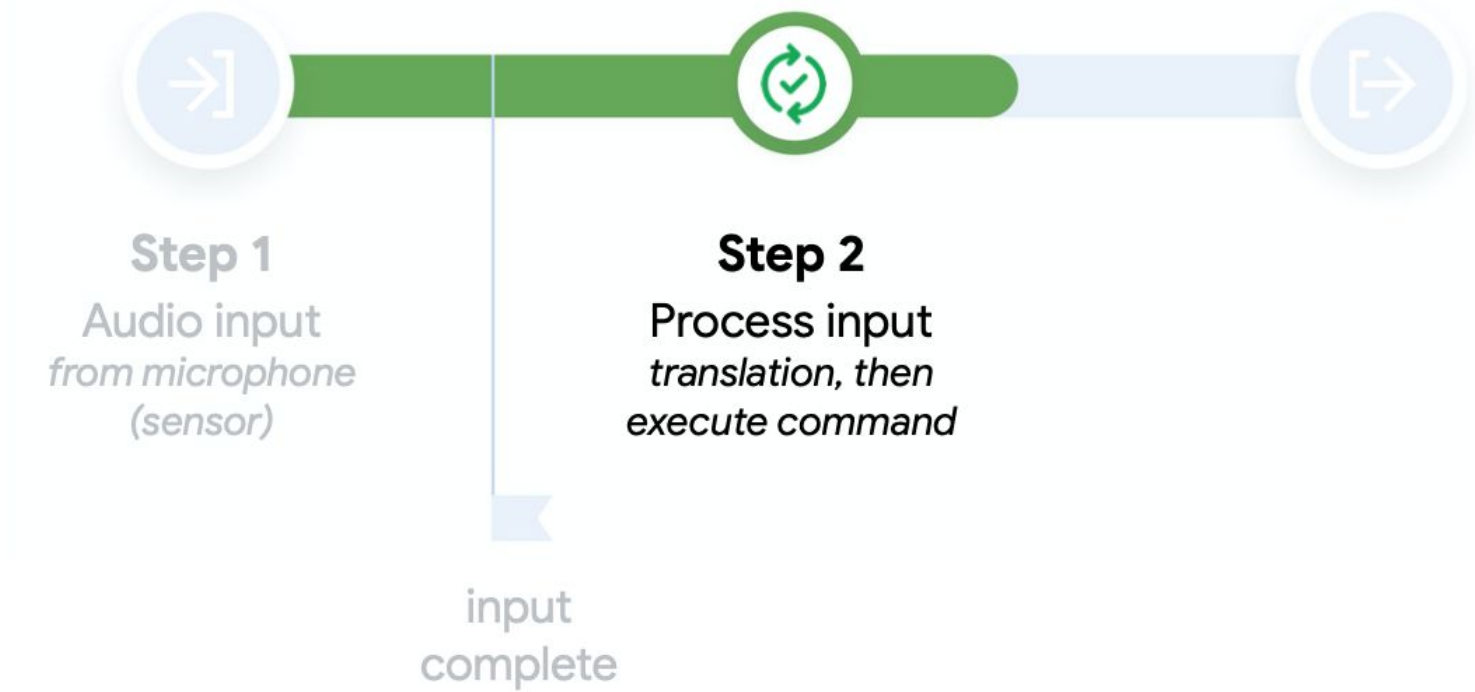


The Three Basic Steps

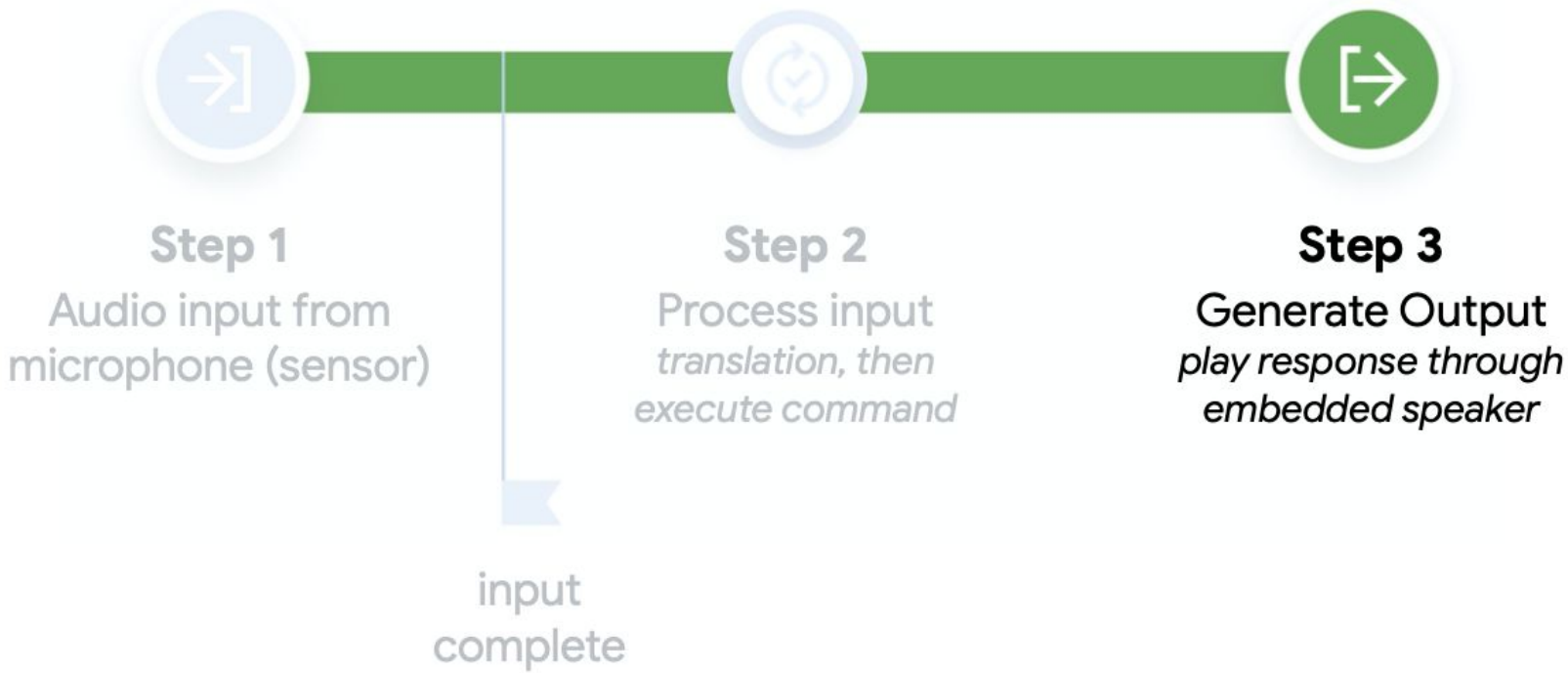
The Three Basic Steps



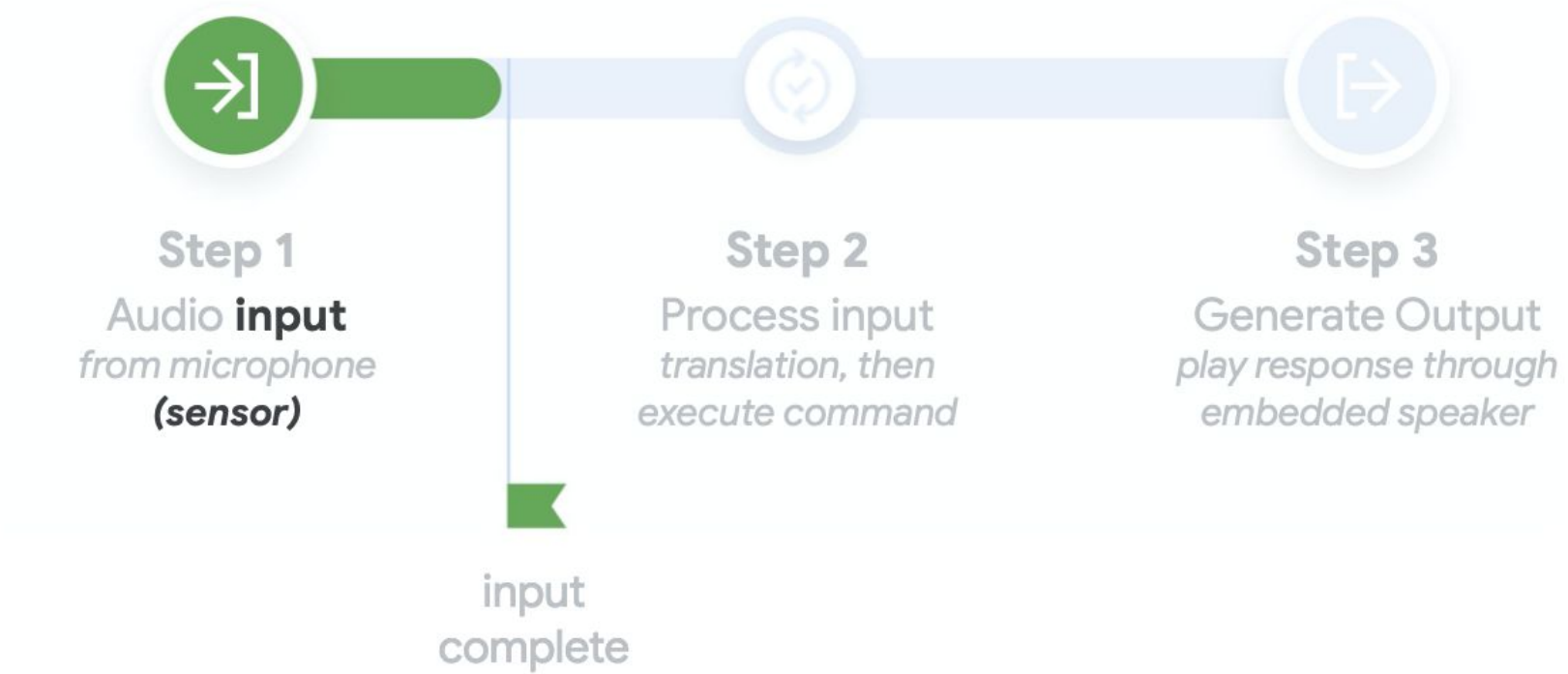
The Three Basic Steps



The Three Basic Steps



Input


Step 1
Audio **input**
from microphone
(sensor)
Step 2
Process input
translation, then
execute command
Step 3
Generate Output
play response through
embedded speaker
input
complete

Endpoints Have **Sensors**, Tons of Sensors

Motion Sensors
Gyroscope, radar, magnetometer, accelerator

Acoustic Sensors
Ultrasonic, Microphones, Geophones, Vibrometers

Environmental Sensors
Temperature, Humidity, Pressure, IR, etc.

