UNIVERSITÀ DELLA CALABRIA
DIPARTIMENTO DI INGEGNERIA INFORMATICA, MODELLISTICA, ELETTRONICA E SISTEMISTICA
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Bigtech

Integrating Machine Learning and Multi-Agent Systems for Fully Enabling Device-Edge-Cloud Continuum in Complex IoT Worlds

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IoTBDS 2023 and COMPLEXIS 2023, Prague.

Outline

1. Internet of Things: where we are and the next future![*]
2. Agents meet the IoT!!![**]
3. The Device-Edge-Cloud continuum Paradigm[***]
4. From Cloud-based Machine Learning to the Embedding Machine Learning and back via the Edge[*****]
5. Integrating ML and Multi-agent Systems: the EU MLSysOps Project (https://mlsysops.eu/)
6. Concluding Remarks

*Giancarlo Fortino, Claudio Savaglio, Giandomenico Spezzano, MengChu Zhou: Internet of Things as System of Systems: A Review of Methodologies, Frameworks, Platforms, and Tools. IEEE Trans. Syst. Man Cybern. Syst. 51(1): 223-236 (2021)

**Giancarlo Fortino, Wilma Russo, Claudio Savaglio, Weiming Shen, Mengchu Zhou: Agent-Oriented Cooperative Smart Objects: From IoT System Design to Implementation. IEEE Trans. Syst. Man Cybern. Syst. 48(11): 1939-1956 (2018)

***https://digital-strategy.ec.europa.eu/en/library/building-ecosystem-where-iot-edge-and-cloud-converge-towards-computing-continuum

***G. Fortino, M. Zhou, M.M Hassan, M. Pathan, S. Karnouskos, Pushing Artificial Intelligence to the Edge: Emerging trends, issues and challenges, Engineering Applications of Artificial Intelligence, 103, 2021,

****C Savaglio, G Fortino, A Simulation-driven Methodology for IoT Data Mining Based on Edge Computing, ACM Transactions on Internet Technology (TOIT) 21 (2), 1-22, 2021

An introduction to IoT

The Internet of Things (IoT) usually refers to a world-wide network of interconnected heterogeneous objects (sensors, actuators, smart devices, smart objects, RFID, embedded computers, etc) uniquely addressable, based on standard communication protocols.

- **Internet of Things**

Everything is able to be networked, discovered and exploited [MSDC2012]

- **Smart Objects**

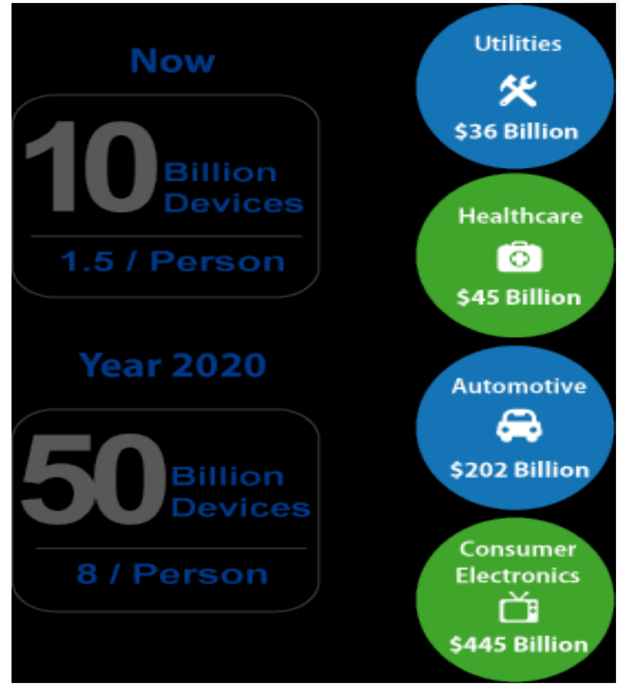
Real world objects with embedded smartness [KKFS2010] [SF21]

[MSDC2012] D. Miorandi, S. Sicari, F. De Pellegrini, and I. Chlamtac, Internet of things: Vision, applications and research challenges, Ad Hoc Networks 10.7 (2012): 1497-1516

[KKFS2010] G. Kortuem, F. Kawsar, D. Fitton, and V. Sundramoorthy, Smart objects as building blocks for the internet of things, IEEE Internet Computing, Vol. 14, n.1, pp. 44-51, 2010.

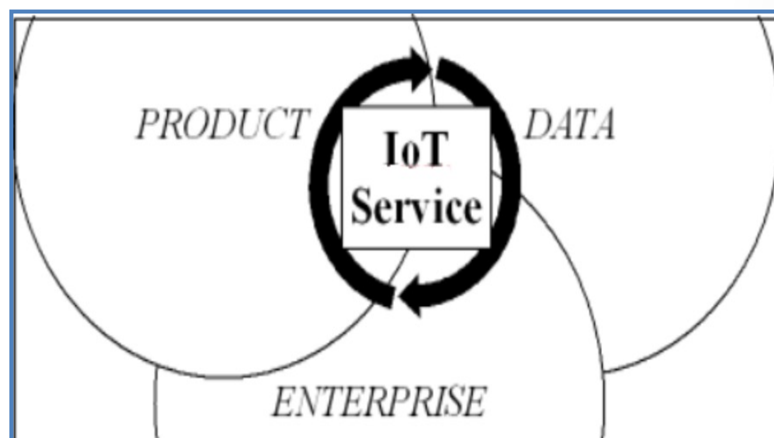
[SF21] Giancarlo Fortino, Claudio Savaglio, Giandomenico Spezzano, MengChu Zhou: Internet of Things as System of Systems: A Review of Methodologies, Frameworks, Platforms, and Tools. IEEE Trans. Syst. Man Cybern. Syst. 51(1): 223-236 (2021)

An introduction to IoT

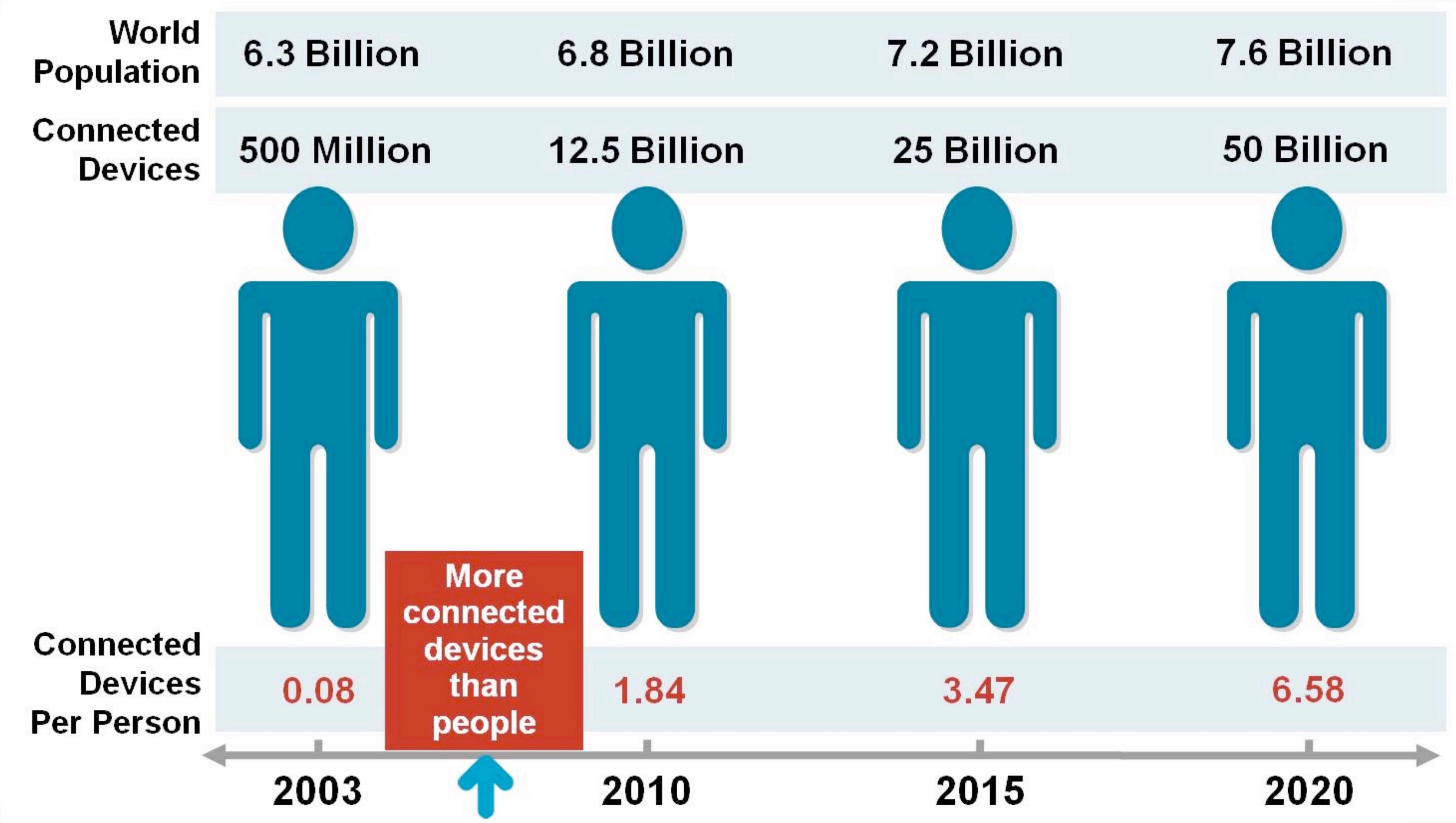


Services are the real IoT drivers, not devices!

Bigger revenues not from IoT devices selling, but from their provided services (''product-service hybrids'').

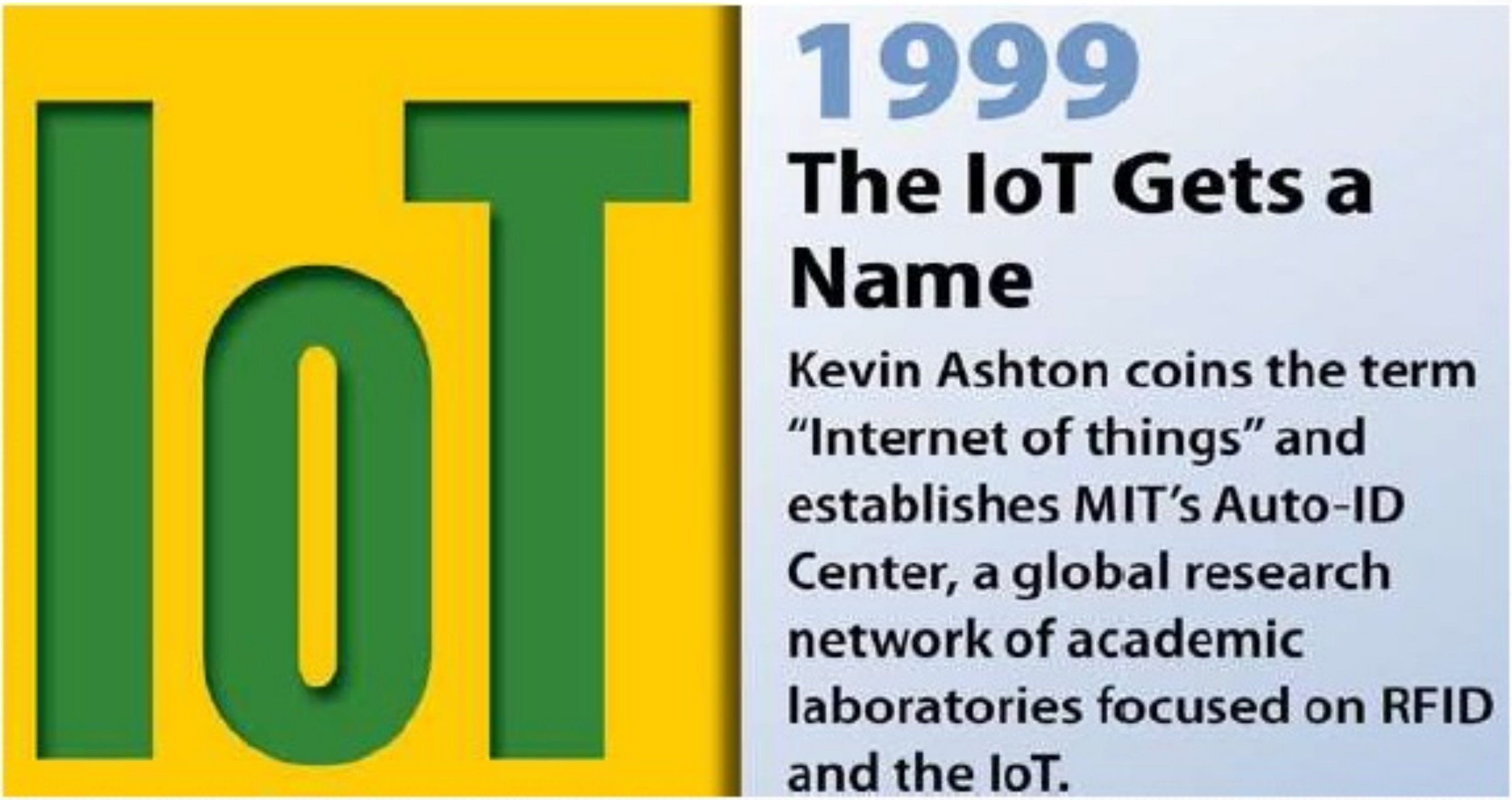


Current Status & Future Prospect of IoT



"Change is the only thing permanent in this world"

IoT History


IoT
1999
The IoT Gets a Name
Kevin Ashton coins the term "Internet of things" and establishes MIT's Auto-ID Center, a global research network of academic laboratories focused on RFID and the IoT.

IoT: Smart Objects

- IoT: which "things"?
  - Objects
  - Machines
  - Buildings
  - Infrastructures
  - Vehicles
  - Pets
  - People
  - Plants
  - … almost everything …

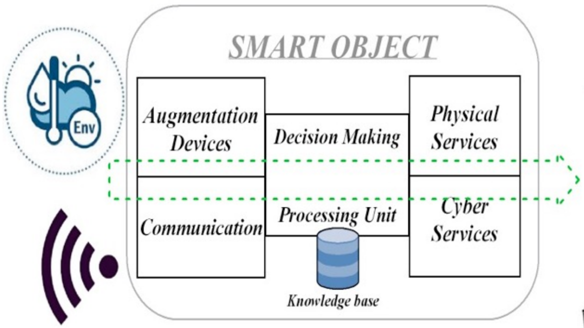
IoT and Smart Objects
A computing perspective

•Beyond the abovementioned *network-oriented IoT definition*, in this talk we will focus on the definition of IoT as a *loosely coupled, decentralized system of cooperating smart objects* (SOs).

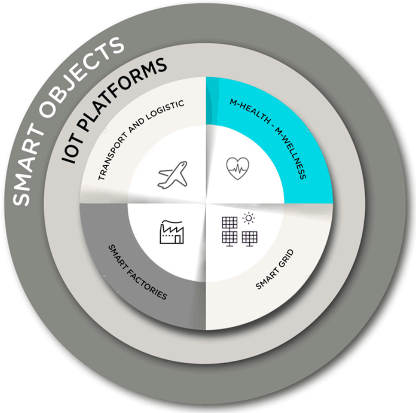
•An SO is an autonomous, physical digital object augmented with sensing/actuating, processing, storing, and networking capabilities.

