



Artificial Intelligent Sensors: The core of Cyber-Physical-Systems From Theory to Practice

Danilo Pau

Advanced System Technology

Agrate Brianza

Introduction

The Cyber-physical Systems

3



Cyber-physical Systems applications

4

Datacenters



2016 Mercedes-Benz GLE

Can be configured over 1,000 different ways

Average inventory of 10/dealer

Approximately 500 vehicles in state of California

Autonomous Cars



Industry 4.0



Cyber-physical Systems



Home/Building



Agriculture 2.0



Cities

Opportunities and Challenges

Computers were big

6

Olivetti M24¹⁹⁸³



- Intel 8086
- 8 MHz
- 128 KB RAM
- 16 KB ROM
- 1.84 W
- 360 \$

Computers were big 7

Olivetti M24¹⁹⁸³



- Intel 8086
- 8 MHz
- 128 KB RAM
- 16 KB ROM
- 1.84 W
- 360 \$



10x

100x

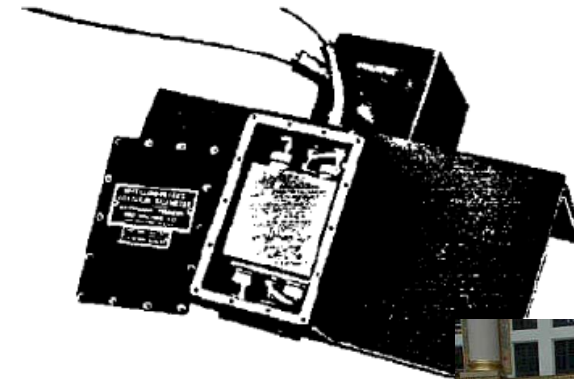
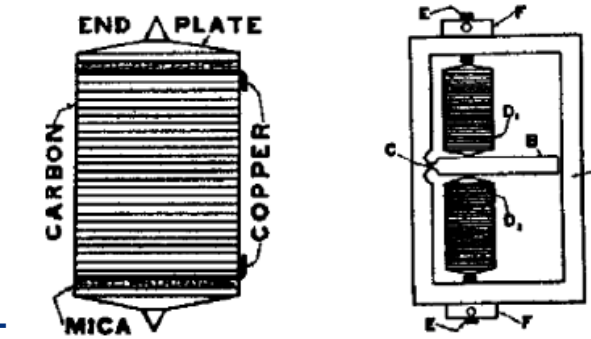
- STM32 MCU L4
- 80 MHz
- 128 KB RAM
- 1 MB Flash
- < 20mW
- < 4 €



Sensors were big

8

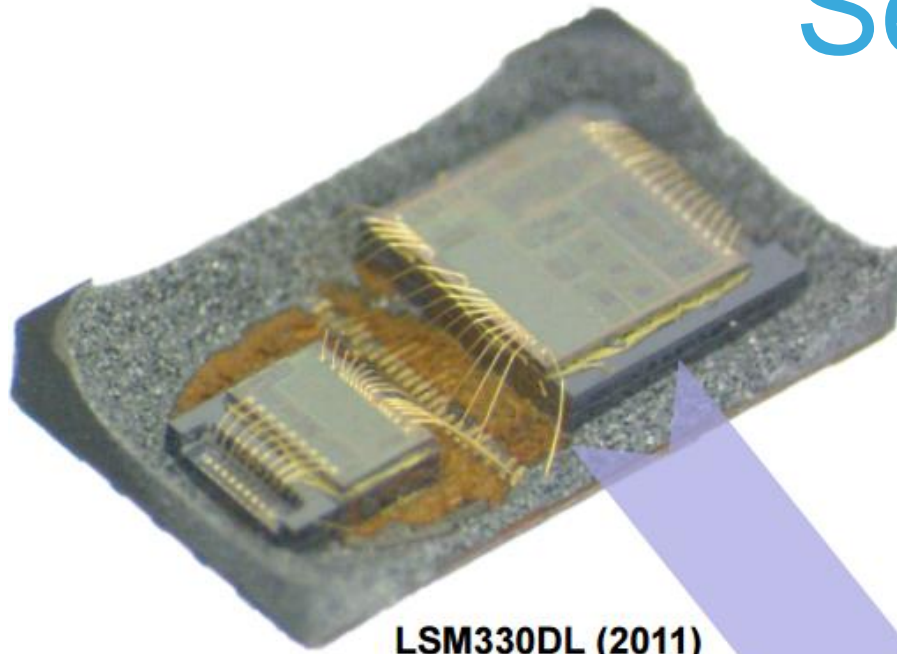
- First accelerometer (1923)
 - Credits: McCollum and Peters
 - Commercialized by 1927 in the US
 - Resistance Bridge type
 - E-shaped frame containing 20 to 55 carbon rings in a tension-compression Wheatstone
 - Half-bridge between the top and center section of the frame
 - Dimensions: $\sim 28 \text{ cm}^3$
 - Resonant frequency $< 2 \text{ kHz}$
 - Application in bridges, dynamometers, and aircraft
- Major revision (1936)
 - 2-axis with up to 100g range
 - Applications vastly increased
- Price: \$420 (\$6,275 at today's rate)



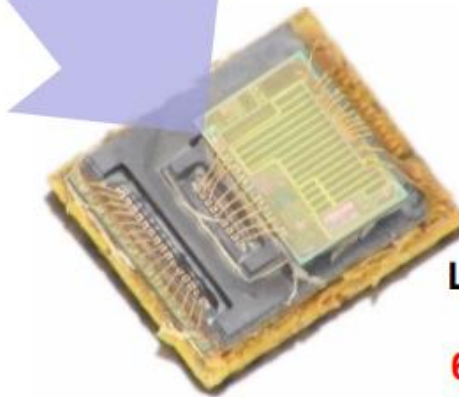
1923 McFarlan
McFarlan Motor Car Co. Connersville, IN
1910-1928

Sensors are miniaturized

9



LSM330DL (2011)
33mm²



LSM330 (2012)
10.5mm²
68% shrinking

STMicroelectronics 6-axis IMU evolution
SiP 3D digital accelerometer and gyroscope

Digital Camera Kodak's Steven Sasson 1973

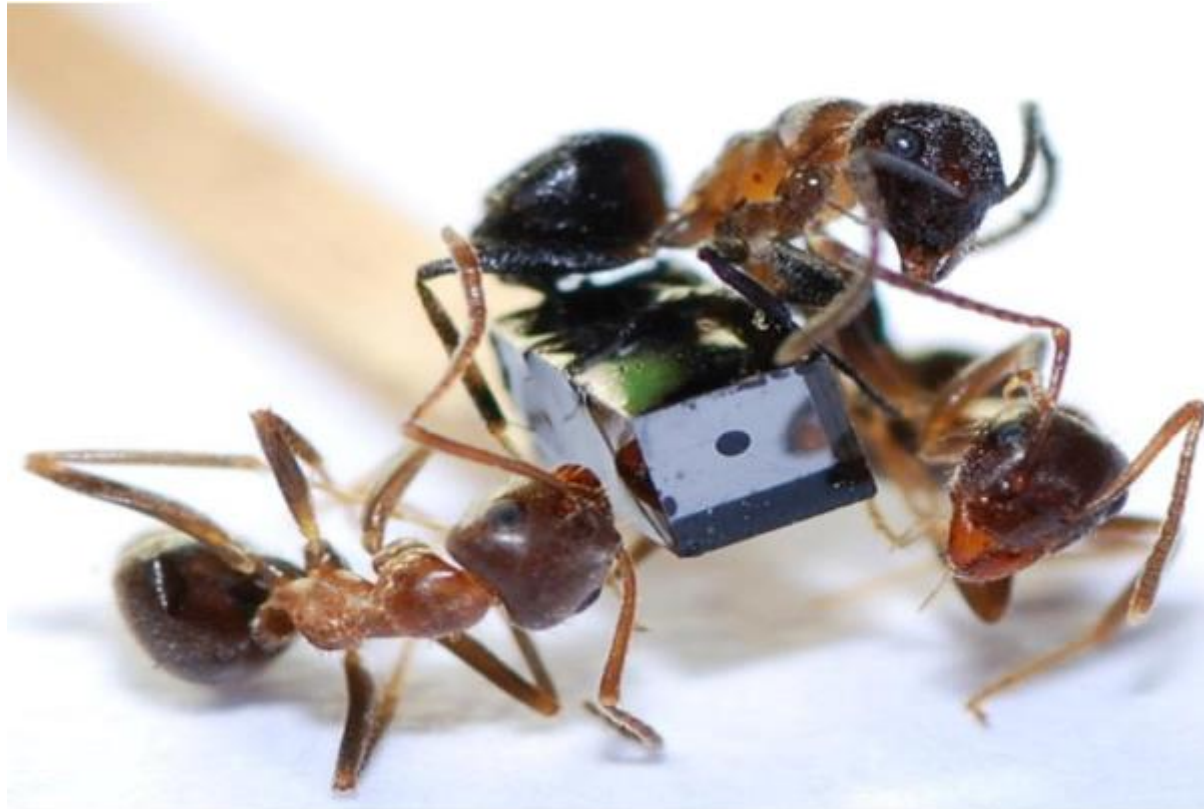
10



- 50 ms to capture the image
- 23 s to record on a tape
- 3.6 kg, 10K pixels.
- black-and-white images.
- Electronic still camera, US patent 4131919 A