Touchscreen Sensors
Capacitive, IR

Image Sensors
Thermal, Image

Biometric Sensors
Fingerprint, Heart rate, etc.

Force Sensors
Pressure, Strain

Rotation Sensors
Encoders

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Pressure, Strain

Rotation Sensors
Encoders

Biometric Sensors

Non-invasive Glucose Monitoring

Fingerprint + Photoplethysmography (**PPG**)

ECG Sensor

Source: Jacobs School of Engineering/UC San Diego

Endpoints Have **Sensors**, Tons of Sensors

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Gyroscope, radar, magnetometer, accelerator

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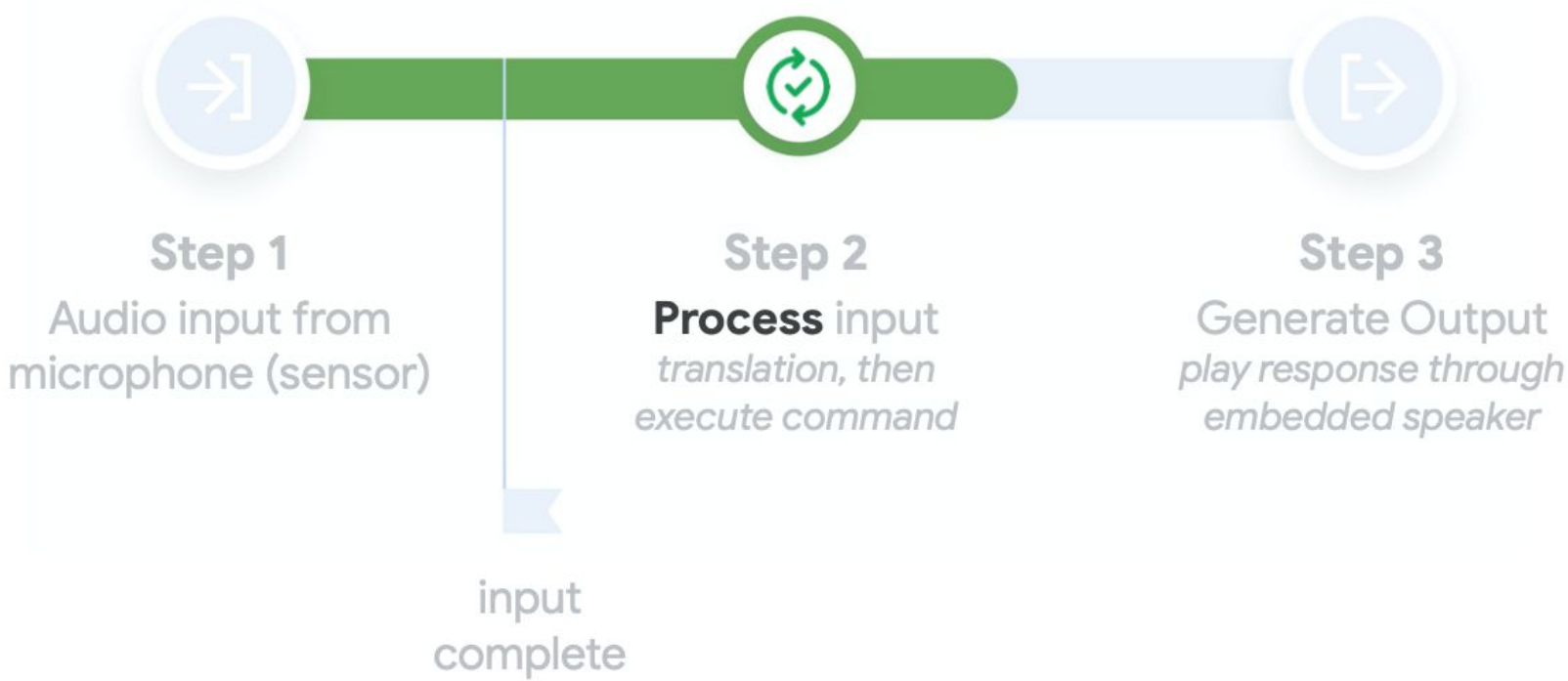
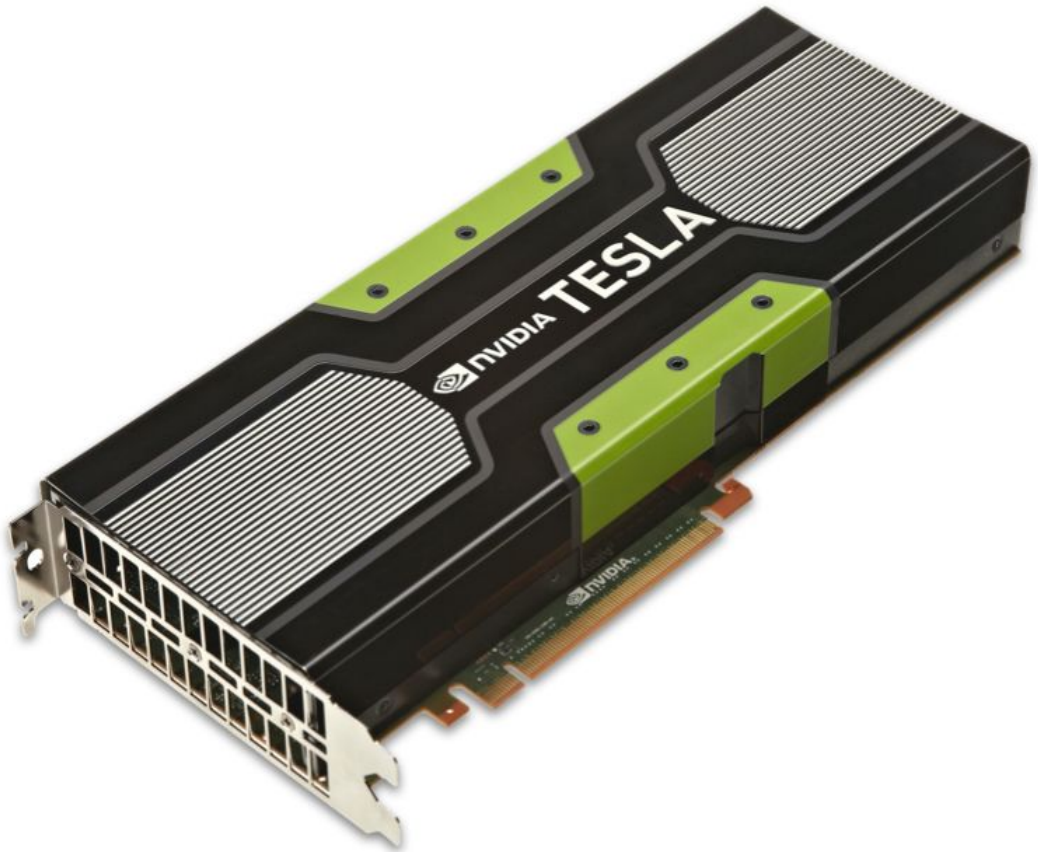
Endpoints Have **Sensors**, Tons of Sensors