•SOs are able to sense/actuate, store, and interpret information created within themselves and around the neighboring external world where they are situated, act on their own, *cooperate* with each other, and exchange information with other kinds of electronic devices and human users.

IoT and Smart Objects
Towards systems of systems

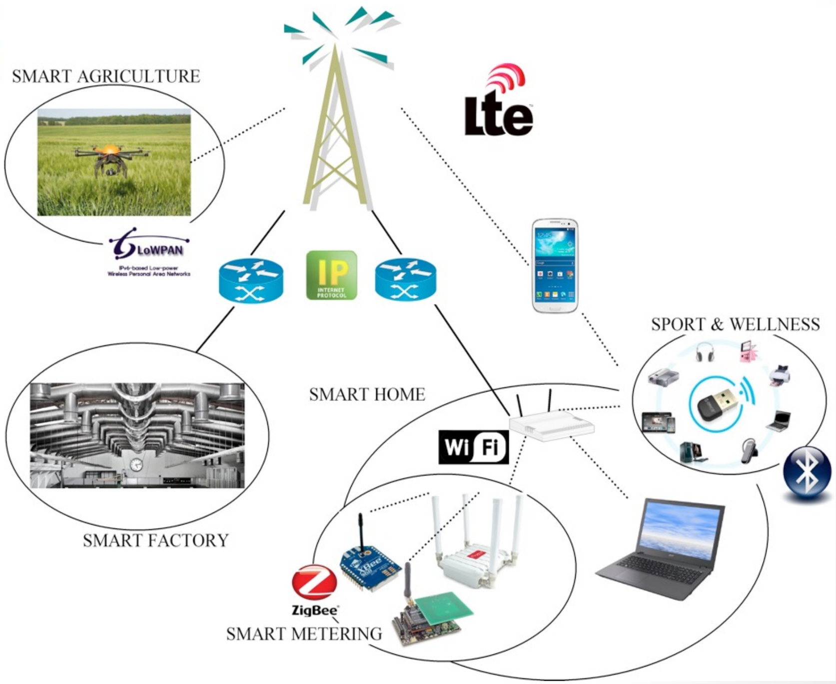


A Smart Object Architecture

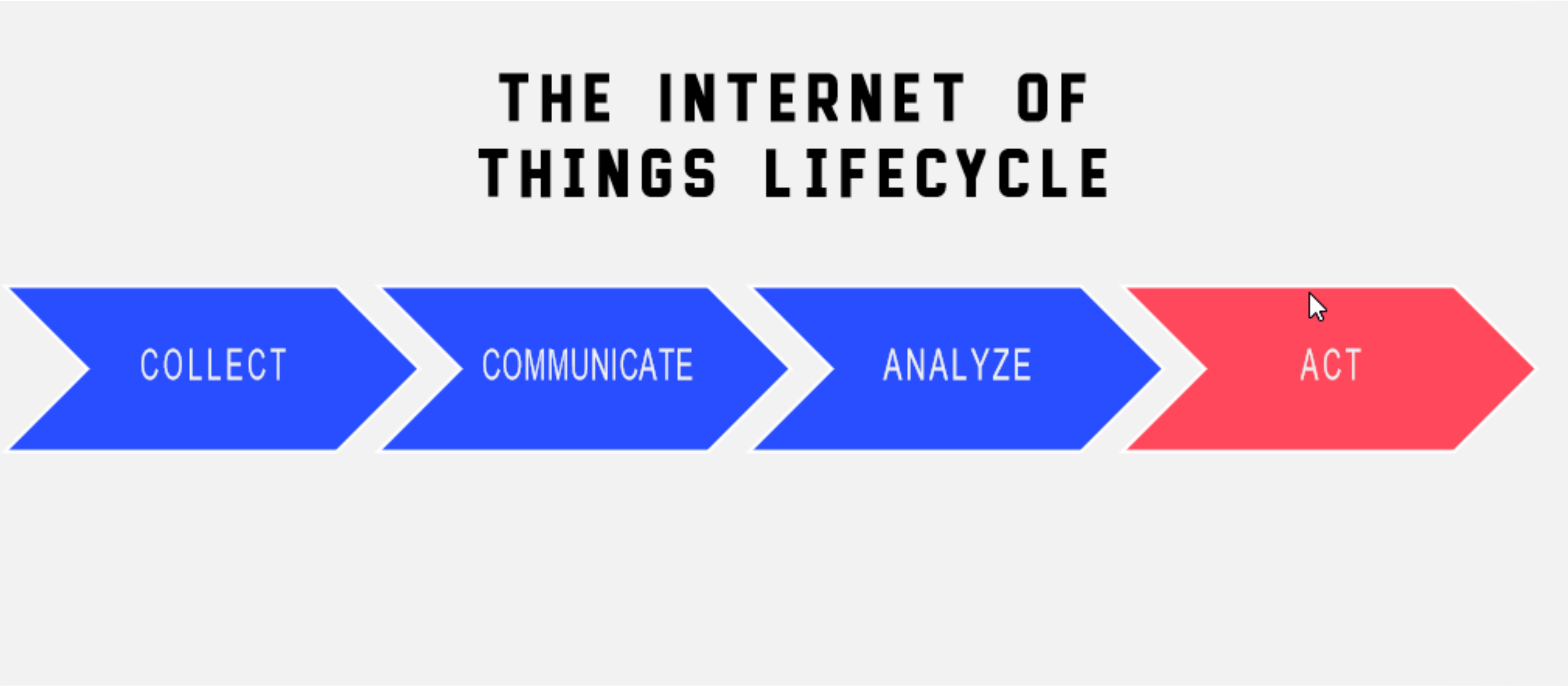


https://inter-iot.eu/

An SO Ecosystem



How IoT works?



How IoT works?

How IoT works?

COMMUNICATION

Sending data and events through networks to some destination

- A cloud platform
- Private data center
- Home network

How IoT works?

ANALYSIS

Creating information from the data

- Visualizing the data
- Building reports
- Filtering data (paring it down)

How IoT works?

ACTION

Taking action based on the information and data

- Communicate with another machine (m2m)
- Send a notification (sms, email, text)
- Talk to another system

Few Applications of IoT

- ✓ Building and Home automation
- ✓ Manufacturing (Industry 4.0)
- ✓ Medical and Healthcare systems (WCS)
- ✓ Media
- ✓ Environmental monitoring
- ✓ Infrastructure management
- ✓ Energy management
- ✓ Transportation (ITS)
- ✓ Better quality of life for elderly (AAL)
- ✓ Urban Computing
- ✓ ... ...

You name it, and you will have it in IoT!

Agents meet the IoT: Why Agents?

- To deal with the IoT system development challenges, we promote exploiting an Agent-based Computing (ABC) paradigm, which is focused on the concept of "agent", as well-defined software engineering and distributed computing paradigm for programming, deploying and managing IoT systems.

- The ABC paradigm models distributed software systems in terms of multi-agent systems (MAS), where agents are networked software entities that can perform specific tasks for a user and have a degree of intelligence that permits them to perform parts of their tasks autonomously by interacting with other agents and with their environment in a useful manner.

- Agents have been to date effectively used in many application domains to analyze and build robust and dynamic distributed systems and applications.

Agents meet the IoT: Why Agents?

- We thus claim that their characteristics also perfectly fit those of IoT systems and their components:
  - *Autonomy*: smart objects as agents should be able to perform the majority of their problem solving tasks without direct intervention of humans or other agents, and they should have a degree of control over their own actions and their own internal state.
  - *Social ability:* smart objects as agents should be able to interact, when they deem appropriate, with other smart objects and even humans in order to complete their own problem solving tasks and to help other smart objects in their activities where appropriate.
  - *Responsiveness*: smart objects as agents should perceive (be aware of) the environment, in which they are situated and which may be the physical world, a user, a set of other smart objects, and respond in a timely manner to changes which occur in it.
  - *Proactiveness*: smart objects as agents should not simply act in response to their environment, but they should also be able to exhibit opportunistic, goal-directed behavior and take the initiative where and when is appropriate.
  - *Mobility*: in order to fulfill physically distributed tasks, mobile smart objects should be able to physically move from one location where they act to another (as mobile software agents can migrate from one environment (machine) to another in a logical environment.

The ACOSO middleware

- The ACOSO middleware allows for the development and management of CSOs, which are modeled as agents that can cooperate with each other and with non-agent cyber-physical entities to fulfill specific goals.

- An ecosystem of CSOs therefore forms a Multi-Agent System (MAS).

- Website: http://acoso.dimes.unical.it

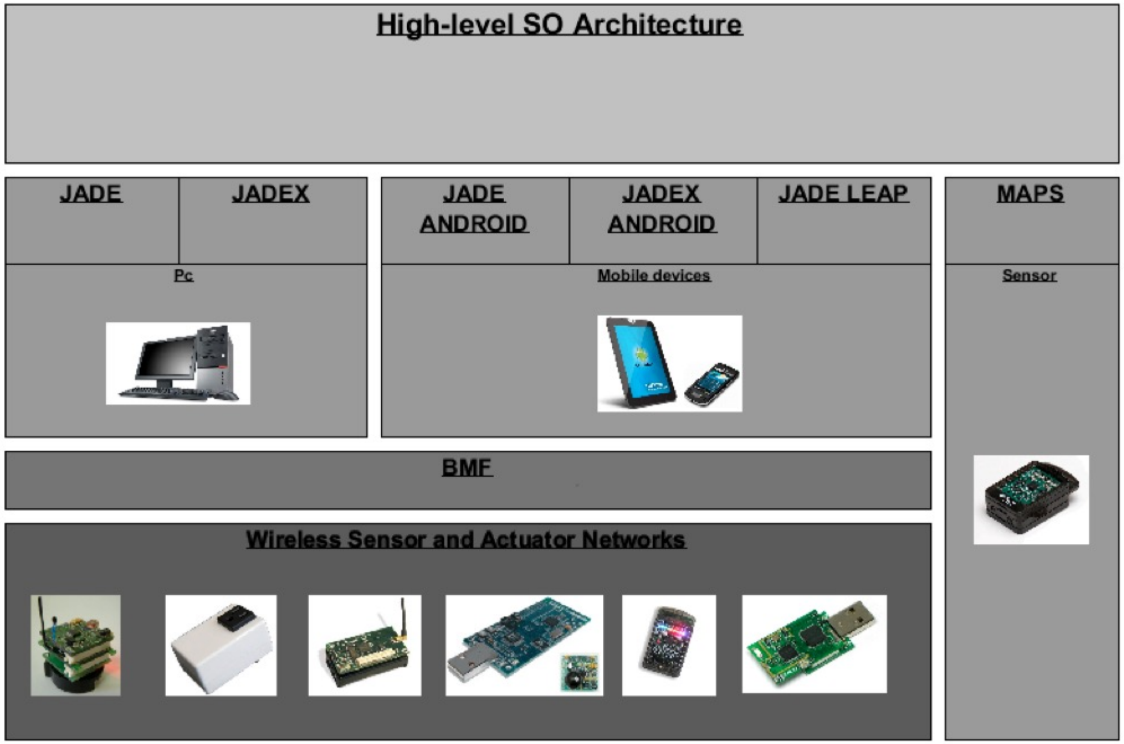
The ACOSO middleware

- ACOSO currently relies on JADE that provides an effective agent management and communication support.

- Specifically, CSOs can be implemented as either JADE or JADEX agents, atop both Java-based and Android-based devices.

- JADE-based CSOs can cooperate by a direct coordination model based on ACL message passing and/or by a spatio-temporal decoupled coordination model relying on a topic-based publish/subscribe mechanism.

The ACOSO middleware: Layers



http://maps.deis.unical.it

http://bmf.deis.unical.it

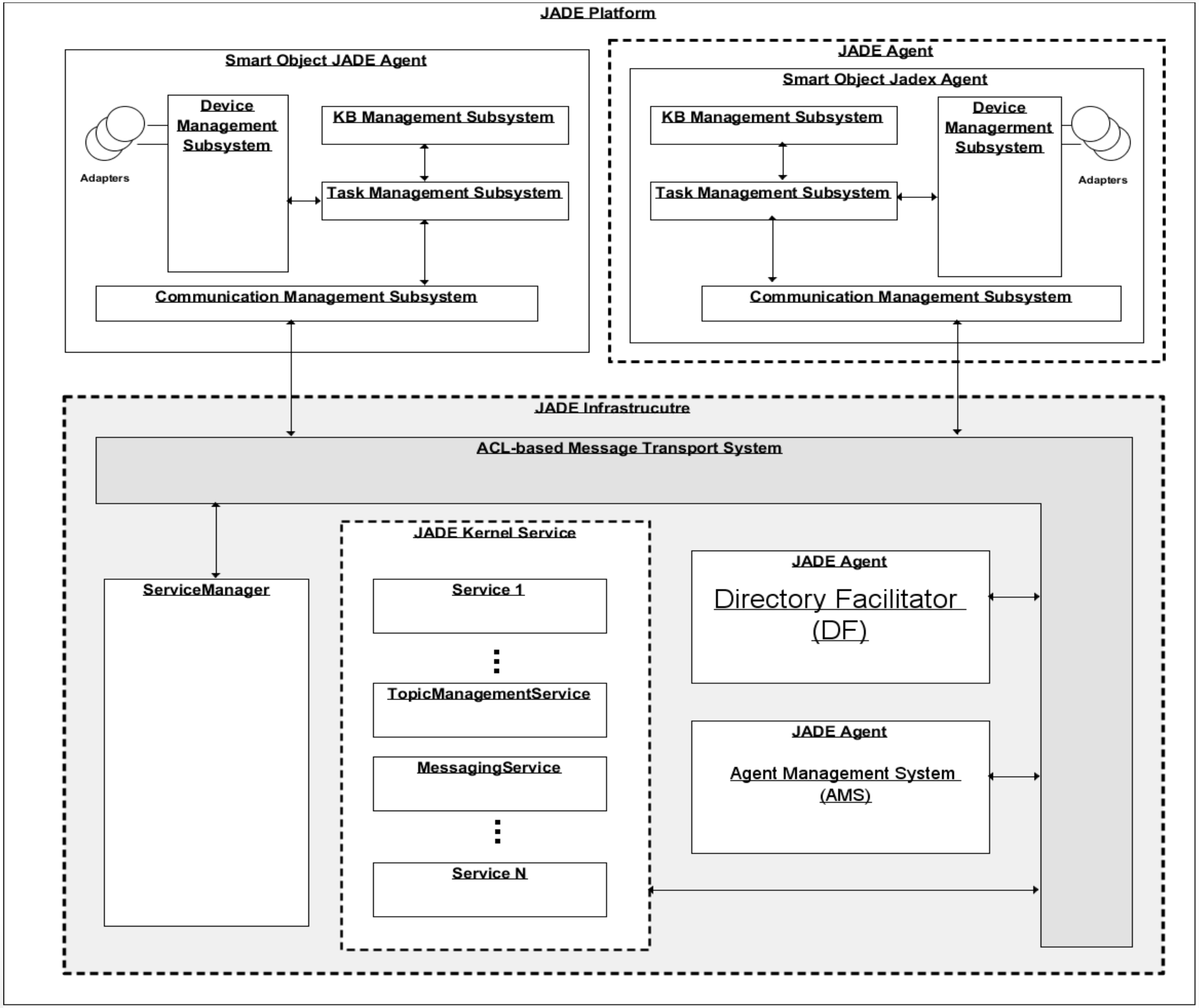
http://spine.deis.unical.it

[MAPS] F. Aiello, G. Fortino, R. Gravina, A. Guerrieri, "A Java-based Agent Platform for Programming Wireless Sensor Networks" The Computer Journal, 54(3), pp.439-454, 2011.

