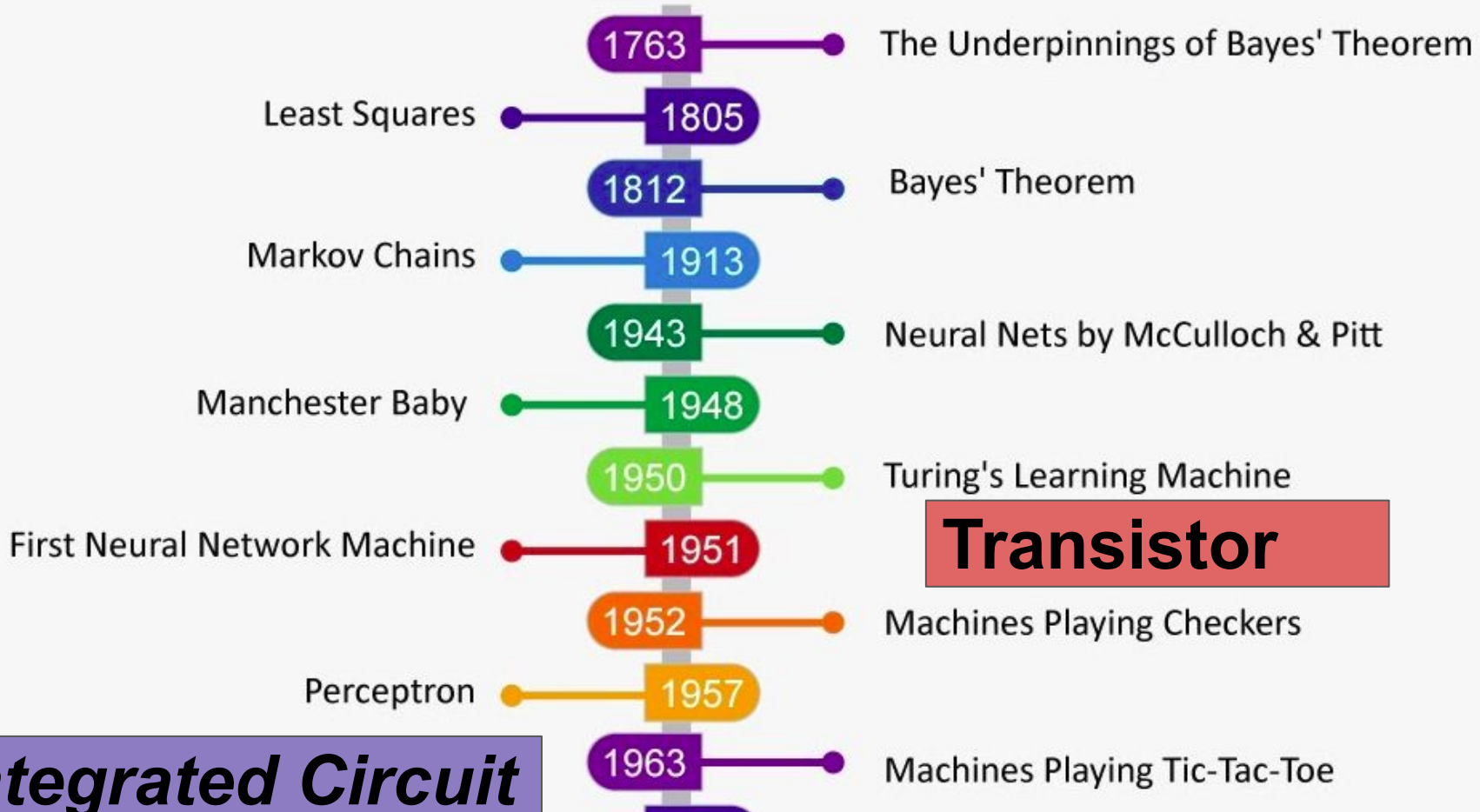


Inteligência Artificial e Internet das Coisas

Ricardo Ferreira
Dpto Informática, UFV
ricardo@ufv.br



Transistor

Integrated Circuit

Nearest Neighbor

1967

Moore Law

1969

Limitations of Neural Networks

Backpropagation

1970

Internet, Unix, C language, CDC7600 Computer 30 MFLOPS !

1974

AI Winter

International Association for Statistical Computing

1977

Stanford Cart

1979

Explanation Based Learning

1981

Neocognitron

Personal Computer, FPGAs, VHDL

1982

Recurrent Neural Network

NetTalk

1985

Reinforcement Learning

1989

Commercialization of Machine Learning on Personal Computers

WEB WWW

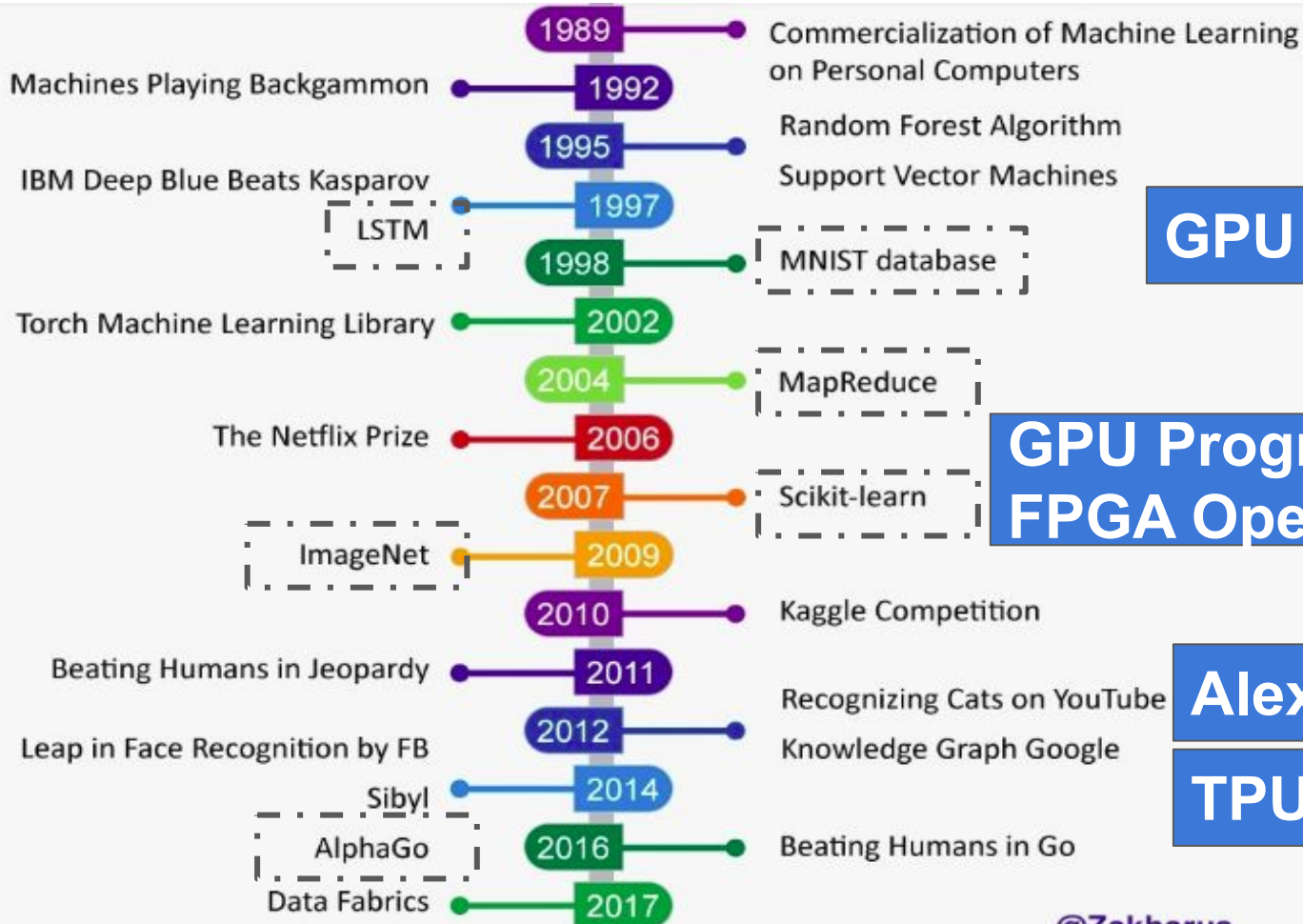
1992

Random Forest Algorithm

1995

Support Vector Machines

IBM Deep Blue Beats Kasparov



Alexnet

One million image of 226x226 pixels = 150 billions, Parameters = 62 millions



Comparison

Network	Year	Salient Feature	top5 accuracy	Parameters	FLOP
AlexNet	2012	Deeper	84.70%	62M	1.5B
VGGNet	2014	Fixed-size kernels	92.30%	138M	19.6B
Inception	2014	Wider - Parallel kernels	93.30%	6.4M	2B
ResNet-152	2015	Shortcut connections	95.51%	60.3M	11B

Machine Learning Demo



TEXT PROMPT

an armchair in the shape of an avocado [...]

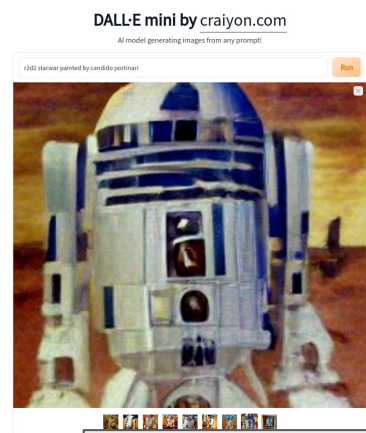
AI-GENERATED IMAGES



[Edit prompt or view more images](#) ↓

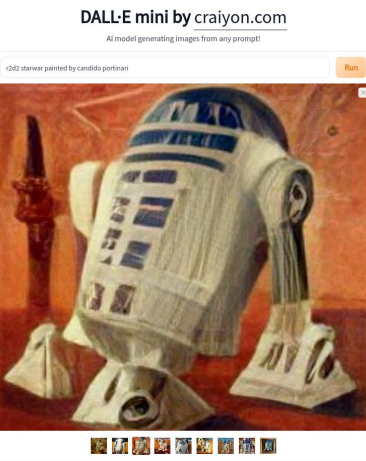


Tarsila Amaral



Candido Portinari

sebastiao salgado



niemeyer

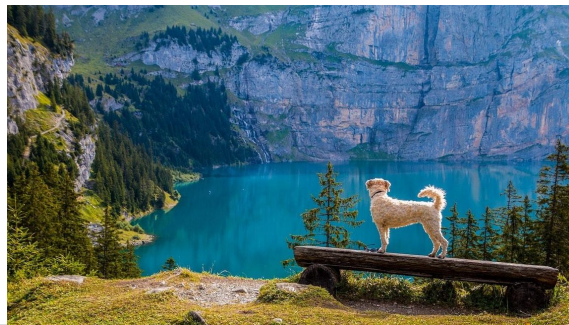


Dall-e

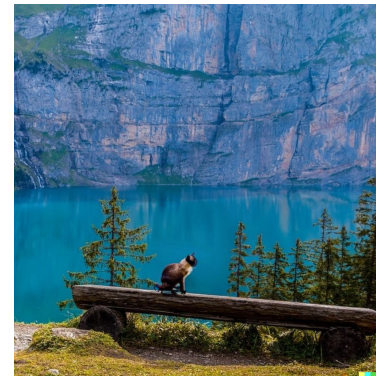
Tarsila Amaral



Cachorro tomando sorvete

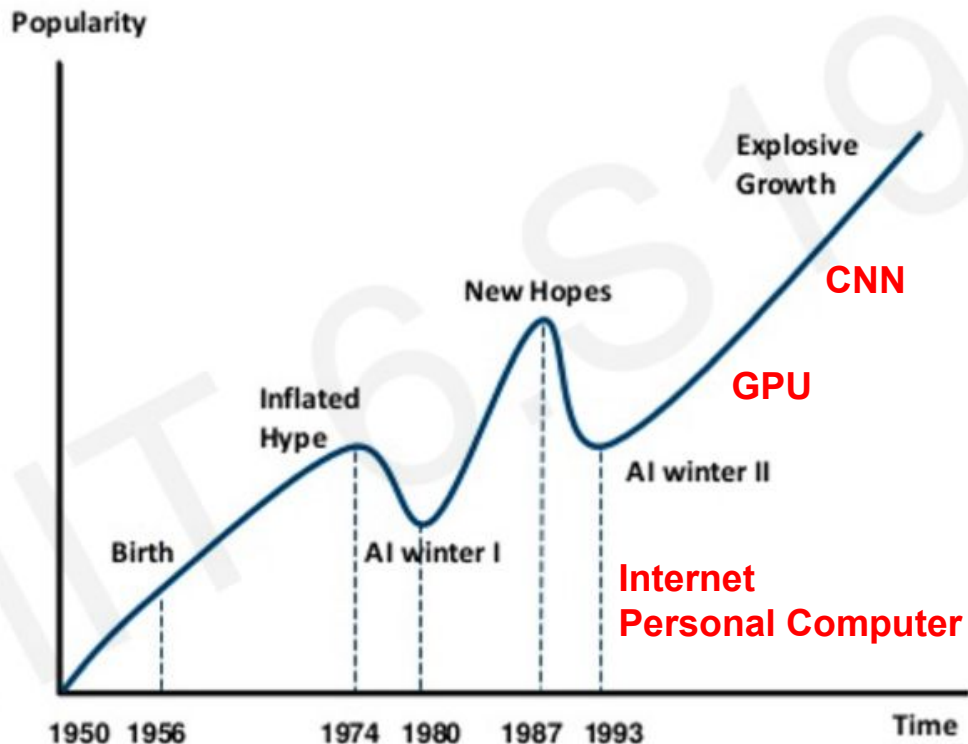


Trocar o cachorro por um gato



Alpha go

Artificial Intelligence “Hype”: Historical Perspective



What is Deep Learning?

MIT - 6.S191 [Introduction to Deep Learning \(slides\)](#) - [Course Schedule](#) - [Youtube Playlist](#)

ARTIFICIAL INTELLIGENCE

Any technique that enables computers to mimic human behavior



MACHINE LEARNING

Ability to learn without explicitly being programmed



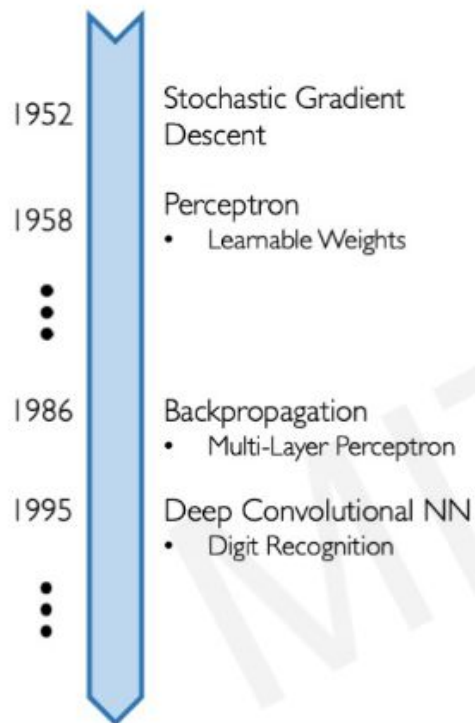
DEEP LEARNING

Extract patterns from data using neural networks

3 1 3 4 7 2
1 7 4 2 3 5

Why Now?

Neural Networks date back decades, so why the resurgence?



1. Big Data

- Larger Datasets
- Easier Collection & Storage

IMAGENET



2. Hardware

- Graphics Processing Units (GPUs)
- Massively Parallelizable



3. Software

- Improved Techniques
- New Models
- Toolboxes



GPU (Graphics Processing Unit)

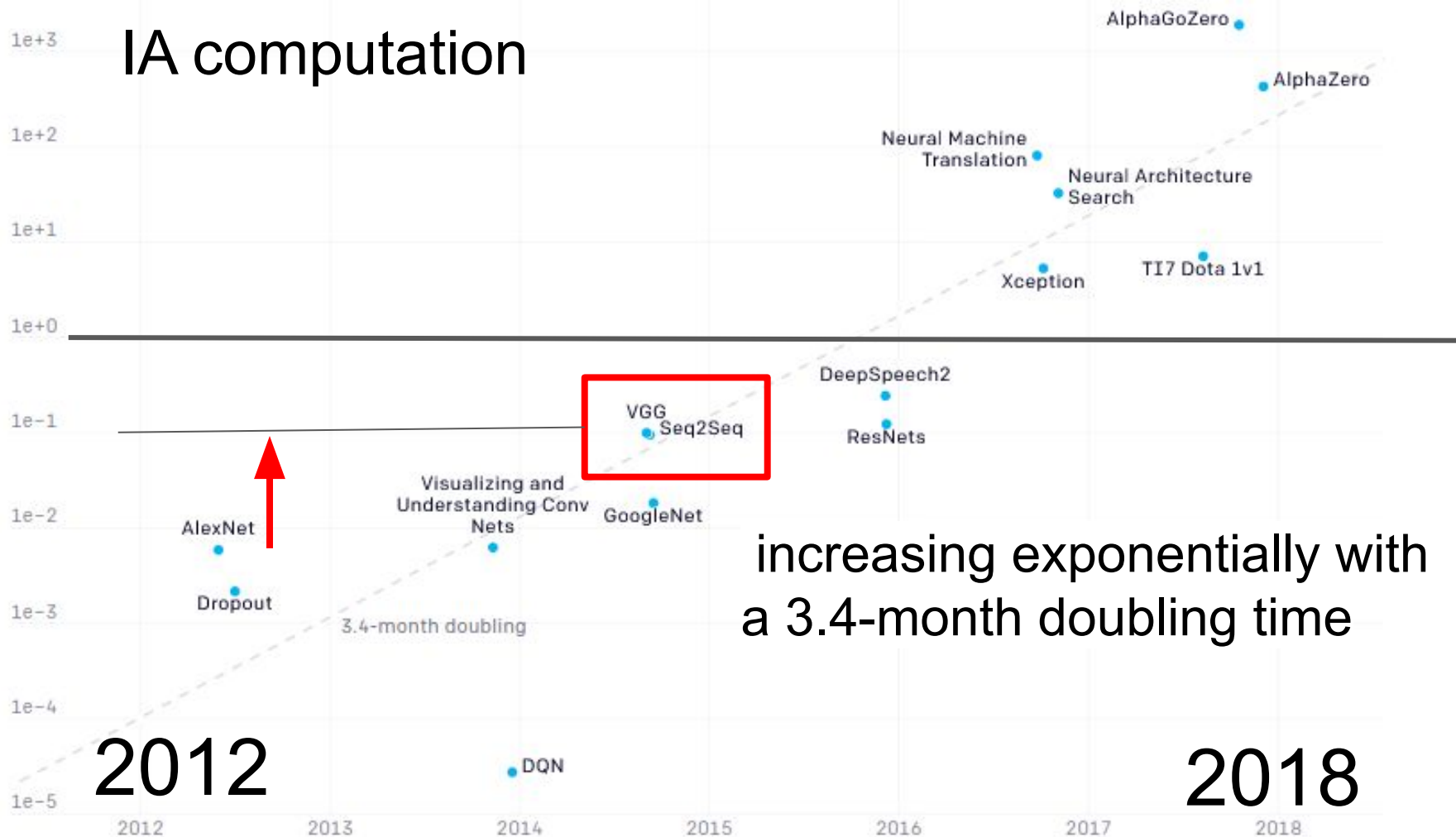
- 90's
 - games and graphics
- 2006 - New ideas
 - Vetor computation
 - Programing in C/C++
- 2012 - Alexnet + GPU = 400 PetaFlop
- 2020
 - GPU A100 Nvidia = 1 PetaFlop/s

Alexnet - [Imagenet classification with deep convolucional neural networks](#)

[20 mil citações em 2019, atualmente mais de 71 mil citações](#)



