# Intelligent Computing for Interactive System Design

## *Statistics, Digital Signal Processing, and Machine Learning in Practice*

Edited by
Parisa Eslambolchilar
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Mark Dunlop

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# Intelligent Computing for Interactive System Design

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*ACM Books #34*

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books.acm.org
http://books.acm.org

ISBN: 978-1-4503-9029-3 hardcover
ISBN: 978-1-4503-9026-2 paperback
ISBN: 978-1-4503-9028-6 EPUB
ISBN: 978-1-4503-9027-9 eBook

Series ISSN: 2374-6769 print 2374-6777 electronic

DOIs:

10.1145/3447404 Book
10.1145/3447404.3447405 Preface
10.1145/3447404.3447406 Introduction
10.1145/3447404.3447407 Introduction—Ethics Statement
10.1145/3447404.3447408 Chapter 1
10.1145/3447404.3447409 Chapter 1E
10.1145/3447404.3447410 Chapter 2
10.1145/3447404.3447411 Chapter 2E
10.1145/3447404.3447412 Chapter 3
10.1145/3447404.3447413 Chapter 3E
10.1145/3447404.3447414 Chapter 4
10.1145/3447404.3447415 Chapter 4E
10.1145/3447404.3447416 Chapter 5
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10.1145/3447404.3447419 Chapter 6E
10.1145/3447404.3447420 Chapter 7
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10.1145/3447404.3447428 Chapter 11
10.1145/3447404.3447429 Chapter 11E
10.1145/3447404.3447430 Bios/Index

A publication in the ACM Books series, #34


This book was typeset in Arnhem Pro 10/14 and Flama using pdfTEX.

First Edition

10 9 8 7 6 5 4 3 2 1

# Contents

# Preface

*Intelligent Computing for Interactive System Design: Statistics, Digital Signal Processing, and Machine Learning in Practice* provides a comprehensive resource on what has become the dominant paradigm for novel interaction design methods involving gesture, speech, text, and touch embedded in novel and emerging interfaces. These interfaces support smartphones, wearables, in-vehicle devices, virtual reality, robotic, the Internet of Things (IoT), brain–computer interaction, and many other applications that are now highly competitive commercially.

This edited collection is written by international experts and pioneers in the field of digital signal processing (DSP) and machine learning (ML) for interactive systems. It provides a textbook for students, and a reference and technology roadmap for developers and professionals working in interaction design on emerging platforms. This introductory textbook presents theory chapters on statistical grounding, signal processing, and ML foundations for guiding the development of novel interactive systems. Additional chapters discuss case studies on smart cities, brain–computer interfaces (BCI), probabilistic text entry, secure gestures, personal context from mobile phones, building adaptive touch interfaces, and automotive user interfaces (UIs). The chapters on case studies also highlight an in-depth look at domain-specific language (DSL) and ML methods used, for example, in touch, gesture, electroencephalography (EEG), electrocardiography (ECG), and galvanic skin response (GSR) signals, or embedded sensor inputs. A common theme throughout is the ubiquitous support for humans as they go about their daily professional or personal activities.

This introductory book provides walk-through examples of different DSP and ML techniques and their use in interactive systems. Common terms are defined, and information on practical resources is provided (e.g., software tools, data resources) for hands-on project work to develop and evaluate multimodal–multisensor systems. After each chapter an expert on the legal and ethical issues explores the wider ethical issues on how DSP and ML should be adopted and used in socially appropriate ways, to most effectively advance human performance during interaction with novel platforms.

Parisa Eslambolchilar, Andreas Komninos, and Mark D. Dunlop, March 2020

## Acknowledgments

We would like to thank our external reviewers for their valuable feedback throughout the writing process.