Ultra Small Imaging Modules

11



With Machine Learning

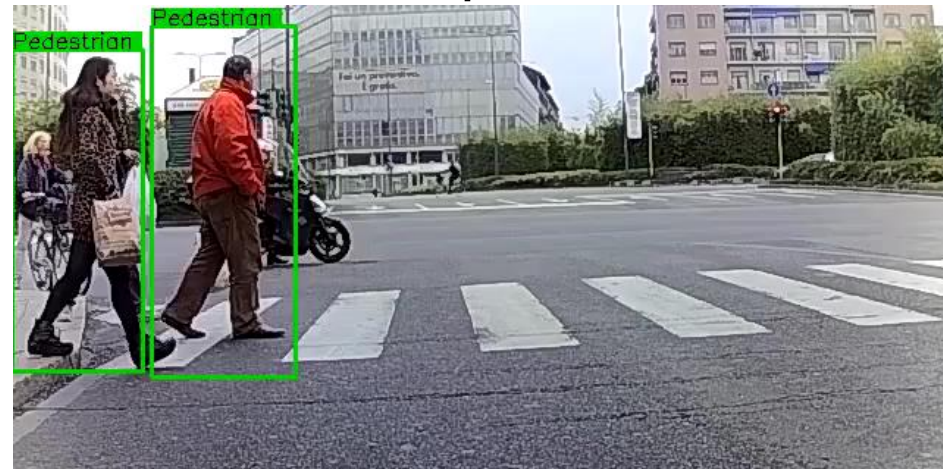
12



Side mirror camera



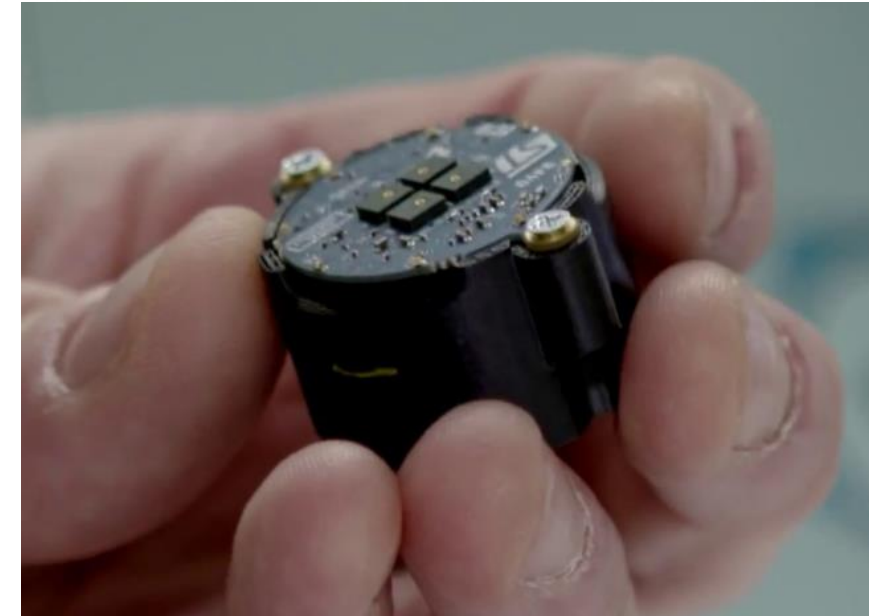
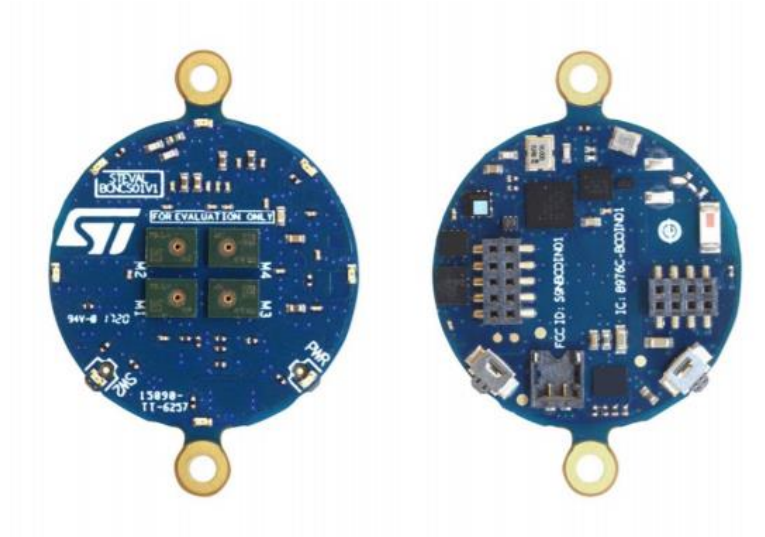
Backup camera



Multi and Heterogeneous sensors hub

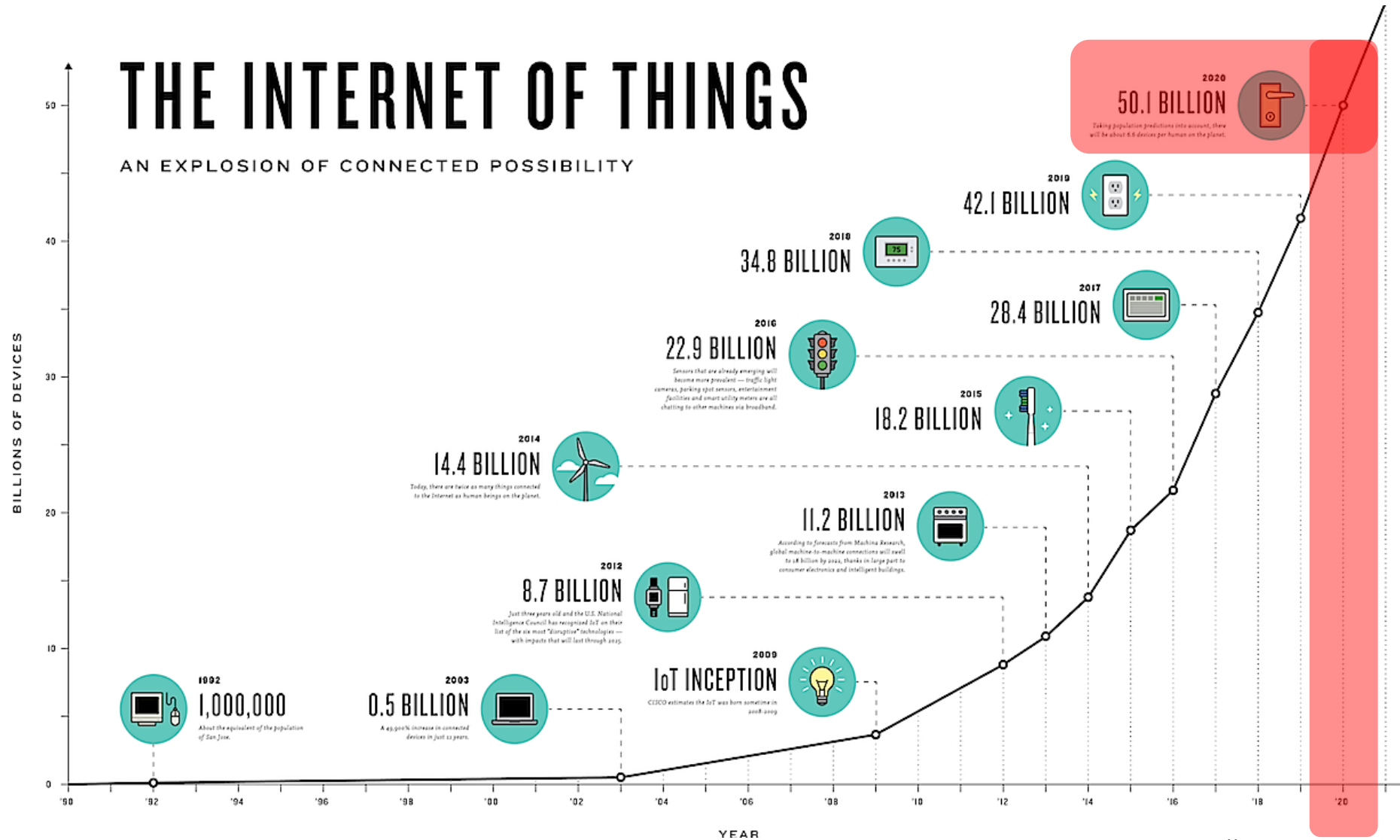
13

- 4x MP34DT04-C1 – 64dB SNR Digital MEMS microphone
- LSM6DSM – iNEMO inertial module: 3D accelerometer and 3D gyroscope
- LSM303AGR – ultra-compact high-performance eCompass module: ultra-low
- LPS22HB – MEMS nano pressure sensor: 260-1260 hPa absolute digital output
- BlueNRG-MS – Bluetooth low energy network processor
- STBC03JR – linear battery charger with 150 mA LDO 3.0 V
- STM32F446 – 32-bit high-performance 180 MHz MCU (ARM® Cortex®-M4 with FPU)