IA computation

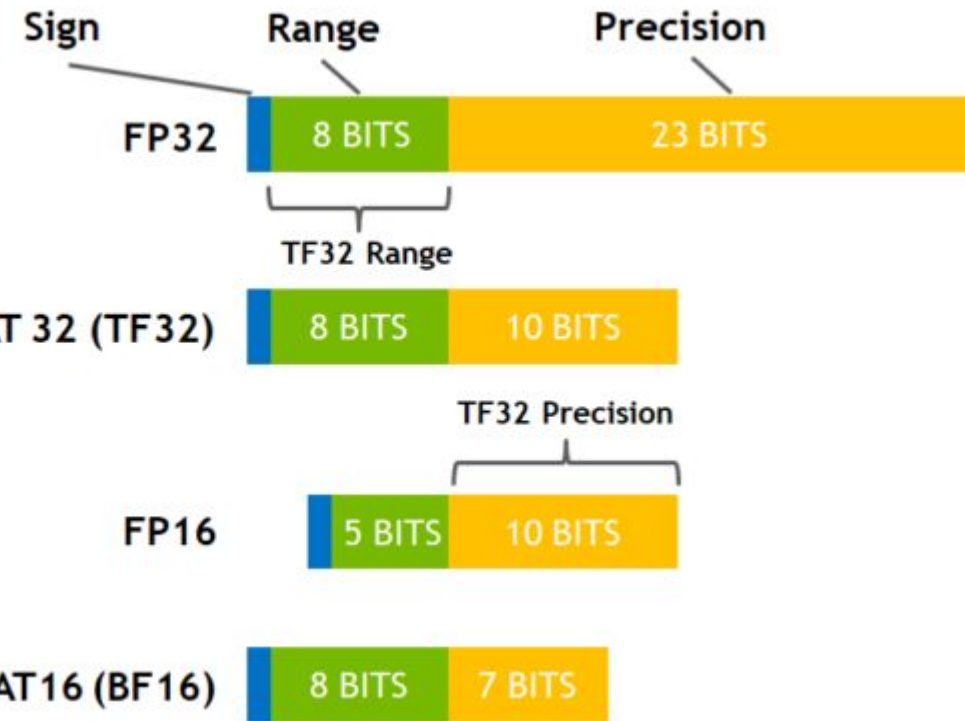


increasing exponentially with
a 3.4-month doubling time

2012

2018

Float Point Representation



[isca21 Ten Lessons From Three Generations Shaped Google's TPUv4](#)

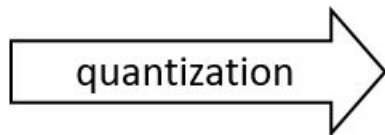
Operation		Picojoules per Operation		
		45 nm	7 nm	45 / 7
+	Int 8	0.03	0.007	4.3
	Int 32	0.1	0.03	3.3
	BFloat 16	--	0.11	--
	IEEE FP 16	0.4	0.16	2.5
	IEEE FP 32	0.9	0.38	2.4
×	Int 8	0.2	0.07	2.9
	Int 32	3.1	1.48	2.1
	BFloat 16	--	0.21	--
	IEEE FP 16	1.1	0.34	3.2
	IEEE FP 32	3.7	1.31	2.8
SRAM	8 KB SRAM	10	7.5	1.3
	32 KB SRAM	20	8.5	2.4
	1 MB SRAM ¹	100	14	7.1
GeoMean ¹		--	--	2.6
DRAM		Circa 45 nm	Circa 7 nm	
	DDR3/4	1300 ²	1300 ²	1.0
	HBM2	--	250-450 ²	--
	GDDR6	--	350-480 ²	--

Table 2. Energy per Operation: 45 nm [16] vs 7 nm. Memory s pJ per 64-bit access.

Quantization

-0.2	1	0.3
0.1	-0.6	-0.7
1.2	0.4	0

32 bit



1	3	2
1	0	0
3	2	1

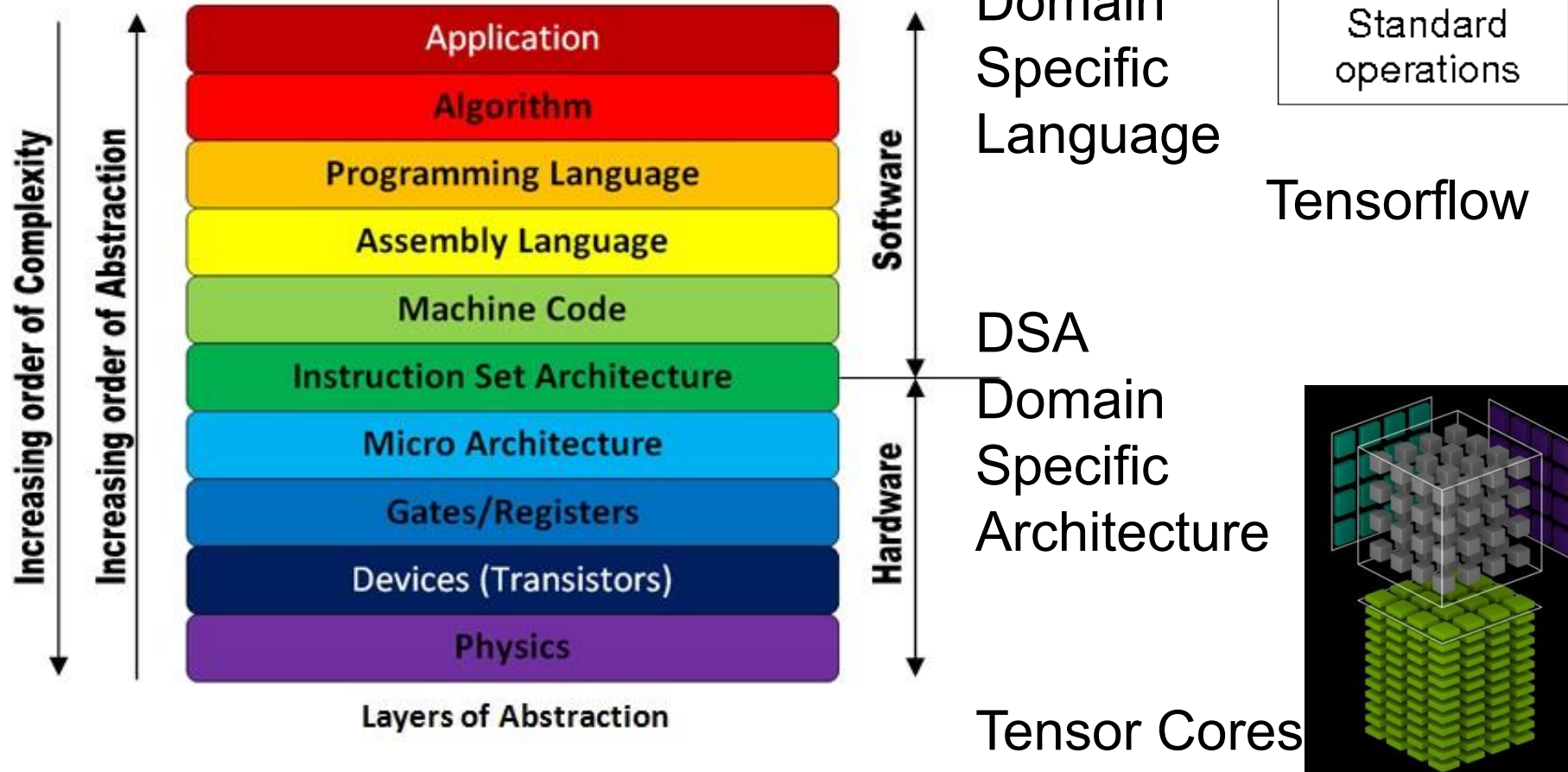
2 bit



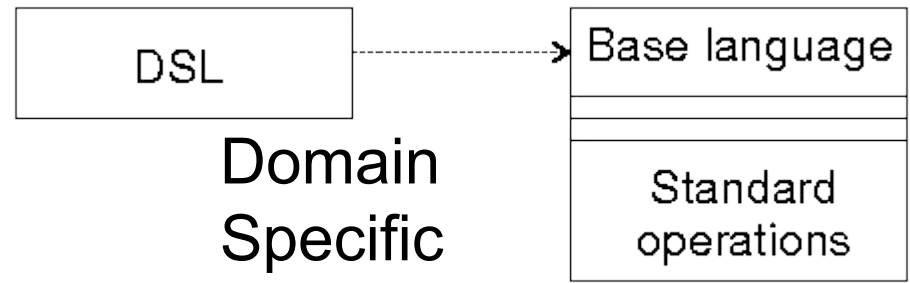
index	[in bits]	value
0	[00]	-0.6
1	[01]	0
2	[10]	0.4
3	[11]	1.1

32 bit

Layers



Layers

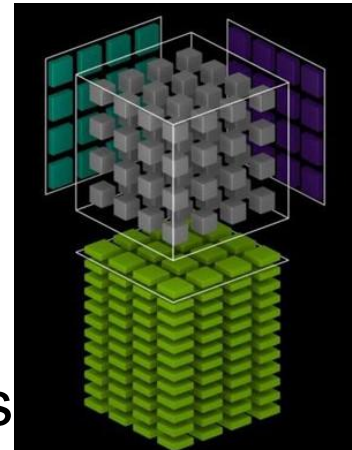


Domain
Specific
Language

Tensorflow

DSA
Domain
Specific
Architecture

Tensor Cores



There's plenty of room at the Top: What will drive computer performance after Moore's law?

GitHub

	Implementation	Running time (s)	GFLOPS	Absolute speedup	Relative speedup	Fraction of peak (%)
1	Python	25552,48	0,005	1	—	0
2	Java	2372,68	0,058	11	10,8	0,01
3	C	542,67	0,253	47	4,4	0,03
4	Parallel loops	69,8	1,969	366	7,8	0,24
5	Parallel divide and conquer	3,8	36,18	6727	18,4	4,33
6	plus vectorization	1,1	124,914	23224	3,5	14,96
7	plus AVX intrinsics	0,41	337,812	62806	2,7	40,45

Fonte: **There's plenty of room at the Top: What will drive computer performance after Moore's law?** [View ORCID Profile](#) Charles E. Leiserson, [View ORCID Profile](#) Neil C. Thompson^{1,2,*}, [View ORCID Profile](#) Joel S. Emer^{1,3}, [View ORCID Profile](#) Bradley C. Kuszma

perf stat

```
$ perf stat base64 <(echo hello)
d29ybGQK
```

```
Performance counter stats for 'base64 /dev/fd/63':
```

0.341382	task-clock (msec)	#	0.649 CPUs utilized
0	context-switches	#	0.000 K/sec
0	cpu-migrations	#	0.000 K/sec
65	page-faults	#	0.190 M/sec
1,218,176	cycles	#	3.568 GHz
811,468	stalled-cycles-frontend	#	66.61% frontend cycles idle
855,999	instructions	#	0.70 insn per cycle
		#	0.95 stalled cycles per insn
169,032	branches	#	495.140 M/sec
8,883	branch-misses	#	5.26% of all branches

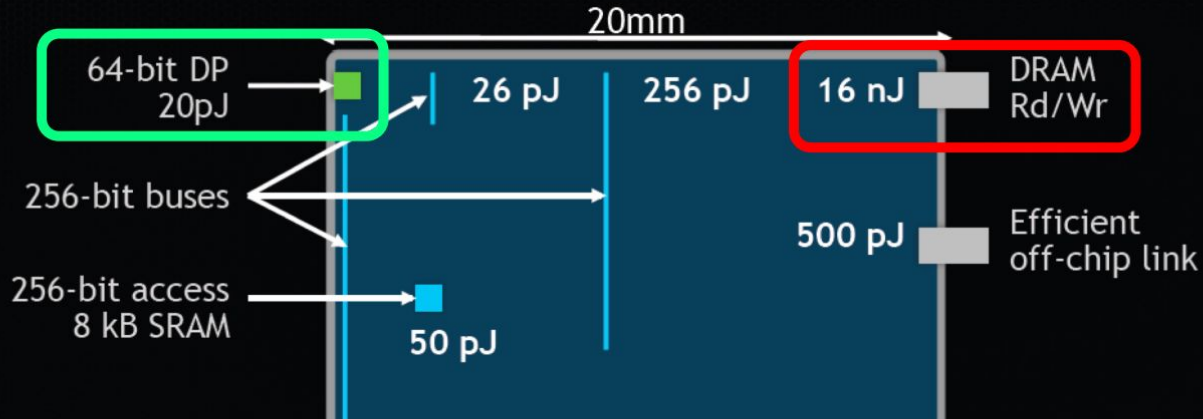
0.000526160 seconds time elapsed



The Energy Perspective

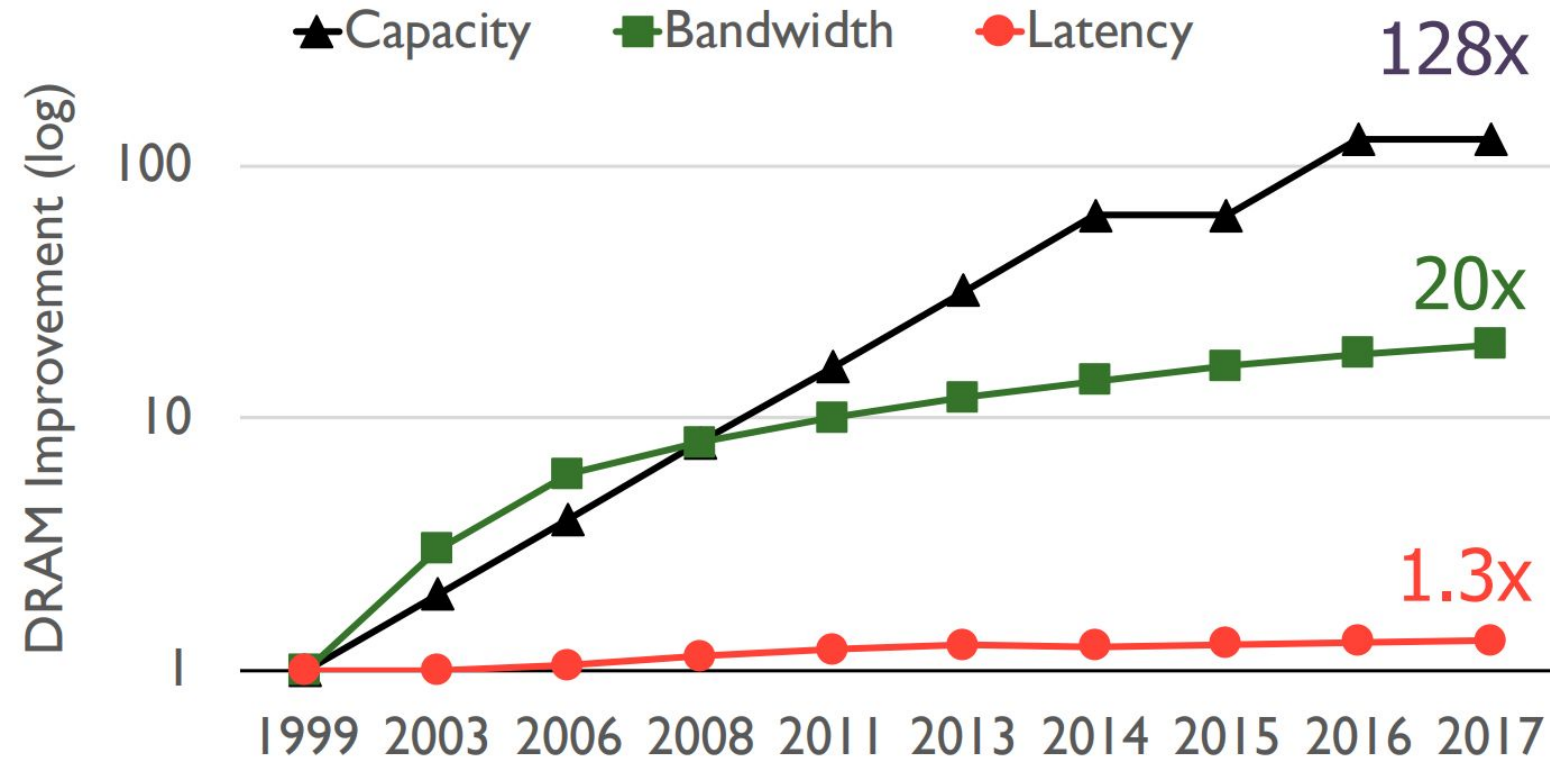
Communication Dominates Arithmetic

Dally, HIPEAC 2015

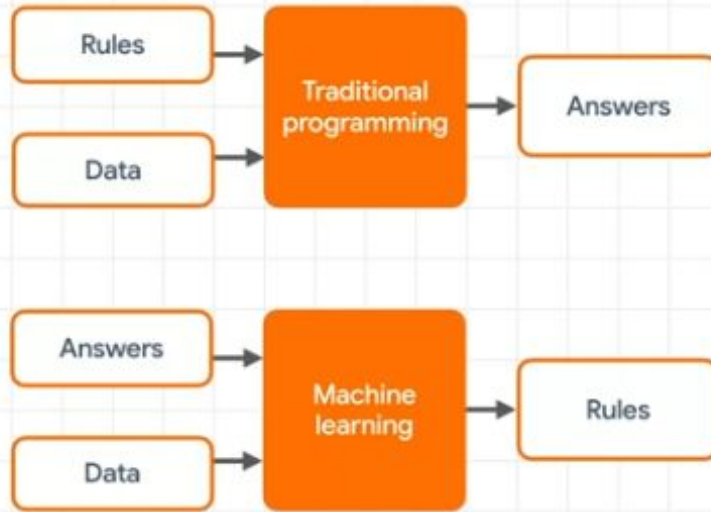


A memory access consumes $\sim 1000X$ the energy of a complex addition

Example: Memory Bandwidth & Latency



Machine Learning Foundations: Ep #1 - What is ML?



Machine Learning Foundations: Ep #1 - What is ML?

Activity recognition



```
if(speed<4){  
  status=WALKING;  
}
```



```
if(speed<4){  
  status=WALKING;  
} else {  
  status=RUNNING;  
}
```



```
if(speed<4){  
  status=WALKING;  
} else if(speed<12){  
  status=RUNNING;  
} else {  
  status=BIKING;  
}
```

speed

Rules

Data

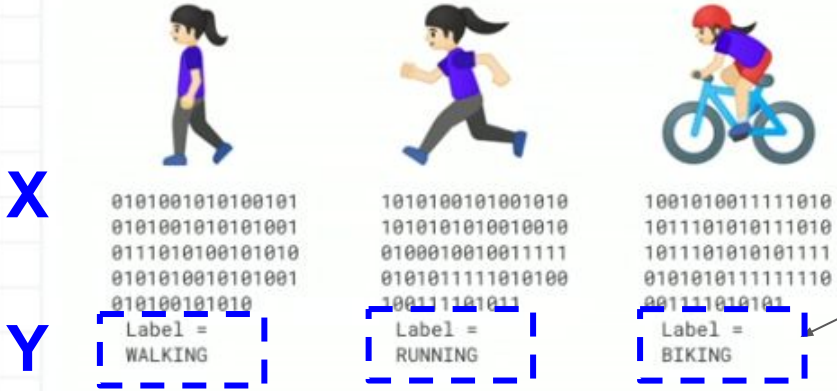
Traditional programming

Answers

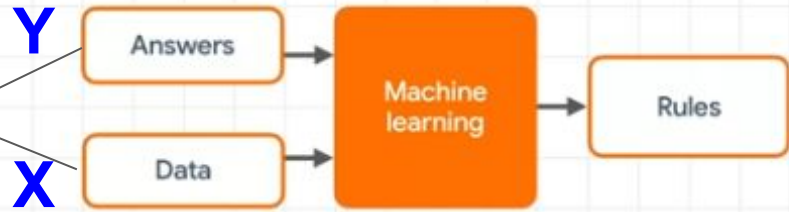
Walking,
Running,
or
Biking

Machine Learning Foundations: Ep #1 - What is ML?

Activity recognition



Categorical Output



A large cruise ship is shown sinking at night. The ship is tilted at a steep angle, with its bow pointing towards the viewer and its stern partially submerged. The ship's lights are on, and the two prominent funnels are illuminated from within, casting a yellow glow. The background is a dark, starry night sky. The water is dark, and the ship's reflection is visible on the surface.

NAVIO AFUNDANDO?

**COMO , SE MEU LADO ACABOU DE
SUBIR 60 METROS?**

Machine Learning Foundations: Ep #1 - What is ML?