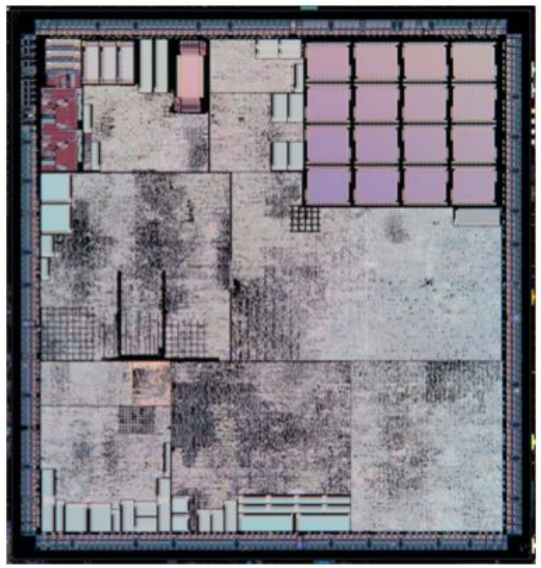
Processing


Step 1
Audio input from microphone (sensor)
Step 2
Process input
translation, then execute command
Step 3
Generate Output
play response through embedded speaker
input complete

Thinking **Big**



Thinking **Big**



Thinking **Big**

Thinking **Small**

BIG

GPU / CPU

561mm²

Thinking **Small**

BIG

GPU / CPU

561mm²

Thinking **Small**

Mobile SoC
83mm²

Thinking **Tiny**

BIG
GPU / CPU
561mm²

SMALL

Mobile SoC
83mm²

Thinking **Tiny**

BIG
GPU / CPU
561mm²

SMALL

Mobile SoC
83mm²

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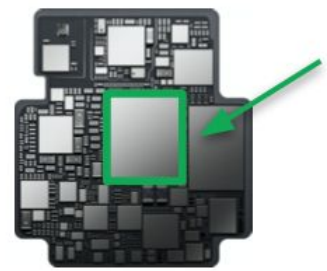
BIG
GPU / CPU
561mm²