IoT with 100s of Billions of Sensors

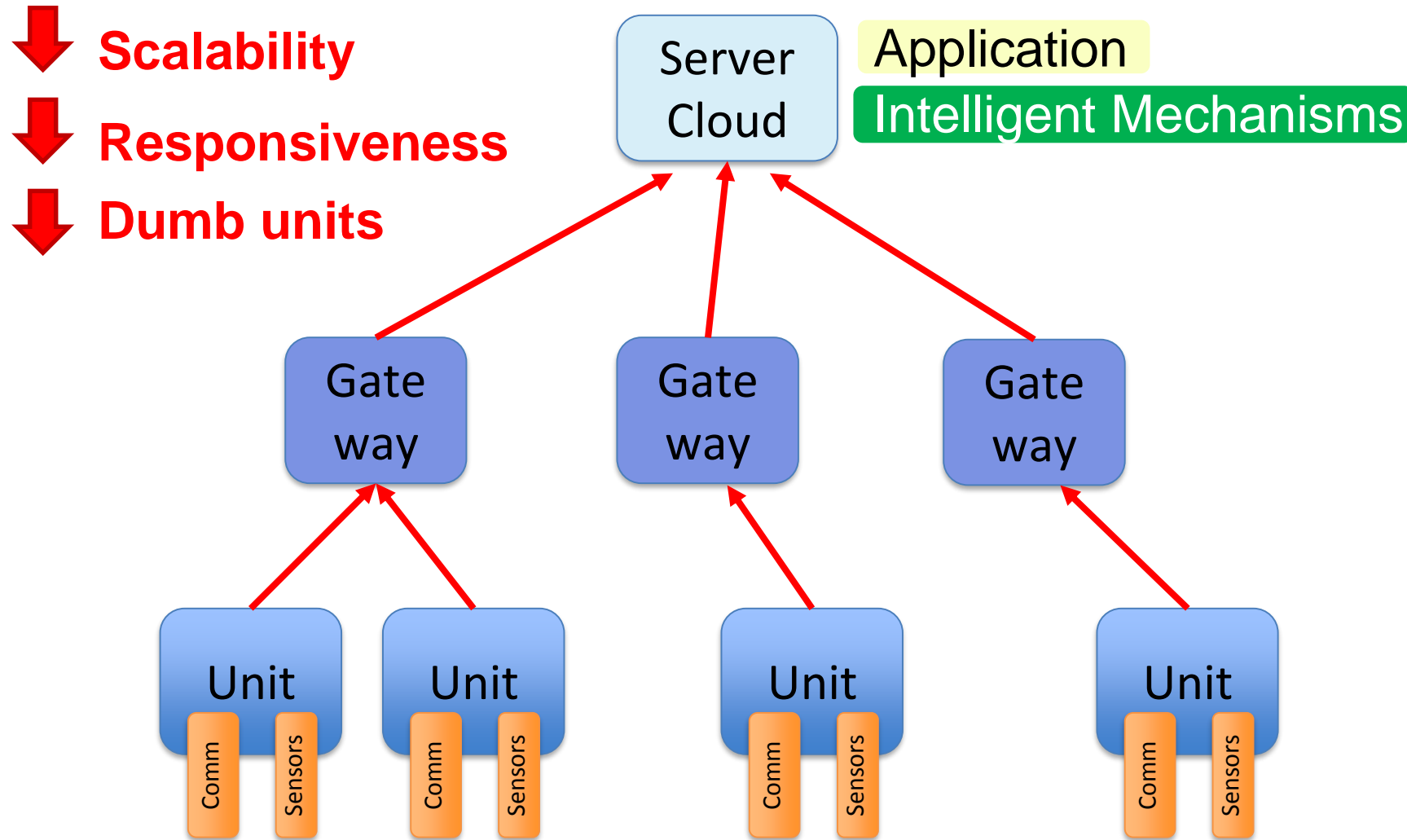
15



Fonte: <https://www.ncta.com>

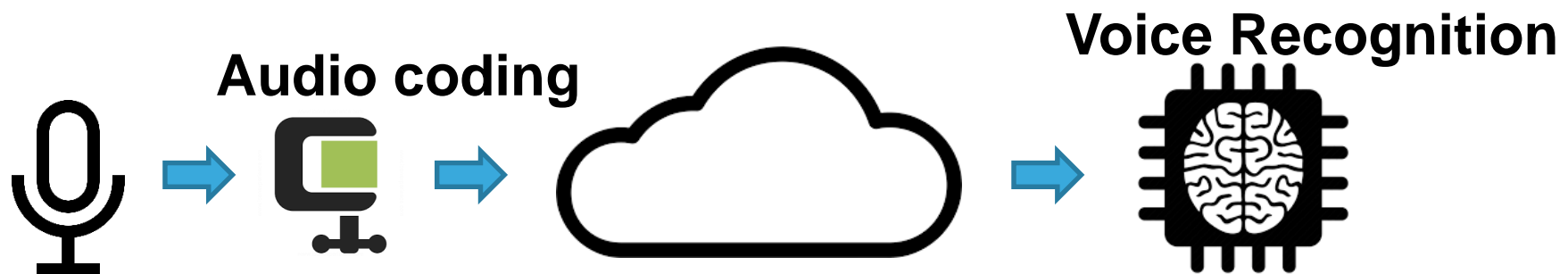
Designing too centralized CPS

16



Example: Cloud based Voice Recognition 17

- Average person's daily utterances as 16,000 words[1] and an average speech rate of 163 words per minute[2], $\rightarrow \approx 98$ minutes of speech per day.
- Multiplying that number by 128 kbps, the result would be **94 MB of voice data per person per day**. \rightarrow 1 million (≈ 94 TB), 10 million (≈ 1 PB) and 100 million (≈ 9 PB)



Predictive Maintenance

18



Time- Cycle Based Maintenance

- Predefined lifetime for replacement
- Unexpected failures



Condition-Based Maintenance

- Adaptively raise alert based on the actual condition of the product and environment
- Focus on critical event prediction

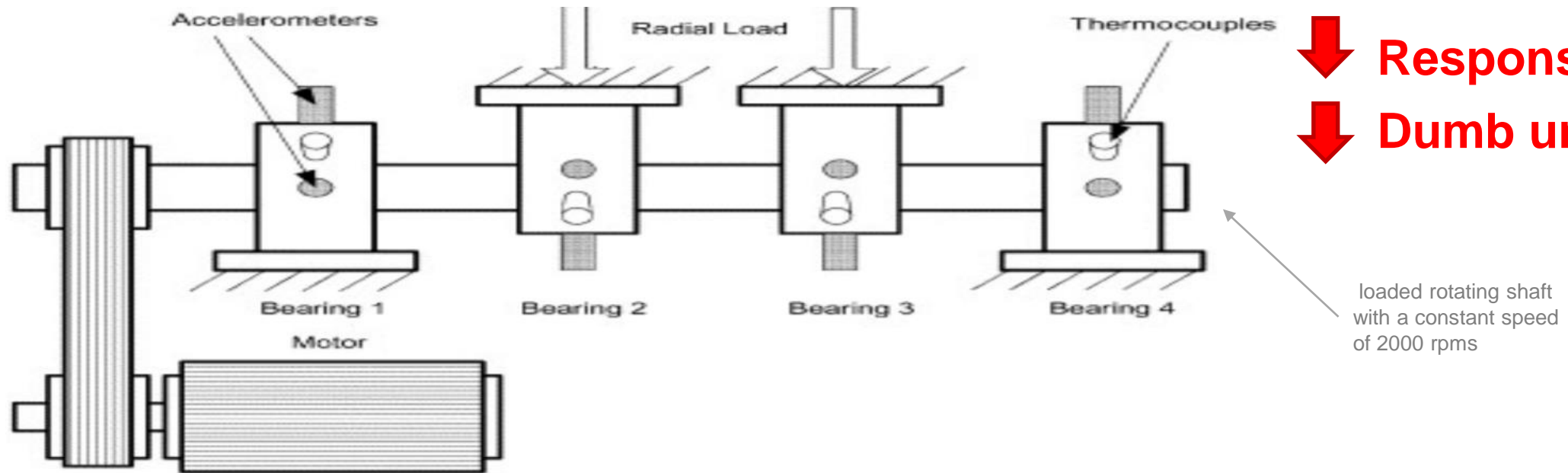


1. **Anomaly detection**: How to classify the present condition into normal and abnormal
2. **Sensor based detection**: How to recognize change-points of the system

Example: Cloud based Predictive Maintenance

19

- 2 X,Y accelerometers on each bearing, times 4
- 20 KHz sampling rate @ 16 bits per axis → 320 Kbytes/s → **27.648 Gbytes/day**



↓ Scalability
↓ Responsiveness
↓ Dumb units

STEVAL-BFA001V1B for Intelligent Edge CM and PdM 20

The **STEVAL-BFA001V1B** is based on 3D digital accelerometer, environmental and acoustic MEMS sensors

Use cases



Motors



Equipment



Environment

Sensing



Vibration and Environmental

- ISM330DLC 6-Axis digital MEMS axel + gyro
- MP34DT05-A Microphone
- LPS22HB MEMS Pressure sensor
- HTS221 Humidity & Temperature Sensor

Connectivity



Wired

- L6362A IO-Link communication transceiver device IC

Processing



Local Processing

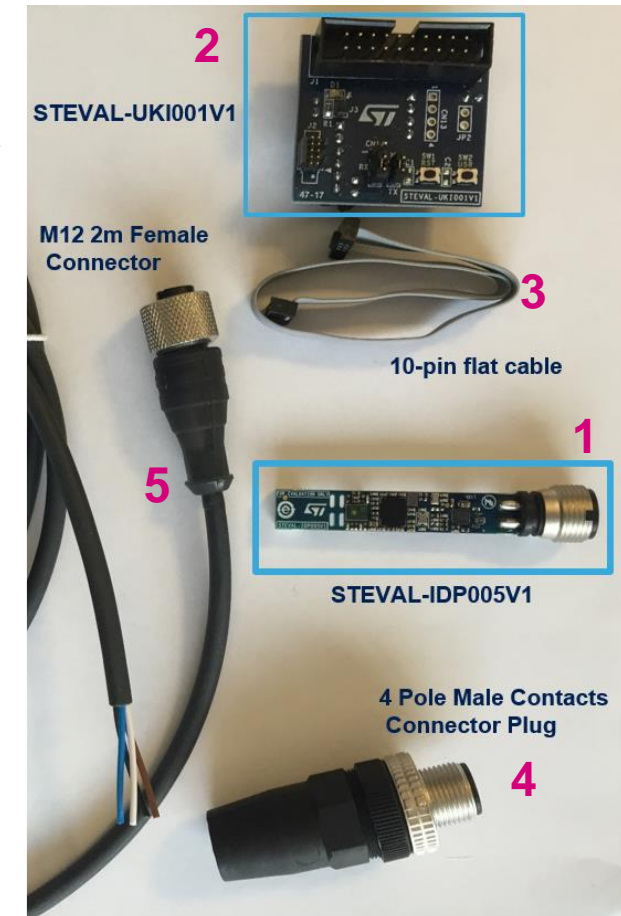
- STM32F469AI 32-bit ARM Cortex-M4 MCU
- 180MHz, 2MB FLASH
- 384+4 KB of SRAM including 64-KB of CCM
- ART for 0-wait state from FLASH
- DSP Instructions

The STEVAL-BFA001V1B includes:

1. STEVAL-IDP005V1- industrial sensor board
2. STEVAL-UKI001V1 - Adapter board for ST-LINK/V2-1
3. 0.050" 10-pin flat cable
4. 4 Pole cable mount connector plug, with male contacts
5. M12 female connector with 2m cable

Designed for:

- Condition Monitoring (CM)
- Predictive Maintenance (PdM)