[BMF] A. Guerrieri, G. Fortino, A. Ruzzelli, G. O'Hare, "A Flexible Building Management Framework based on Wireless Sensor and Actuator Networks", Journal of Network and Computer Applications, Elsevier, 35(6), 1934–1952. 2012.

[SPINE] G. Fortino, R. Giannantonio, R. Gravina, P. Kuryloski, R. Jafari, "Enabling Effective Programming and Flexible Management of Efficient Body Sensor Network Applications", in IEEE Transactions on Human-Machine Systems, vol. 43, no. 1, pp. 115–133, Jan. 2013.

The (J)ACOSO middleware: JADE-based Architecture



The Device-Edge-Cloud continuum

The symbiotic relationship between cloud computing, edge computing and IoT is reflected on the term cloud/edge/IoT computing continuum. The latter is a way of visualizing the relationship between cloud computing, edge computing, and the Internet of Things (IoT). It represents the different layers of the computing infrastructure that work together to support different applications. Specifically:

- At the top of the continuum is cloud computing, which provides a highly scalable and flexible infrastructure for storing, processing, and analyzing data based on a single or multiple clouds (e.g., hybrid clouds).
- In the middle of the continuum is edge computing, which brings the computing and storage resources closer to the IoT devices themselves.
- At the bottom of the continuum is the IoT itself, which consists of a vast network of connected devices that generate and transmit data. IoT includes a wide variety of devices, from sensors and wearables to industrial machinery and smart appliances.

At each layer, different technologies and architectures are used to meet the specific requirements of enterprise applications. By working together, these layers form a continuum that enables the seamless and efficient processing of data from IoT devices. Modern enterprises are expected to invest in the different layers of the continuum to meet the requirements of their applications and improve their business results.

The Device-Edge-Cloud continuum

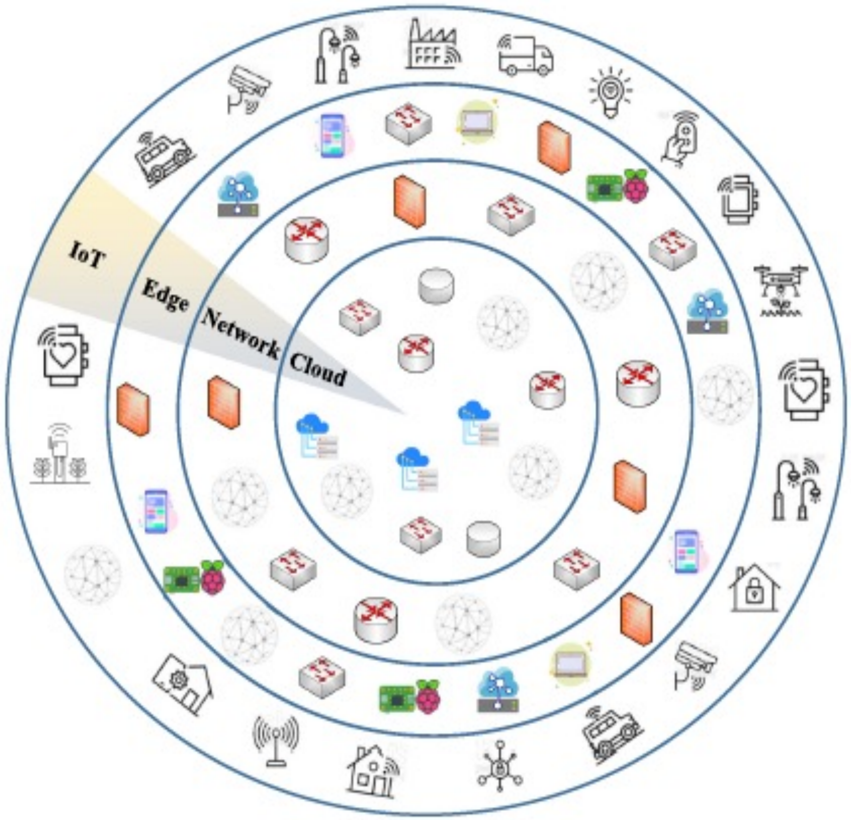


Fig. 1. 4-tier architecture — the outer layer is composed of IoT devices generating data and transmitting these to Edge devices (second layer). The Innermost layer is comprised of a Cloud datacenter, with a data network connecting these layers.

Khaled Alwasel, Devki Nandan Jha, Fawzy Habeeb, Umit Demirbaga, Omer Rana, Thar Baker, Scharam Dustdar, Massimo Villari, Philip James, Ellis Solaiman, Rajiv Ranjan, IoTSim-Osmosis: A framework for modeling and simulating IoT applications over an edge-cloud continuum, Journal of Systems Architecture, Volume 116, 2021, https://doi.org/10.1016/j.sysarc.2020.101956.

The Device-Edge-Cloud continuum

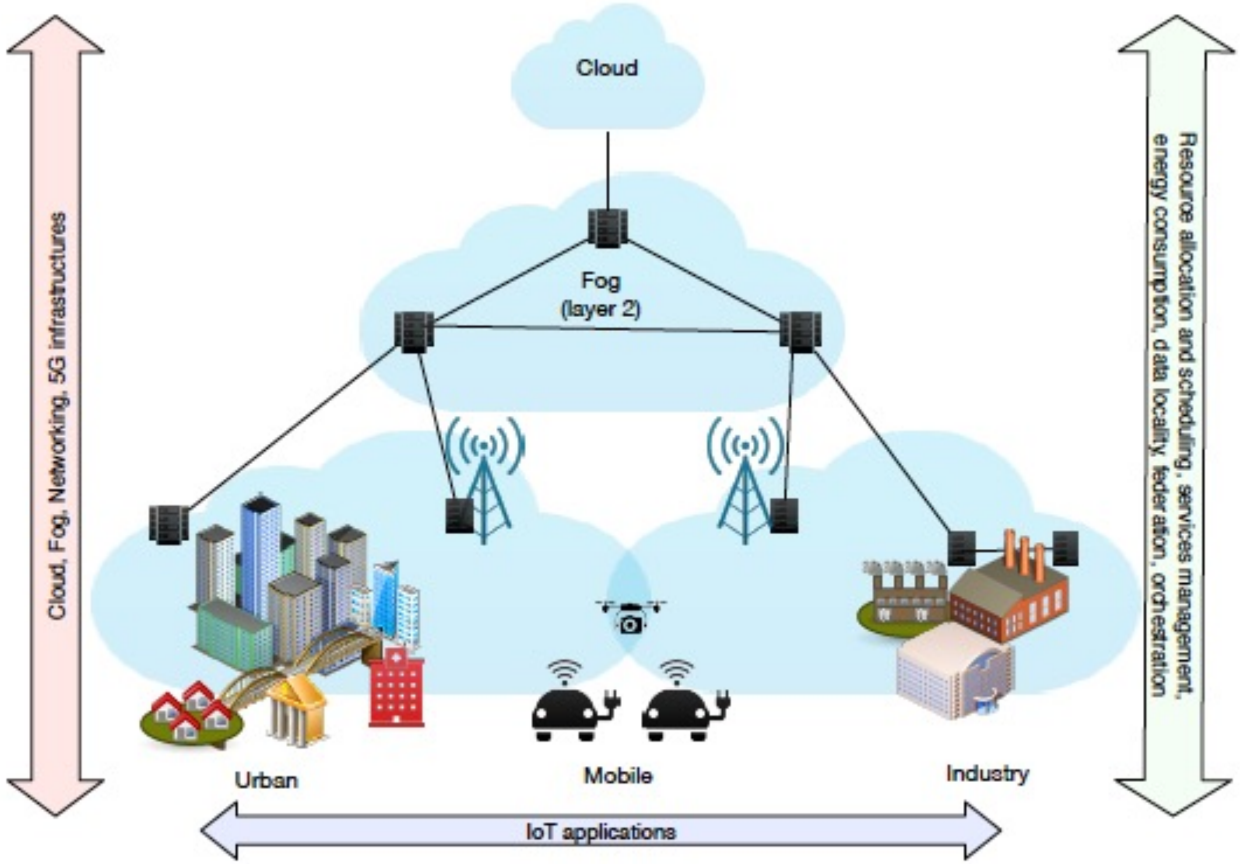


Figure 1: Illustrative overview, within the IoT-Fog-Cloud infrastructure, of topics covered in this paper.

Luiz Bittencourt, Roger Immich, Rizos Sakellariou, Nelson Fonseca, Edmundo Madeira, Marilia Curado, Leandro Villas, Luiz DaSilva, Craig Lee, Omer Rana, The Internet of Things, Fog and Cloud continuum: Integration and challenges, Internet of Things, Volumes 3–4, 2018, Pages 134-155, https://doi.org/10.1016/j.iot.2018.09.005.

The Device-Edge-Cloud continuum

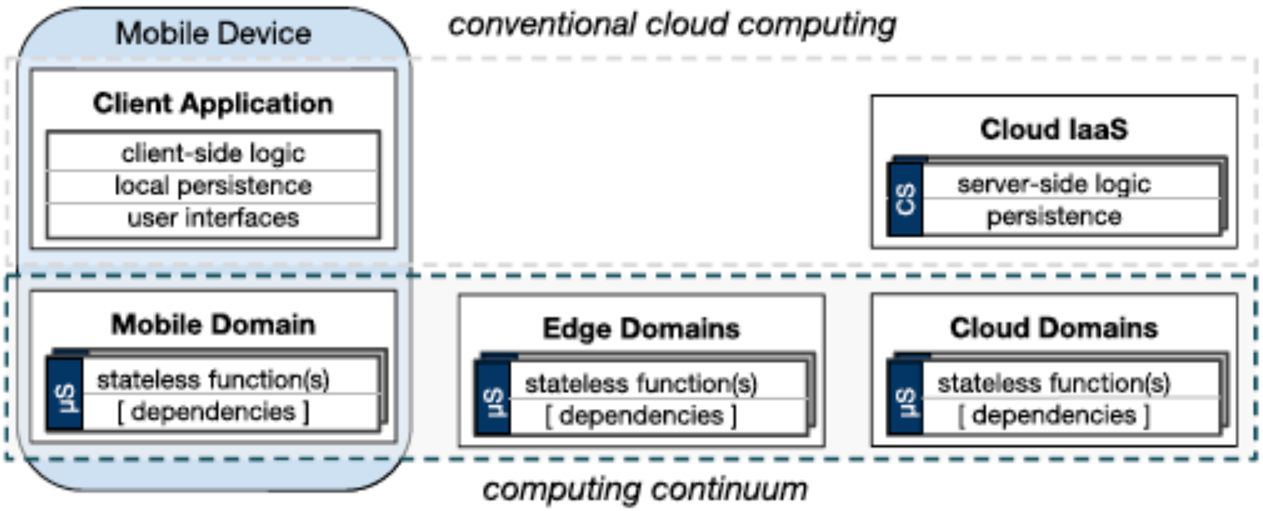


Fig. 1. The high-level architecture of a mobile application exploiting both the computing continuum, by means of μ-services (μS) provided by mobile, edge, and cloud domains, and conventional mobile/cloud computing, by means of local computation and cloud services (CSs).

L. Baresi, D. F. Mendonça, M. Garriga, S. Guinea, and G. Quattrocchi. 2019. A Unified Model for the Mobile-Edge-Cloud Continuum. ACM Trans. Internet Technol. 19, 2, Article 29 (April 2019), 21 pages. DOI:https://doi.org/10.1145/3226644

A Deep Learning Approach on Edge-Fog-Cloud Framework for Driving Behavior Detection and Monitoring

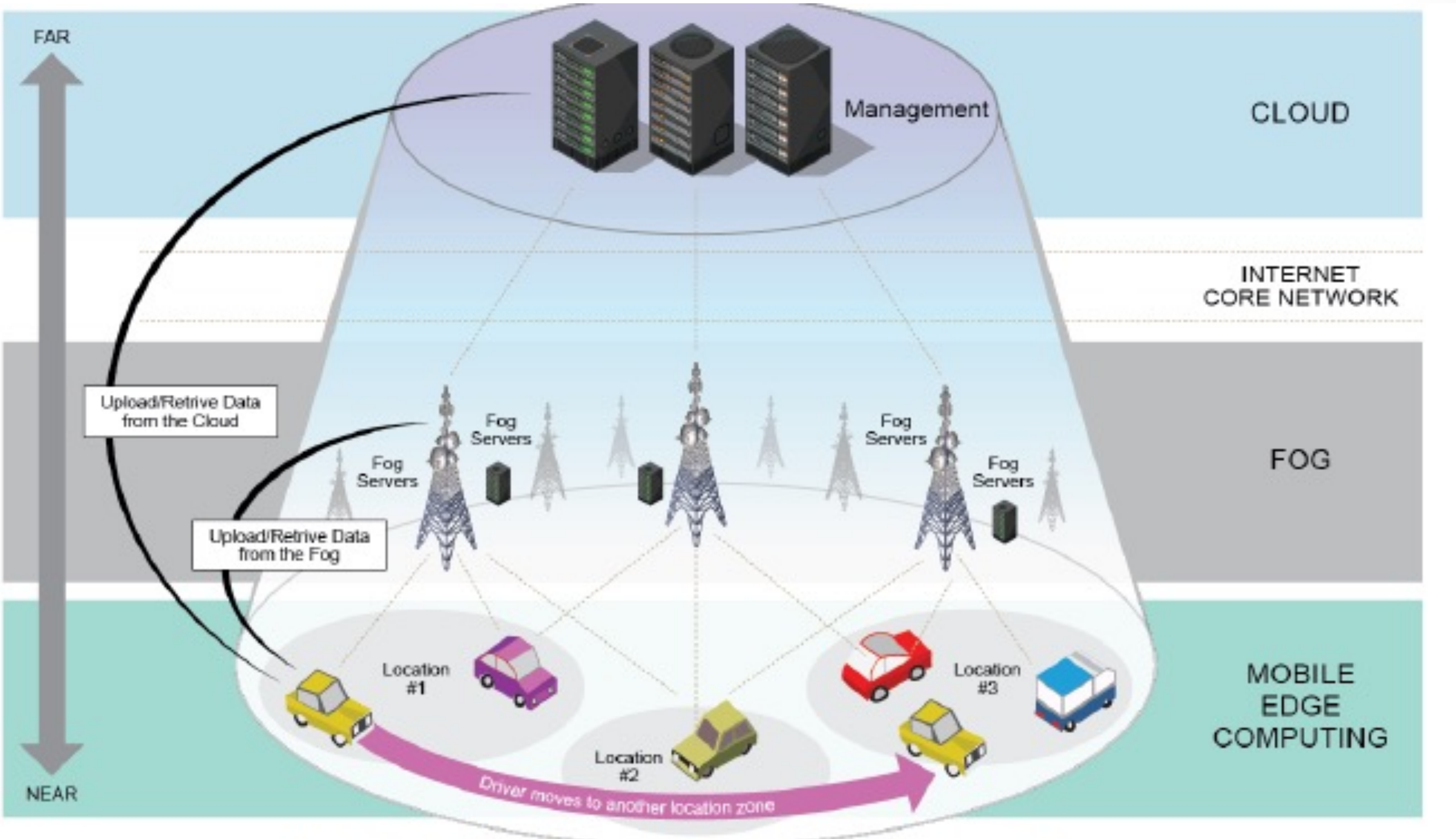


Fig. 1. Edge-Fog-Cloud Framework for Driving Behavior Detection and Monitoring

Mabrook S. Al-Rakhami, Abdu Gumaei, Mohammad Mehedi Hassan, Atif Alamri, Musaed Alhussein, Md. Abdur Razzaque and Giancarlo Fortino, "A Deep Learning Approach on Edge-Fog-Cloud Framework for Driving Behavior Detection and Monitoring," CAE Elsevier, to appear.