SMALL

Mobile SoC
83mm²



Thinking **Tiny**

Thinking **Record-breaking**

Mobile SoC
83mm²

Apple 0778
30mm²

world's smallest ARM-Powered MCU

48MHz, 32KB flash, 20-pin

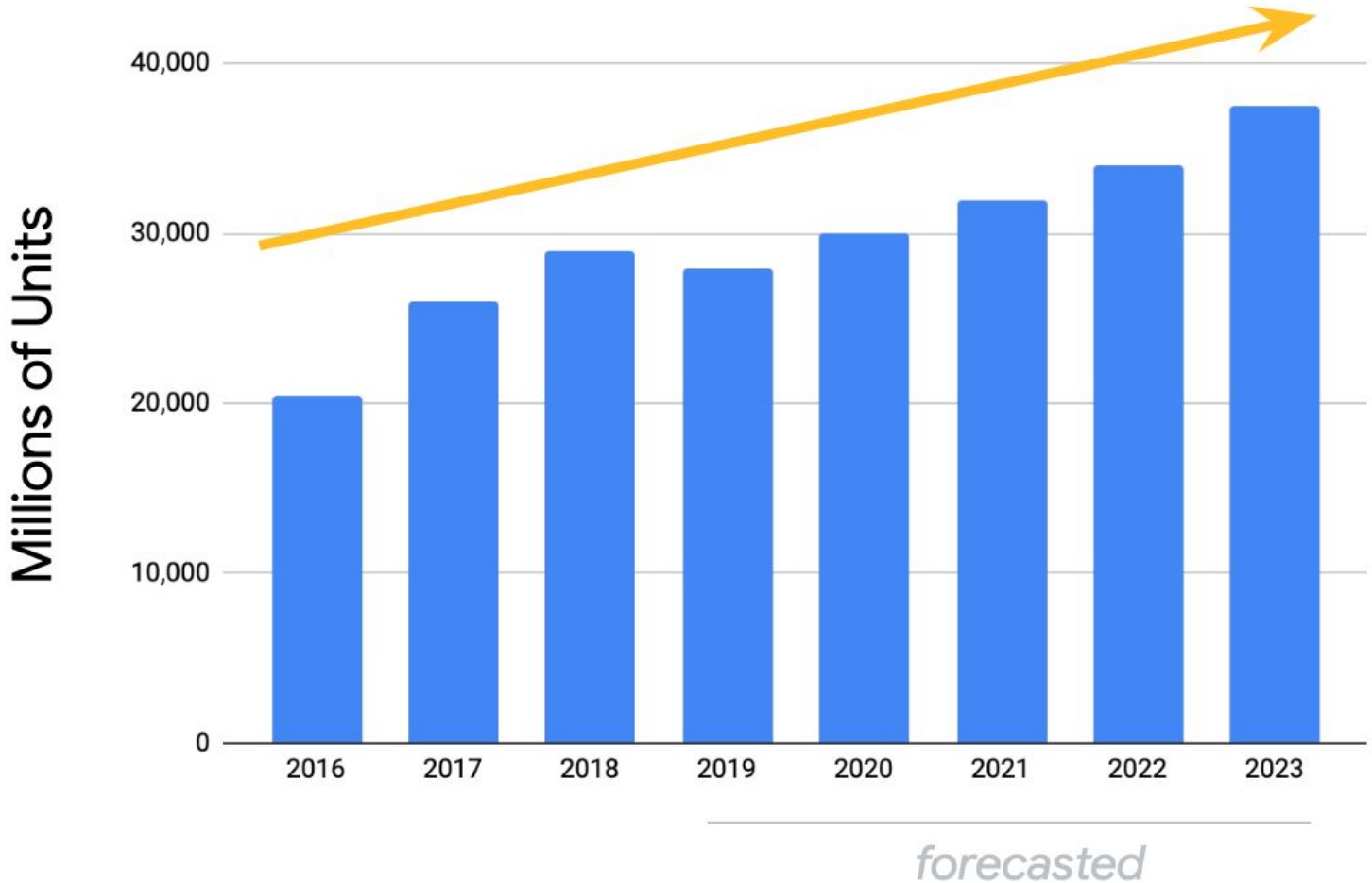
Kinetis KL03
3.2mm²


2.0 mm
1.6 mm

250 Billion

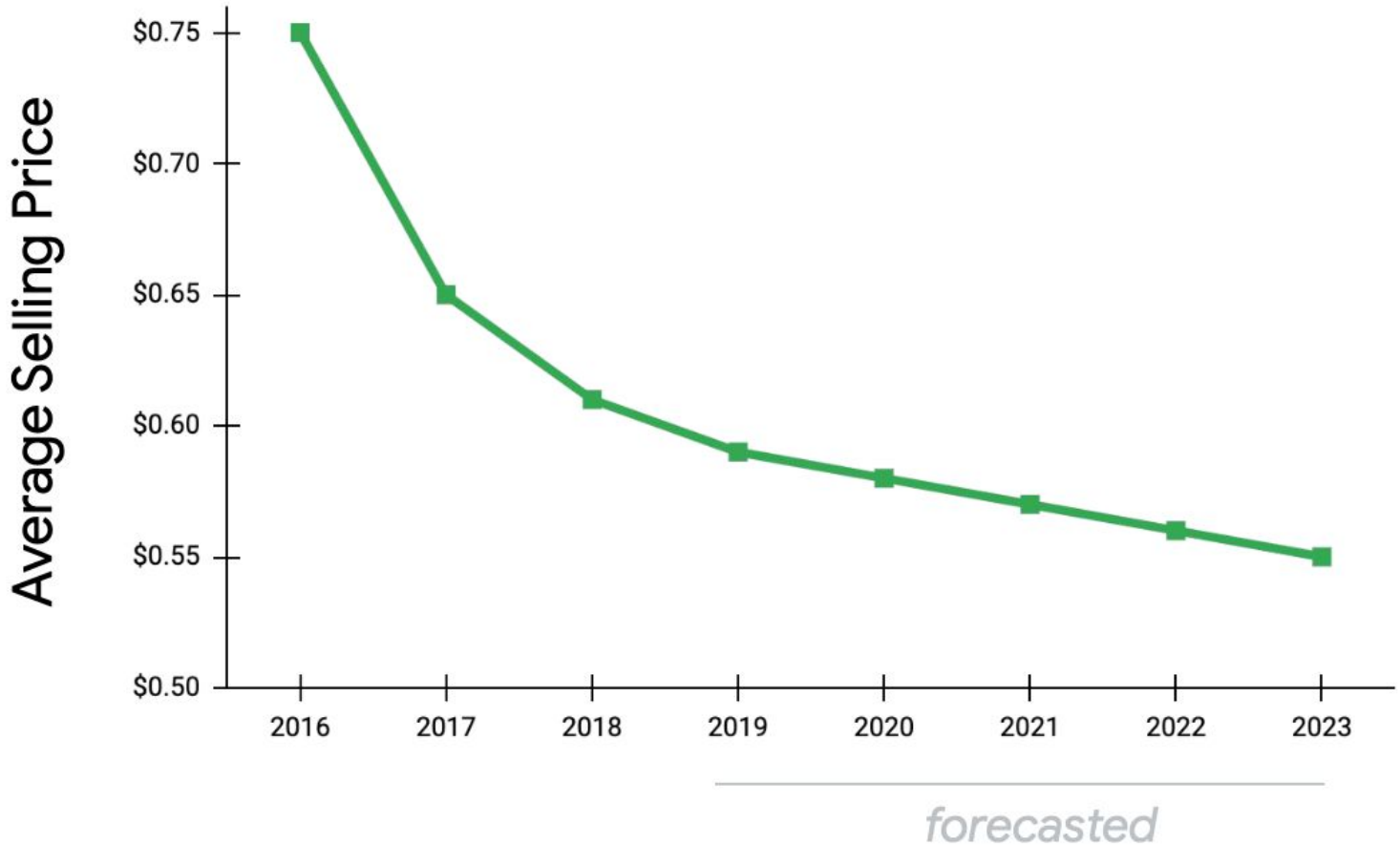
MCUs today

MCU Demand Forecast



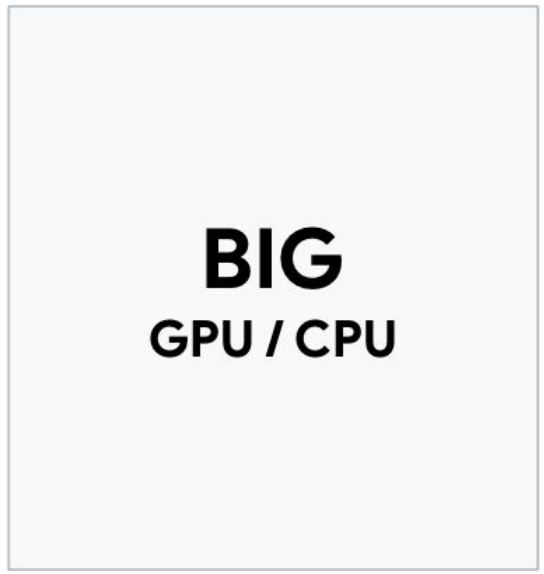
Source: IC Insights