<https://www.st.com/en/evaluation-tools/steval-bfa001v1b.html>

The effects on the Applications

21



**Faults, Errors,
Uncertainty,
Malfunctioning,
Intrusions**



**Cyber-
physical
Systems**



**Performance reduction,
cascade effects
on Applications**

**Changes:
Nonstationary,
seasonality, periodicity**



IoT DDoS, screwing Dyn, Oct 2016

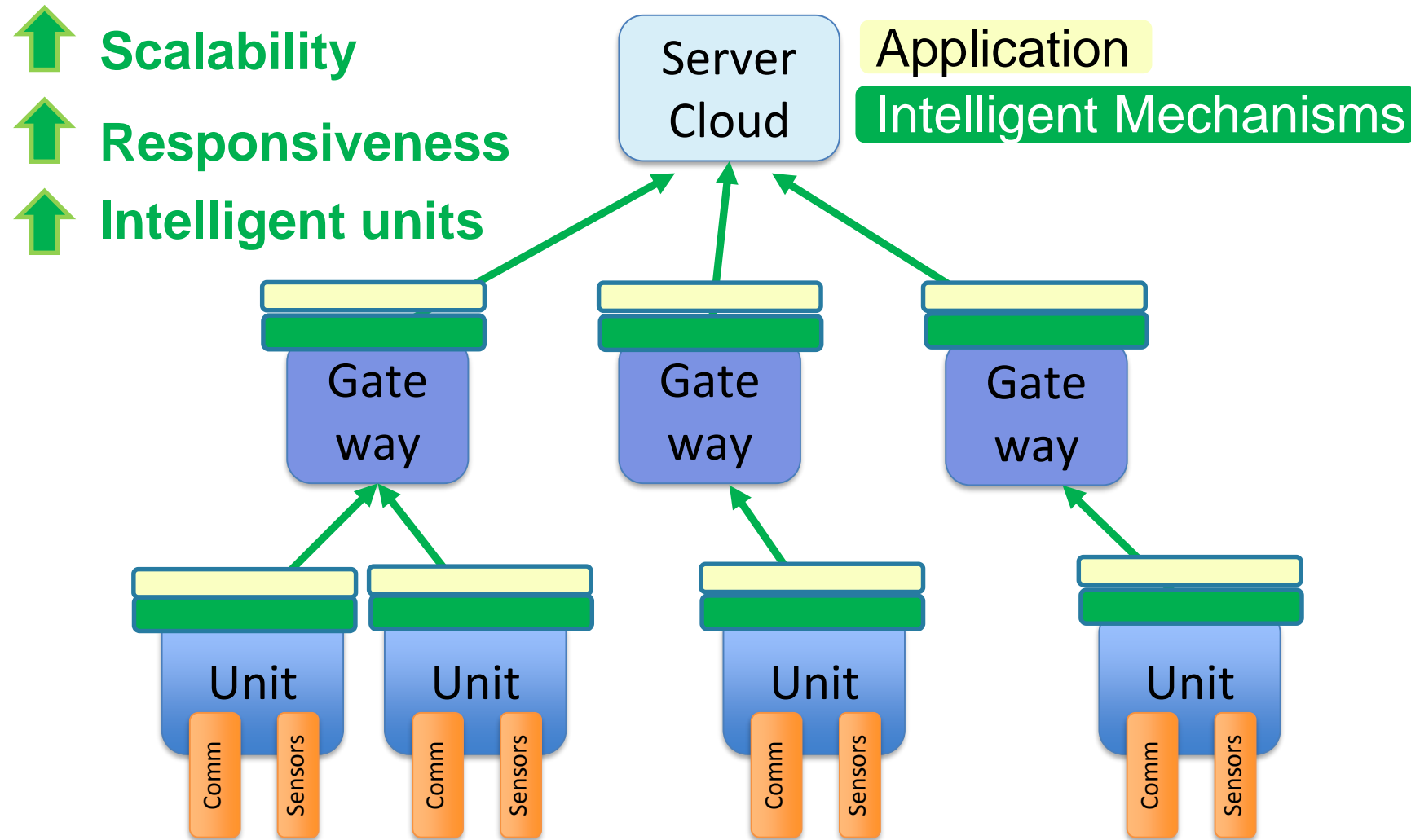
22



- Many IoT devices e.g. refrigerators, thermostats, and toasters were the attackers.
- From 09:30 to 18:00 ET, Dyn's servers were attacked in three DDoS waves. It was based on Mirai code
- Cyberattack, affected **Twitter**, **Amazon**, **Reddit**, **Netflix**, and more since they used **Dyn DNS** provider.
- A group called "*New World Hackers*" has claimed responsibility for the attack.

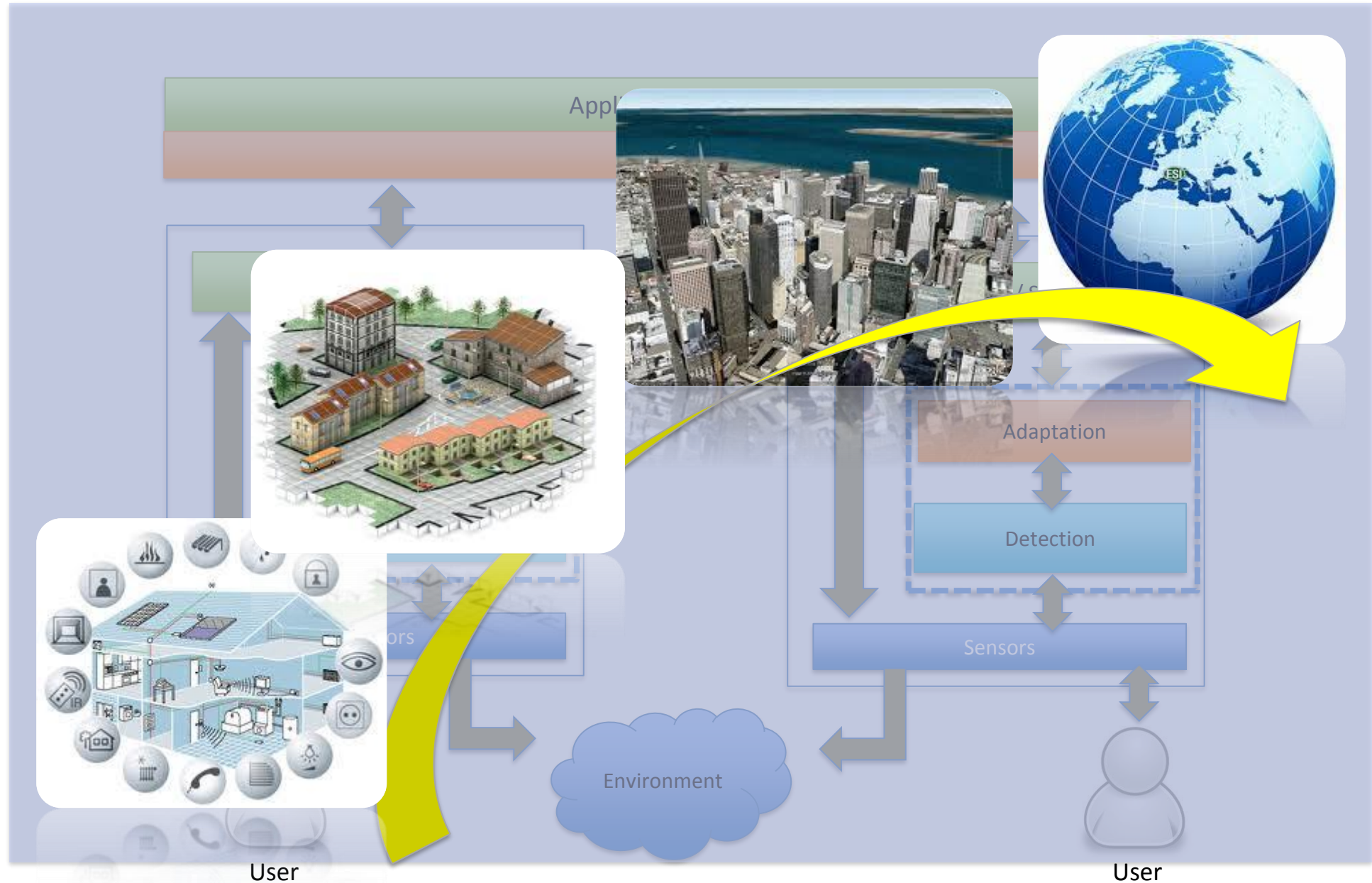
Designing Intelligent and distributed CPS

23



IoT need to achieve hyper scalability

24





HAUSI A. MÜLLER is a professor of computer science and the Associate Dean of Research of the Faculty of Engineering at the University of Victoria. He is also the 2016–2018 vice president of Technical and Conferences Activities for the IEEE Computer Society. Contact him at hausimuller@gmail.com.



CPSs have risen from the field of embedded systems to the realm of digital ecosystems and are becoming increasingly intelligent as a result of analytics and machine-learning capabilities being readily available in the cloud and accessible over networks.

The Rise of Intelligent Cyber-Physical Systems

Hausi A. Müller, University of Victoria

It's expected that the cyber-physical systems revolution will be more transformative than the IT revolution of the past four decades.

Why is this CPS revolution happening now? The primary reason is the recent confluence of technologies, including adaptive systems and run-time models, an increasingly instrumented world due to pervasive sensing and actuating capabilities, advanced real-time and networked control, analytical and cognitive capabilities, and compute and storage clouds. With the advent of cognitive intelligent assistants readily available on personal devices, human-in-the-loop CPSs are proliferating in our lives.

<https://www.computer.org/csdl/mags/co/2017/12/mco2017120007.pdf>

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The Next Step for Artificial Intelligence Is Machines that Get Smarter on Their Own

Deep learning enables computers to do a better job than humans at mastering skills and making decisions

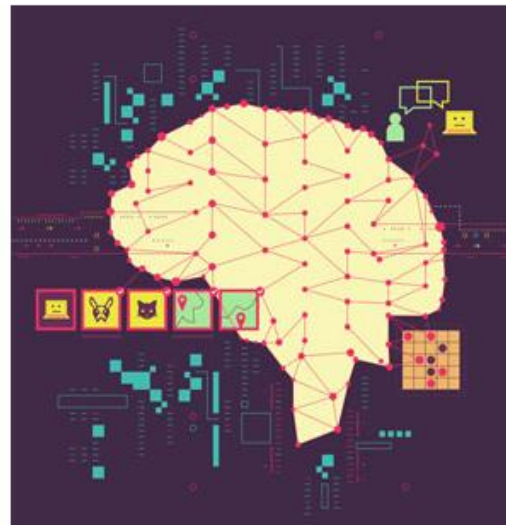
By MONICA ROZENFELD 1 June 2016



19

Have you ever used a voice-activated service such as Apple's Siri only to find it completely missed what you were saying? Or played a game against a computer and felt it didn't even put up a fight? That's about to change with advances in deep learning, which improves computers' ability to process information and make decisions—like people do, and oftentimes even better.