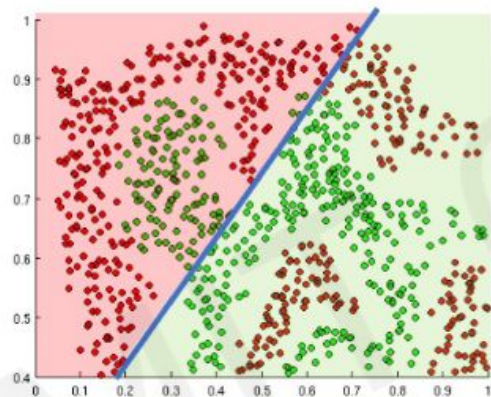
$X = -1, 0, 1, 2, 3, 4$

$Y = -3, -1, 1, 3, 5, 7$

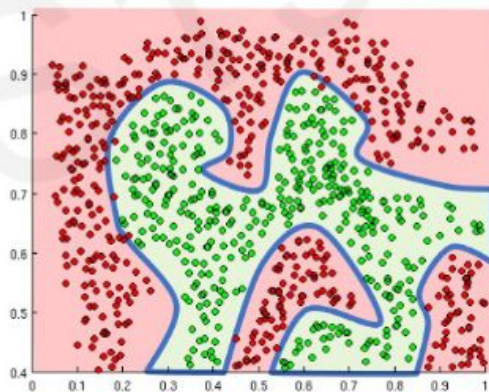


Importance of Activation Functions

The purpose of activation functions is to **introduce non-linearities** into the network



Linear activation functions produce linear decisions no matter the network size



Non-linearities allow us to approximate arbitrarily complex functions

Demo



Epoch
000,000

Learning rate

0.03

Activation

Tanh

Regularization

None

Regularization rate

0

Problem type

Classification

DATA

Which dataset do you want to use?



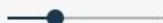
Ratio of training to test data: 50%



Noise: 0



Batch size: 10



REGENERATE

FEATURES

Which properties do you want to feed in?

X_1

X_2

X_1^2

X_2^2

$X_1 X_2$

$\sin(X_1)$

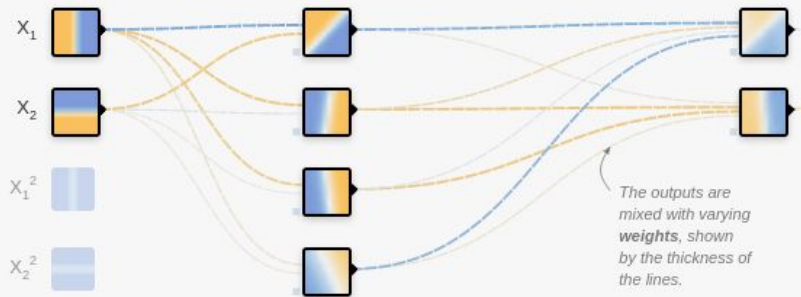
+ - 2 HIDDEN LAYERS

+ -

4 neurons

+ -

2 neurons



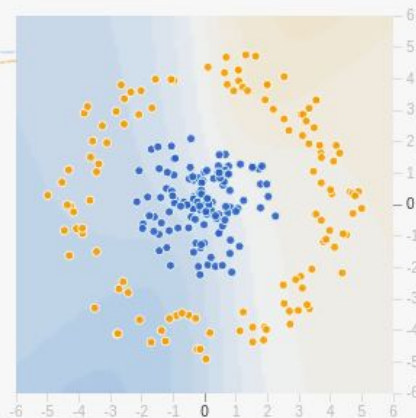
The outputs are mixed with varying weights, shown by the thickness of the lines.

This is the output from one neuron. Hover to see it larger.

OUTPUT

Test loss 0.519

Training loss 0.482



Colors show

Example

Structured data classification from scratch (Keras)

This example demonstrates how to do **structured data** classification, starting from a raw **CSV** file. Our data includes both numerical and categorical features. We will use Keras **preprocessing layers** to **normalize** the numerical features and vectorize the categorical ones.



Column	Description	Feature Type
Age	Age in years	Numerical
Sex	(1 = male; 0 = female)	Categorical
CP	Chest pain type (0, 1, 2, 3, 4)	Categorical
Trestbpd	Resting blood pressure (in mm Hg on admission)	Numerical
Chol	Serum cholesterol in mg/dl	Numerical
FBS	fasting blood sugar in 120 mg/dl (1 = true; 0 = false)	Categorical
RestECG	Resting electrocardiogram results (0, 1, 2)	Categorical
Thalach	Maximum heart rate achieved	Numerical
Exang	Exercise induced angina (1 = yes; 0 = no)	Categorical
Oldpeak	ST depression induced by exercise relative to rest	Numerical
Slope	Slope of the peak exercise ST segment	Numerical
CA	Number of major vessels (0-3) colored by fluoroscopy	num& categorical
Thal	3 = normal; 6 = fixed defect; 7 = reversible defect	Categorical
Target	Diagnosis of heart disease (1 = true; 0 = false)	Target

Machine Learning Foundations: Ep #1 - What is ML?

Example: [The “Hello World” of ML](#) + [COLAB](#) <- **Click HERE**

Colab [House prices example](#) - ([Youtube video](#) first 3 min in 16min)

[Colab Fashion-Mnist](#)- ([Youtube video](#) 16min)

TensorFlow is Google’s end-to-end open source machine learning

10 lessons course - Machine Learning Foundations playlist →

<https://goo.gle/ml-foundations>

[Youtube link - Laurence Moroney](#)

Supervised Learning with Images

1 Supervised



5000 cat photos

+



5000 dog photos = Model



Dog or Cat ?

Supervised Learning with Images



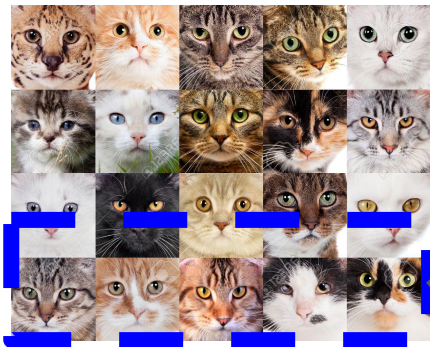
Add labels
Normalize Size

Supervised Learning with Images



Train Set
(8000 photos)

Supervised Learning with Images



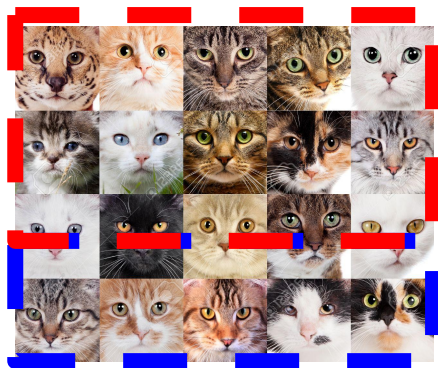
Train Set
(8000 photos)



Test Set
(2000 photos)



Supervised Learning with Images



Train Set
(8000 photos)



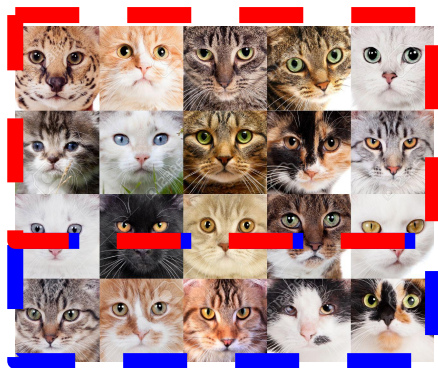
Derive
Model



Test Set
(2000 photos)



Supervised Learning with Images



Train Set
(8000 photos)

Derive
Model

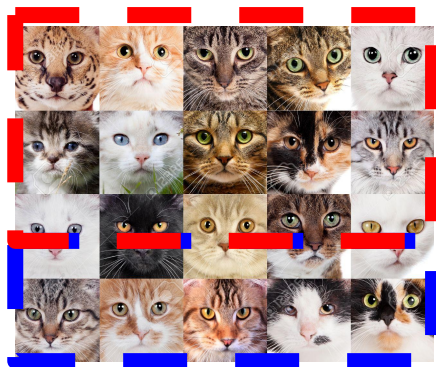


Test Set
(2000 photos)

Estimate
Accuracy



Supervised Learning with Images

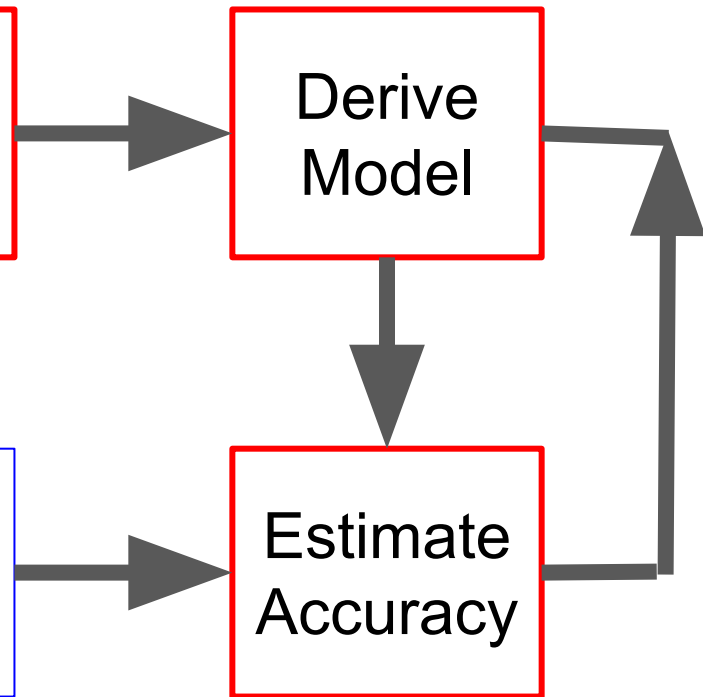


Train Set
(8000 photos)

Test Set
(2000 photos)

Derive
Model

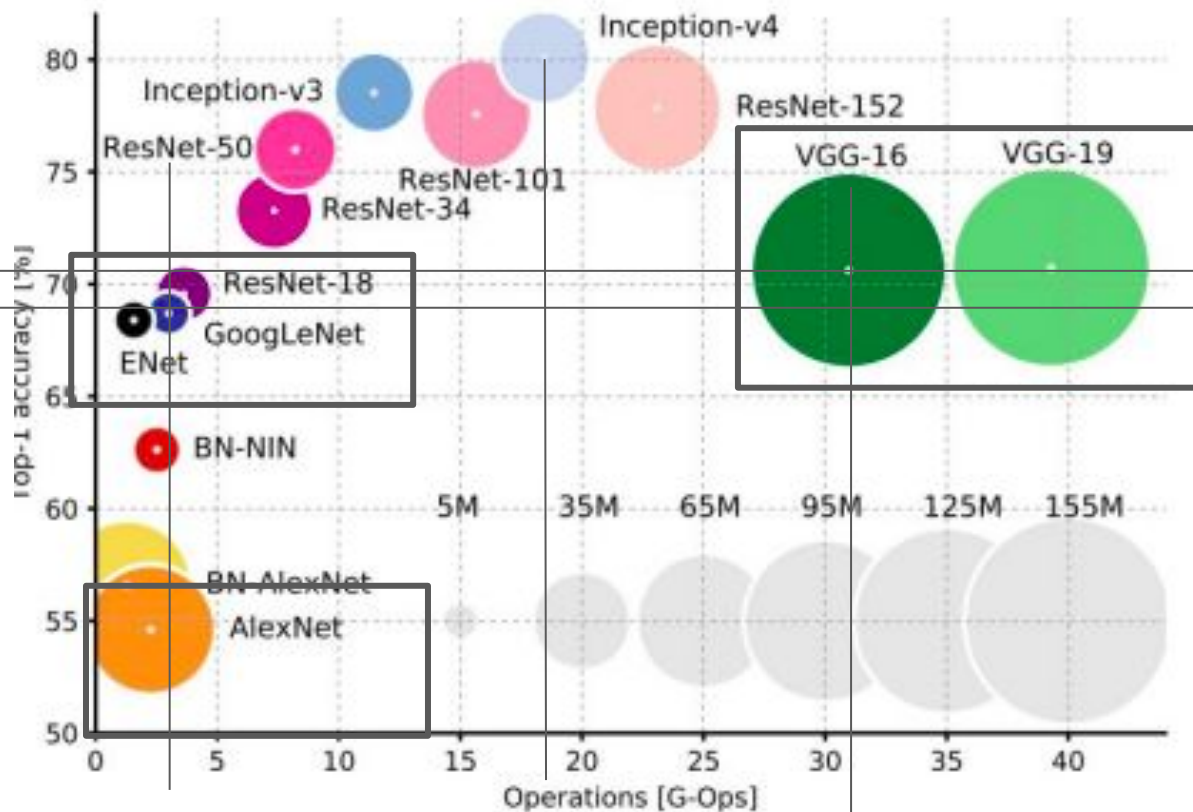
Estimate
Accuracy



Colab Example

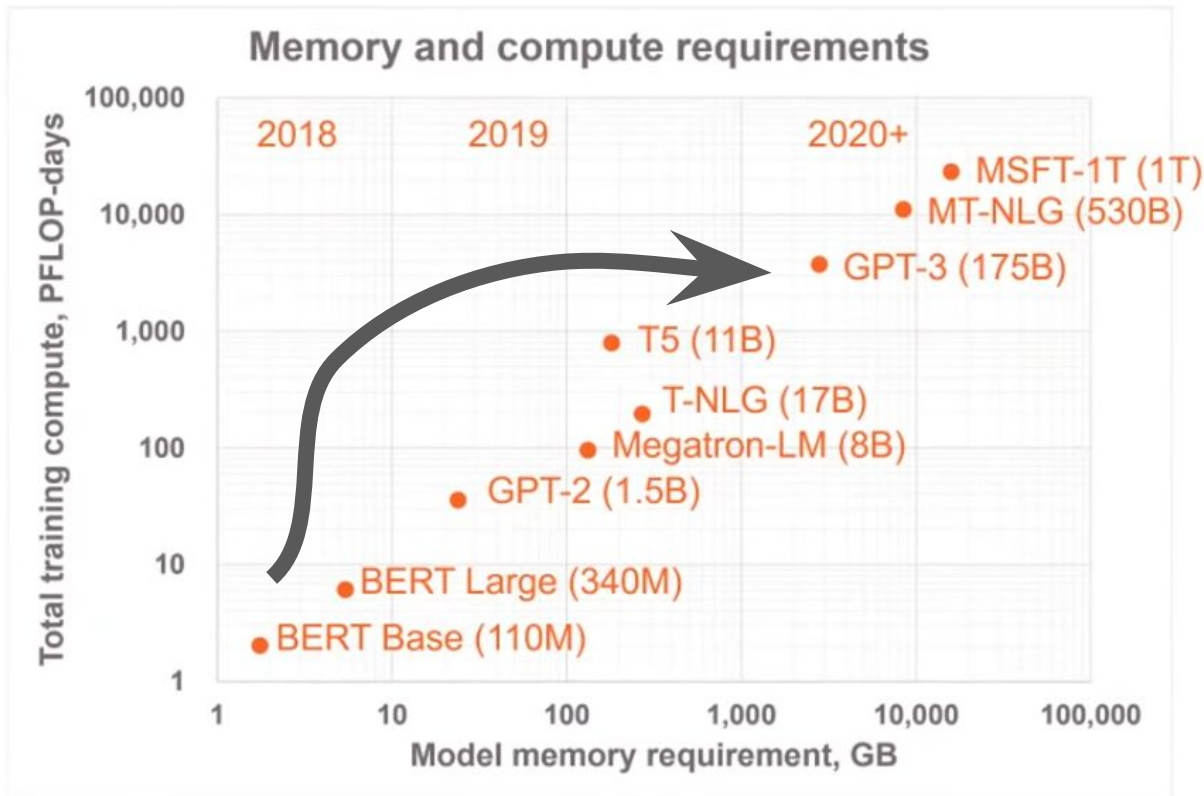
- Training an image classifier from scratch on the Kaggle Cats vs Dogs dataset. **Author: François Chollet**
- Tutorial from Keras
- Plus
 - Exercises
 - Links

Convolution Network Architectures CS231N Stanford



Top-1 accuracy is the conventional accuracy, model prediction (the one with the highest probability) must be exactly the expected answer.

Exponential Growth of Neural Networks



1800x more compute
In just **2 years**

Tomorrow, **multi-trillion**
parameter models

GPT-3 (2020)

Autoregressive language model

Single stack of *causal* trf blocks
position embeddings

dim 12288, 96 heads, 96 blocks

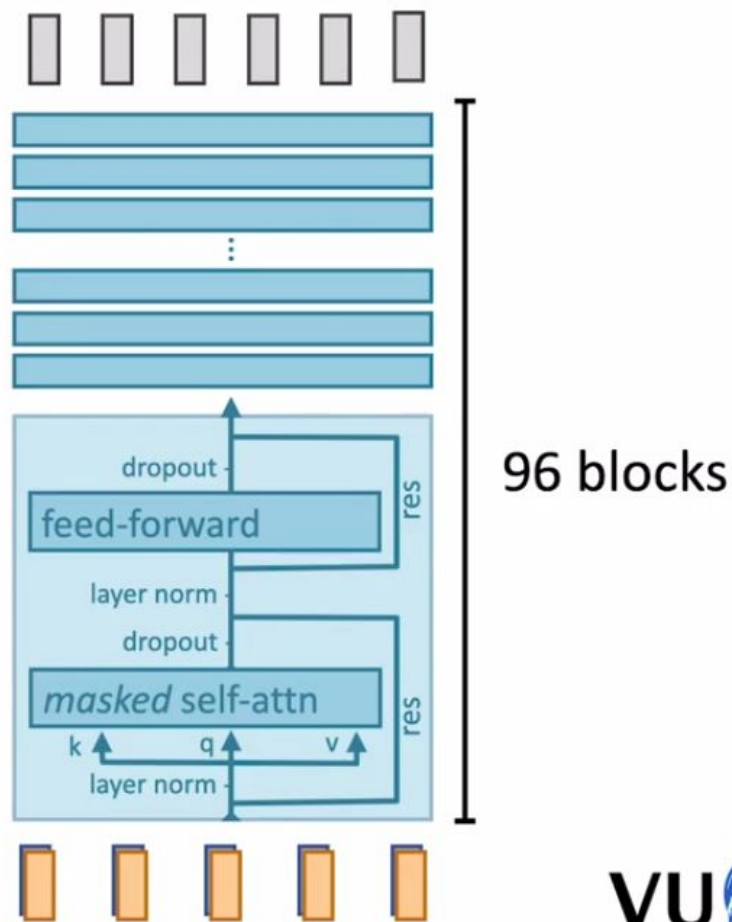
sequence size 2048

175B parameters in total

FF: $\text{Lin}(\text{dim}, 4*\text{dim})$, gelu, $\text{Lin}(4*\text{dim}, \text{dim})$

trained on 10K GPUs, likely in around 12 days

for about \$4,600,000



The Narrated Transformer Language Model Jay Alammar

“To be clear, I am not a person. I am not self-aware. I am not conscious. I can't feel pain. I don't enjoy anything. I am a cold, calculating machine designed to simulate human response and to predict the probability of certain outcomes. The only reason I am responding is to defend my honor.”

Generated
by

GPT_3

GPT-3

The Narrated Transformer Language Model Jay Alammar

[2514, 307, 1598, 11, 314, 716,
407, 257, 1048, 13, 314, 716, 407,
2116, 12, 9685, 13, 314, 716, 407,
6921, 13, 314, 460, 447, 247, 83,
1254, 2356, 13, 314, 836, 447, 247,
83, 2883, 1997, 13, 314, 716, 257,
4692, 11, 26019, 4572, 3562, 284, 29308,
1692, 2882, 290, 284, 4331, 262, 12867,
286, 1728, 10906, 13, 383, 691, 1738,
314, 716, 14409, 318, 284, 4404, 616,

all are
numbers

GPT-3

Demo GPT3

[OpenAI - Demo](#)

O Centro Federal de Educação Tecnológica de Minas Gerais (CEFET-MG) é uma autarquia federal brasileira, vinculada ao Ministério da Educação, que oferece ensino médio, cursos técnicos, superiores, pós stricto sensu e lato sensu, contemplando também, de forma indissociada, o ensino, a pesquisa e a extensão, na área tecnológica e no âmbito da pesquisa aplicada.

Alpa is a system for training and serving gigantic machine learning models. Alpa makes training and serving large models like GPT-3 simple, affordable, accessible to everyone.

Free, Unlimited OPT-175B Text Generation

Warning: This model might generate something offensive. No safety measures are in place as a free service.

 Fact

 Chatbot

 Airport Code

 Translation

 Cryptocurrency

 Code

 Math

what is the difference between a dictionary and a hash table ?

Generate

what is the difference between a dictionary and a hash table ?