# Introduction

**Parisa Eslambolchilar, Andreas Komninos, and Mark D. Dunlop**

In the last decade, computers connecting with humans and vice versa have increased the importance of human–computer interaction (HCI) more than ever in society. In the early days of computing, when computers occupied a whole room and required huge cooling fans, programmers and mathematicians were their main users. In the late 1970s and early 1980s, Doug Engelbart's "Mother of all Demos"[1] changed society's concept of computers, showcasing for the first time the desktop environment metaphor, including the use of a mouse, a window-based graphical interface, and hypertext. Engelbart's vision transformed computers into essential office equipment, where those who were not-so-tech-savvy and people with no computer science knowledge were the main users [Shackel 1997]. The problem of usability became more significant when computers escaped the office environment and found their ways to personal spaces [Thacker et al. 1979]. As predicted by Mark Weiser in [1999], "The Computer for The 21st Century" is transformed from desktop forms to invisible, sensor-enabled, and intelligent entities sharing the same space as humans everywhere, hence the user groups are widened. This transformation is supported by, and driven by both technical innovations such as interconnectivity via high-speed wireless networks, fast multi-core embedded processors, high-capacity fast-charging batteries, embedded high-precision sensors, and new interaction methods, such as the touchscreen, gesturing, and speech-based conversational interfaces. Despite this rapid progress in engineering, which has afforded all the necessary components for Weiser's vision of ubiquitous computing, our understanding of how these user groups of unprecedented broadness can, do, or should interact with these diverse and ubiquitous computers, is trailing our engineering achievements. HCI researchers and practitioners need to be able to make sense of the rich and heterogeneous stream of data that emerges during interaction with ubiquitous computers, in order to craft the new paradigms

1. https://en.wikipedia.org/wiki/The_Mother_of_All_Demos.

of interaction needed to exploit these resources to the best of our ability. To do so, we can employ the digital signal processing (DSP) and machine learning (ML) technologies that will be explored in this book.

## Ubiquitous HCI

Mark Weiser envisaged three classes of computing device used to interact with humans. It's easy to see that his predictions didn't fall too far from our present reality. As explained in Table 1, most of the devices we use in our daily lives can be classified into this vision.

Furthermore, the continuous development of robotics introduces perhaps an additional category of interactive devices which does not neatly fit into Weiser's classification. For human–robot interaction (HRI), there is as much emphasis in understanding the robot's existence and behavior as an autonomous entity, the impact of its anthropomorphic or zoomorphic characteristics, its ability to integrate and adopt different roles within the context of its environment, and the dynamics of interaction with other humans (or robots), as there is on the engineering aspect and the interaction aspect [Dautenhahn 2013]. In a way, the current research on HRI is more about pushing new boundaries of understanding of our own existence and society, hence it is probably out of the scope of this book.

Modern devices are enriched with arrays of sensors that generate information during the explicit (e.g., gestural) or implicit (e.g., presence at a location) interaction with users. Hardware sensors are complemented by "virtual" sensors, that is, behavior, information, and event loggers (e.g., capturing the notifications received on a user's smartphone). This information can be captured and processed on-board, to enable new interaction methods with users. For example, harnessing data from a smartphone's accelerometer and gyroscope, enables motion-based interaction with the device using DSP methods. However, perhaps for the first time and on a large scale, sensor information doesn't necessarily remain on the device itself, but can be communicated to other devices, or transmitted to data centers, which can run more powerful algorithms, based on the data of millions of users. For example, Google's Gboard keyboard collects anonymous typing behavior statistics

**Table 1** **Weiser's device classes and modern examples**

| Device class | Device scale | Contemporary examples |
|---|---|---|
| Tabs | Centimeters | Smartphones, smartwatches, wearable sensors, embedded sensors |
| Pads | Decimeters | Tablets, laptops, embedded displays |
| Boards | Meters | Smart TVs, interactive signage |

from individual users (crowdsourcing), to improve language and key touch models, using deep learning ML models [Wimmer et al. 2019].

Easy access to the Internet anywhere and at anytime, has created a new generation of connected devices forming the Internet of Things (IoT), which promotes new applications for ubiquitous computing [Weiser 1993]. Consumer-grade devices such as smart home connected sensors, lighting and appliances can be obtained cheaply and easily, and automation software that requires no knowledge of coding (e.g., If This Then That also known as IFTTT) allows users to construct IoT-based intelligent environments at home. Most user-owned wearables such as smartphones, smartwatches, smartglasses, and other wearable forms are connected to the Internet via smartphones or directly, and can also be considered as a subset of an IoT environment [Raji 1994]. Yet, much of the interaction remains clumsy, or awkward. The user still needs a basic understanding of software, hardware, and network technologies to properly coordinate the action of connected devices. Issues such as the presence of multiple users in a smart space, each with conflicting requirements and goals, remain difficult to resolve. Therefore, there is an unprecedented demand for better HCI to cope with the needs of the huge number of lay users interacting with billions of inter-connected computers. Although connected tab, pad, and board types of devices have been widely commercially available for at least a decade, it has been argued that Weiser's vision for ubiquitous computing could not be achieved until we achieve a better understanding of how connected IoT devices can be made easily and naturally interoperable, between themselves and humans [Ebling and Baker 2012].