Deep-learning techniques allow a



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Computers are designed to be programmable and not evolvable

Posted: May 1, 2015

...
NICK BOSTROM
SUPERINTELLIGENCE
Paths, Dangers, Strategies



Dave Morton
Call me!



Arjeus Guevarra
Member
Total posts: 6
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Computers are designed to be programmable and not evolvable

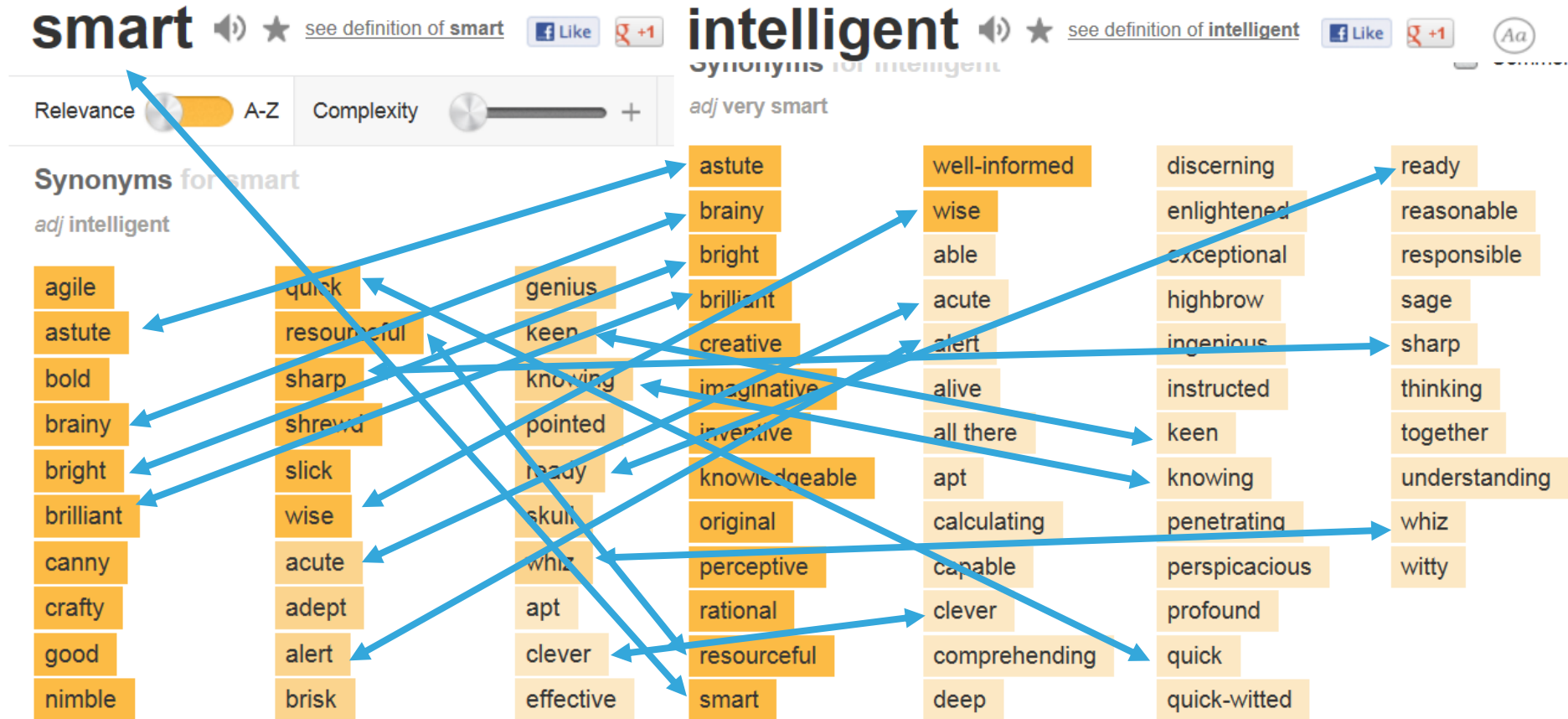
Computers are anticipated, if properly programmed, can achieve human level artificial intelligence and eventually super intelligence. However, the computer architectures that we had today are designed for maximum programmability. The source code or designed are input to the compiler or synthesis tool, and after that an executable or computer logic is synthesised. Thus, the output is a programmed/hardware developed system that can execute the code or instructions. The case is here, the computer will only execute the program. The computer is designed to achieve maximum execution speed. The computer/IC is aimed to be designed to possess speed intelligence only.

What does this imply to achieving true artificial intelligence? The requirement of artificial intelligence is that it has to learn, not just execute the instructions. It should ideally rewrite its own code. The system has to possess qualitative intelligence, not just speed intelligence, as Nick Bostrom from his popular book "Superintelligence" has defined. What is happening now is that the best we could do on these programmable computers is that we compile a source code that emulates learning on top of a frozen code, right? My opinion is that some machine learning aspects are innately ineffective in von Neumann architectures or other conventional hardware. It may possibly worsen the performance on every increase in machine learning complexity. In other words, machine learning cannot be efficient as computers see the program as intelligent, but as a finite set of instructions with maximum flexibility.

There's a chance that further adding features of more generalized intelligence will result in a computational bottleneck that will greatly reduce "speed intelligence" to compensate for "quality intelligence", cancelling the accumulated effects the two intelligences previously mentioned. Or at a lesser extent, the expected speed increase in machine intelligence

Smart vs Intelligent

28



Approximating a function

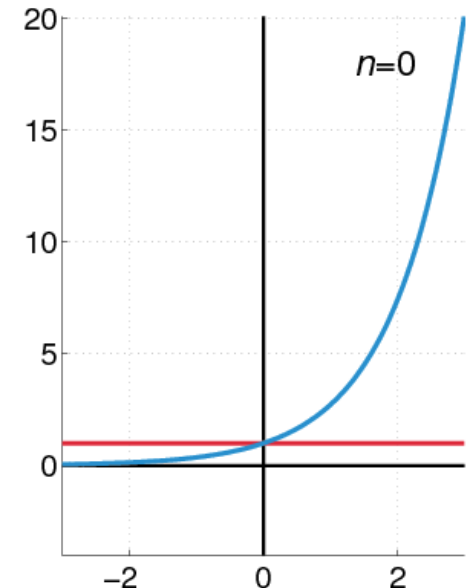
29

- Given $y = f(\mathbf{x}), \mathbf{x} \in \mathbb{R}^d$
- Assuming we can calculate the function's derivatives at a single point in a range of \mathbf{x} and given a Taylor series:

$$T(x_1, \dots, x_d) = \sum_{N=0}^{\infty} \sum_{n_1 + \dots + n_d = N} \frac{(x_1 - a_1)^{n_1} \dots (x_d - a_d)^{n_d}}{n_1! \dots n_d!} \left(\frac{\partial^N f}{\partial x_1^{n_1} \dots \partial x_d^{n_d}} \right) (a_1, \dots, a_d).$$

- For $N \rightarrow \infty$ according to Cantor-Bernstein-Schröder Theorem

$$\|f - T\| < \varepsilon$$



No more Analytical Expressions

Just raw data

30

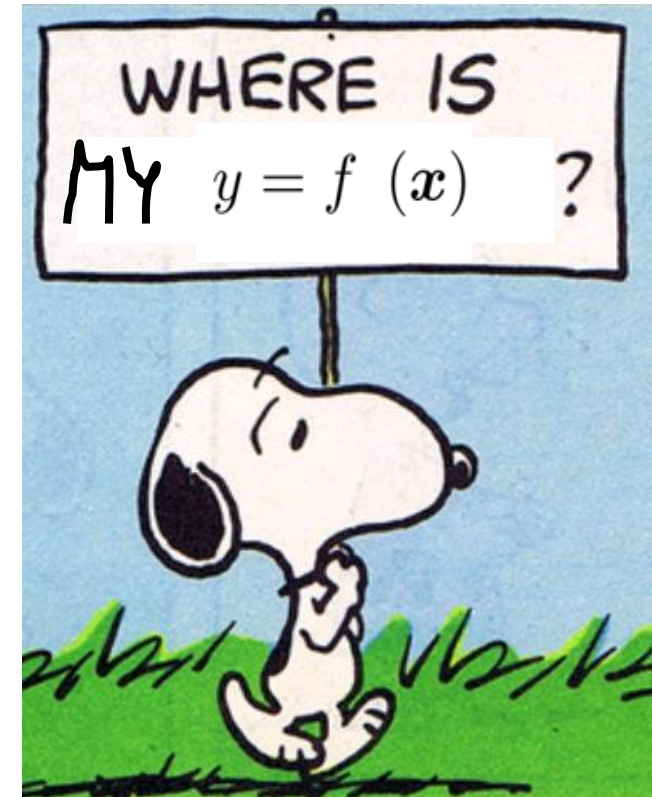
- Given $y = f(x), \quad x \in \mathbb{R}^d$

$x =$



This is just a
label

➡ $y = \text{Lulu'}$



Neural Networks as powerful approximator 31

- Universal approximation theorem (*Cybenko*¹⁹⁸⁹, *Hornik*¹⁹⁹¹)
 - Given $y = f^*(\mathbf{x}), \mathbf{x} \in \mathbb{R}^d$
 - MLP Approximator is $\tilde{y} = \mathbf{w} \cdot g(\mathbf{W}\mathbf{x} + \mathbf{c}) + c, \mathbf{W} \in \mathbb{R}^{h \times d}, \mathbf{w}, \mathbf{c} \in \mathbb{R}^h, c \in \mathbb{R}$