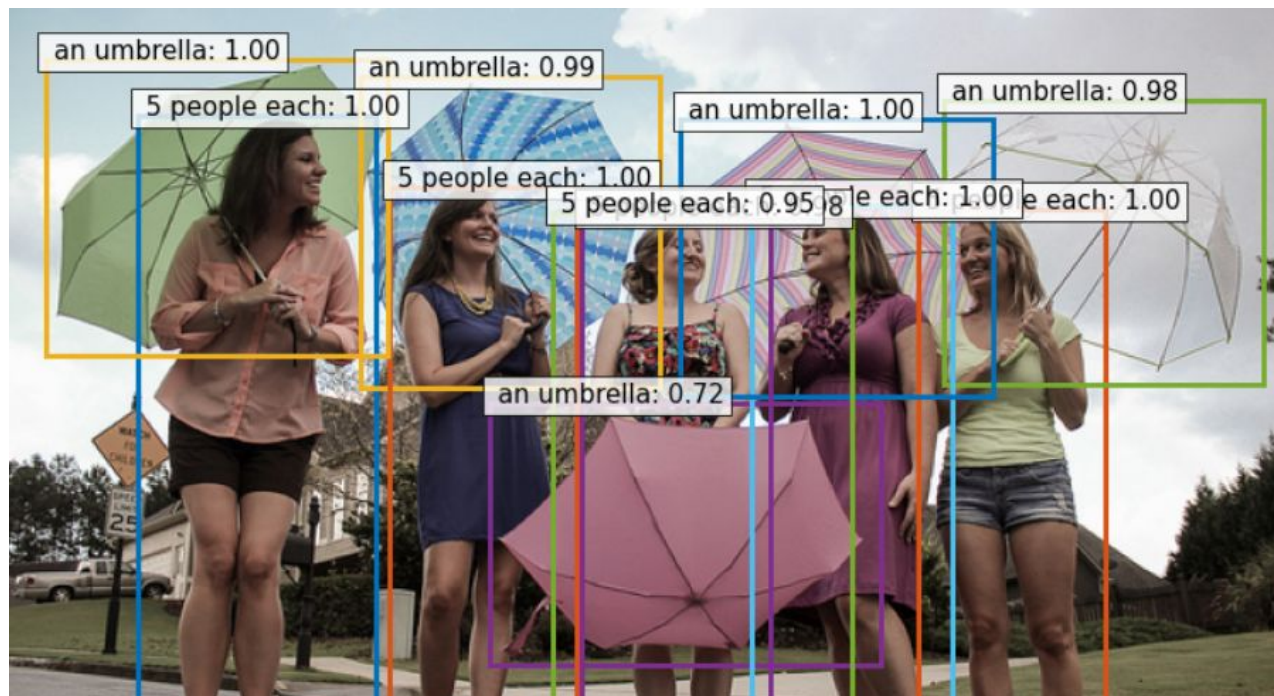
A dictionary is a hash table that's also a list.

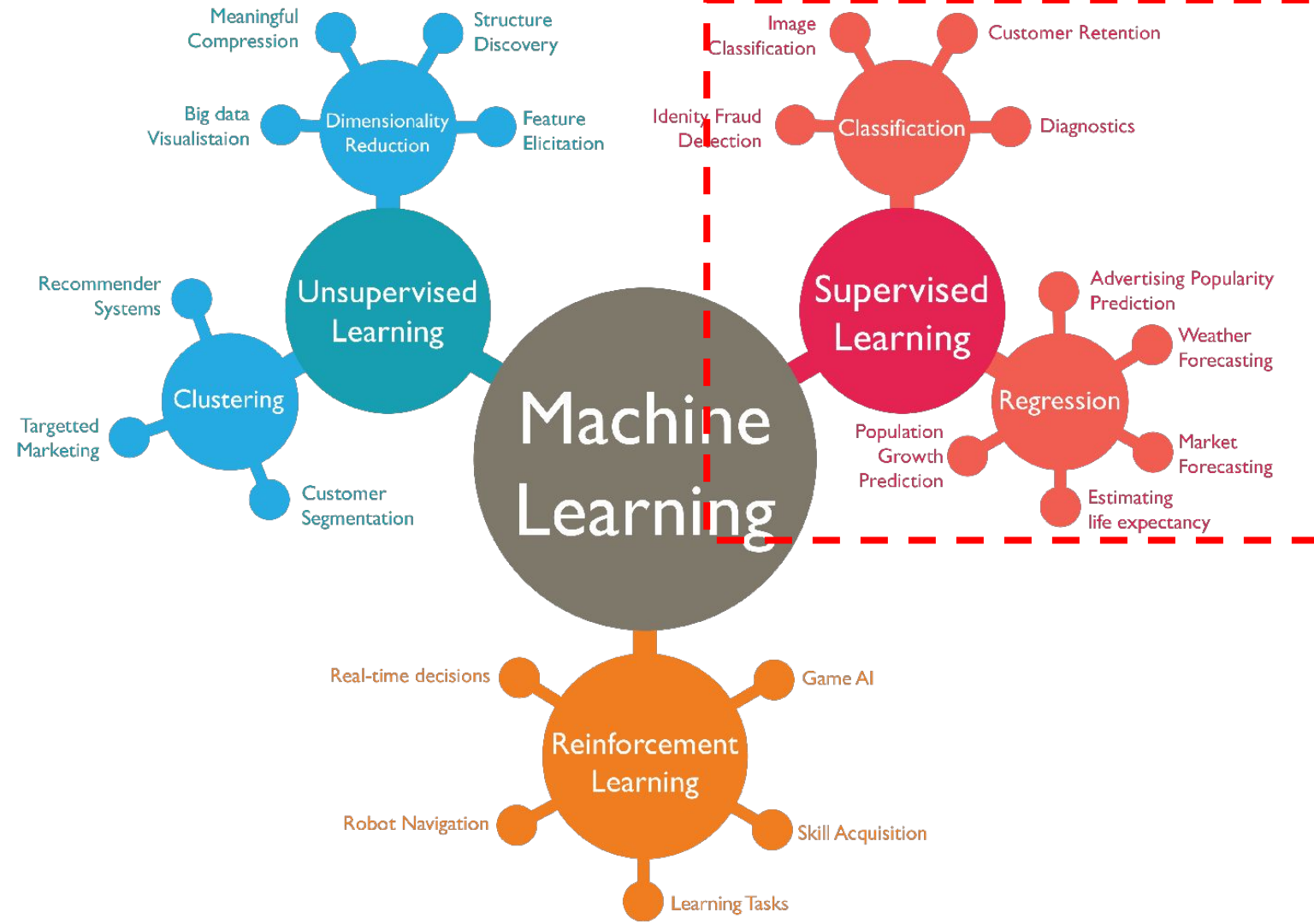
I'd say a dictionary is a hash table that can be accessed in $O(1)$ time.

MDETR - Modulated Detection for End-to-End Multi-Modal

Understanding Colab

`plot_inference(im, "5 people each holding an umbrella")`





História da Internet em 1969...



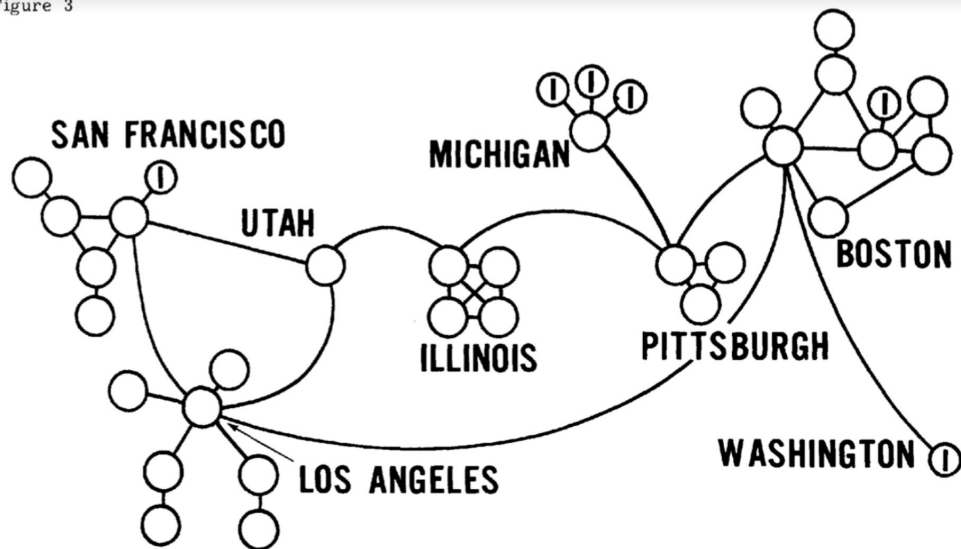
Um pequeno passo ...

grande salto...

Um grande salto....

1. Criação da Internet
2. Unix (Linux)
3. Linguagem C
4. Protocolo TCP/IP
5. CDC 7700

Figure 3

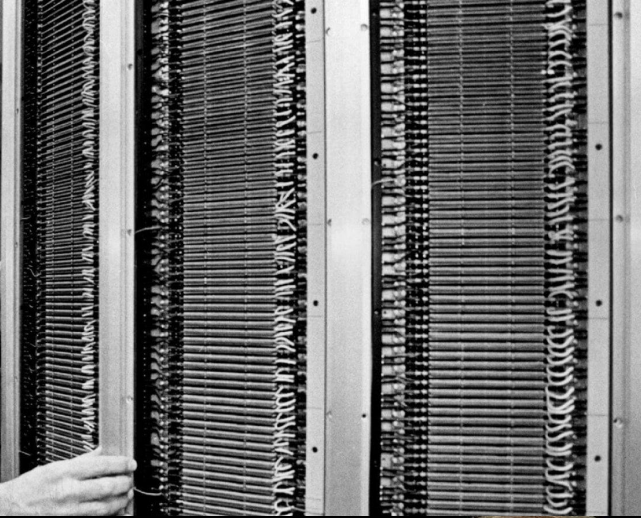


ARPA COMPUTER NETWORK*

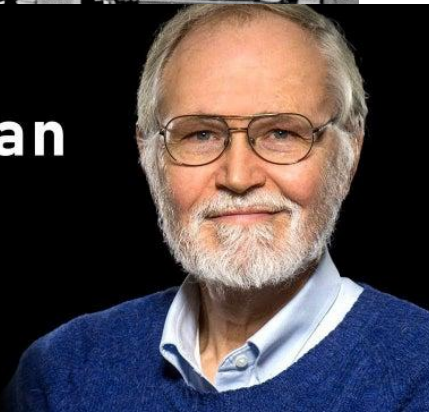
- REPRESENTS A TIME-SHARED COMPUTER
- Ⓜ REPRESENTS A SINGLE USER CONSOLE COMPUTER

* NOT FINAL, ESTIMATE AS OF JUNE 1967

Cientistas.....



**Brian
Kernighan**
#109
Lex
Fridman



O que é Internet das Coisas (IoT) ?

Linha Temporal

1969 - Internet, anos 80 com email,

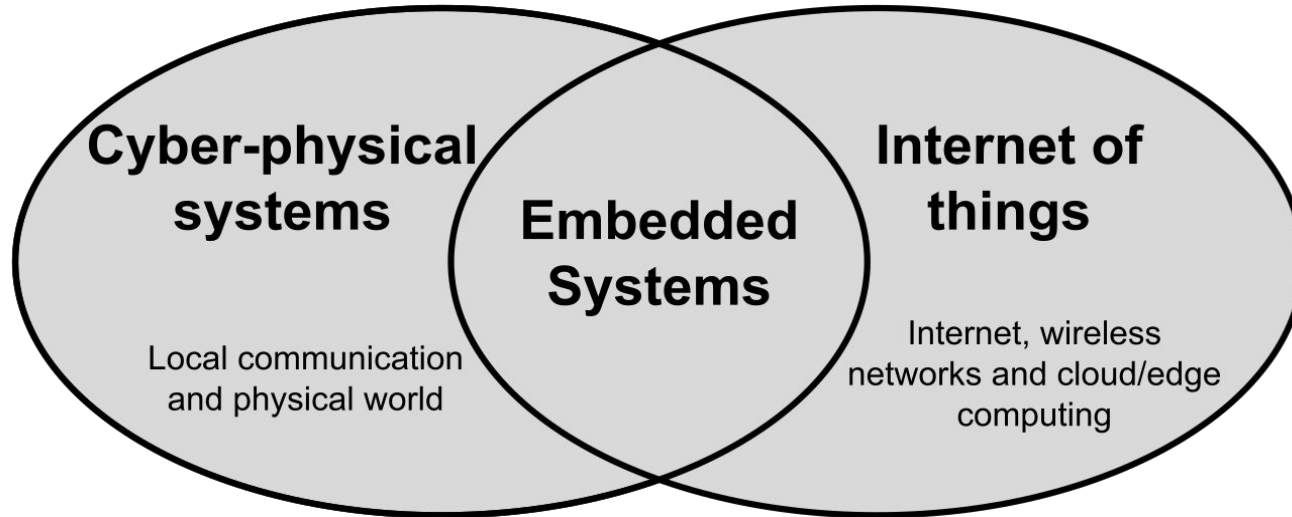
1985 - Termo IoT

Anos 90 - Navegadores e ferramentas de busca

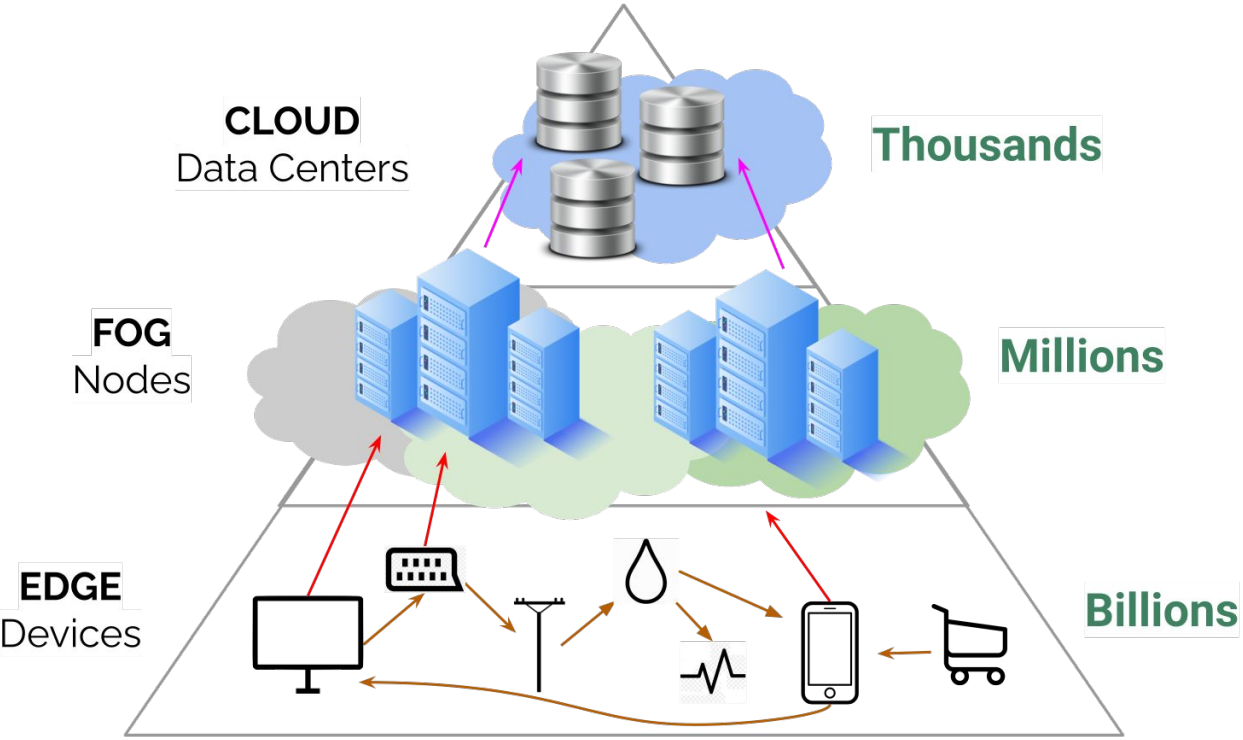
2000 em diante: Redes Sociais, Computação na Nuvem, Big Data, Ciência de Dados, Inteligência Artificial.....



O que é Internet das Coisas (IoT)



Paradigmas



Camadas

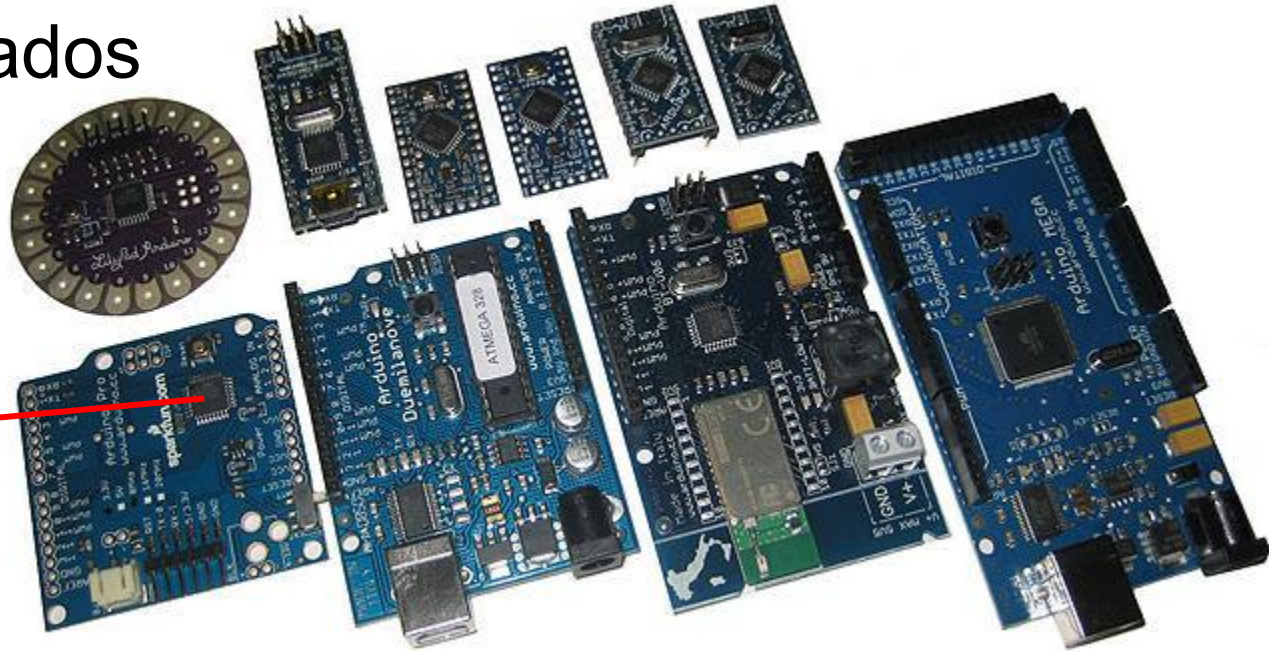
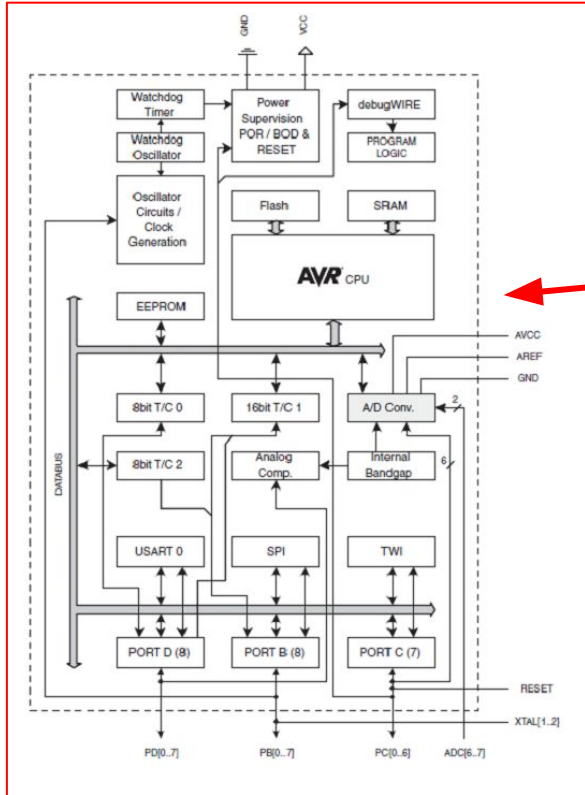
1. **Aplicação**

2. **Rede (network)**

3. **Percepção**

Percepção

Sistemas Embarcados



Tudo integrado em um único circuito

Processador, Memória, Conversores Analógicos, Temporizadores, Interfaces de Comunicação (SPI, I2C, Serial)

Popularização com Arduino = simplicidade

Microcontroladores existem desde 1971.....TMS1000 da Texas, 8048 da Intel

2003 Linguagem Wiring (simples, semelhante a linguagem C)

Ambiente de Programação e as Placas


2004 Arduino = Gerou uma “**padronização**”

Vantagens: Baixo Custo, Popularidade, Simplicidade, Conectividade, Muitas aplicações, baixo consumo, suporte

Desvantagens: baixo poder de processamento

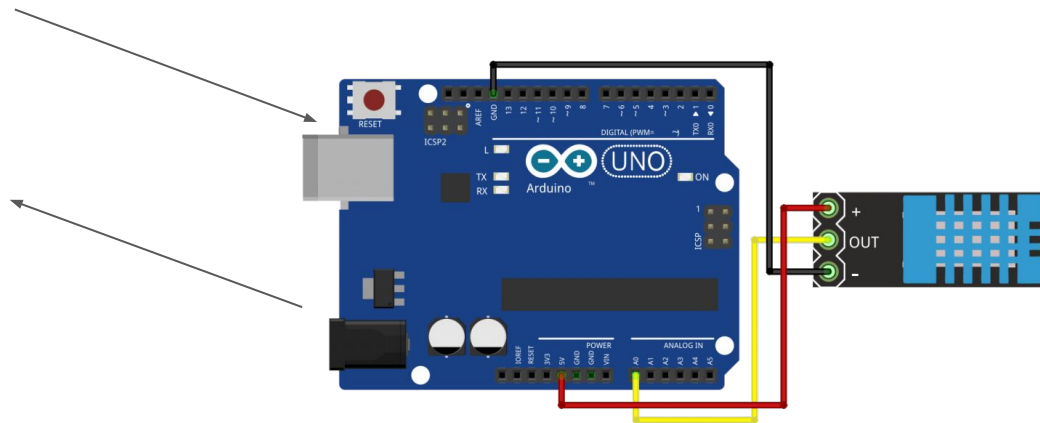
Arduino

Ambiente Simples de Programação, gravação no Arduino e Comunicação para teste, vários exemplos



```
sketch_jan04a | Arduino 1.8.5
File Edit Sketch Tools Help
sketch_jan04a$
void setup() {
  // put your setup code here, to run once:
}
void loop() {
  // put your main code here, to run repeatedly:
}
1 Arduino/Genuino Uno on COM1
```

Muitos sensores e atuadores no Mercado com baixo Custo e fáceis para conectar e testar.