MCU Pricing Forecast



Source: IC Insights

Comparing Power



300W
NVIDIA Tesla K80

3.64W
Apple A12

Neural Decision Processor

Always-on deep learning
speech/audio recognition

Ultra low power, 128KB SRAM,
12-pin, 2.52mm^2

140 µW
Syntiant NDP100

Comparing Power

Use case: button cell battery

Neural Decision Processor

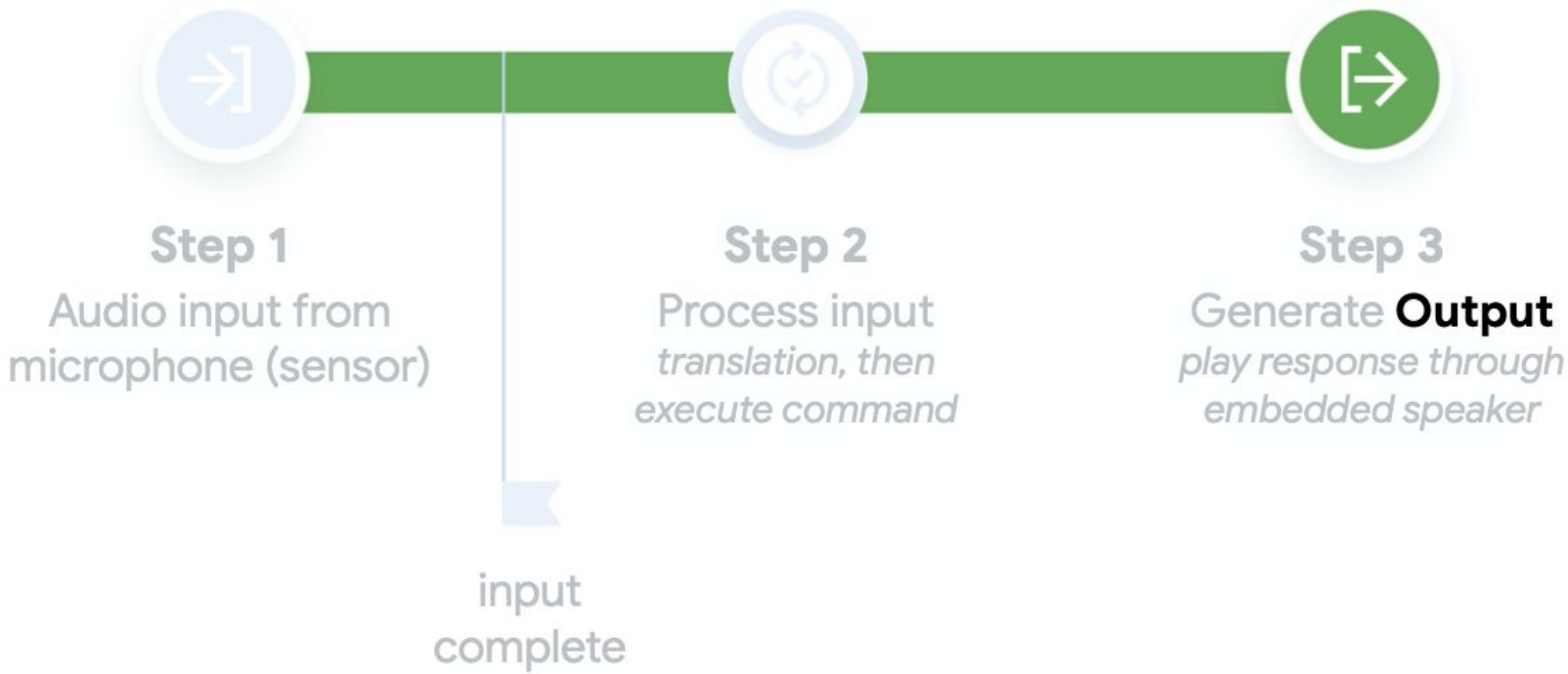
Always-on deep learning speech/audio recognition