$[f^*($



$) - \mathbf{w} * g(\mathbf{W}\mathbf{x} + \mathbf{c}) + c] < \varepsilon$

MLP approximates f with a small error at will

Break-through on Artificial Neural Networks

32

1. *Computing Machinery and Intelligence*, Oxford University Press, **1950**
Alan Turing on Artificial Intelligence. → Imitation Game
2. *Universal approximation theorem*, **Cybenko, 1989** → A MLP can be the right approximator of any function
3. *Reducing the Dimensionality of Data with Neural Networks*, by **Hinton & Salakhutdinov, Science, 2006** → end to end Autoencoder trained on data based on probabilistic neurons (RBM) approximated faces

Reservoir Computing: Recursive Neural Gas

33

- Neurons Compete, Coordinate and Adapt while Self Organizing to find optimal data approximation.
- In RNG, the set of neuron Units U becomes

$$U := \{(\mathbf{w}_i^{in}, \mathbf{w}_i^{rec})\}, \quad \mathbf{w}_i^{in} \in \mathbb{R}^d, \quad \mathbf{w}_i^{rec} \in \mathbb{R}^n, \quad i \in \{1, \dots, n\}.$$

$$\tilde{v}_i(t) = \exp \left(-\alpha \|\mathbf{w}_i^{in} - \mathbf{x}(t)\|^2 - \beta \|\mathbf{w}_i^{rec} - \mathbf{v}(t-1)\|^2 \right)$$

$$v_i(t) = (1 - \gamma)v_i(t-1) + \gamma\tilde{v}_i(t)$$

arXiv.org > cs > arXiv:1807.09510

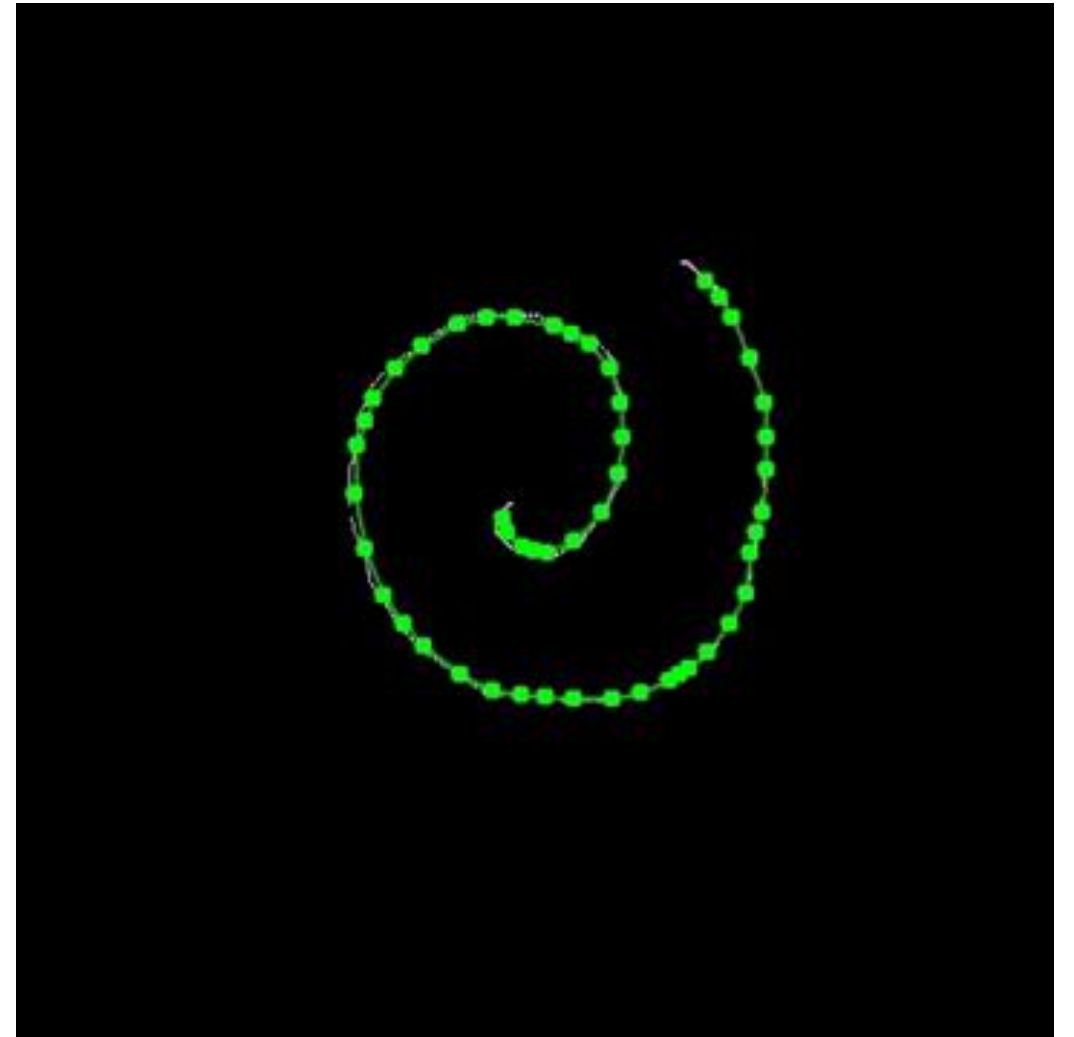
Computer Science > Machine Learning

Pre-trainable Reservoir Computing with Recursive Neural Gas

Luca Carcano, Emanuele Plebani, Danilo Pietro Pau, Marco Piastra

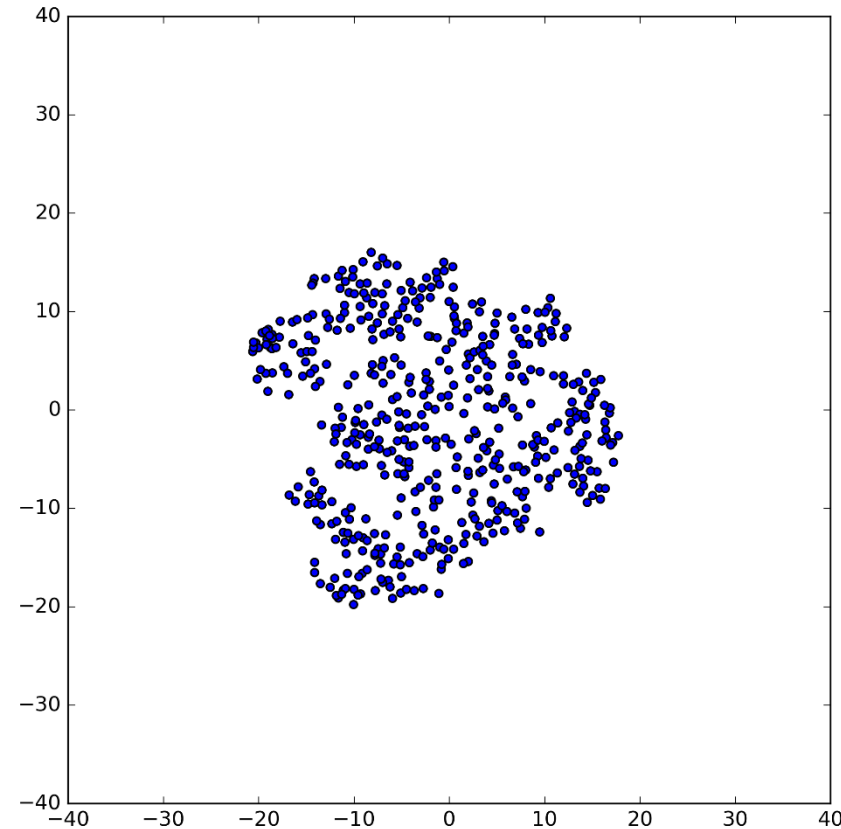
(Submitted on 25 Jul 2018)

<https://arxiv.org/abs/1807.09510>



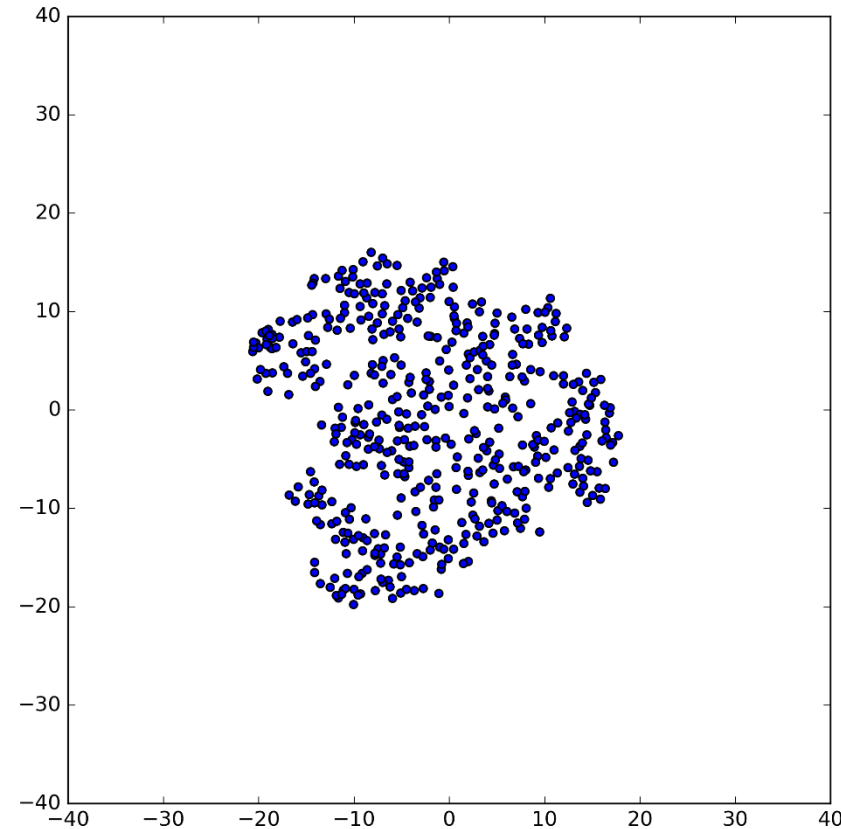
On Line Self Organizing Neural Network Human Activity Recognition t-SNE view