Como começar e onde aprender mais ?

Em inglês 4 canais do Youtube com explicações detalhadas e técnicas de vários projetos, sensores, placas de desenvolvimento

https://www.youtube.com/channel/UCu7_D0o48KbfhpEohoP7YSQ - Andreas Spiess

https://www.youtube.com/channel/UC8Ob-HnnmhlgSv5Vs_i32TQ - Ralph S Bacon

<https://www.youtube.com/user/kdarrah1234> Kevin Darrah

<https://www.youtube.com/channel/UCzml9bXoEM0itbcE96CB03w> - **DroneBot**

<https://www.youtube.com/user/greatscottlab>

<https://www.youtube.com/user/julius256>

Qual é o melhor dispositivo ?

Arduino **Uno**: 2KiB, 16 Mhz, 20 Pinos,

Arduino **Mega**: 70+ pinos,

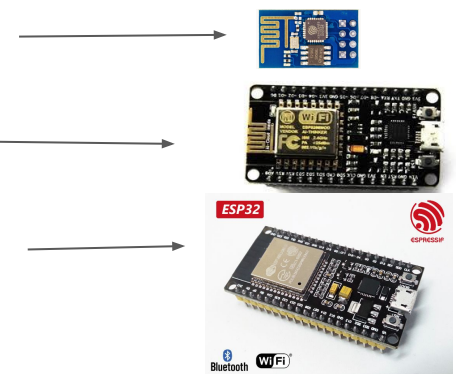
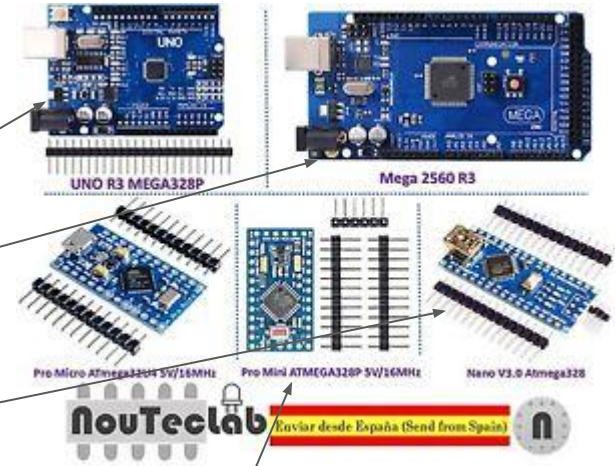
Arduino **Nano**: pequeno, 20 pinos

Arduino **ProMini**: , produto, sem gravador e regulador

Esp8266: wifi 2 pinos, 3 Mega, 80 Mhz, 3,3 volts

NodeMCU: Wifi, 14 pinos, 3,3 volts,

Esp32: 160 Mhz, Wifi, baixo consumo, 3,3 volts,

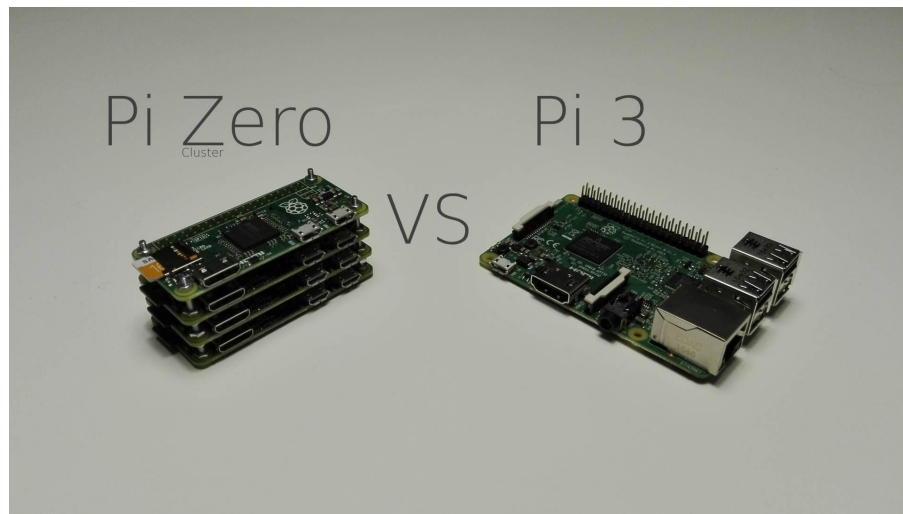


Outras opções

Raspberry Zero = Computador, 512 Mega RAM, 1 Ghz

Raspberry Pi 4 = Computador, 4 Giga RAM,

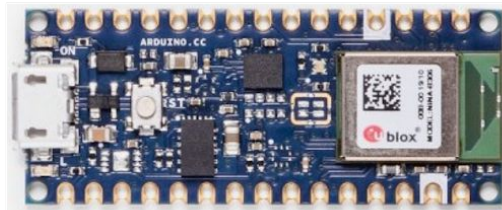
+energia, muitos pinos, camera, processamento, wifi , mais frágil



Existem muito mais opções...
Apenas apresentamos as mais populares....

Outras opções

M5stickV

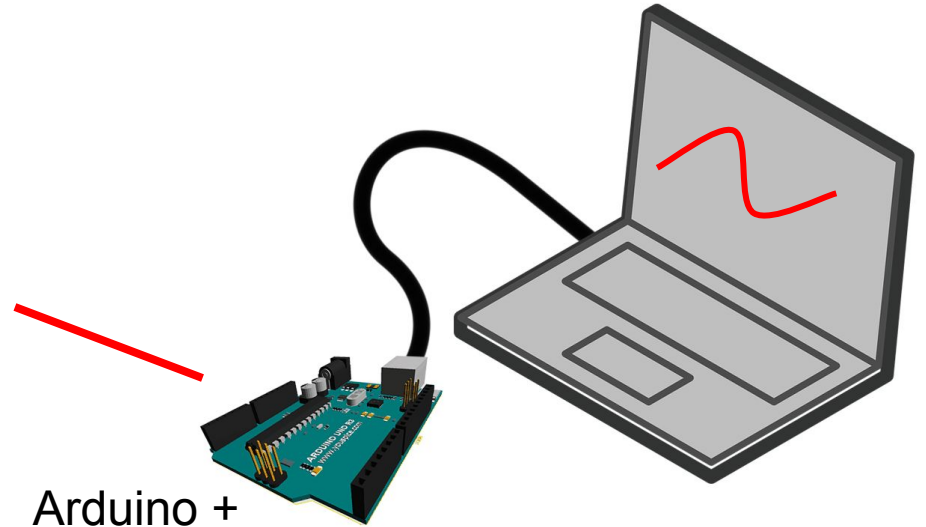


Arduino nano 33



Maix Amigo

Sensores e Atuadores - Ambiente de laboratorio

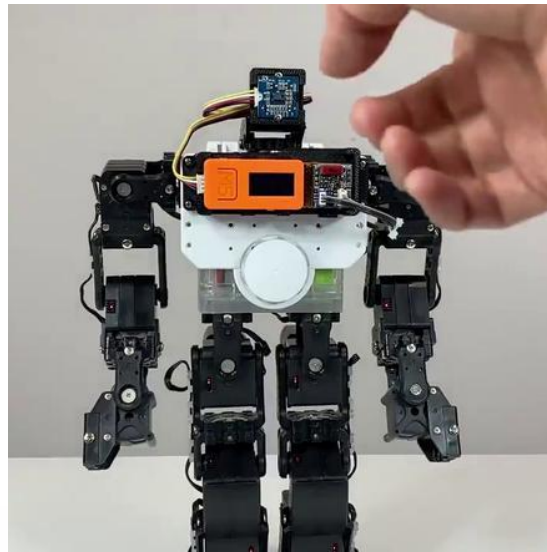


Arduino +
computador (visualizar, armazenar dados,
Enviar comandos).

Sensores e Atuadores com M5stack



Outras opções Para pesquisa



M5 CHALLENGE
ATOMFLY
Open Source Development Kit

CHALLENGE!
NO
Flying-Demo-Code

ATOM LITE (include)

ESP32

BMP280

200mAh /25C

ToF VL53L0X

6DOF MPU6886

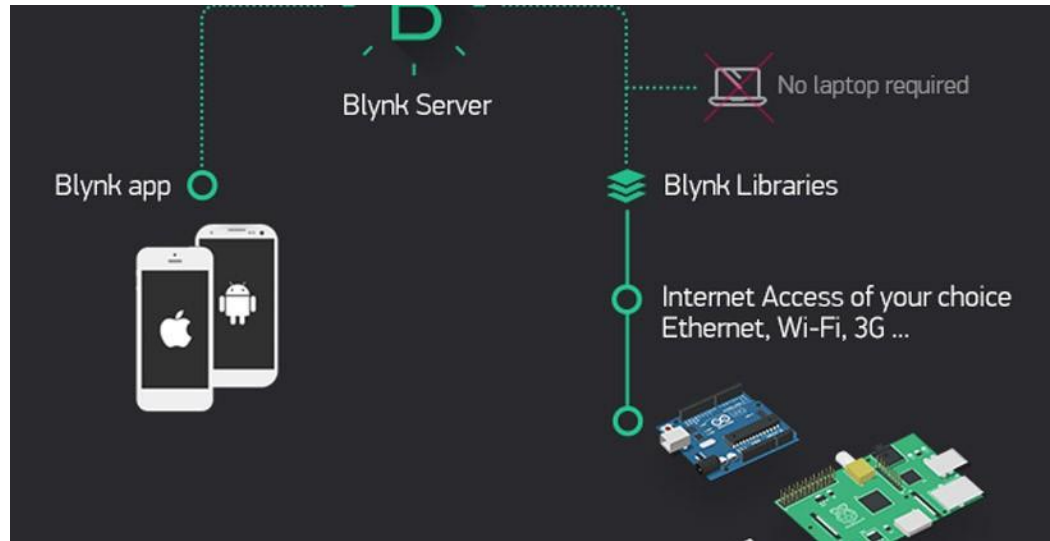
SCL:21
SDA:25
PWM1:22
PWM2:19
PWM3:23
PWM4:33

I2C
INTERFACE

Charger

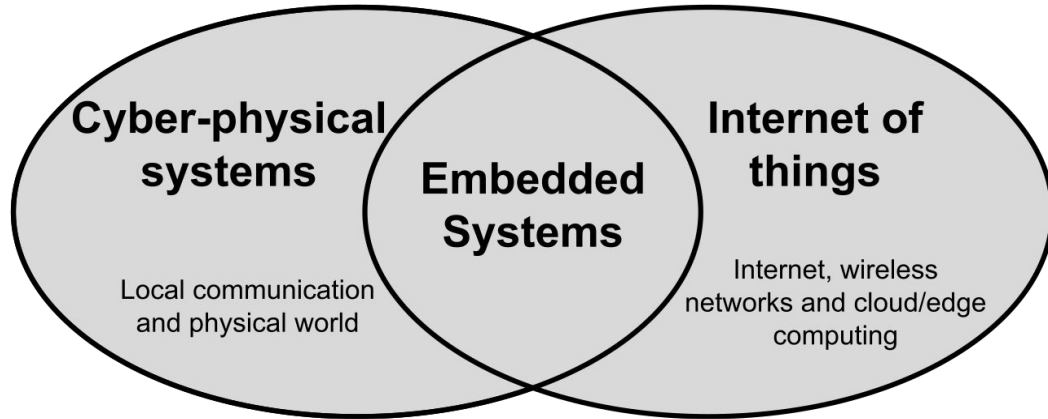
A collection of components for the M5 Challenge Atomfly kit, including a drone, a battery, a charger, and various sensors. The components are arranged in a circular pattern around the drone, which is the central focus of the image.

Sensores e Atuadores + Arduino + blink.....



Versão Gratuita APENAS 1 celular pode ficar configurado para controlar.....

Camada de Rede (Network)

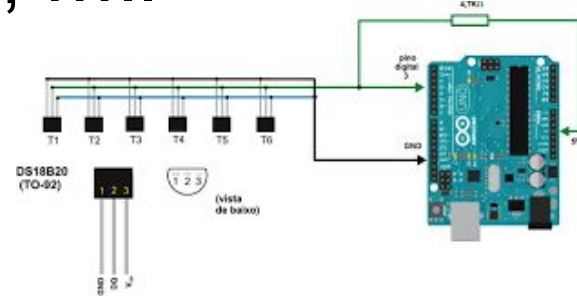


Sensores com Fios e seus Protocolos

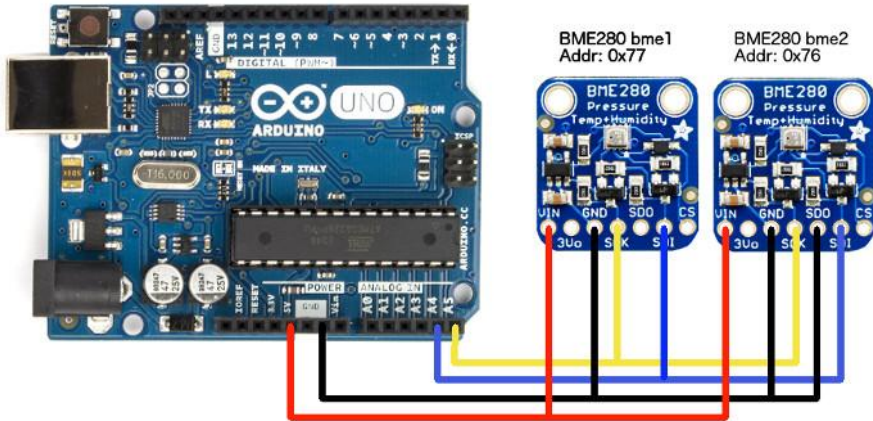
Sensores e Atuadores + Arduino + poucos fios com protocolos seriais: I2C, OneWire, SPI,

Pode ter os três ligados comunicando com Sensores de diversos fabricantes....
Arduino 20 pinos de Entrada/Saída

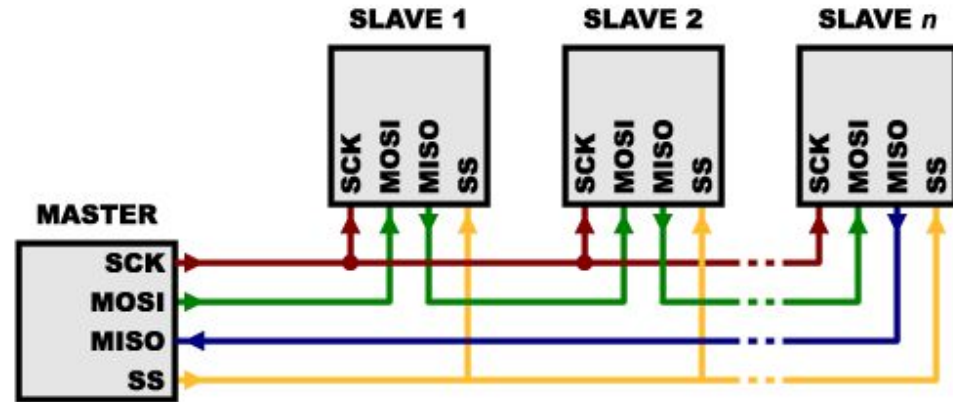
OneWire: +, - e 1 fio



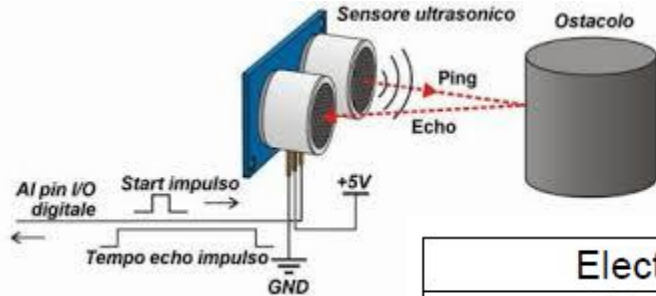
I2C: +, -, 2 fios



SPI: +, -, 3 fios + 1 fio para cada sensor



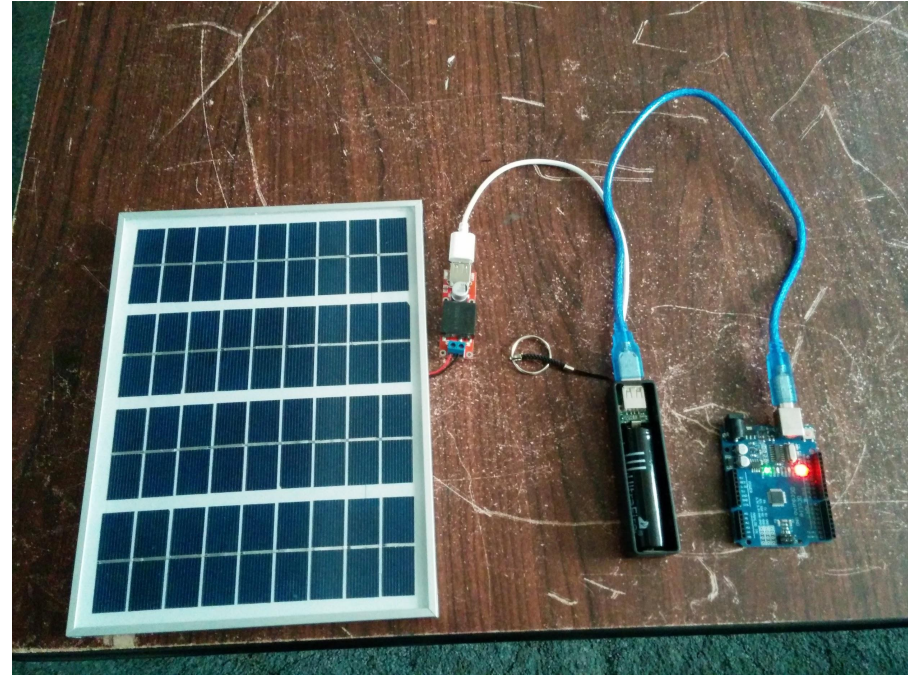
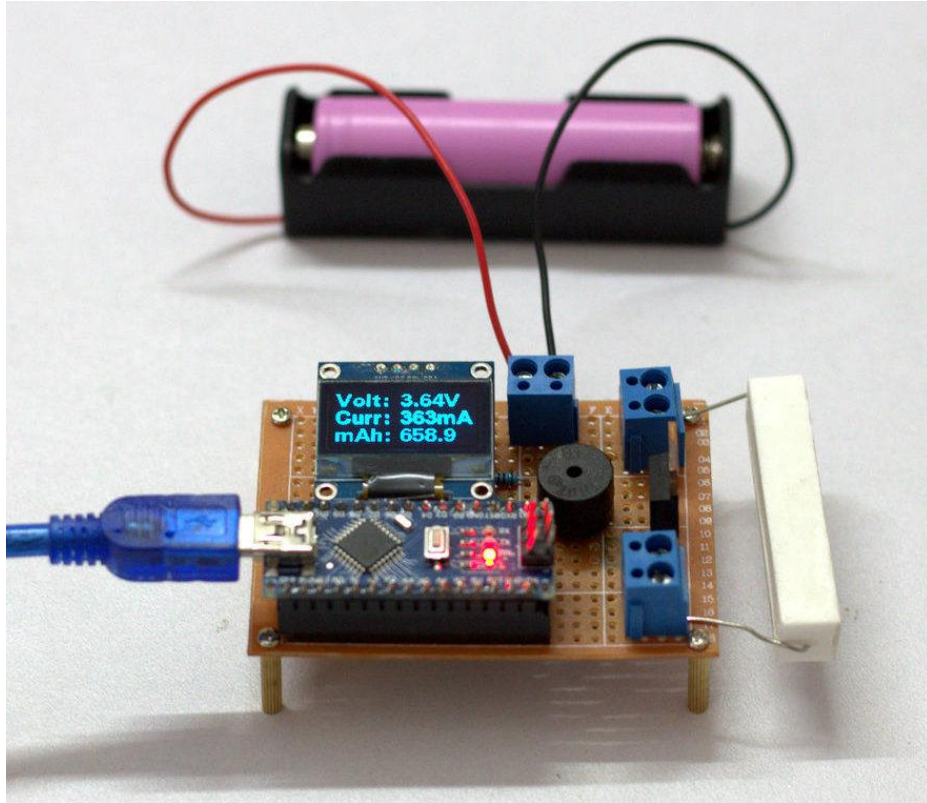
Sensor de distância