Ultra low power, 128KB SRAM, 12-pin, 2.52mm^2

140 µW

Syntiant NDP100

Output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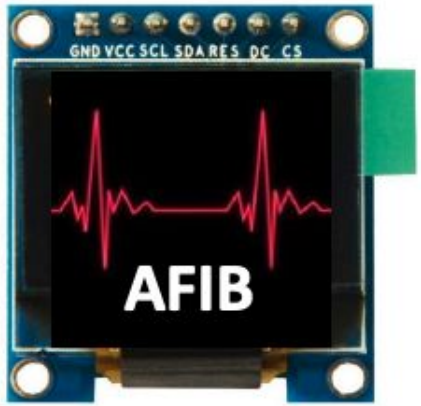
Audio input from microphone (sensor)
Step 2
Process input
translation, then execute command
Step 3
Generate Output
play response through embedded speaker
input complete

Output


GND VCC SCL SDA RES DC CS
AFIB

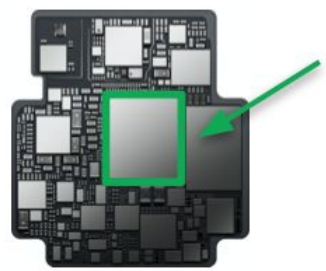

Properties
103 FIF
103 Fife Street
Nashville, TN 37206
Noise Risk Score
30 minutes
Living Room
Hot Tub
Patio