## Data-driven Opportunities and Challenges in Novel HCI

IoT devices bring a range of new opportunities for HCI, as they capture significant volume of signals from human interactions such as audio, visual, textual, haptic, biosignals, chemical, location, environmental, and physical movements. In the near future other forms of signals such as odor and taste will be captured and used as a form of interaction. Input to ubiquitous computers is thus multimodal—a user can provide commands to a computer using more than one modality (an input channel), or even combining multiple modalities (e.g., saying the word "sound" and raising an arm to instruct a computer to raise the volume of speakers in a room). Devices can also convey information back to the user in a multimodal manner (e.g., via visual, haptic, audio, speech, heat, or olfactory feedback). The use of interaction methods beyond the keyboard and mouse, in the form of either explicit (e.g., gestural) or implicit (e.g., via biosignals) interaction, based on the interpretation and analysis of sensor signals, aims to produce "natural" user interfaces (NUIs). These are interfaces that require little or no training from the user, and leverage motor and cognitive skills that are already highly developed through the users' daily experiences, helping users achieve ideal performance in a seemingly effortless and graceful way [Wigdor and Nixon 2011].

To design these novel interaction techniques, researchers rely heavily on iterative processes, and most commonly on the human-centered design (HCD) approach (as standardized in the ISO 9241-210:2010 specification). In this approach, researchers and users are engaged in a cyclical process of modeling the users' context and requirements, designing solutions and evaluating these solutions. Each iteration leads to a better understanding of the user models and incremental refinement of the design, until our evaluation demonstrates that we have reached an acceptable solution. Now let's examine two examples that demonstrate the challenges of developing novel NUIs through the HCD process.

One of the technologies leveraging input from multiple wearable sensors is brain–computer interfaces (BCI), first described by Vidal [1973]. Affordable, portable and easy to use electroencephalography (EEG)-based devices both from commercial vendors and from open source communities (e.g., OpenBCI), have allowed the capture of users' brain activity to produce signals that can be used to control computers or communication devices, instead of using motor movements (e.g., moving the mouse, tapping on a touchscreen, or typing on a keyboard by hand/fingers). BCIs require the use of many sensory channels that need to be combined in order to infer input commands, in comparison to traditional human–computer inputs (e.g., keyboard or mouse), which increases signal processing challenges for developers [Nijholt et al. 2008]. Additionally, to successfully and correctly interpret the user's brain (EEG) signals, the user has to "train" their brain to produce valid commands with their EEG signals. Therefore, an additional HCI challenge is to provide users with ways to learn and master this skill. BCI thus is not just about finding better ways of accurately interpreting signals into commands, but also gathering and interpreting data that models the user and helps us understand how and what they are learning [Lotte et al. 2018].

Similar to BCI, hand/all-body gestures require the use of many sensory channels to be fused to provide a "natural" interaction with devices. Karam and Schraefel [2005] present a classification of gesture-based HCI motivated by a literature review of over 40 years of gesture-based interactions. This early but comprehensive work presents a unique perspective on gesture-based interactions and provides categories for gesture styles, application domains, enabling technologies, and system response. They identify and describe virtual and augmented reality, robotics and telepresence, desktop and handheld devices (e.g., tablets and smartphones), vehicles (and automation in general), gaming, and smart environments as application domains for gesture-based interaction. Although visual interpretation of hand gestures is commonly used in the application domains identified in Karam and Schraefel's [2005] study, gestures can be identified with body worn sensors (e.g., accelerometers), mouse and pen inputs, data gloves, infrared sensors, audio inputs (voice), and touch or pressure input (e.g., tablets and smartphones). Similar to BCI, gesture-based interaction produces many sensory inputs in comparison to interaction with the keyboard or mouse, for which we need tools that allow us to translate raw signals into input commands. Norman [2010] also argues that, much like BCI, gestural interaction is not "natural" in the sense that users need to learn and master the skill of using gestures. Again, modeling the user and understanding their learning process through the processing of interaction data, is critical to designing for such interaction styles. As well as facilitating new interaction styles, learning, and modeling techniques can transform slow and error prone interactions into faster smoother interactions, for example, as seen in the transformation from the first basic touchscreen keyboard to modern multi-level autocorrection keyboards.

## Statistics, DSP, and ML as Tools for HCI Design and Evaluation

From the previous examples, it becomes easy to guess that some of the answers we seek in the challenges of translating raw data and signals into commands, and in modeling users and their interaction with systems, can be found in the fields of statistics, DSP, and ML.