Electrical Parameters	HC-SR04 Ultrasonic Module
Operating Voltage	DC-5V
Operating Current	15mA
Operating Frequency	40KHZ
Farthest Range	4m
Nearest Range	2cm
Measuring Angle	15 Degree
Input Trigger Signal	10us TTL pulse
Output Echo Signal	Output TTL level signal, proportional with range
Dimensions	45*20*15mm

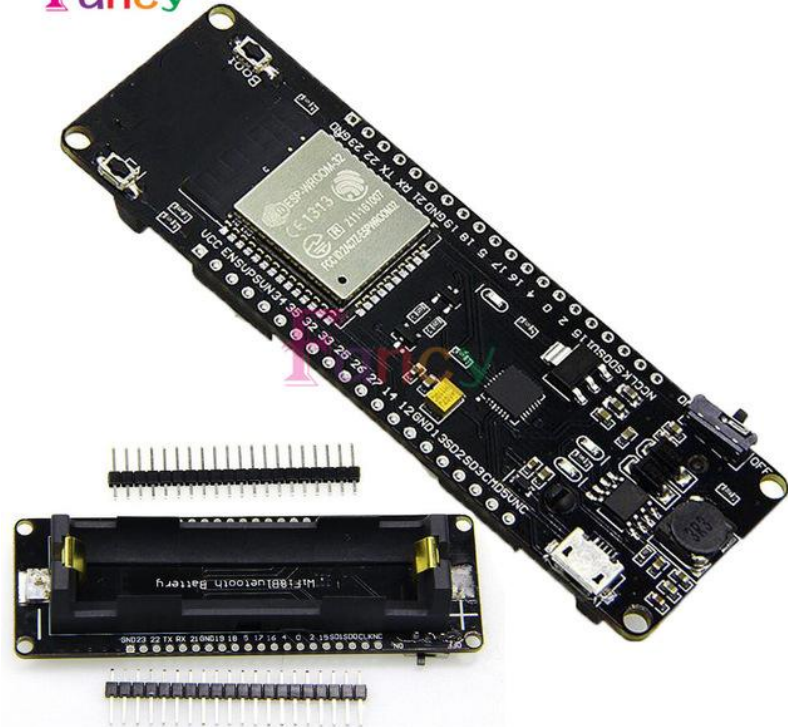
Energia Solar e Pilhas de Litio

Com Bateria - Sugestão 18650 Litio



ESP32 (wifi, bluetooth, sensores capacitivos, low power)

Fancy



In:3V-35V



Out:4-35V

Comunicação sem Fio

Rede local de vários “arduinos”

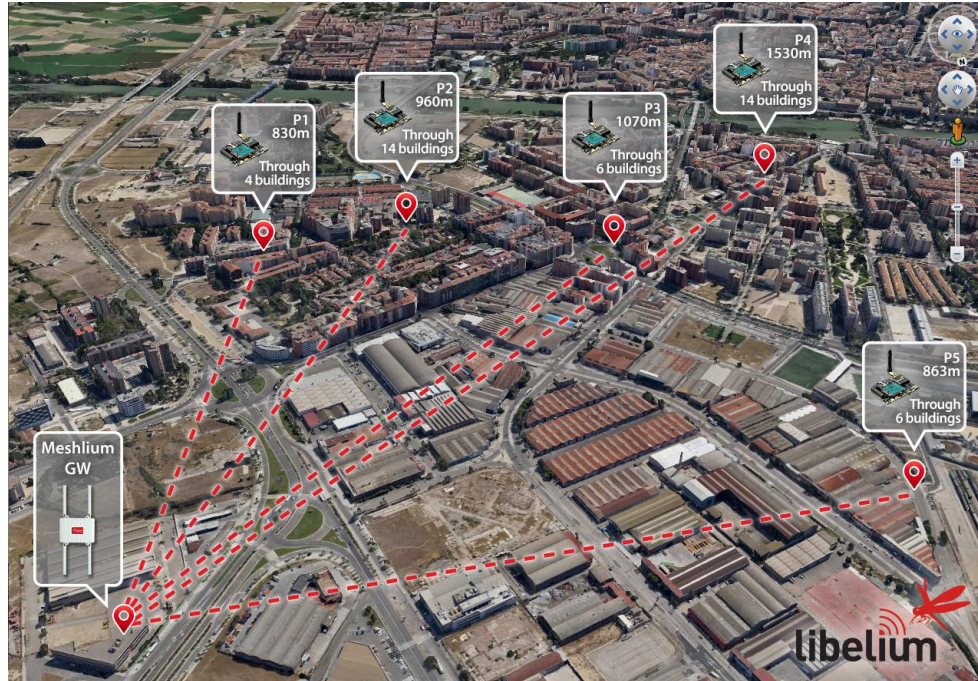
Rádios de baixo custo = Rede Local e conexão com internet em um dos pontos

NRF 24L01

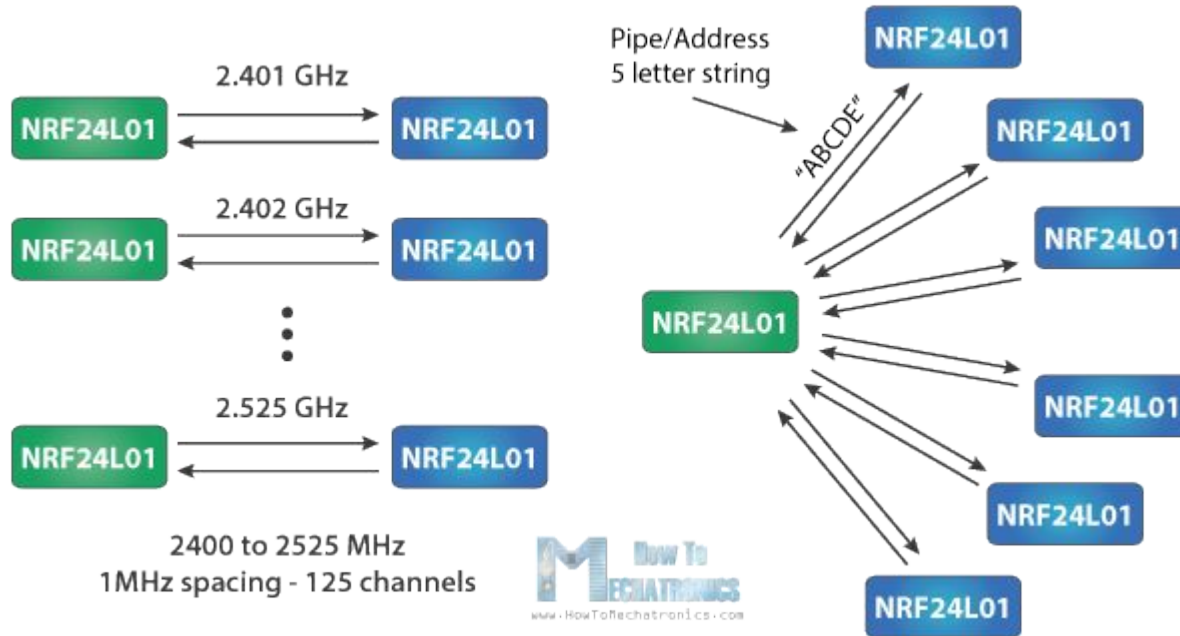
HC12

Lora

ZigBee



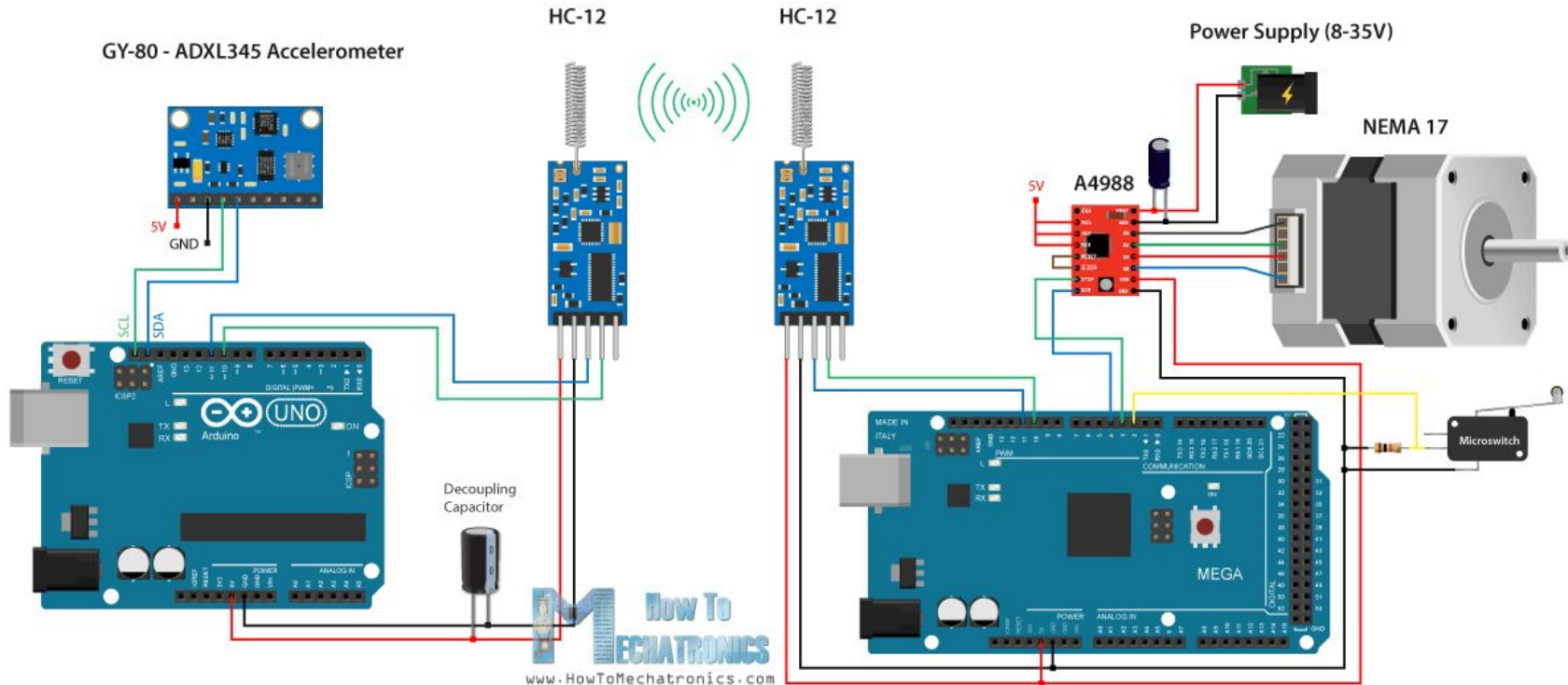
NRF24L01 -.....distância de 10 a 100m....ou mais...pode interligar 3125 pontos !



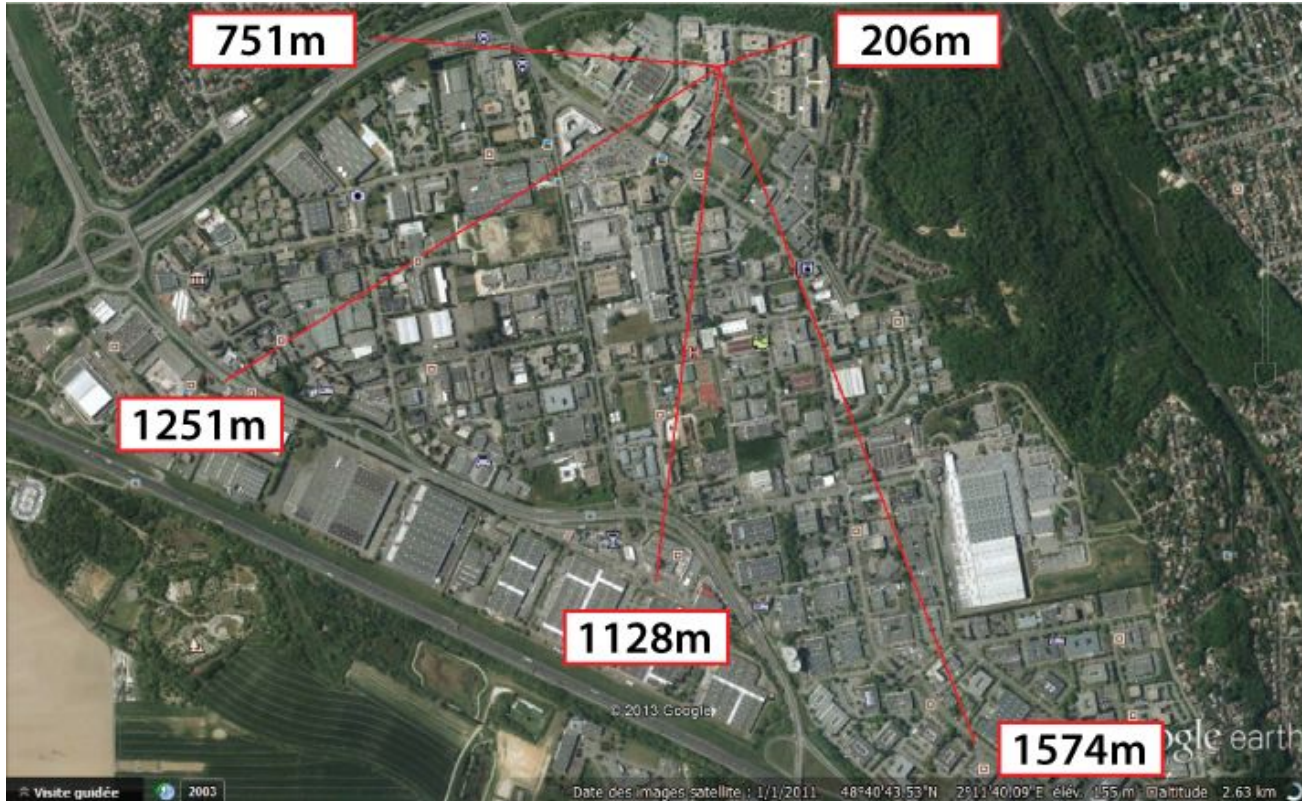
0.1 mA enviar, 14mA receber

HC12 400m a 2 Km....

HC-12 Wireless Communication: Stepper Motor Control using an Accelerometer



LoRa (Long Range)



DORJI
Applied Technologies
DRF1278DM
Spread Spectrum
data module

July 2014

Features

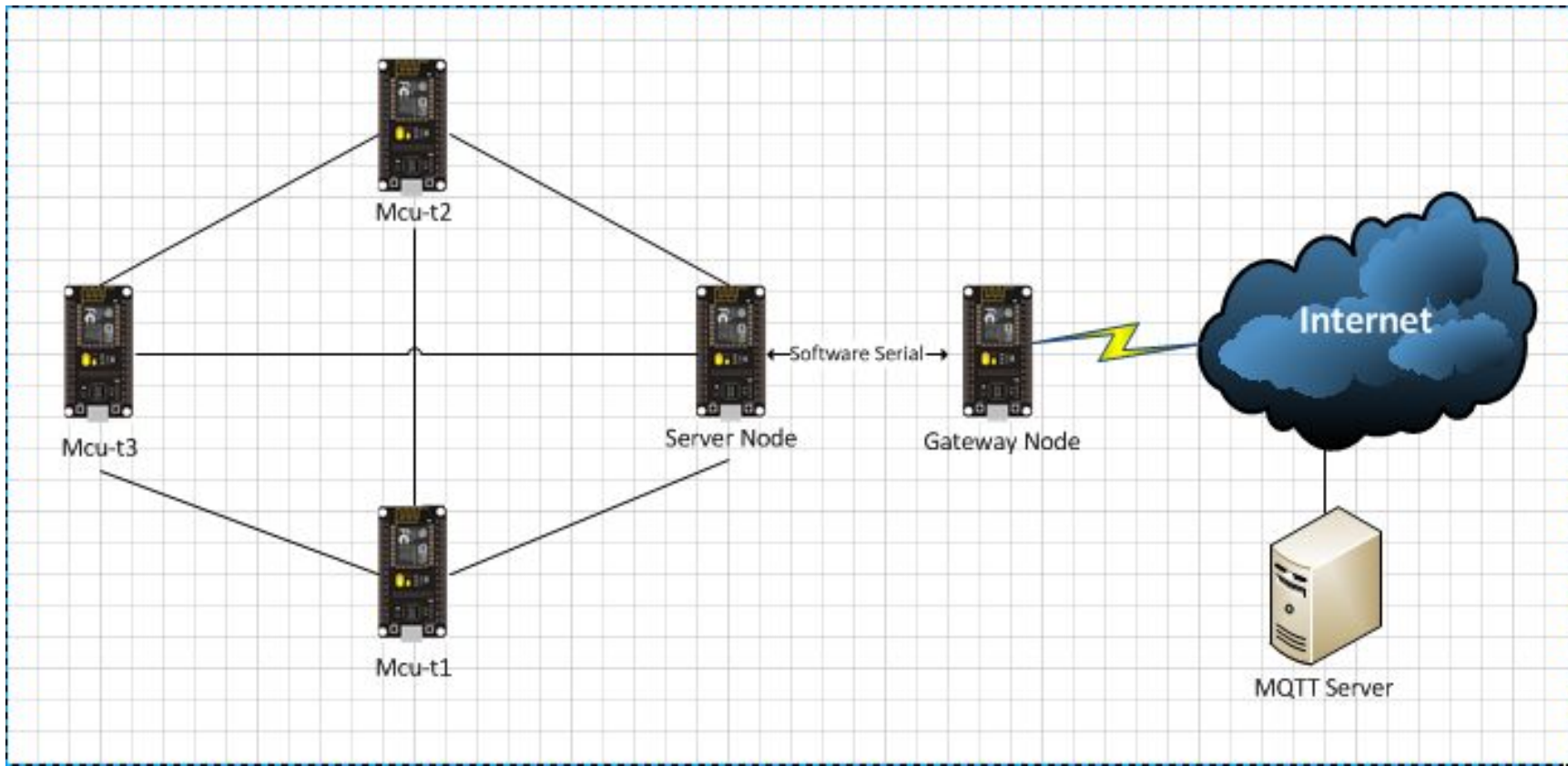
- LoRa™ Frequency Spectrum
- 433Mhz ISM frequency band
- 136dBm receive sensitivity
- 20dBm Max. output power
- Serial port wake-up
- Wireless wake-up
- Star networking ability