A Deep Learning Approach on Edge-Fog-Cloud Framework for Driving Behavior Detection and Monitoring

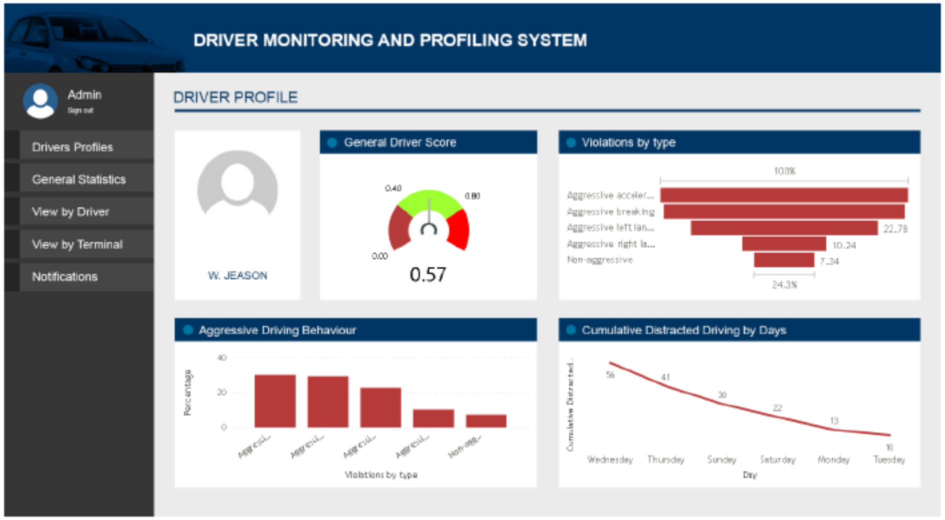


Fig. 23. System dashboard for d

Table 1
The driving behaviour classes with numbers, names and labels.

Behaviour Class Number	Behaviour Class Name	Behaviour Class Label
0	Non-aggressive	NonAgr
1	Aggressive breaking	AgrBrk
2	Aggressive acceleration	AgrAce
3	Aggressive left lane change	AgrLefLanCha
4	Aggressive right lane change	AgrRigLanCha

Table 2
ADBs dataset Total Samples.

Behaviour Class Label	Number of Samples
NonAgr	24000
AgrBrk	24000
AgrAce	24000
AgrLefLanCha	24000
AgrRigLanCha	24000
Total	120000

Table 4
Results of precision, recall, and F1-score

Behavior Class Label	Precision	Recall	F1-score
NonAgr	0.745	0.864	0.800
AgrBrk	0.720	0.749	0.734
AgrAce	0.765	0.624	0.687
AgrLefLanCha	0.749	0.734	0.741
AgrRigLanCha	0.770	0.775	0.773
Micro avg.	0.749	0.749	0.749
Macro avg.	0.750	0.749	0.747
Weighted avg.	0.750	0.749	0.747

Table 5
Comparison of accuracy results of DNN model against the current related work

Authors [Ref.]	Model	Accuracy (%)
Alamri et al. [18]	DCNN	71.95% on processed dataset 1 and 73.02% on processed dataset 2
Proposed work	DNN	74.86% on original dataset

Mabrook S. Al-Rakhami, Abdu Gumaei, Mohammad Mehedi Hassan, Atif Alamri, Musaed Alhussein, Md. Abdur Razzaque and Giancarlo Fortino, “A Deep Learning Approach on Edge-Fog-Cloud Framework for Driving Behavior Detection and Monitoring,” CAE Elsevier, to appear.

Simulation-Driven Platform for Edge-Based AAL Systems

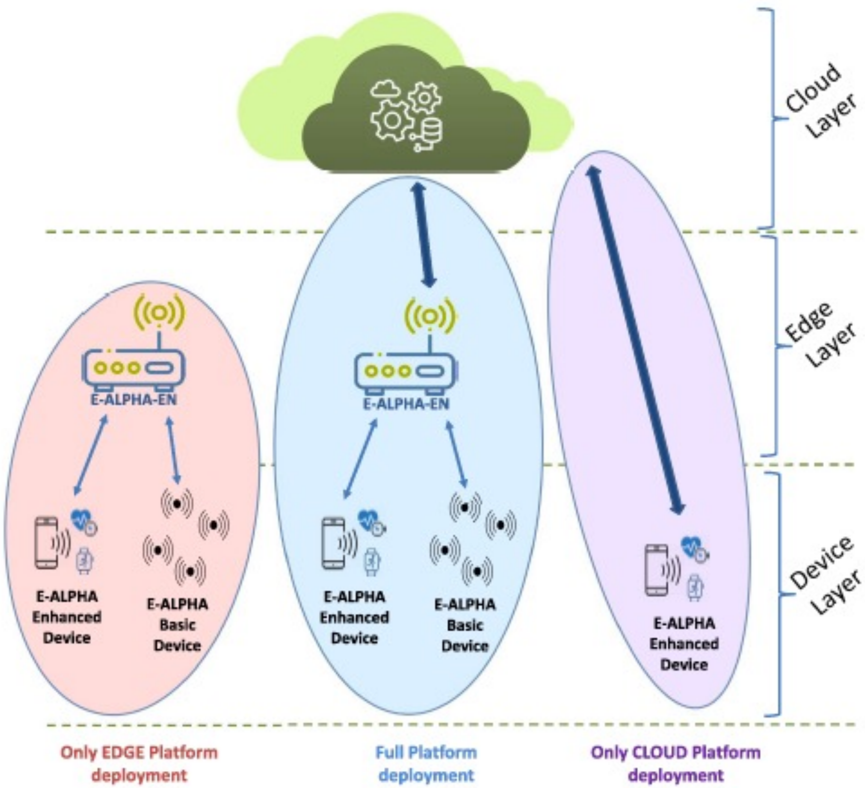


Fig. 1. A flexible and configurable three-tier (cloud/edge/devices) architecture.

Fig. 2. High-level communication architecture of the E-ALPHA system.

G. Aloi, G. Fortino, R. Gravina, P. Pace and C. Savaglio, "Simulation-Driven Platform for Edge-Based AAL Systems," in *IEEE Journal on Selected Areas in Communications*, vol. 39, no. 2, pp. 446-462, Feb. 2021, doi: 10.1109/JSAC.2020.3021544.

Simulation-Driven Platform for Edge-Based AAL Systems

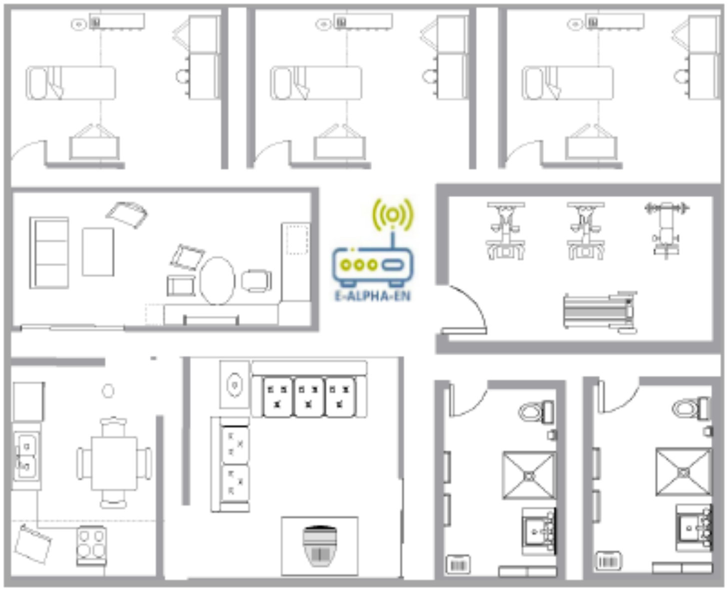


Fig. 7. Layout of the simulation environment: a care facility.

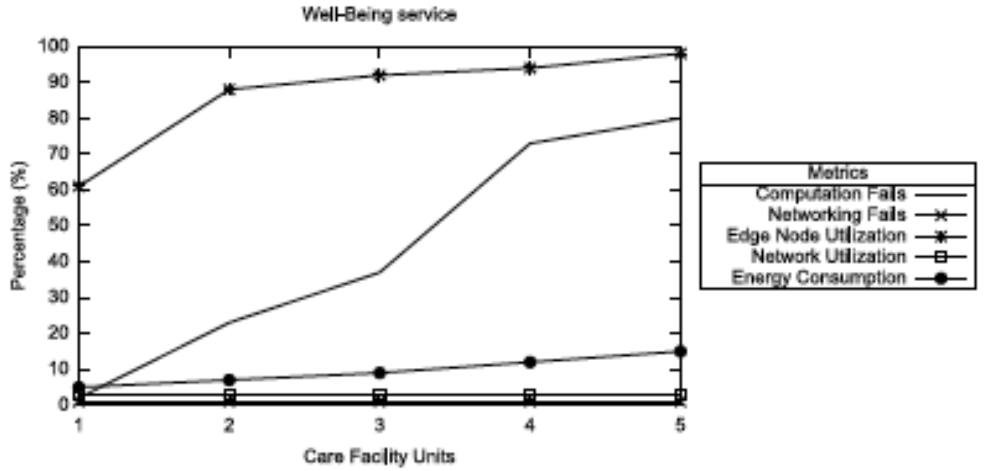


Fig. 8. Well-being services performances with multiple care facility units served by one edge node.

TABLE III
DETAILED EHEALTH SERVICE PERFORMANCE WITH RESPECT TO THE DIFFERENT DEPLOYMENTS SUPPORTED BY E-ALPHA AND A 3G-BASED CONNECTIVITY

Deployment Type	Metrics		
	Service Time (s)	Networking Time (s)	Fails (%)
OnlyEdge	13.1	0.9	32
OnlyCloud	10.3	2.2	88
FullPlatform	11.0	2.3	30

From Current to Future World of Wearables:

Conventional WCS Architecture and data provided by WCS

Categories	*Data Signals*	*Application Foci*	*Main Application Domains*
Physiological	Cardiorespiratory parameters, PPG, Body temperature, SpO2, EDA, Blood glucose	Vital signs monitoring, Emotion recognition, Diabetic monitoring, Sleep monitoring	Healthcare, Wellness, Fitness, Sport, Emergency response
Inertial	Acceleration, Orientation, Magnetometer values	Gesture/Movement recognition, Fall detection	Sports, Healthcare, Wellness, Emergency response
Visual	Image &depth map, Image	Aiding low-vision people, Fall detection, environment recognition	Healthcare, Emergency response
Audio	Environmental sounds, Throat sounds, Voice	Ingestive behavior monitoring, Activity and Voice recognition	Healthcare, Emergency response
Strain	Strain	Activity recognition, Ingestive behavior monitoring	Healthcare, Fitness, Sport
Force	Force	Gait analysis, Activity recognition	Healthcare, Fitness, Sport, Emergency response
RFID	RF signal	Activity recognition, Man-Environment interaction	Manufacturing, Logistics

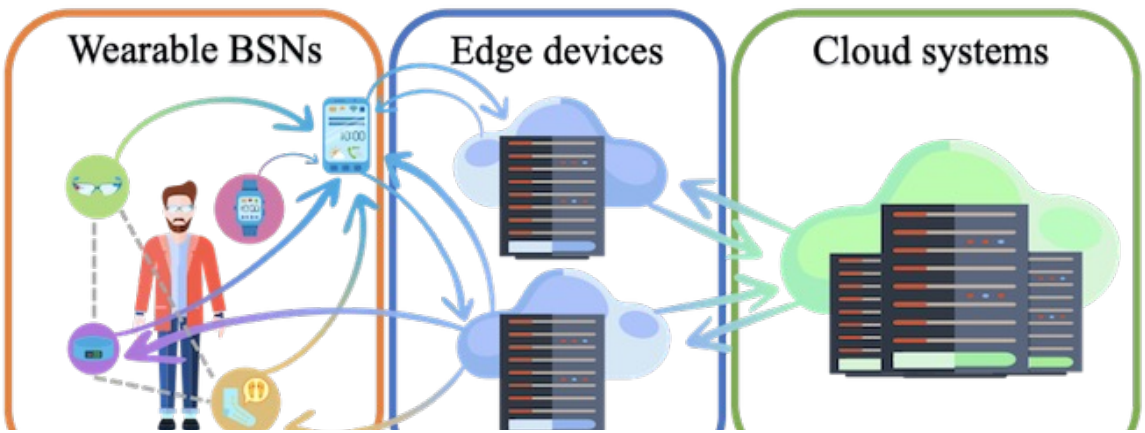


Figure 1.1: Conventional WCS Architecture and data provided by WCS

SPINE Body-of-Knowledge
https://projects.dimes.unical.it/spine-bok/

- The **SPINE Body of Knowledge (BoK)** has been created over the last 15 years in the context of the **open-source SPINE project**, and includes models, methods, algorithms, frameworks, tools and systems for the systematic and full-fledged development of **wearable computing systems based on body sensor networks**.

- SPINE covers many different **application domains**: Healthcare, Fitness, Sport, Factory, Transportation, Gaming, Social interactions, Defence.

- The SPINE project was **originally established in 2006** at the Telecom Italia/Pirelli Wireless Sensor Networks Lab in Berkeley (CA). The founders were University of Calabria (G. Fortino), Telecom Italia/Pirelli WSN Lab (M. Sgroi), Telecom Italia Lab (F. Bellifemine), and University of Berkeley (A. Sangiovanni-Vincentelli). Since 2013, the project is **fully driven and managed by the Prof. Fortino's research group** at University of Calabria. Many R&D groups from Academia and Industry contributed to SPINE BoK, both with research contributions and with contribution to the **open-source code**.

- In particular, the **SPINE BoK includes**: the SPINE framework and related methodology (SPIME-DM), the SPINE extension frameworks (SPINE2, C-SPINE, A-SPINE, SPINE-*), the BodyCloud infrastructure and related methodology, the BodyEdge infrastructure, and a rich set of application-specific multi-sensor data fusion algorithms.