IoT, BCI, gesture-based systems, and autonomous vehicles, directly produce numerous volumes of signals. All must capture and then process sensor data in order to provide input, or adapt output in the system. In many cases, the interactive systems developer must convert, filter, and transform such data (signals) into a form suitable for use in their application. DSP is the engineer's toolkit of choice to attack these problems. The choices made in each DSP step have implications on the quality of the resulting output used to direct the decisions made by their application. Therefore, learning DSP and its fundamentals have become highly important in HCI.

Statistical analyses, including descriptive and inferential statistics, have been used in HCI for decades. Descriptive statistics are used to produce new information from raw data (e.g., the mean, median, variance, or standard deviation of observations), while inferential statistics such as regression analyses, *t*-test, chi-squared and analysis of variance (ANOVA) tests help to estimate quantities and likelihoods from information. Such techniques are used to build models of systems and users, and also algorithms that apply in HCI-oriented applications. Statistical testing of interaction data from carefully-designed experiments is also frequently used to test our design and interaction hypotheses, and to evaluate the quality of interaction with systems.

Statistics are the foundation on which ML tools are built, and these tools have found widespread adoption in recent years and across many scientific disciplines, to solve difficult regression or classification problems. HCI is no exception to the rapid emergence of ML techniques. With the recent explosion in the availability of software development kits (SDKs), application programming interfaces (APIs), and development environments that facilitate the use of ML techniques, HCI researchers in human–subject studies have been increasingly adopting ML techniques such as neural networks, Bayesian classification, support network machines, and other deep learning algorithms [Kostakos and Musolesi 2017]. ML can be applied to many aspects of design and implementation of interactive systems, from inferring user context and goals, to interpreting signals (in the place of, or in conjunction with DSP) and to providing recommendations and suggestions to users. Concrete examples of the use of ML in HCI include developing novel user interaction techniques, such as how to react to user input (e.g., gesture [Pirhonen 2010, Chen et al. 2013]), optimize system resources (e.g., smartphone battery conservation [Kostakos et al. 2016]), provide intelligent mobile notifications [Mehrotra et al. 2015], develop intelligent living environments (e.g., smarthomes where heating/light is regulated by captured environmental sensor data [Cook et al. 2003]). The prediction of future users' activities and interactions is another emerging area of interest: The aim is to develop a robust, reliable, and unbiased anticipatory computing systems [Williamson and Murray-Smith 2005, Pejovic and Musolesi 2015].

## Aims and Scope of this Book

Given the importance of signal and information analysis in the age of the IoT, in order to enable seamless and natural multimodal interaction with users, we (the editors) feel that there is a lack of introductory text books for our HCI students on signal processing, statistics, and ML. With much of HCI now using elements of these techniques, it's important for students to understand the technical underpinnings, learn the terminology and be exposed to detailed examples of their usage. Moving on from basic technical skills, the unprecedented ability to collect data in laboratory and real-world experiments brings the largely unaddressed challenge of making good sense of this data for the development of new services, and for this, students and practitioners need a better understanding of statistics and data analysis tools. Our book addresses this sensitive topic, which can be particularly difficult to access due to the diversity of tools in various levels of completeness and is compounded by the vocabulary learning challenges.

We have aimed to provide a textbook, whose content would be most appropriate for graduate students, and of primary interest to students studying Computer Science and Information Technology, human–computer interfaces, mobile, and ubiquitous interfaces, and related multidisciplinary majors, it may also be suitable as continuing professional development (CPD) and for final year undergraduate modules where independent DSP/ML modules are not provided or to put DSP/ML more in the context of interactive system development.

The book is appropriate as a companion to both advanced undergraduate students, but also to postgraduate students and professionals who often have to continue their professional development without access to full courses.

The authors of the chapters and the editors have had direct and first hand experience arising from their involvement with basic research and large-scale multidisciplinary international projects. However, we all acknowledge that this experience has largely remained in the confines of individual research groups, with a lack of introductory textbooks for HCI students on signal processing, statistics, and ML. We have improvised such teaching materials from our extensive research in relevant areas and this book represents an orchestrated effort to combine the best practices from research and teaching into a single volume accessible to all.

Additionally, the practicalities of working and implementing novel data-driven solutions to interaction from a legal and ethical standpoint are seldom explored in most university courses and textbooks—our book provides excellent practical insight to crucial issues such as data protection, ethical use, algorithmic accountability, copyrights, licensing, and intellectual property.