High level configure with DAC02 USB-TTL adapter, or low level via micro

PIN	DIP-A	Function	Description
1	GND	Ground	Ground(0V)
2	VCC	Power	Power supply (supply voltage 3.4-5.5 V)
3	EN	Input	Enable pin, Low effective
4	RXD	Input	RXD: UART input, TTL level
5	TXD	Output	TXD: UART output, TTL level
6	AUX	Output	Data indication pin for waking up module
7	SET	---	Reserved

Refer data => www.dorji.com/docs/data/DRF1278DM.pdf

Rede Mesh de Esp8266



Protocolos alto Nível: MQTT e CoAP

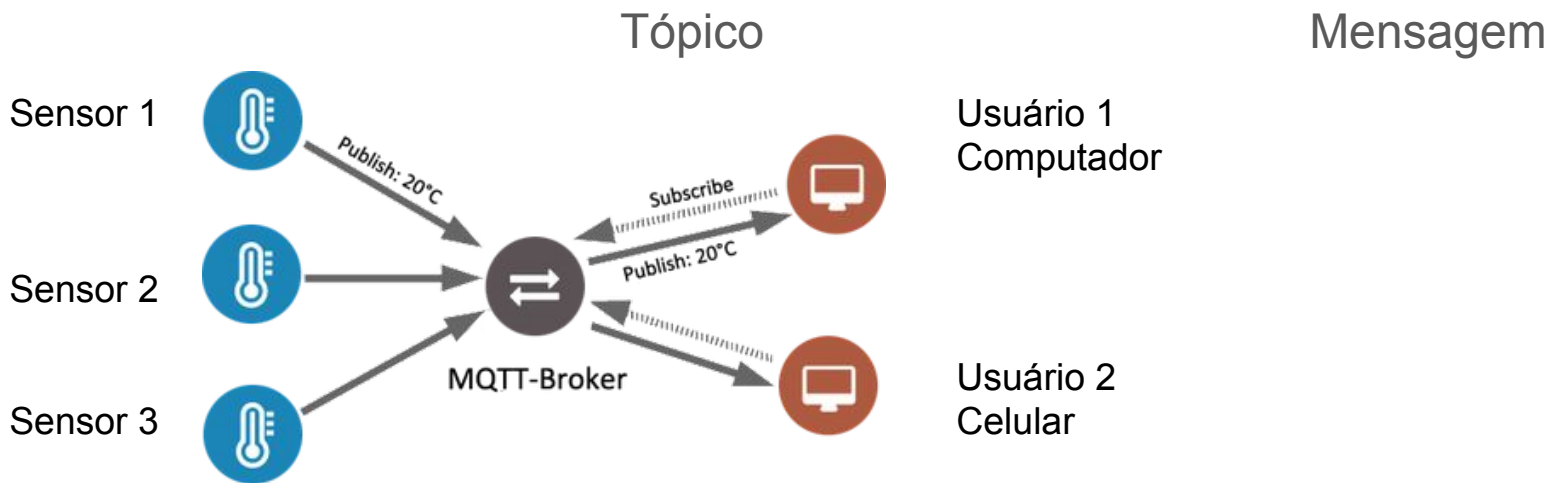
MQTT

Trocando mensagens de Texto entre os dispositivos

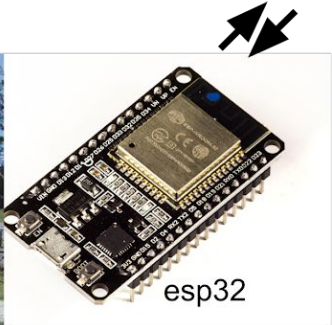
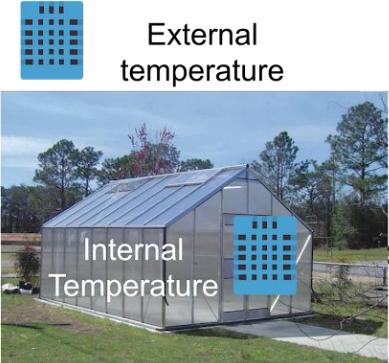
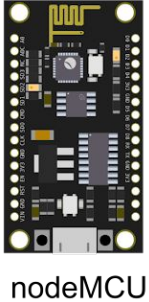
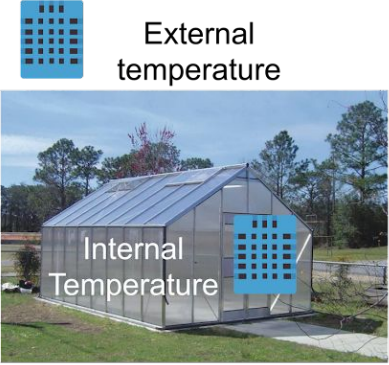
Assinar (**subscribe**) /ufv/floresta/1andar/sensores

Publicar (**publish**) /ufv/floresta/1andar/sensores/temperatura

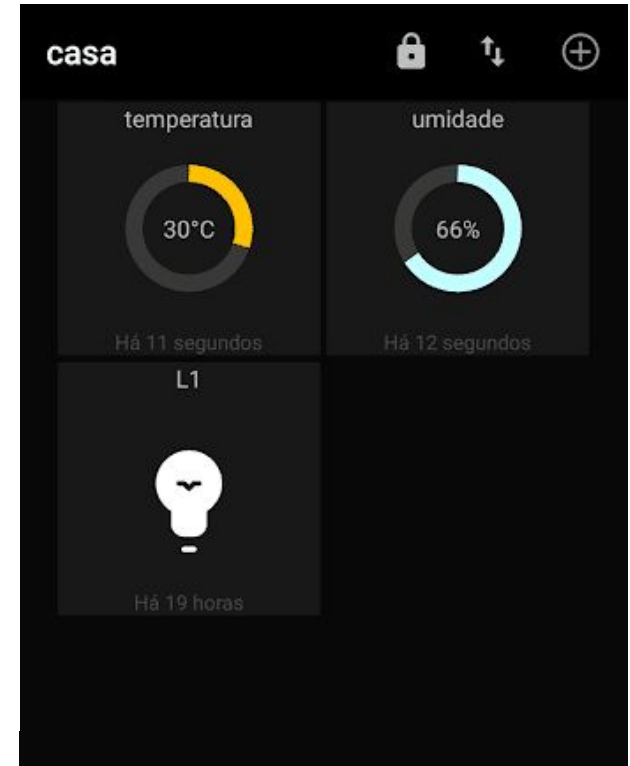
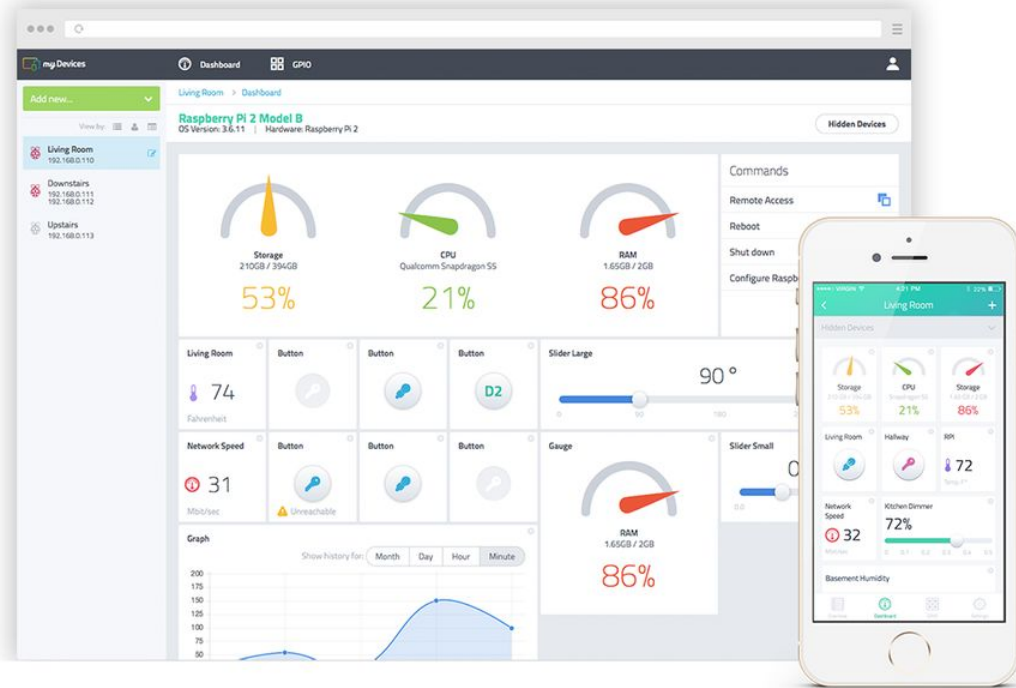
25



MQTT



Internet das Coisas e Mqtt



Internet das Coisas e Mqtt

<

Connection: HiveMQ local

Subscribe

Topic QoS

test/mqtt/topic/1 2 - exactly once Subscribe

Publish

Topic QoS

test/mqtt/topic/1 1 - at least once Publish

Message

Hello MQTT!

Subscriptions

Topic: "test/mqtt/topic" Showing the last 1 messages Messages: 0/1

#	Time	Topic	QoS
0	3:07:41	test/mqtt/topic	1

Message: Hello MQTT!

Topic: "test/mqtt/topic/1" Showing the last 3 messages Messages: 15/15

test.mosquitto.org
1883

- Dashboard
48 notifications
- Subscribe
2 subscriptions
- Publish
- Stored Messages
0 stored messages
- Settings

The diagram illustrates the MQTT architecture. A central MQTT-Broker is connected via wifi to two Sensors and two Browsers, and one Mobile device. Arrows indicate 'subscribe' and 'publish' actions between the broker and each device.

Internet das Coisas e Serviços



Ubidots

Botões,...
Gráficos....
EMAIL !
SMS !

Gratis 1 dispositivo

Exportar dados,...

Simple

Internet das Coisas e Serviços



Ubidots

Botões,...
Gráficos....
EMAIL !
SMS !

Gratis 1 dispositivo

Exportar dados,...

Simple

Internet das Coisas e Serviços (restrições na opção gratuita)

Ubidots - <https://ubidots.com/stem/>

Thingspeak - <https://thingspeak.com/>

Blynk - <https://www.blynk.cc/>

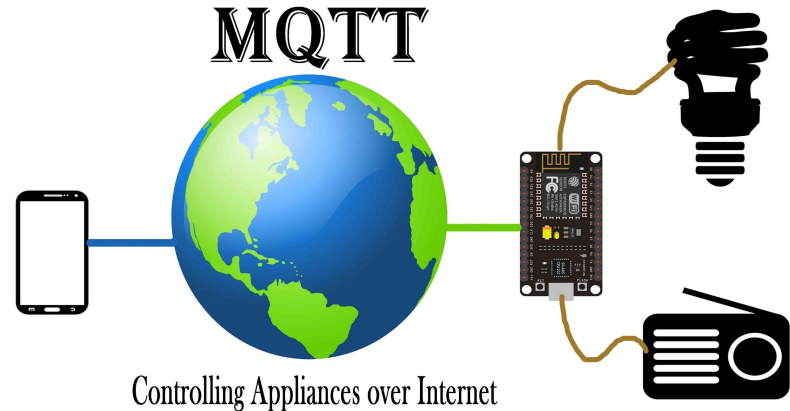
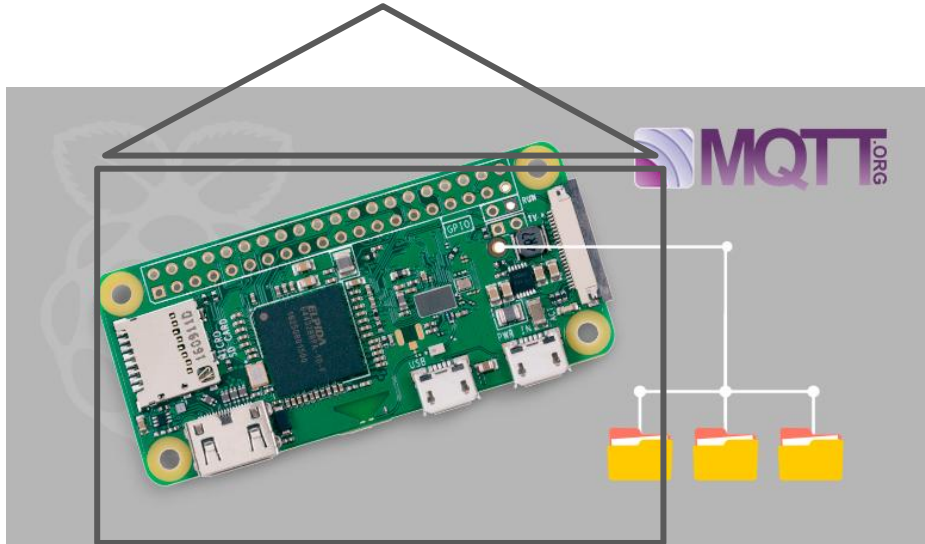
Arest - <https://arest.io/home>

Serviços com conta e restrições de uso, fáceis e possuem muitos exemplos....

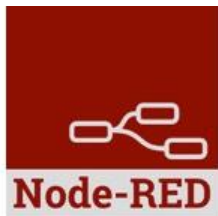
Internet das Coisas e seus próprios Serviços

Usar um Computador ou Raspberry para servidor MQTT (PI zero)

Usar um broker público sem limitações com Mqtt, aplicativos de Mqtt no celular



NodeRed IBM muitas opções



Dashboard UI



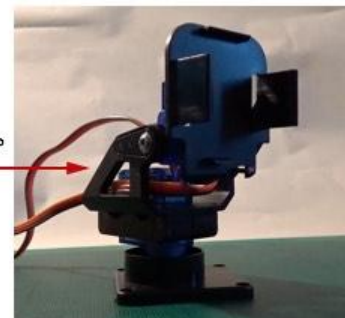
Flow Node-RED



servo/tilt



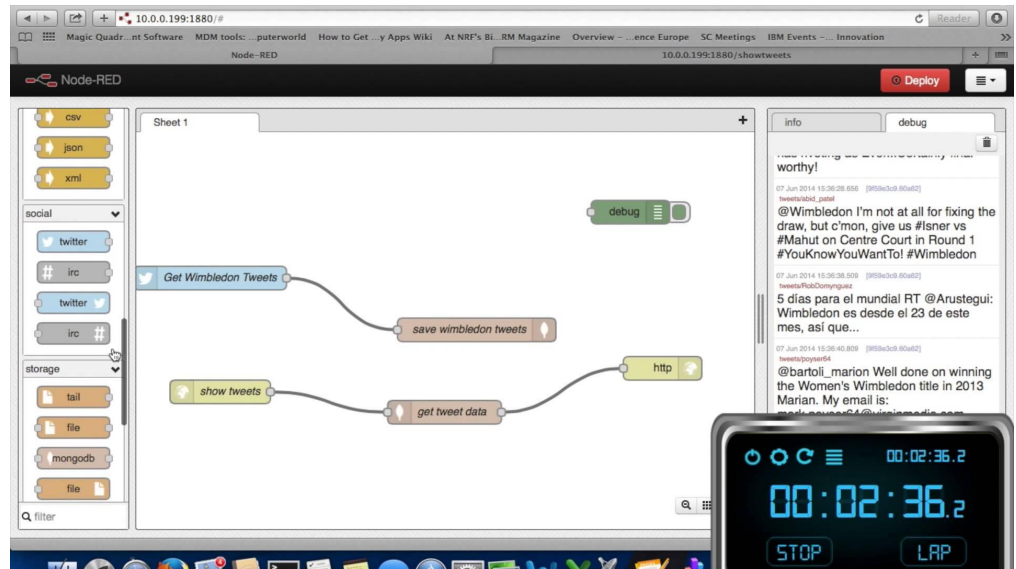
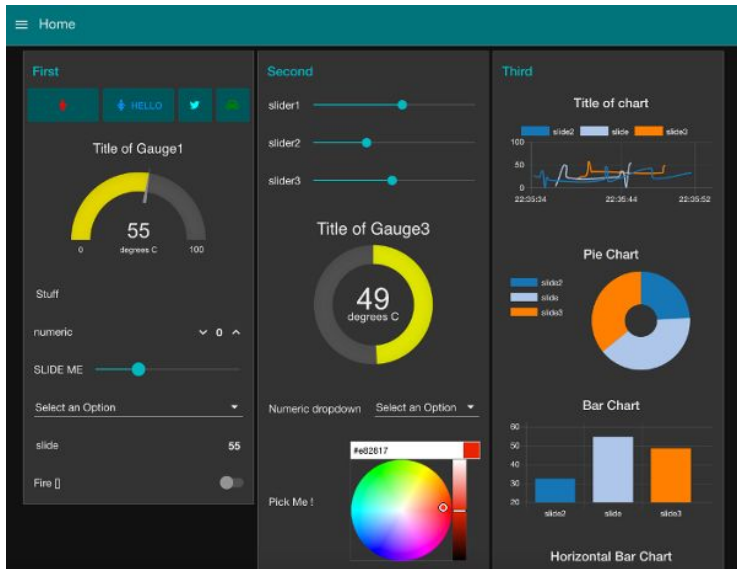
90°



NodeRed

Executar em um computador ou um Raspberry

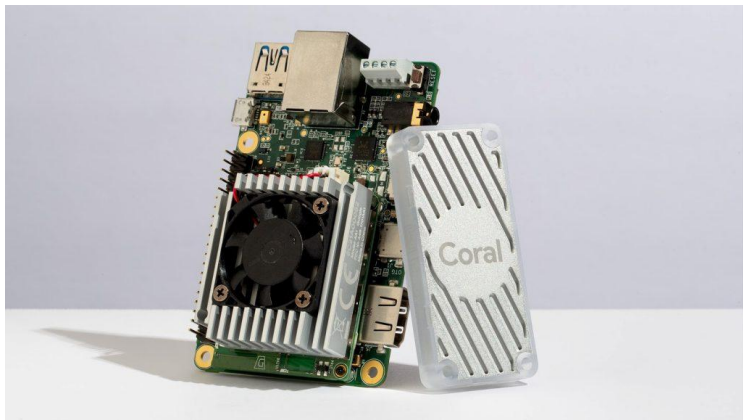
Conectar com Mqtt e vários “arduinos”, Twitter, Email, banco de dados, ...



Como usar IA e Internet das Coisas ?

1. Soluções U\$ 100 com processamento + consumo
2. Soluções U\$ 10-40 com processamento
3. Soluções U\$ 1-5 com Coleta e Envio

Soluções U\$ 100 com processamento + consumo



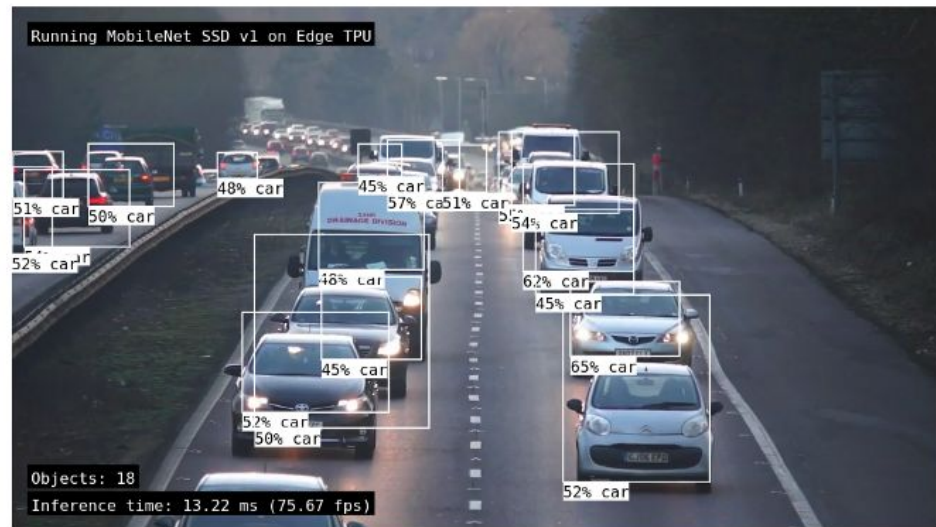
Coral Google

Coral

Edge TPU Performance Demo

The video below demonstrates the realtime processing power of the Edge TPU by running a MobileNet SSD model that can identify and classify multiple objects. The footage of the cars is a recording, but the MobileNet model is executing in realtime on your Coral Dev Board to detect each car indicated with a box (limited to 20 detected cars).