SPINE Body-of-Knowledge

https://projects.dimes.unical.it/spine-bok/

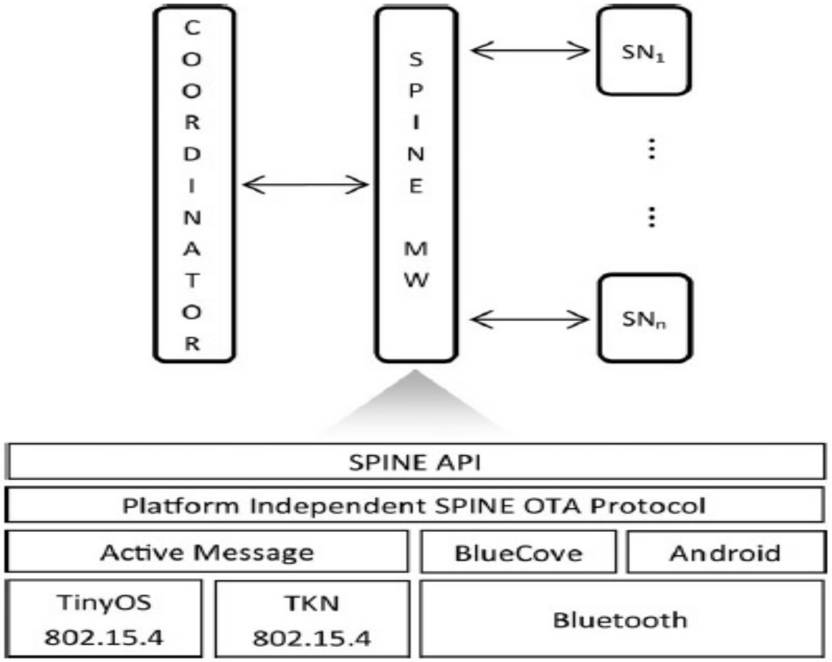
Overall, the SPINE research and **dissemination activities produced 100+ papers**, **notably 40+ in top-level journals** (e.g. IEEE-THMS, IEEE-SensorsJ, IEEE-IoTJ, IEEE-Network, IEEE-WCM, IEEE-TASE, INFFUS, FGCS, JNCA), **5000+ number of citations** according to Google Scholar with an **h-index=30**, and **five highly cited papers** according to Web of Science.

The SPINE reference paper "*Giancarlo Fortino, Roberta Giannantonio, Raffaele Gravina, Philip Kuryloski, Roozbeh Jafari: Enabling Effective Programming and Flexible Management of Efficient Body Sensor Network Applications. IEEE Trans. Hum. Mach. Syst. 43(1): 115-133 (2013)*" received the prestigious **A. P. Sage Best SMC Transactions Paper Award 2014**.

Our **book** includes the overall SPINE BoK contents: *Giancarlo Fortino, Raffaele Gravina, Stefano Galzarano. Wearable Computing: From Modeling to Implementation of Wearable Systems based on Body Sensor Networks. ISBN: 978-1-119-07880-7. April 2018 Wiley-IEEE Press.*

Prof. Fortino is Distinguished Lecturer of IEEE Sensors Council disseminating the SPINE BoK with lectures on "Wearable Computing Systems based on Body Sensor Networks: State-of-the-art and Future Research Challenges".

The SPINE (Signal Processing In-Node Environment) Project



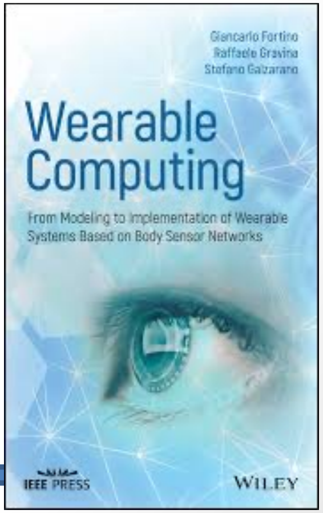
http://spine.deis.unical.it

Project Contributors:

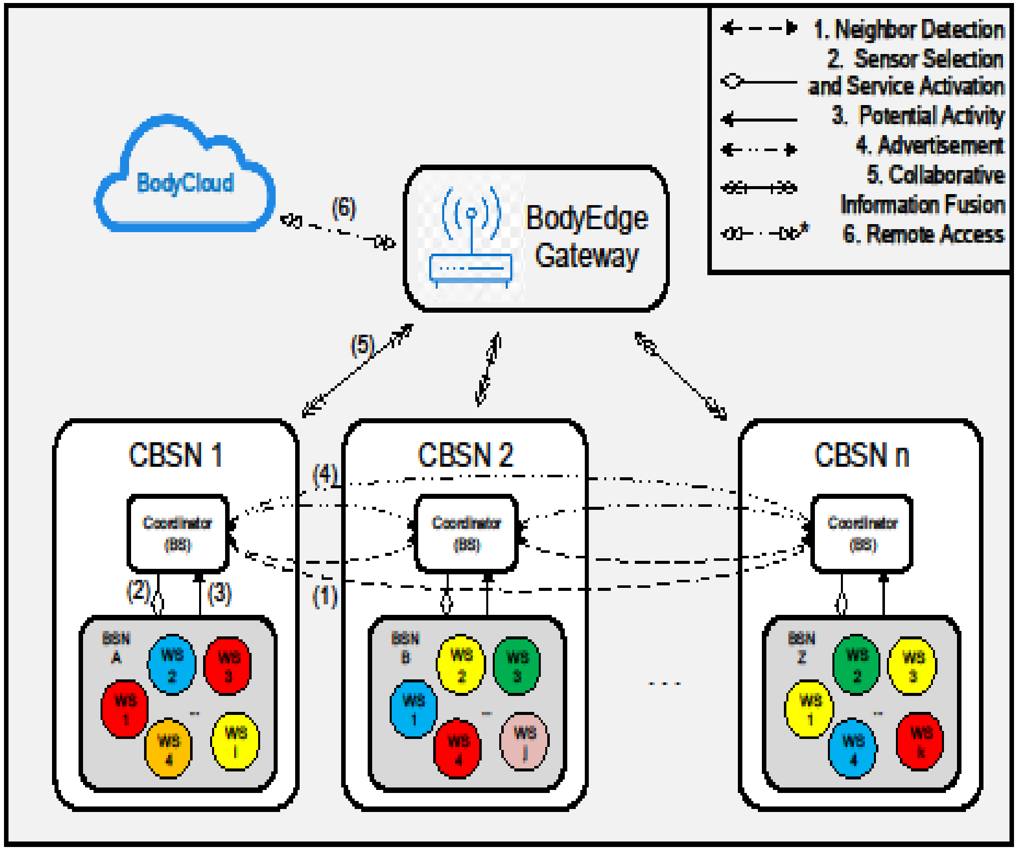
- Telecom Italia (F. Bellifemine)
- UT Dallas (R. Jafari)
- UC Berkeley (A. Sangiovanni-Vincentelli)
- ...

- G. Fortino, R. Giannantonio, R. Gravina, P. Kuryloski, R. Jafari, "Enabling Effective Programming and Flexible Management of Efficient Body Sensor Network Applications", IEEE Transactions on Human-Machine Systems, vol. 43, no. 1, pp. 115-133, Jan. 2013.
Award: 2014 Andrew P. Sage Best IEEE SMC Transactions
(from Web of Science Core Collection) Highly Cited Paper

-G. Fortino, S. Galzarano, R. Gravina, *Wearable Systems and Body Sensor Networks: from modeling to implementation*, Wiley, USA, 2018.



EDGE-CLOUD C-SPINE-based Architecture



1) Neighbor Detection: it detects neighbor CBSNs among co-located people in a specific range.

2) Sensor Selection and Service activation: when neighbors have been detected, all of BSNs will activate/ select sensing on their own nodes and necessary (processing) services will be activated. This step will allow the system saving energy which means sensor will only activated when it is needed.

3) Potential Activity: once a one-sided potential activity occurs on a BSN, the corresponding BS will be notified.

4) Advertisement: the coordinator will send a message to all neighbor CBSNs to request if there is a corresponding reaction for detecting multi-user activity.

5) Collaborative Information Fusion: low-level data and recognized individual activity will be sent to BodyEdge; the edge layer will perform decision-level fusion according to specific classification algorithms to detect the multi-user activity.

6) Remote Access: if large amounts of data are needed for computation or storage, the BodyCloud layer will provide proper support.

*G. Fortino, D. Parisi, V. Pirrone, G. Di Fatta, *BodyCloud: A SaaS Approach for Community Body Sensor Networks*, *Future Generation Computer Systems*, vol. 35, n. 6, pp. 62-79, 2014.

*G. Fortino, S. Galzarano, R. Gravina, W. Li: *A framework for collaborative computing and multi-sensor data fusion in body sensor networks*. Information Fusion 22: 50-70 (2015)

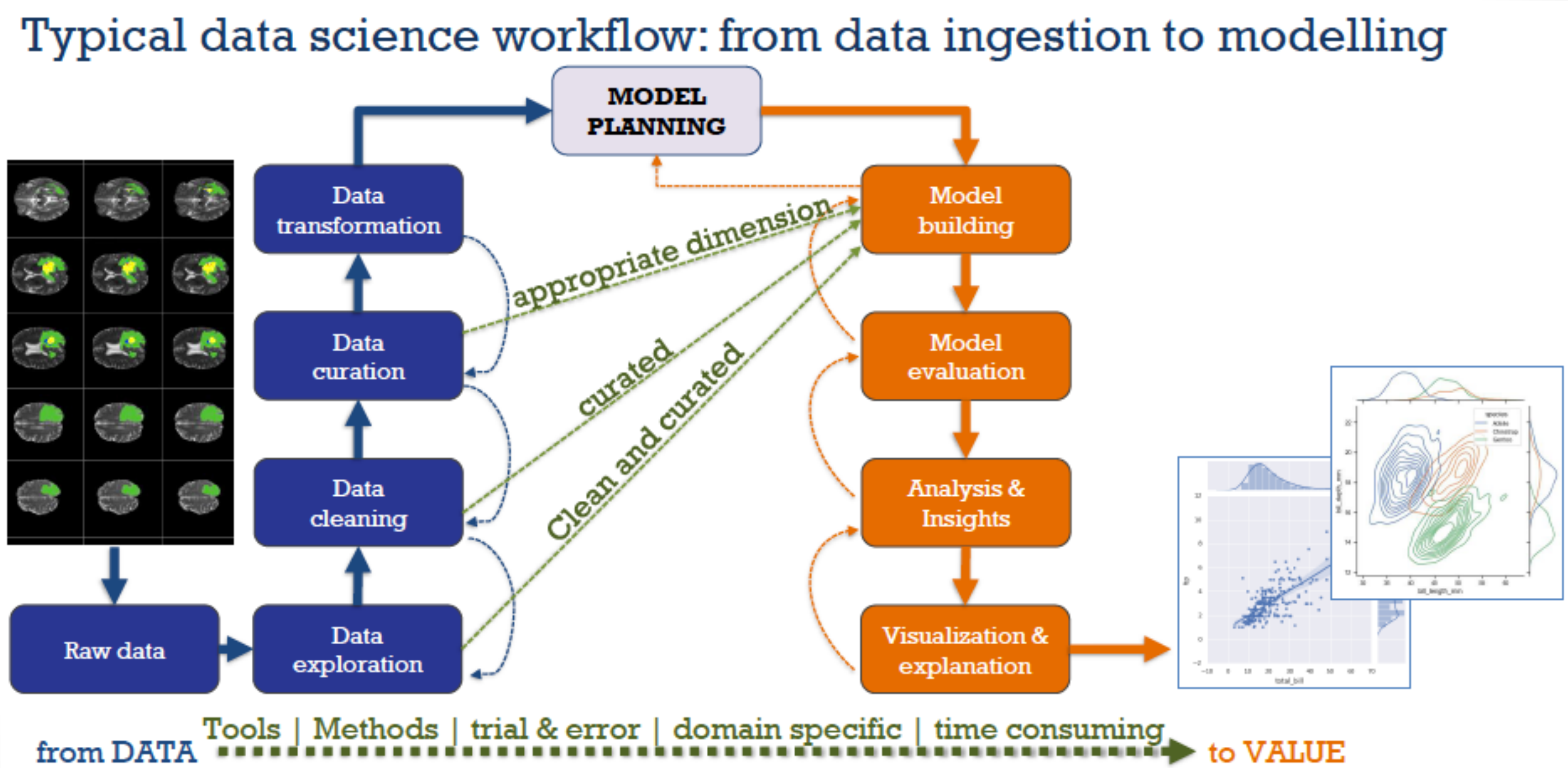
*P. Pace, G. Aloi, R. Gravina, G. Caliciuri, G. Fortino, Antonio Liotta: *An Edge-Based Architecture to Support Efficient Applications for Healthcare Industry 4.0*. IEEE Trans. Ind. Informatics 15(1): 481-489 (2019)

Machine Learning & IoT

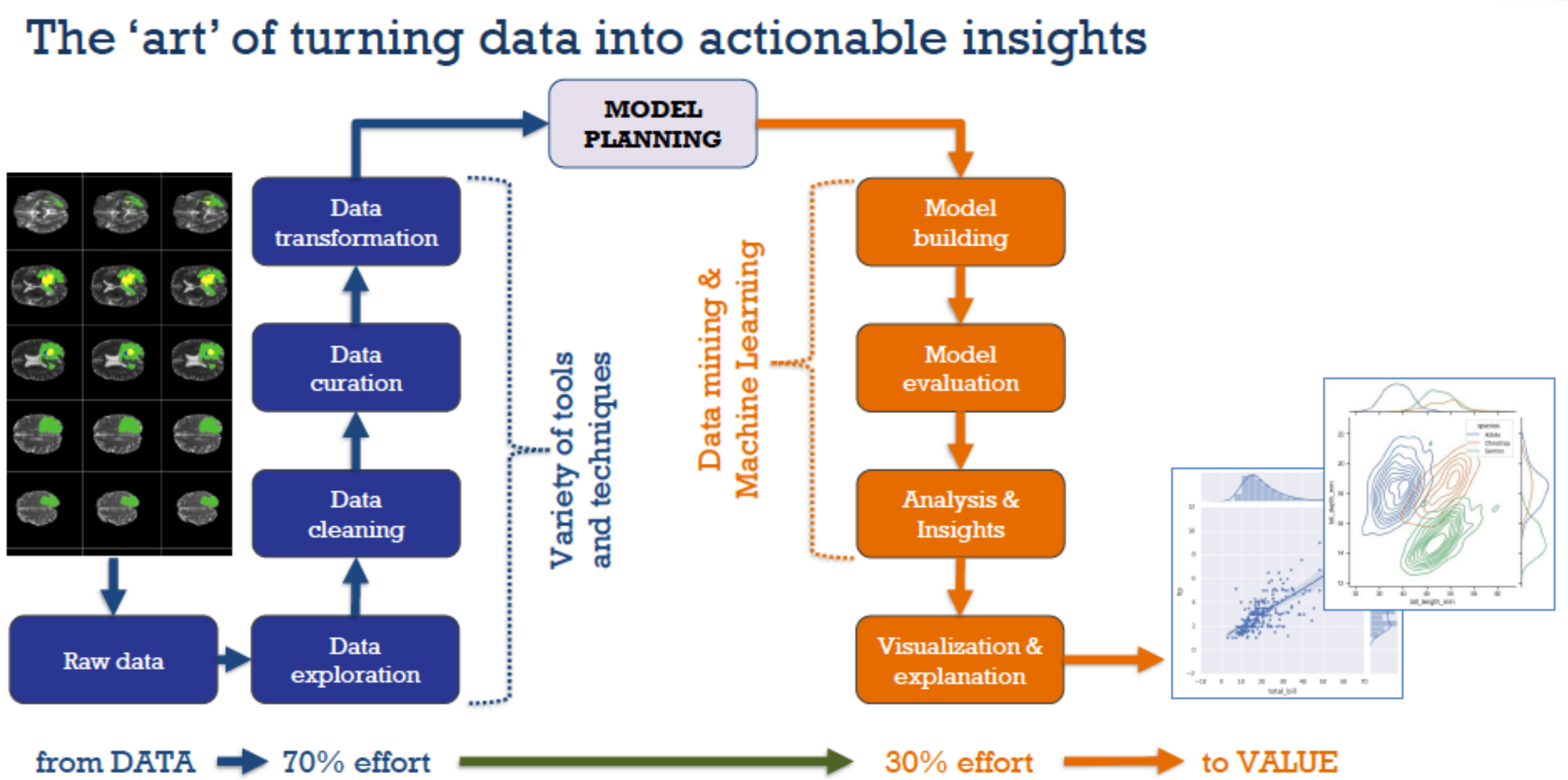
1. **Statistical significance** is always critical (spatio-temporal series)
2. **Data fusion** is challenging (heterogeneity of objective & subjective sources)
3. **Data is intrinsically unreliable and incomplete** (collection constraints)