MCUs enable **TinyML**

SIZE

LOW POWER

LOW COST

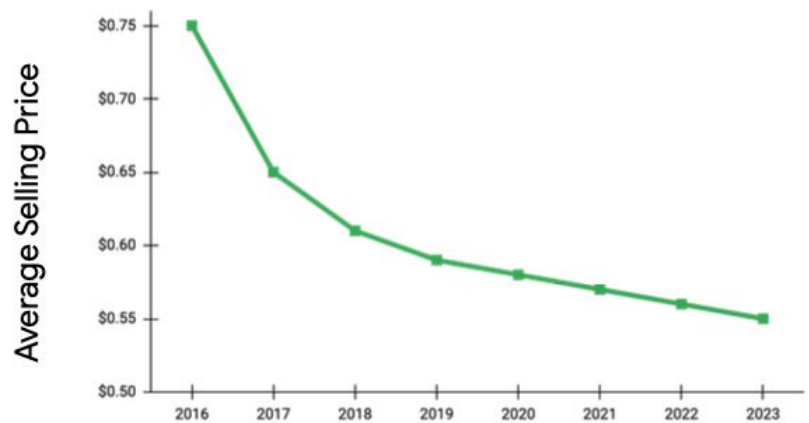


MCUs enable **TinyML**

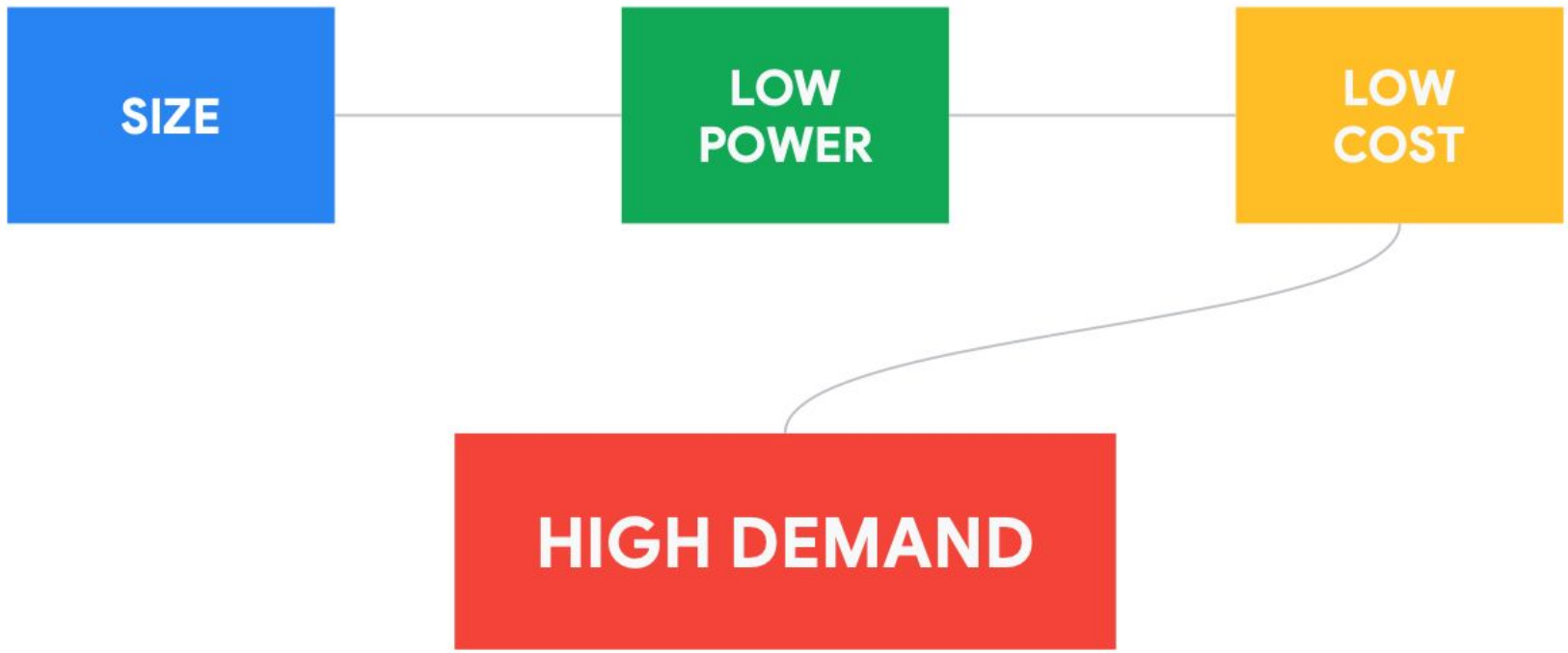
< 140 µW

Syntiant NDP100

MCUs enable **TinyML**



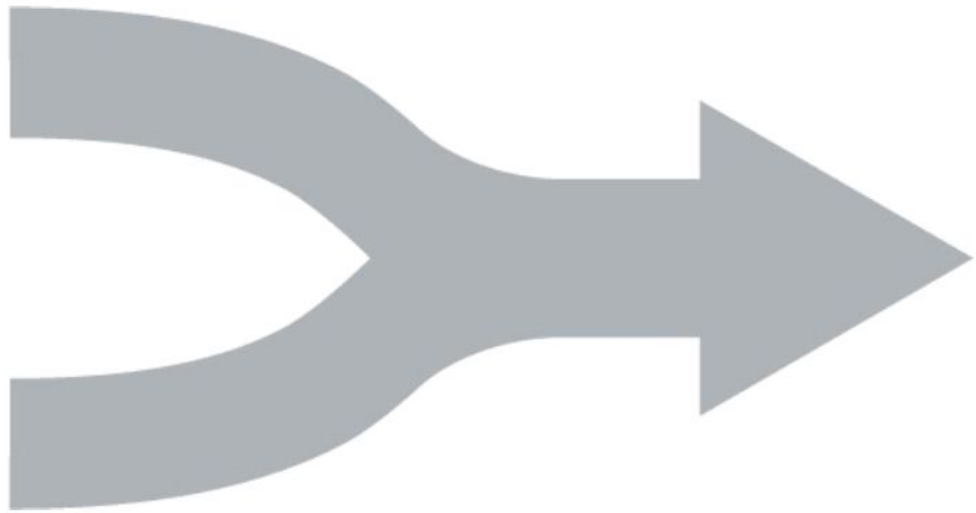
MCUs enable TinyML



What Makes TinyML?

Embedded Systems

Machine Learning



TinyML

Reading Material

Main references

- Harvard School of Engineering and Applied Sciences - CS249r: Tiny Machine Learning
- Professional Certificate in Tiny Machine Learning (TinyML) – edX/Harvard
- Introduction to Embedded Machine Learning - Coursera/Edge Impulse
- Computer Vision with Embedded Machine Learning - Coursera/Edge Impulse
- Fundamentals textbook: "Deep Learning with Python" by François Chollet
- Applications & Deploy textbook: "TinyML" by Pete Warden, Daniel Situnayake
- Deploy textbook "TinyML Cookbook" by Gian Marco Iodice

I want to thank Shawn Hymel and Edge Impulse, Pete Warden and Laurence Moroney from Google and specially Harvard professor Vijay Janapa Reddi, Ph.D. student Brian Plancher and their staff for preparing the excellent material on TinyML that is the basis of this course at UNIFEI.

The IESTI01 course is part of the **TinyML4D**, an initiative to make TinyML education available to everyone globally.

Thanks

UNIFEI