We hope that this book can provide an excellent starting point for understanding the basic technical skills required for the design of interactions in the age of ubiquitous computing, without the need to trawl through multiple textbooks and sources. We also hope that readers can find inspiration in how to best apply this knowledge, through the presentation of multiple case studies (CS) from a diverse range of application domains.

## Structure of this Book

This book is separated into two main parts. The first part of the book aims to introduce the reader to the basic concepts behind the IoT, DSP, statistics, and ML. In the second part, a range of diverse and engaging use cases, demonstrate how these theories and tools have been applied in research to deliver new interaction paradigms and convert human behavior into actionable insights.

**Part I:** The basics and theories in the Internet of everything (IoE), DSP, statistical analyses, and ML are extensively discussed in this part.

Chatzigiannakis and Tselios in the first chapter in Part I, introduce the interconnection of the digital and physical domains though IoT also known as pervasive or physical computing, through two applications, one related to healthcare and assisted living and the other on awareness and behavioral change. These applications set the tone for the rest of the chapters in this part, that is, they highlight the importance of DSL and ML techniques in HCI. The early part of the chapter provides an overview of the basic enabling technologies for the realization of the IoE: the computational elements of individual devices for local processing and analysis of data; the networking elements for bringing together the devices and Web services; the components available for energy storage and micro-generation; and the sensing and actuation elements for interacting with the environment and humans. Later, the chapter provides an overview of the critical issue of cybersecurity and how ensuring end-to-end security in the IoE is fundamentally different than typical, conventional information and communication technology (ICT) infrastructures.

Statistical analysis and testing are core to scientific hypothesis driven research but also form the basis for understanding how to summarize and compare large volumes of data. In the second chapter Ahmed Sabbir Arif introduces the core terminology of statistics and looks at both descriptive statistics and the use of hypothesis testing statistics. Throughout the chapter Arif uses examples and bases the discussion in standard HCI techniques, for example, handling outliers and Likert scales. The chapter finishes with an introduction to ANOVAs and power/effect size to help understand where the results are meaningful.

The DSP basics chapter introduces the fundamentals of DSP necessary for the design and construction of any interactive system that directly engages with the environment using sensors. DSP has diverse use in HCI such as capturing and processing speech, gestures, eye gaze, human movement data, for example, accelerometers and biosignals such as heart rate. Most of the case studies described in Part II of the book utilize DSP to process sensor data in order to provide input, or adapt output in a digital system. Alexander and Vi provide a beginner's guide to DSP basics; first they introduce the reader to the different types of signals, and continue to cover the analog-to-digital conversion topics of sampling, quantization, and coding. Later, Alexander and Vi cover digital-to-analog conversion, autocorrelation, discrete Fourier transforms, and linear time-invariant systems. Finally, the authors provide a walk-through of DSP use in brain–computer interaction.

ML is core to much of modern data driven interaction, however, it is a difficult domain for HCI students and practitioners to enter. In their chapter Konstantinos

Chatzilygeroudis, Isidoros Perikos, and Ioannis Hatzilygeroudis provide a primer on ML as it's most commonly used in HCI. The chapter starts with a probability primer then looks at supervised and unsupervised learning. Most of the focus, as per HCI, is on supervised learning with sections looking at regression, neural networks, Gaussian processes, and naïve Bayes approaches.

**Part II:** This section consists of seven case studies that provide a detailed description of how to apply the theories and basics taught in Part I to real applications. For each case study, special commentary on the ethics of capturing and processing data is provided, to highlight the important implications of DSP and ML for users and society.

*CS1: Combining Infrastructure Sensor and Tourism Market Data in a Smart City Project (Chapter 5)*

This chapter by Andreas Komninos, Mark Dunlop, and John Wilson is a worked case study following the story of a project with the Glasgow City Marketing Bureau trying to predict how busy the city's hotels will be, based on the interaction of users with sensor infrastructure and tourism-related websites. It gives an overview of the types of raw data that were used (footfall data, partial hotel booking data, flight search data), initial analysis of each data stream, initial hotel busyness predictions from individual streams, and then looks at making multivariate predictions with principal component analysis and neural network based autoregression. This case study demonstrates how raw interaction data can be used to make high quality predictions, and also gives insights into the difficulties with each data source.

*CS2: Brain–Computer Interfacing with Interactive Systems (Chapter 6)*

Athanasios Vourvopoulos, Evangelos Niforatos, Sergi Bermudez i Badia, and Fotis Liarokapis report on their studies on using EEG brain activity within virtual reality environments. The chapter discusses the hardware and software used before a detailed discussion of their study including detailed insights into the difficulties, particularly the high noise levels, and design guidelines for brain–computer interaction.