Intelligent processes must start at the micro-edge (concurrent sensing and learning)

Machine Learning & IoT

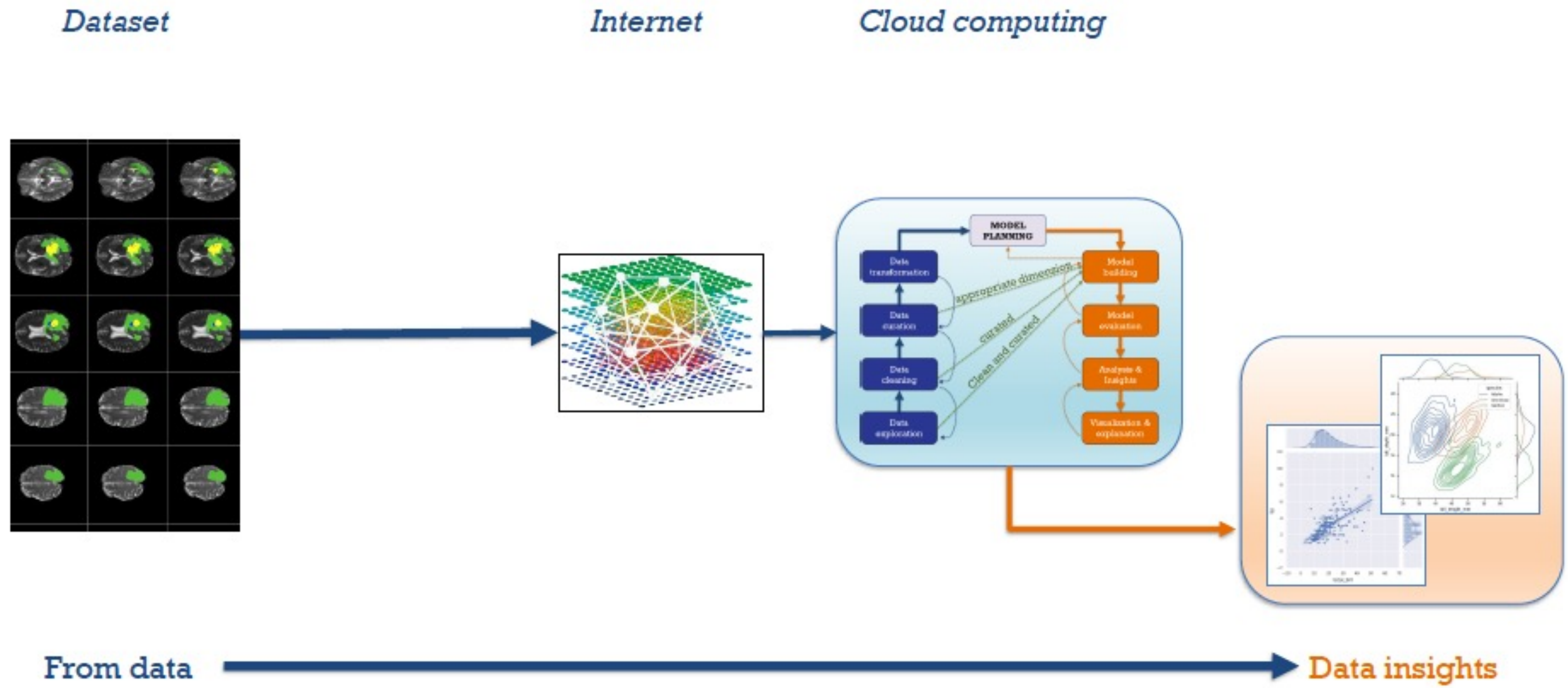


Machine Learning & IoT

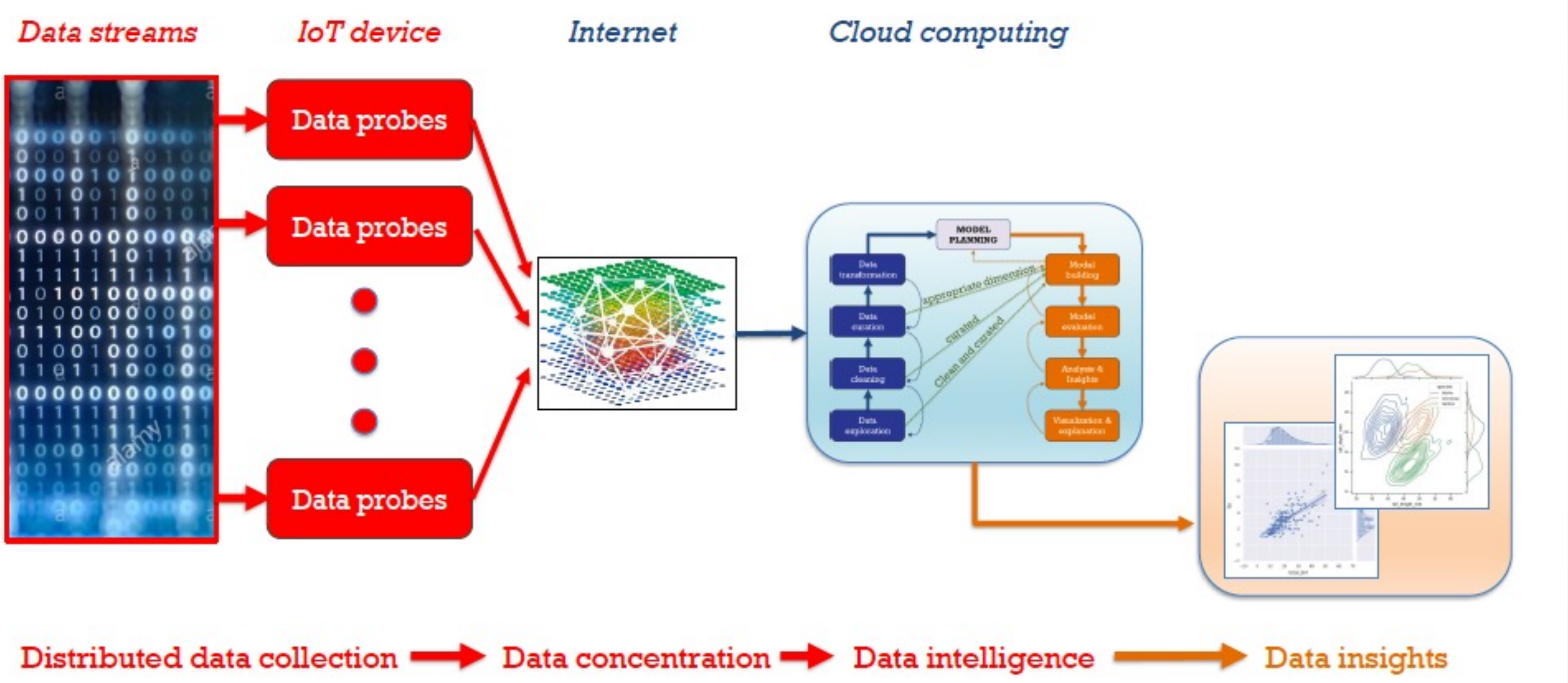


Machine Learning & IoT:
Cloud-based Approach

Implementation:
Data-intensive processes are virtually centralized

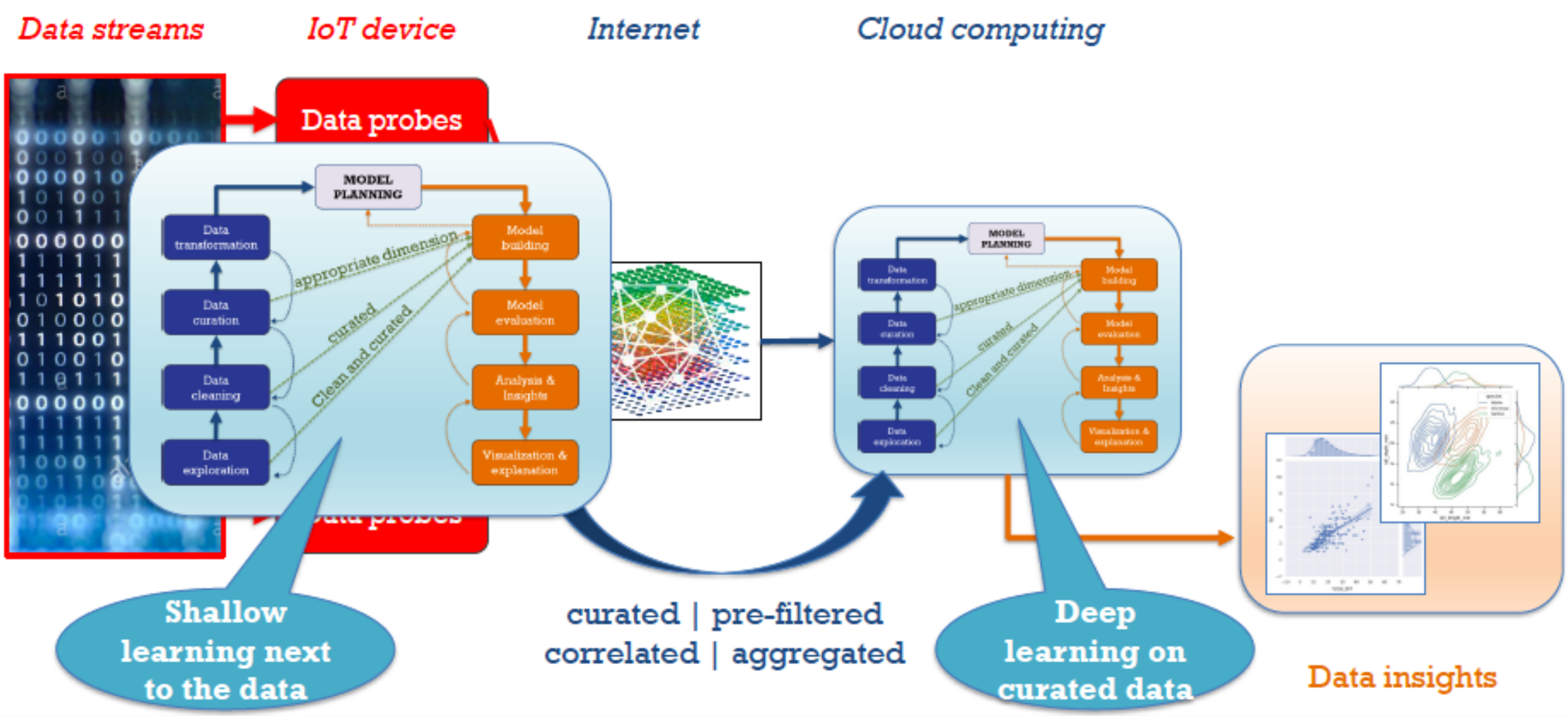


Machine Learning & IoT:
Cloud-based Approach



Machine Learning & IoT:
Hybrid Device- and Cloud-based Approach

IoT intelligence must start at micro-edge level

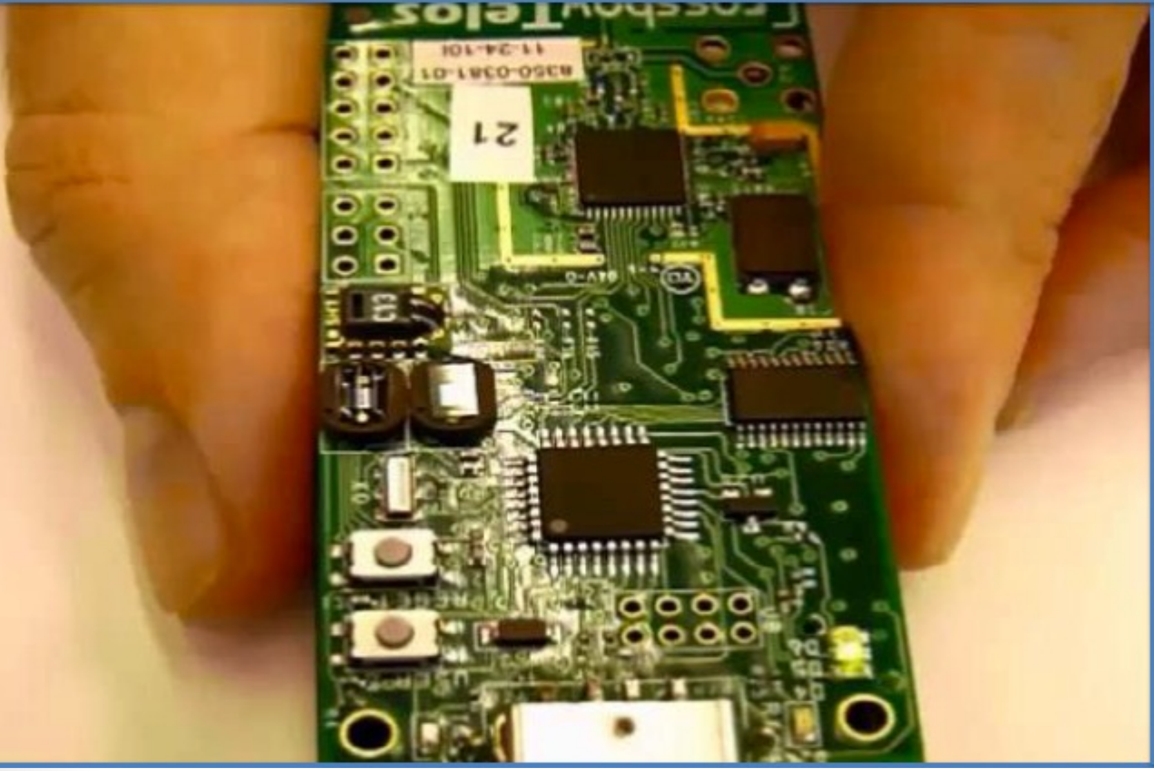


Short-long term anomaly detection in wireless sensor networks based on machine learning and multi-parameterized edit distance https://doi.org/10.1016/j.inffus.2018.11.010

*Francesco Cauteruccio, Giancarlo Fortino, Antonio Guerrieri, Antonio Liotta, Decebal Constantin Mocanu, Cristian Perra, Giorgio Terracina, Maria Torres Vega: *Short-long term anomaly detection in wireless sensor networks based on machine learning and multi-parameterized edit distance*. Inf. Fusion 52: 13-30 (2019)

Machine Learning & IoT:
Embedded Machine Learning

In-node shallow Learning:
Concurrent sensing and learning for anomaly detection



TelosB mote specs

- TI MSP430 controller, 8Mhz
- 10kB RAM
- IEEE 802.15.4 compliant
- 250 kbps data rate radio
- TinyOS 1.1.10 or higher