34



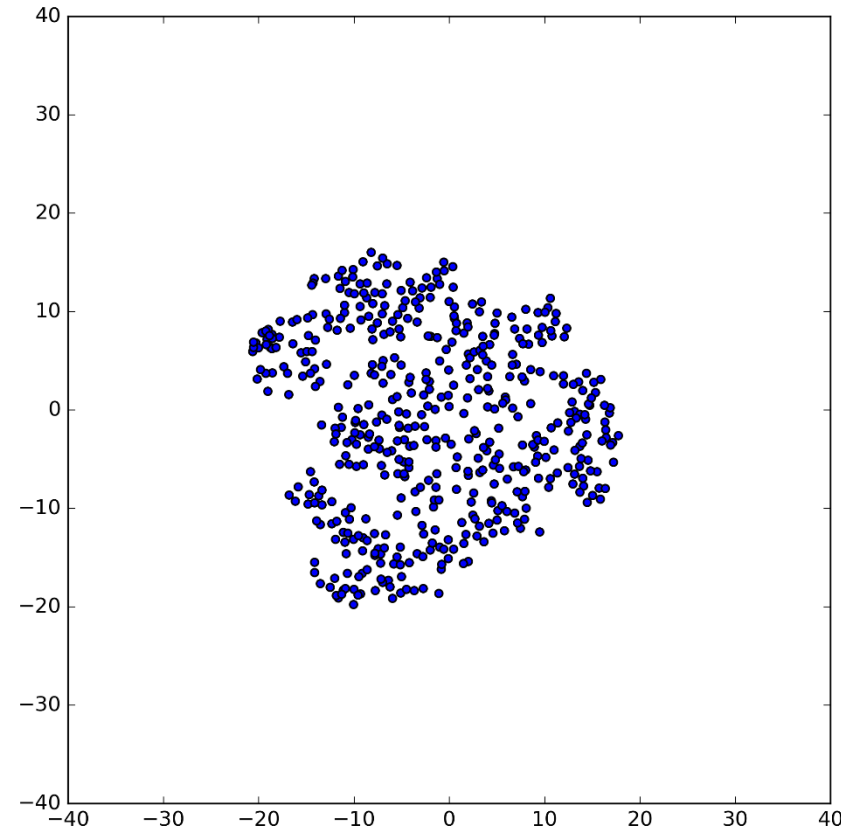
On Line Self Organizing Neural Network Human Activity Recognition t-SNE view

35



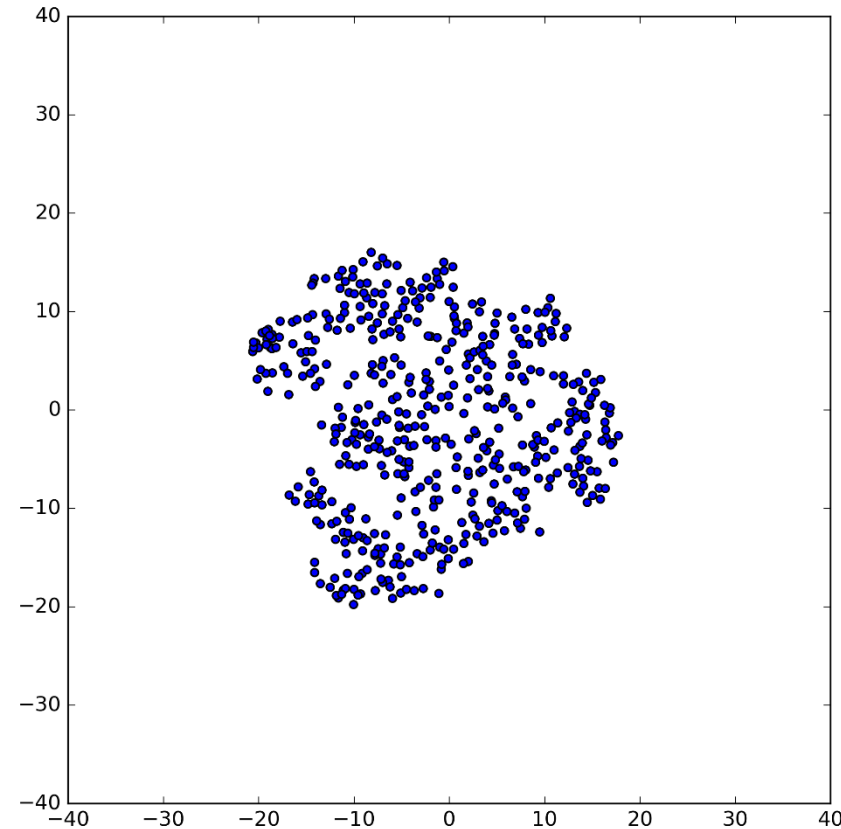
On Line Self Organizing Neural Network Human Activity Recognition t-SNE view