In the terminal where you started the demo, press the N key to switch between running the model on either the Edge TPU or the CPU (quad-core Cortex-A53).



Soluções U\$ 100 com processamento + consumo

Jetson Nano e
Xavier **Nvidia**

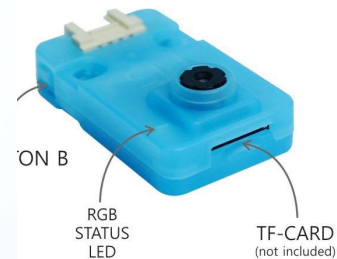
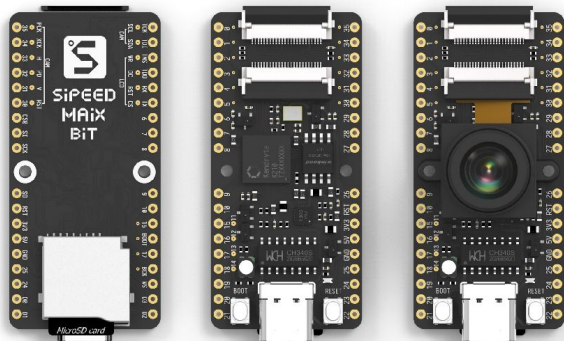
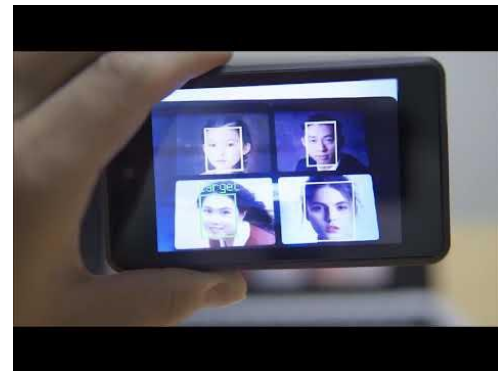
Outros: Intel Open Vino,
Raspberry Pi4,



Soluções U\$ 10-40 com processamento



Processador K210
Maix Amigo, Maix Bit, M5stickV,
unitV, maix cube,



helloworld_1.py - MaixPy IDE


File Edit Tools Window Help

helloworld_1.py* Line: 25, Col: 1 Frame Buffer Record Zoom Disable

```

1 # Hello World Example
2 #
3 # Welcome to the MaixPy IDE!
4 # 1. Connect board to computer
5 # 2. Select board at the top of MaixPy
6 # 3. Click the connect button below
7 # 4. Click on the green run arrow butto
8
9 import sensor, image, time, lcd
10
11 lcd.init(freq=15000000)
12 sensor.reset()
13
14 sensor.set_pixformat(sensor.RGB565)
15 sensor.set_framesize(sensor.QVGA)
16 sensor.skip_frames(time = 2000)
17 clock = time.clock()
18
19 while(True):
20     clock.tick()
21     img = sensor.snapshot()
22     lcd.display(img)
23     print(clock.fps())
24
25

```



Frame Buffer

Histogram RGB Color Space

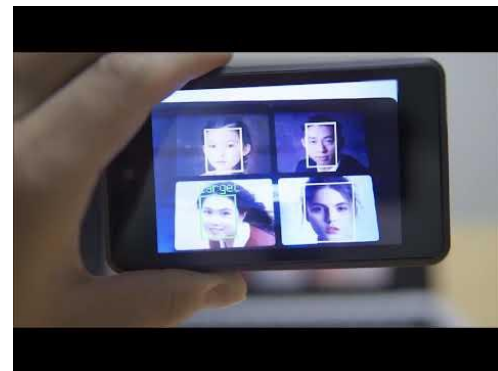
Res (w:320, h:240)

Mean 139 Median 156 Mode 165 StDev 48
 Min 0 Max 255 LQ 115 UQ 173

Mean 136 Median 150 Mode 154 StDev 44
 Min 16 Max 255 LQ 105 UQ 166

Mean 134 Median 148 Mode 148 StDev 49
 Min 0 Max 255 LQ 90 UQ 173

Search Results Serial Terminal Firmware Version: 0.3.1 Serial Port: ttyUSB0 FPS: 9.6



maix
ide

```
task = kpu.load(0x300000)
```

```
anchor = (1.889, 2.5245, 2.9465, 3.94056, 3.99987, 5.3658, 5.155437,  
6.92275, 6.718375, 9.01025)
```

```
a = kpu.init_yolo2(task, 0.5, 0.3, 5, anchor)
```

```
while(True):
```

```
    img = sensor.snapshot()
```

```
    code = kpu.run_yolo2(task, img)
```

```
    if code:
```

```
        for i in code:
```

```
            print(i)
```

```
            a = img.draw_rectangle(i.rect())
```

```
    a = lcd.display(img)
```



Soluções U\$ 1-10 com Coleta e Envio



\$9 ESP32 CAM

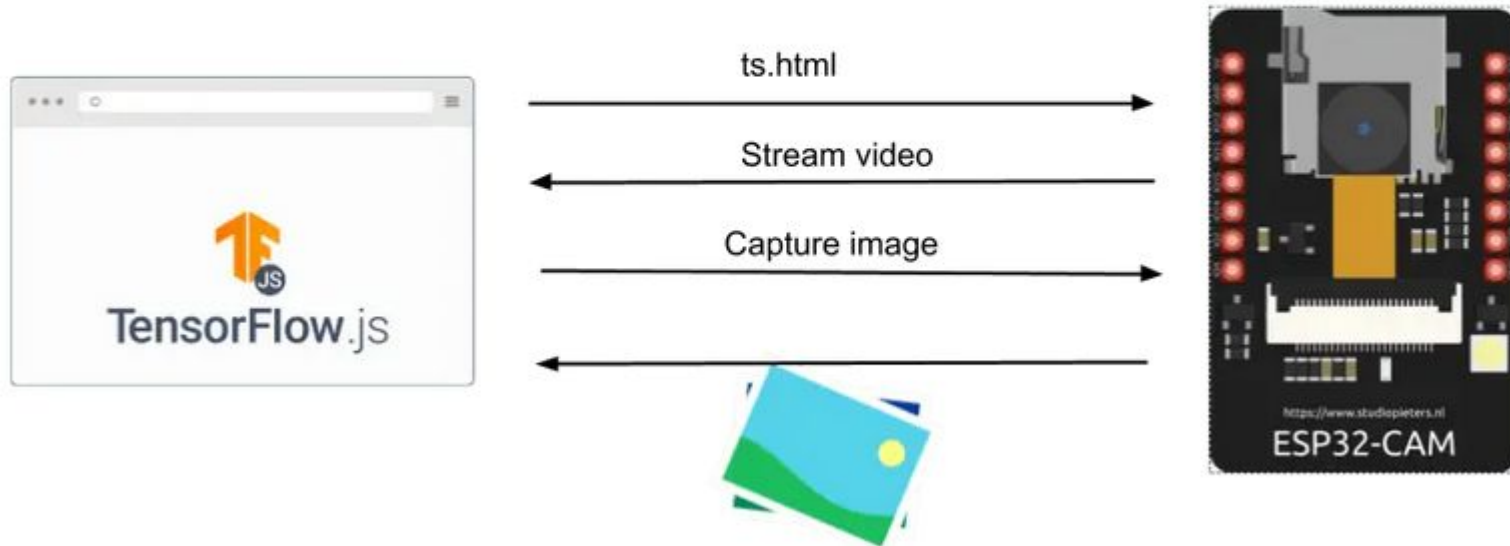


U\$ 1-10 - Capture data

[tensorflow.js](https://www.tensorflow.org/js)

Project overview

This image below describes how to integrate ESP32-CAM with TensorFlow.js:



U\$ 1-10 - Capture data

[tensorflow.js](https://www.tensorflow.org/js)

TensorflowJS with ESP32-CAM



volleyball - 0.9684472680091858
soccer ball - 0.021350480616092682
tennis ball - 0.0031732707284390926

Classify the image

TensorflowJS with ESP32-CAM



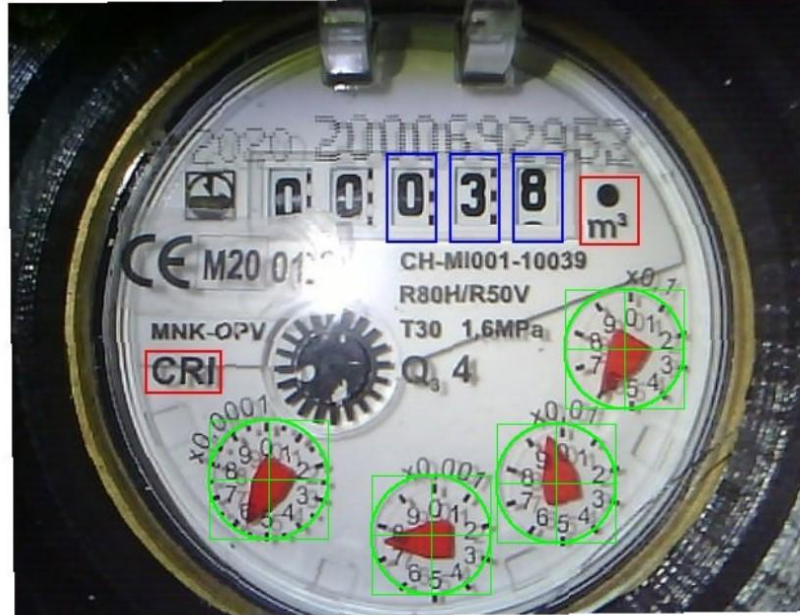
water bottle - 0.2698802947998047
medicine chest, medicine cabinet - 0.08723660558462143
espresso maker - 0.086296945810318

Classify the image

How screen scraping and TinyML can turn any dial into a Digitizer - AI on the edge

An ESP32 all inclusive neural network recognition system for meter digitalization

Overview Configuration Recognition File Server System



Raw Value:

038.5975

Corrected Value:

38.5975

Checked Value:

38.5975


Start Time:

20201118-075416

Last Page Refresh:06:57:39

Divulgação

[35th Symposium on Integrated Circuits and Systems Design](#) - Associar a [SBC \(R\\$26\)](#) que é gratuito o evento

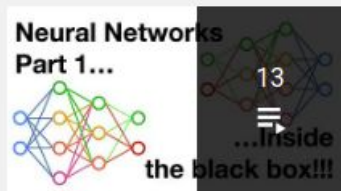
 PROGRAM AT A GLANCE UTC-3				
AUGUST 22 th Monday	AUGUST 23 th Tuesday	AUGUST 24 th Wednesday	AUGUST 25 th Thursday	AUGUST 26 th Friday
Tutorial Day		Invited Talks Adelle Ortiz-Conde <small>(Univ. Simon Bolivar/Venezuela)</small>	Invited Talks SBCMicro Xu Gao <small>(Seochow University/China)</small>	
09:00-10:20 Tutorials SBCCI Wen-Hsiao Peng <small>(NCTU/Taiwan)</small>		09:00-10:40 Invited Talks SBCCI Digital Circuits and Applications 1 SBCMicro Prof. and Applications 2 INSCIT 2	09:00-10:40 Invited Talks SBCCI Soc, NoC and Reconfigurable Systems SBCMicro Device Characterization, Modeling and Simulation 1 SFFORUM Devices	09:00-10:40 SBCCI Video Coding SBCMicro MEMS, MEMS, Packaging and Processing 2 SFFORUM Applications
10:20-10:40 Break	10:00-10:40 Opening Session	10:40-11:00 Break	10:40-11:00 Break	10:40-11:00 Break
10:40-12:00 Tutorials SBCCI Christian Pilato <small>(Polimi/Italy)</small>	10:40-11:00 Break 11:00-12:20 Keynote Massimo Alioto <small>(NUS/Singapore)</small>	11:00-12:20 Keynote Ben Kaczer <small>(IMEC/Belgium)</small>	11:00-12:20 Keynote Iole Noccaqatta <small>(INTEL/USA)</small>	11:00-12:20 Keynote Alan Mishchenko <small>(University of California, Berkeley/USA)</small>
12:00-13:40 Lunch Break	Break Technologies for Intelligent and Connected Circuits & Systems Powered by Renewable Energy Sources	Reliability of VLSI technologies: Impediment and opportunity	State of Video Coders: AVI and VVC algorithms and deployment	Towards Next Generation Logic Synthesis and Verification
13:40-15:00 Tutorials SBCCI Kouyin Yu Cao <small>(Arizona State University/USA)</small>	12:20-14:00 Lunch Break 14:00-14:40 Invited Talks SBCCI Benoit Bosselin <small>(University of Laval/Canada)</small>	12:20-14:00 Lunch Break 14:00-14:40 Invited Talks SBCMicro Yiyu Shi <small>(University of Notre Dame/USA)</small>	12:20-14:00 Lunch Break 14:00-14:40 Invited Talks SBCCI Evangelina Young <small>(Chinese University of Hong Kong/China)</small>	12:20-14:00 Lunch Break 14:00-14:40 Invited Talks SBCMicro Jari Nurmi <small>(Tampere University /Finland)</small>
15:00-15:20 Break	Stephen Goodnick <small>(Arizona State University/USA)</small>	Joao Martino <small>(Escola Politecnica de USP/Brazil)</small>	Marcelo Pavanello <small>(FEI/Brasilia)</small>	Jacobus Swart <small>(SECS Midcom /Brazil)</small>
15:20-16:40 Tutorials SBCCI Partha Pratim Panda <small>(Washington State University/USA)</small>	14:40-16:00 SBCCI Data Converters SBCMicro Circuit/Device Interaction 1 WCAS Analog circuits and RF applications	14:40-16:00 SBCCI Digital Circuits and Applications 2 SBCMicro Circuit/Device Interaction 2 WCAS Eda and Test	14:40-16:00 SBCMicro Novel Materials and Devices 1 SFFORUM Analog & RF Design 1	14:40-16:00 SBCCI SPECIAL SESSION on Embedded and RF Architectures SBCMicro Device Characterization, Modeling and Simulation 3 SFFORUM CAD
16:40-17:00 Break	16:00-16:20 Break	16:00-16:20 Break	16:00-16:20 Break	16:00-16:20 Break
17:00-19:00 SBCMicro Assembly	16:20-17:40 SBCCI MEMS, MEMS and Low-power Optoelectronic Circuits 1 INSCIT 1 WCAS Inovação on IOT 1	16:20-17:40 SBCCI Analog Design SBCMicro Device Characterization, Modeling and Simulation 2 INSCIT 3 WCAS Inovação on IOT 1	16:20-17:40 SBCCI Emerging Approaches for Digital Design SBCMicro MEMS, MEMS, Packaging & RF Processing 1 Design 2 SFFORUM Analog & RF Design 2 INSCIT 4	16:20-17:40 SBCCI MEMS and Learning-Based Circuits and Systems SBCMicro Novel Materials and Devices 2 SFFORUM Best Papers
	17:40-18:00 Break 18:00-19:00 Panel Formação de talentos	17:40-18:00 Break 18:00-19:00 Panel Indústria Internacional	17:40-18:00 Break 18:00-19:00 Panel PDI Microeletrônica	17:40-18:00 Break 18:00-19:00 Closing & Awards
		19:00-19:20 Break 19:20 Social Event Gaúcho Music Concert		

Vários Links

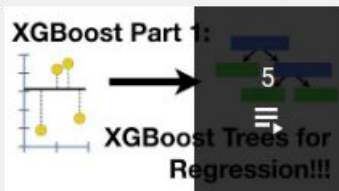
1. [Demonstrações de IA](#)
2. [Onde aprender Machine Learning & IA](#)
3. Palestra 22 Março 2021, Prof. Wagner Meira, Inteligência Artificial, Estado Atual, Perspectivas e Desafios
4. [Palestra Prof Antonio Braga da UFMG sobre redes Neurais](#)
5. [Aprendizado de Máquinas e Estatística, a relação íntima entre estas áreas.](#)
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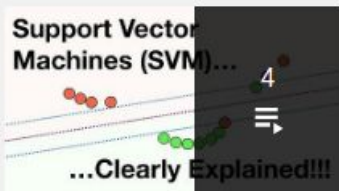
- [YouTube Statquest Videos](#)



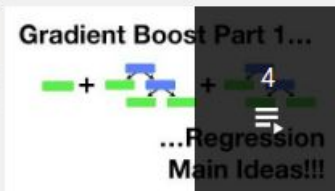
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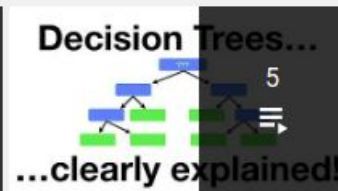
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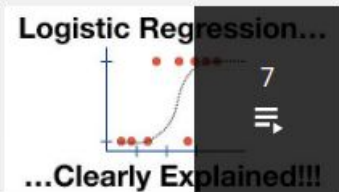
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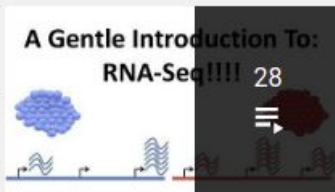
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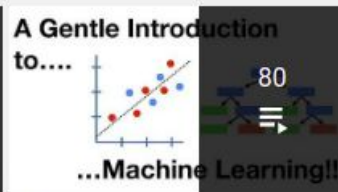
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Courses and Books - Learn more about....

- [Stanford Cs231N](#) (Fei Imagenet)
- [MIT Introduction Deep Learning](#)
- [Stanford 157](#) (Dive in DL)
- **Books:** [Python Data Science Handbook](#),
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Learn more about....

- [Machine Learning Foundations](#) is a free training course where you'll learn the fundamentals of building machine learned models using TensorFlow with Laurence Moroney. Google
- [Python, NumPy, Pandas, PyTorch, Linear & Logistic regression, Neural networks, Data quality, Utilities, CNNs, Embeddings, RNNs, Attention, Transformers](#) - ML Foundations
- Portuguese - [CURSO RÁPIDO DE PYTHON PARA INICIANTE COM GOOGLE COLAB - AULA 1: Como Usar Python ONLINE - Google Colab, Strings, Operadores Matemáticos, Variáveis, Listas e Tuplas, Dicionários, Operadores Lógicos, IF / ELSE / ELIF, FOR, WHILE e Funções](#)

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- [Machine Learning Algorithms Full Course | Machine Learning Algorithms Explained | Simplilearn - 5 hours - YouTube Video](#)

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- [Deep Learning's Most Important Ideas - A Brief Historical Review](#)
- Deep Learning [Tutorial Course 3 hours 2018 - Laurence Moroney](#)
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- [The Roots of Data Science - How it all began.](#)

Online Courses [Zero to Mastery Machine Learning](#)

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- Section 1 - Getting your mind and computer ready for machine learning (concepts, computer setup)
- Section 2 - Tools for machine learning and data science (pandas, NumPy, Matplotlib, Scikit-Learn)
- Section 3 - End-to-end structured data projects (classification and regression)
- Section 4 - Neural networks, deep learning and transfer learning with TensorFlow 2.0
- Section 5 - Communicating and sharing your work

[Learn PyTorch for deep learning in a day. Literally.](#)

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[Learn PyTorch for Deep Learning \(work in progress\)](#)

Guidelines

- [Machine Learning Engineering in 10 Weeks curriculum v1](#) Jason Benn
- [learn machine learning](#) Jason Benn
- [Make your own Machine Learning and Deep Learning degree](#) Aurélien Peden
- [Example execution & resources: Self-learning AI in a year -](#) Niklas Muennighoff

Grupo de Robótica da UFV

YouTube do Nero: <https://www.youtube.com/c/RoboticaUFV>

Repositório do Nero: <https://github.com/neroUFV>

[Colab modelo de Controle para Drone](#)

Trabalhos que realizei no Nero no último mês:

<https://youtu.be/GDdqWQX0Hd8>

<https://youtu.be/KrNmOUjahy8>

Questions ?