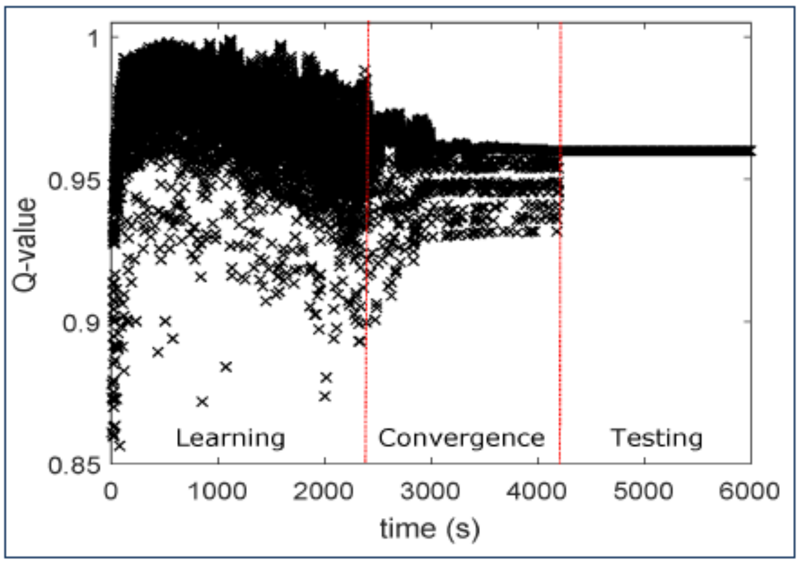
Shallow learning algorithms

- Sliding window mean
- Recursive Least Sq.
- Extreme learning machines
- Polynomial Function Approximation
- Ensembles

Machine Learning & IoT:
Embedded Machine Learning

In-node reinforcement learning: Spectrum and energy efficiency

Transmission power convergence



- ATxmega256A3U
- CPU: 32 MHz
- Flash memory: 256 Kbytes
- SRAM: 16 Kbytes
- IEEE 802.15.4
- Low-power transceiver (11mA in receiving mode)
- Development platform: atmel studio (20% of avail. memory)

Battery lifetime (deep-sleep mode) 14-23 days longer

Intelligence at the Edge of Complex Networks: The Case of Cognitive Transmission Power Control
IEEE Wireless Communications https://doi.org/10.1109/MWC.2019.1800354

*Pasquale Pace, Giancarlo Fortino, Yin Zhang, Antonio Liotta: *Intelligence at the Edge of Complex Networks: The Case of Cognitive Transmission Power Control*. IEEE Wirel. Commun. 26(3): 97-103 (2019)

Machine Learning & IoT:
Federated Learning Edge-Cloud (FL, FTL, FD)

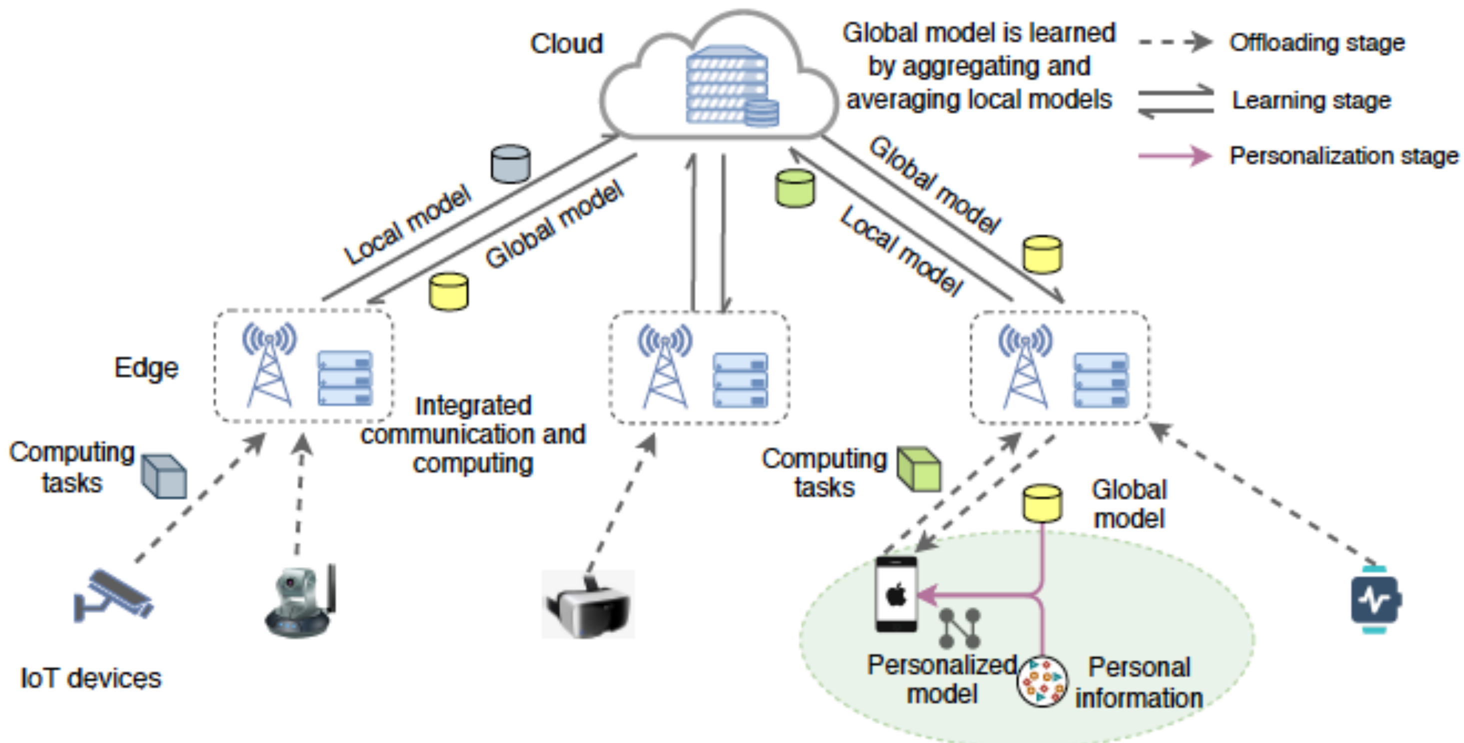


Fig. 1. The personalized federated learning framework for intelligent IoT applications, which supports flexible selection of personalized federated learning approaches.

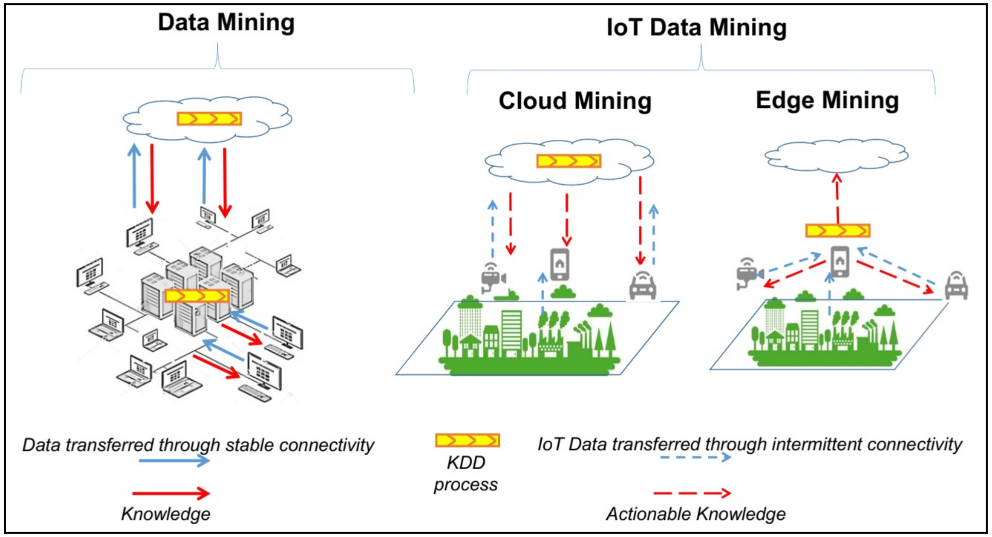
Q. Wu, K. He and X. Chen, "Personalized Federated Learning for Intelligent IoT Applications: A Cloud-Edge Based Framework," in IEEE Open Journal of the Computer Society, vol. 1, pp. 35-44, 2020, doi: 10.1109/OJCS.2020.2993259.

IoT Data Mining @ the Edge: The EdgeMiningSim Methodology

C Savaglio, G Fortino, A Simulation-driven Methodology for IoT Data Mining Based on Edge Computing, ACM Transactions on Internet Technology (TOIT) 21 (2), 1-22, 2021.

IoT Data Mining: Motivations

Does the straightforward use of traditional Data Mining technologies over smart devices allow an effective and efficient analysis of the data generated at the IoT Edge?



	Data Mining	IoT Data Mining
Objective	Knowledge Disclosure	Actionable Knowledge Disclosure
Task	Descriptive, Predictive	Descriptive, Predictive
Goal	Technical significance	Technical significance & Business interest
Exploited technique	Automatic, semi-automatic	Semi-automatic
Process	Data-driven	Data-driven & Domain-driven
Locus of computation	Servers, Cloud Servers	IoT devices, Cloud Servers
Data sources	Computing systems, sensors	Every IoT device
Data	Disk-resident transactional, refined dataset	Real life, untreated data(stream)
Resources availability	High and stable	Limited and instable
Importance of Simulation	Limited	Key

IoT Data Mining: Motivations

Does the straightforward use of traditional Data Mining technologies over smart devices allow an effective and efficient analysis of the data generated at the IoT Edge?

Table 1. Comparison between Data Mining and IoT Data Mining

	Data Mining	IoT Data Mining
Objective	Knowledge Disclosure	Actionable Knowledge Disclosure
Task	Descriptive, Predictive	Descriptive, Predictive
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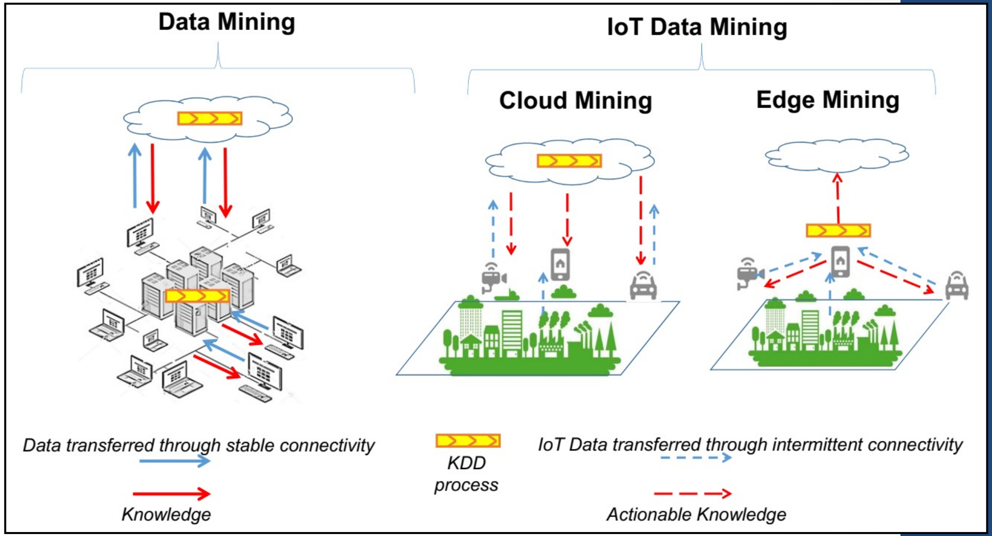


Different requirements, constraints and goals for different IoT domains
->
systematic guidelines needed

IoT Domain	Example of Data Mining Task	Main Requirement
Smart Video Surveillance	Classification-based object recognition	Bandwidth Efficiency
Smart Agriculture	Clusterized WSNs	Energy Efficiency
Smart Health	Outline detection from ECG signal	Responsiveness
Smart Home	Cluster-based user behavior analysis	Privacy
Smart Transportation	Classification-based fatigue detection systems	Safety
Smart Grid	TS-based prediction on consumer's energy expenditure	Accuracy
Social IoT	Community detection among heterogeneous IoT devices	Interoperability
Smart City	Classification-based parking management	Scalability

EdgeMiningSim

- A simulation-driven methodology inspired to software engineering principles for enabling the IoT Data Mining.
- Supports manifold (algorithmic, infrastructural and contextual) aspects, so far only partially or individually analyzed in the narrow literature of IoT Data Mining.
- General purpose (widely stable across varying applications), interactive (strategic decisions taken by the user), iterative (possibility of backtracking to previous steps) and tool/technique independent but supportable (like C.R.I.S.P.).

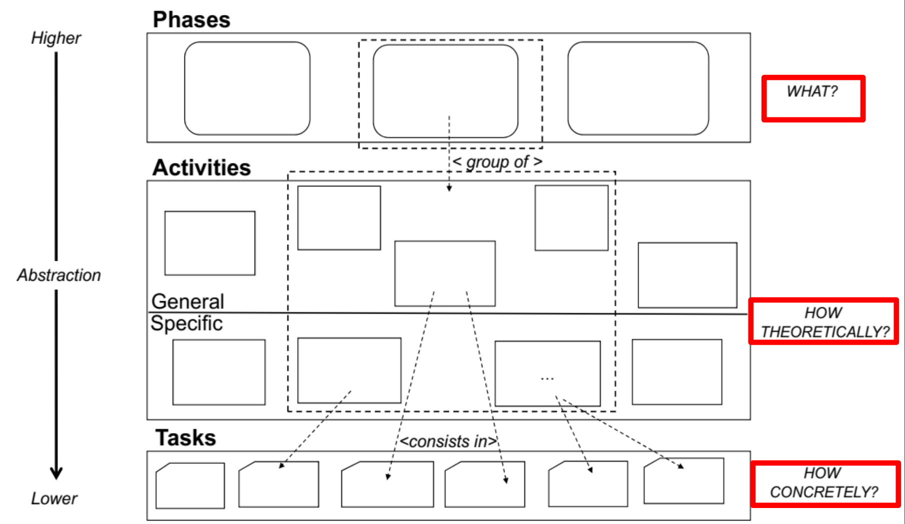


Fig. 2. Three-level organization of EdgeMiningSim (with dashed lines, the breakdown example of one Phase, its constituent Activities and the Tasks concretely implementing some of them)

Goal: driving (through simulation) the domain experts in disclosing actionable knowledge, namely **descriptive or predictive models for taking effective actions in the IoT scenario**.