36



On Line Self Organizing Neural Network Human Activity Recognition t-SNE view

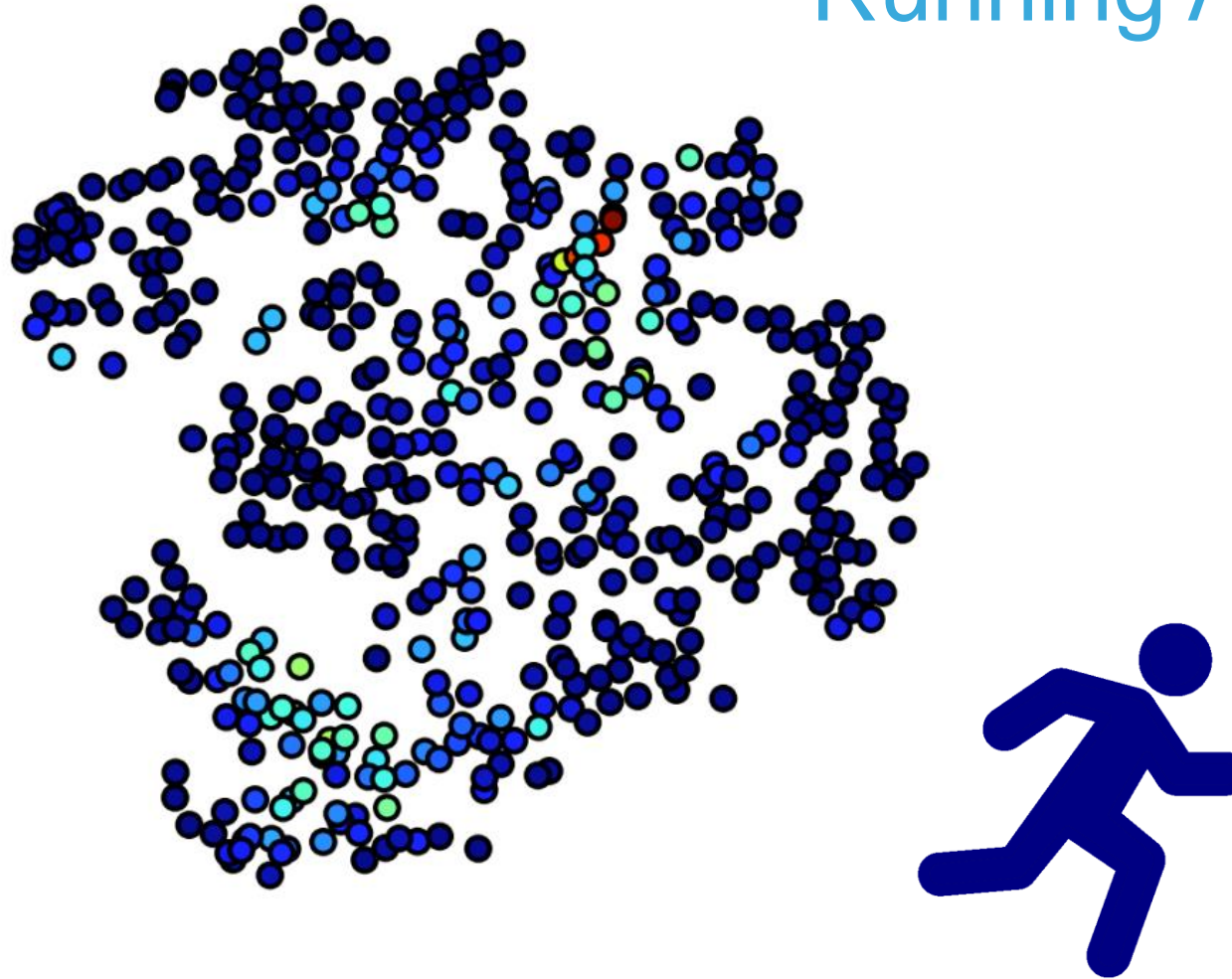
37



Case study: Human Activity Classification

Running Activity

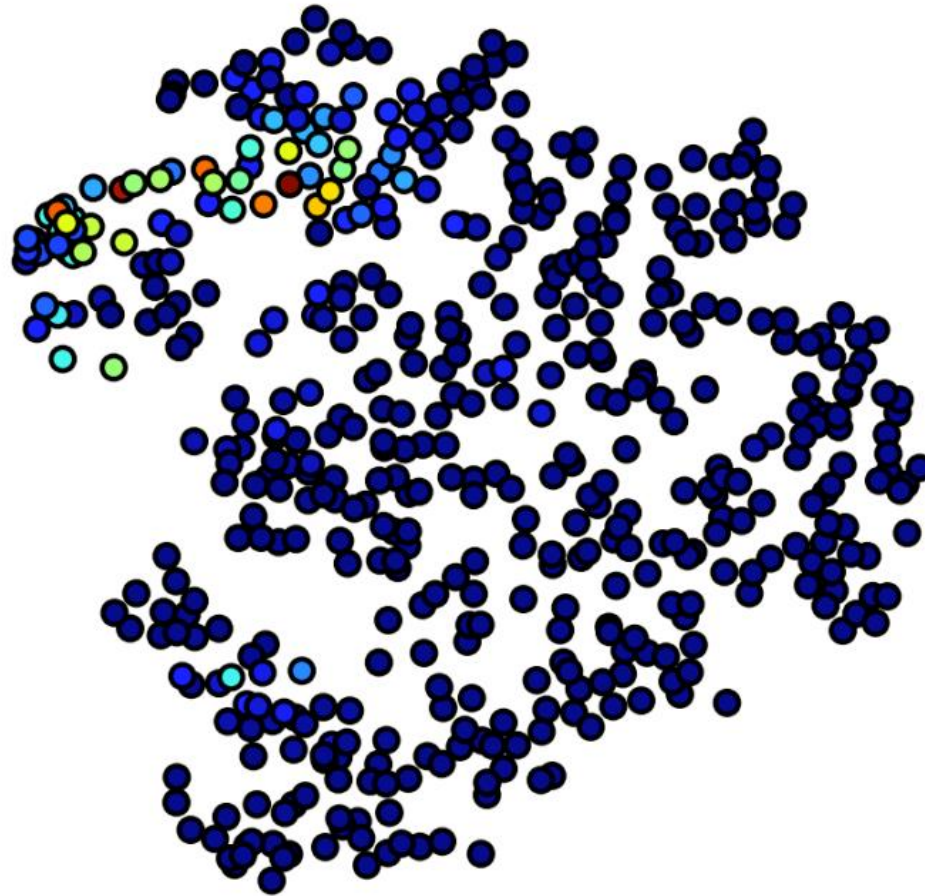
38



Case study: Human Activity Classification

Walking Activity

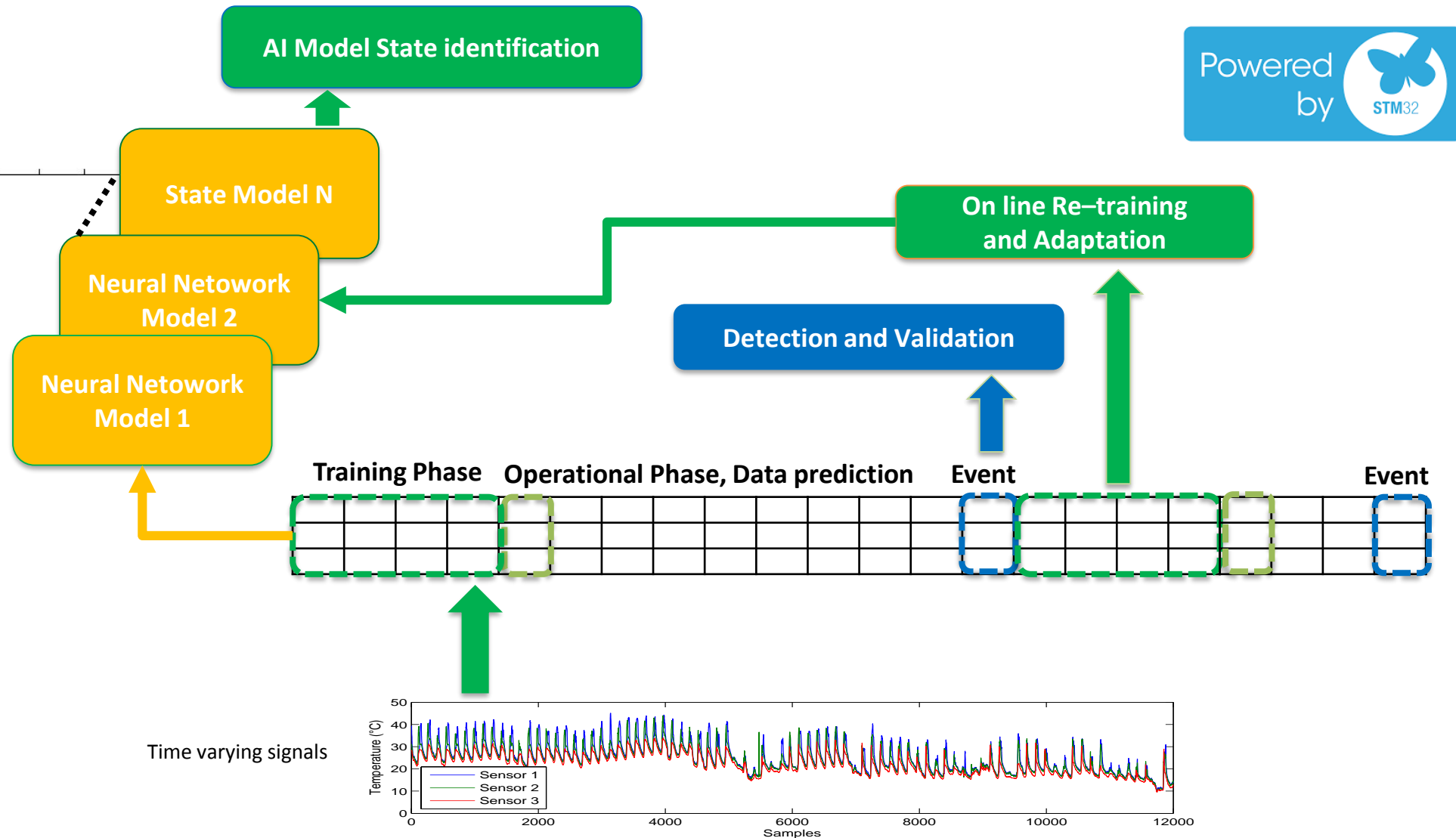
39



AI based Anomaly Detection

Operating in remote and harsh environments

40



Self Learning Statistical models

Self Learning Artificial Neural Network

Machine Learning

STMicroelectronics CPS related publications

41

- **Intelligent Cyber-Physical Systems for Industry 4.0**, to be published @ 1st IEEE International Conference on Artificial Intelligence for Industries, Septembre 26-28 2018
- **Detecting changes at the sensor level in cyber-physical systems**: Methodology and technological implementation, Neural Networks (IJCNN), 2017 International Joint Conference on, 14-19 May 2017, DOI: 10.1109/IJCNN.2017.7966066
- **Event-Driven Cooperative-Based Internet-of-Things (IoT) System**, Proceedings of International Conference on IC Design and Technology, June 4–6, 2018, Otranto Italy
- **Testing a Mobile Visual Search application using a novel open source CPS simulator**, GTTI Thematic Meeting on Multimedia Signal Processing 2017, January 29-31 2017, <http://www.isip40.it/gtti.mmsp2017/>
- **Accurate Cyber Physical System Simulation for Distributed Visual Search Applications**, Proceedings of 3^o International Forum on Research and Technologies for Society and Industry, Modena, Italy, September 11-13 2017
- **An Open-Source Extendable, Highly-Accurate and Security Aware Simulator for Cloud Applications**, Proceedings of 21st Conference on Innovation in Clouds, Internet and Networks (ICIN 2018), 20-22 February 2018 Paris, France
- **Designing a Mobile Visual Search application with the help of a novel open source CPS simulator**, GTTI Thematic Meeting on Multimedia Signal Processing 2018, January 22-23 2018, <http://webmagazine.unitn.it/evento/disi/28651/gtti-thematic-meeting-2018-on-multimedia-signal-processing/>



life.augmented

Invited talk - COSSIM: An Open-Source Integrated Solution to Address the Simulator Gap for Systems of

Systems; Euromicro DSD/SEAA 2018 August 29 – 31, 2018, Prague | Czech Republic <http://dsd->

[2018.fit.cvut.cz/main/DSD_2018_DetailedProgram.pdf](http://dsd-2018.fit.cvut.cz/main/DSD_2018_DetailedProgram.pdf)

STMicroelectronics A.I. related publications

42

- **A 2.9 TOPS/W Deep Convolutional Neural Network SoC in FD-SOI 28nm for Intelligent Embedded Systems**, IEEE ISSCC February 2017 and 17th INTERNATIONAL FORUM ON MPSoC for software-defined hardware, <http://www.mpsoc-forum.org/agenda.html>
- **Intelligent Embedded and Real-Time ANN-based Motor Control for Multi-Rotor Unmanned Aircraft Systems**, Proceedings of 25th IFIP/IEEE International Conference on Very Large Scale Integration (VLSI-SoC) Abu Dhabi, UAE October 23 - 25, 2017
- **Efficient Light Harvesting for Accurate Neural Classification of Human Activities**, Proceedings of 2018 IEEE International Conference on Consumer Electronics (ICCE), Las Vegas, USA, January 12-14, 2018
- **Complexity and Accuracy of Hand-Crafted Detection Methods Compared to Convolutional Neural Networks**, Proceedings of 19th international Conference on Image Analysis and Processing, ICIAP 2017, 11-15 Sept 2017 Pre-trainable Reservoir Computing with Recursive Neural Gas; L Carcano, E Plebani, DP Pau, M Piastra - arXiv preprint arXiv:1807.09510, 2018
- **Pre-trainable Reservoir Computing with Recursive Neural Gas**; L Carcano, E Plebani, DP Pau, M Piastra - arXiv preprint arXiv:1807.09510, 2018
- **Artificial Intelligent Sensors: the core of Cyber-Physical-Systems From Theory to Practice**, 18th International Forum on MPSoC for Software defined Hardware, 7/29 – 8/3 Snowbird, Utah
- **Embedded Real-Time Fall Detection with Deep Learning on Wearable Devices**; Euromicro DSD/SEAA 2018, August 29 – 31, 2018, Prague | Czech Republic
- **Studying the Effects of Feature Extraction Settings on the Accuracy and Memory Requirements of Neural Networks for Keyword Spotting**, Consumer Electronics Berlin (ICCE-Berlin), 2018. ICCEBerlin 2018. IEEE 8th International Conference on
- **A CNN Architecture for Efficient Semantic Segmentation of Street Scenes**, Consumer Electronics Berlin (ICCE-Berlin), 2018. ICCEBerlin 2018. IEEE 8th International Conference on; Conference 2nd Best Paper
- **Automated generation of Single Shot Detector C library from a high level Deep learning framework**, 4th International Forum on Research and Technologies for Society and Industry; Palermo, Italy, September 10-13 2018



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Parallelized Convolutions for Embedded Ultra Low Power Deep Learning SoC, 4th International Forum on Research and Technologies for Society and Industry; Palermo, Italy, September 10-13 2018

I, robot 2004

43



Isn't ironic ?

44



<https://www.nextrembrandt.com/> , 2016