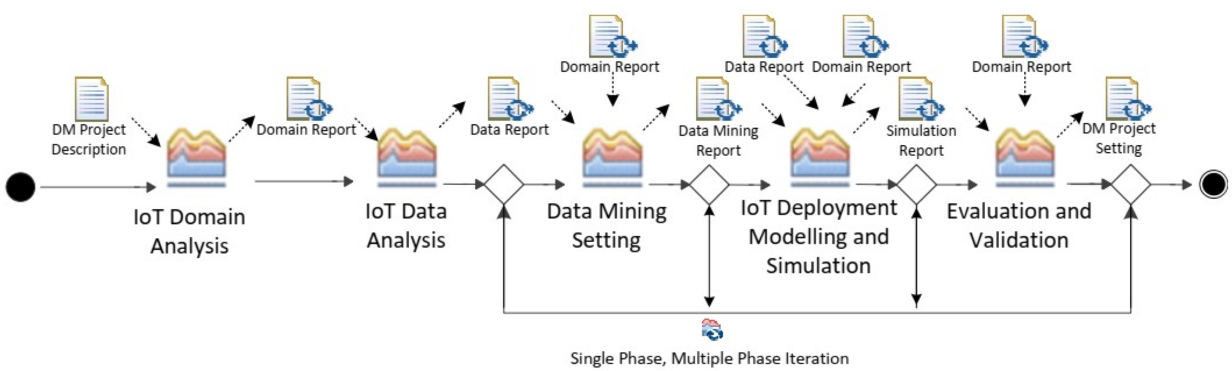


Fig. 3. Phases and Work-Products constituting EdgeMiningSim

EdgeMiningSim

Table 3. Breakdown of the proposed methodology in its constitutive elements (specific activities are starred)

Phase (ID)	**Activity (ID)**	**Task**	**Work-product (ID)**	**Actor**
IoT Domain Analysis (P1)	Application Characterization (P1.a)	UML modelling, User storytelling	Domain Report (WP1)	Business expert, Technical expert
	Requirements Identification (P1.b)	Joint Interview, Requirements ranking		
	Device Characterization (P1.c)	Datasheet analysis		
	Scenario Characterization (P1.d)	Network infrastructure analysis, Topology analysis		
IoT Data Analysis (P2)	Data format understanding (P2.a)	ASIS HL7 standard	Data Report (WP2)	Business expert, Technical expert
	Data lifecycle understanding (P2.b)	DFD modelling		
	Data quality problem identification (P2.c)*	Outline detection, Missing data analysis		
	Data preparation (P2.d)*	Data cleaning, Data aggregation,		
Data Mining Setting (P3)	DM Goal identification (P3.a)	DM Framework analysis	Data Mining Report (WP3)	Technical expert
	DM Task identification (P3.b)	DM Framework analysis		
	DM Algorithm identification (P3.c)	DM Framework analysis		
	DM Algorithm customization (P3.d)*	Heuristic, Algorithm optimization		

EdgeMiningSim

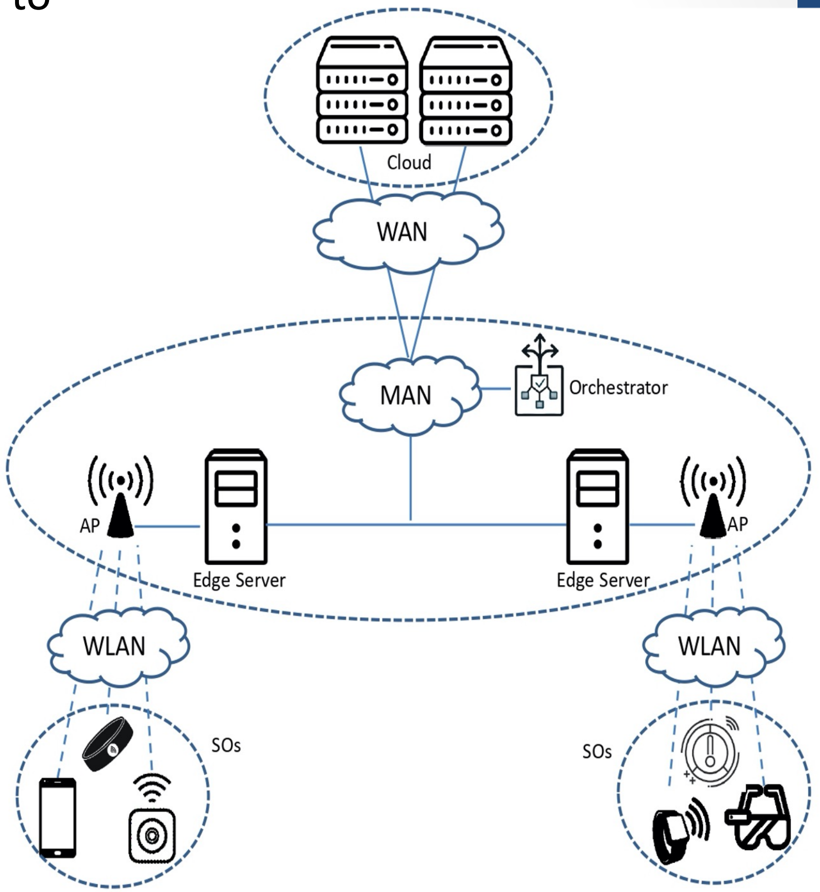
IoT Deployment Modelling and Simulation (P4)	Simulation scenario Modelling (P4.a)	Architectural design, Network modelling, Topology definition	Simulation Report (WP4)	Technical expert
	Devices Modelling (P4.b)	Mobility modelling, Energy modeling		
	Application Modelling (P4.c)	Task generation modelling		
	Simulator Selection (P4.d)	SOTA-analysis		
	Simulator Customization (P4.e)*	Models set extension, Statistics edit		
	DM Algorithm Preliminary Setting (P4.e)*	Time-window assessing, Clusters' SSE analysis, Training-set definition		
	Simulation execution (P4.f)	Performance criteria specification, Results plotting		
Evaluation and Validation (P5)	Simulation Result evaluation (P5.a)	Comparative analysis respect WP1	DM Project Setting (WP5)	Business expert, Technical expert
	Trade-off Management (P5.b)	Settings tuning Backtracking		
	Simulation Result validation (P5.c)	Testbed design, Discussion with Business expert		

EdgeCloudSim

EdgeCloudSim is a simulator built upon CloudSim to address the specific demands of Edge Computing research and support necessary functionality in terms of computation and networking abilities.

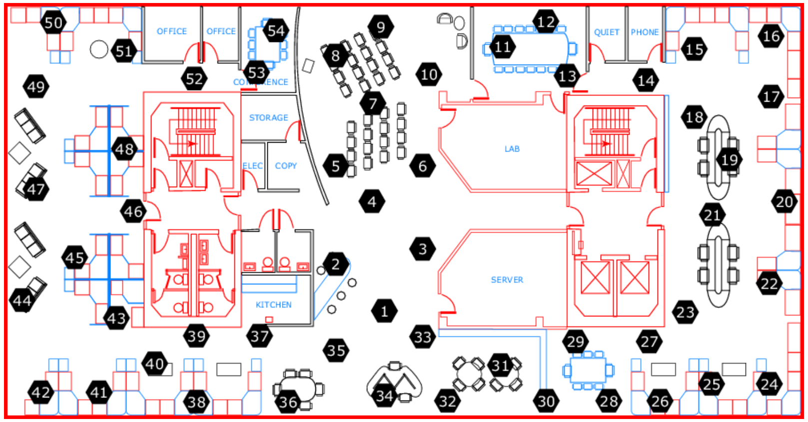
EdgeCloudSim (event-driven) architecture:

- Mobile SOs dynamically organized in LAN
- Static Edge Server (e.g., RaspberryPi), one per per LAN, provided with a wireless Access Point
- Both SO and EdgeServers can talk with each other and with the Cloud
- If needed, EdgeServers can be coordinated by an Orchestrator (e.g., load balancing)



EdgeMiningSim: A Use Case

A case study related to Smart Environment for showing the application of EdgeMiningSim and the trade-off analysis among Cloud and Edge Mining



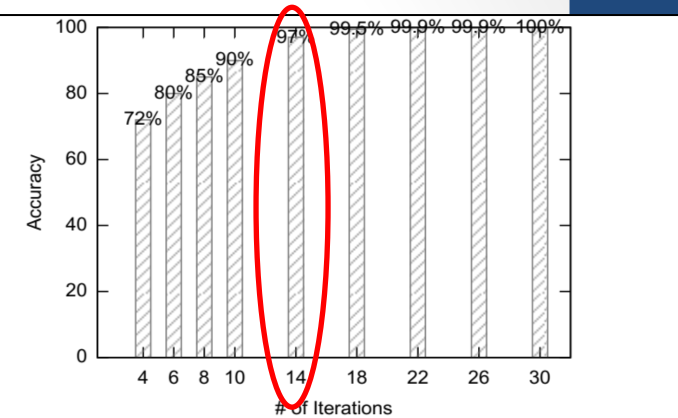


Fig. 4. The full convergence of K-Means (100% accuracy) demands for 30 iterations.

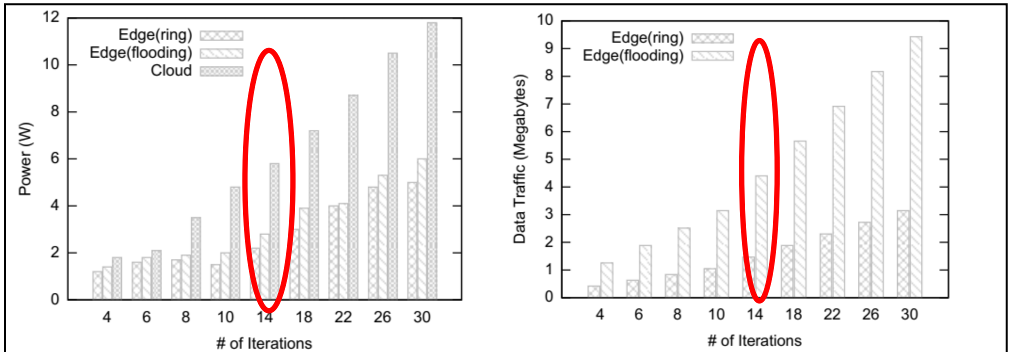


Fig. 5. (a) K-Means energy depletion according to the Cloud- and Edge-based version (with both message-passing models) and the number of algorithm iterations (b) Bandwidth depletion according to both the message-passing models of Edge-based K-Means version and the number of algorithm iterations.

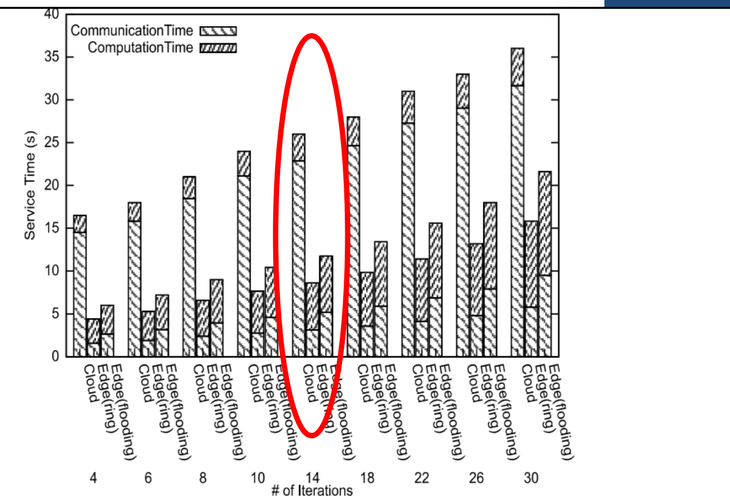


Fig. 6. K-Means execution times, with separated computation and communication contributions, according to the Cloud- and Edge-based version (with both message-passing models) and the performed iterations.

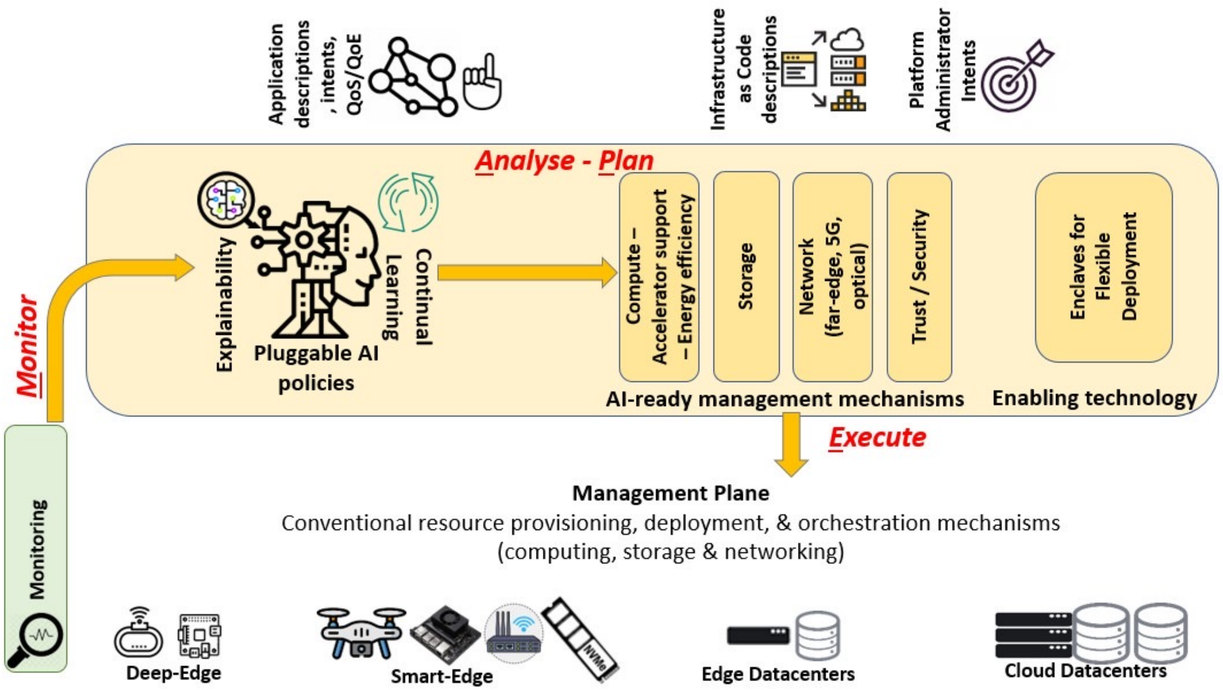
EdgeMiningSim: A Use Case

IoT Domain Analysis	*IoT Data Analysis*	*Data Mining Setting*	*IoT Deployment and Modelling Simulation*	*Evaluation and Validation*

Table 4. WPs resulting from the application of the proposed methodology on the case study.

Domain Report (WP1)	**Data Report (WP2)**	**Data Mining Report (WP3)**	**Simulation Report (WP4)**	**DM Project Setting (WP5)**
P1a: Smart Monitoring, indoor environments	P2.a: 2.3 million readings, REAL timestamped data, temperature, humidity, light, voltage values	P3.a: descriptive model	P4.a: Cloud- and Edge-based deployment	P5.a: see Figs. 4-6
P1.b: accuracy, bandwidth, energy efficiency	P2.b: packets of 65 bytes every 31 sec	P3.b: clustering task	P4.b, P4.c: according to WP1, WP2 and WP3	P5.b: Edge-based deployment, 18 iterations, ring message-passing model
P1.c: 54 MICA2Dot sensors, AWS server	P2.c: noisy and missing data	P3.c: distributed K-Means	P4.d: EdgeCloudSim	P5.c: see Fig. 7
P1.d: grid deployment		P3.d: ring and flooding message-passing models	P4.e: energy model of [29]	
			P4.f: k=3, n=4	

The MLSysOps Project (see external slide)



Use Cases

SMART AGRICULTURE

SMART CITIES

Conclusions

- IoT-Edge-Cloud continuum is becoming a best practise!!!
- Pushing intelligence and machine learning to the IoT Edge is becoming a “must”!!!
- From embedded machine learning to distributed machine learning at the edge, limiting data mining on the cloud!!!
- Methodologies are key for the next-generation IoT development!!!
- Towards autonomic systems based on the Integration of IoT-Edge-Cloud continuum with Multi-Agent Systems

Thank you!

Question?

Contact: g.fortino@unical.it