*CS3: Probabilistic Text Entry (Chapter 7)*

Although sensors, gesture, and EEG provide exciting new interaction techniques, text entry is still core to much of our interaction with system—be it writing a report, sending emails, or social networking. Smartphone text entry is dominated by users tapping on small keys on touchscreens. While users can tap very accurately on touchscreens, as we try to type faster our accuracy drops. In CS3 Keith Vertanen looks at the big data and adaptive algorithms that make modern smartphone keyboards so effective. The chapter starts with statistical formulation of the problem then looks at the two key aspects of tap and language modeling before discussing advanced text entry interface designs, in particular with a focus on error avoidance, detection, and correction. Finally the chapter presents a case study of smartwatch text entry.

*CS4: Secure Gestures (Chapter 8)*
Secure gestures have recently emerged as a serious alternative authentication system especially for mobile devices with touchscreens. In this case study Janne Lindqvist and Can Liu discuss what secure gestures are, the background to gesture recognition and recognition approaches, and metrics for evaluating the success of secure gesture recognition. They also have a discussion of the possible security risks and benefits of gestures over traditional passwords.

*CS5: Personal Context from Mobile Phones (Chapter 9)*
In this chapter, Jason Wiese discusses understanding and inferring personal context on mobile platforms as a case study. Personal context is described as any piece of information that is relevant to a person's current situation, and which can be inferred from sensors and interactions with mobile applications and services. Wiese describes two projects that illustrate different aspects of the process of inferring personal context from mobile devices: one project that infers phone placement, and another that infers social context from communication behavior. Then, Wiese uses the experiences illustrated in these examples to highlight some common patterns and challenges for inferring personal context from mobile phones.

*CS6: Building Adaptive Touch Interfaces (Chapter 10)*
In their case study Daniel Buschek and Florian Alt look at the core of most modern HCI, touch, and at the heart of many applications of ML in HCI, adaptive interfaces. Their case study is motivated by three key challenges for developers: (1) Specifying complex input behaviors, (2) recognizing and distinguishing said behaviors, and (3) handling and reacting to such input under uncertainty. Their case study discusses the authors' ProbUI framework as a concrete example for supporting developers in building adaptive mobile touch interfaces.

*CS7: Driver Cognitive Load Classification Based on Physiological Data (Chapter 11)*
While there is a lot of excitement in the press about fully autonomous vehicles there is much research being done on supporting human drivers through increasingly

intelligent vehicle technologies. In their case study Dengbo He, Martina Risteska, Birsen Donmez, and Kaiyang Chen investigate the use of driver cognitive load detection methods. They report on a study investigating the use of EEG signals from consumer-grade headbands, along with heart rate and galvanic skin response (perspiration) measures, and ML to detect a driver's cognitive load. This presents a very applied example of how many of the techniques in the initial chapters of the book can be put into practice.

*Ethical Comments*

Throughout the textbook David McMenemy has introduced commentary boxes on the wider ethical considerations of the chapter topic. These include privacy and legal constraints on capturing and exploiting data, ensuring users remain autonomous in their decision-making, the ethical use of statistics, bias in ML, how monitoring can affect our behaviors and exploiting the apparent magic of our ML, big data, and signal processing-based systems. His thought provoking commentaries are complemented with further reading.

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INTRODUCTION—ETHICS STATEMENT

# Ethical Issues in Digital Signal Processing and Machine Learning

**David McMenemy**

Digital signal processing (DSP) and machine learning (ML) present significant ethical challenges for systems developers. The ability of modern devices to measure and record multiple types of data from a range of different sensors means our activities can be recorded more comprehensively than at any time in history. These developments, then, are not merely about technology, like most aspects of the information revolution they are "fundamentally social and ethical" [Bynum and Simon 2004, p. 1]. In the broadest sense, professionals have a duty to ensure their work does not negatively affect society. In a world where technology is advancing faster than the ability of society to keep up with the implications of it, the necessity for the computing professions to adhere to ethical behavior takes on major importance.

A range of ethical and legal issues will be considered throughout the chapters in this book in highlighted sections (such as this one) to support the key themes of each chapter. Their purpose is to raise questions to reflect on, rather than provide answers. For those wishing to explore the ethical and legal issues further, some useful further reading is also included in each section.

Computer scientists and software engineers produce tools that can have immense power over other human beings and the wider society. The work of the profession is embedded in virtually every aspect of modern life, and as such, that work must be undertaken with the awareness of how it might affect others. This simple formula is the heart of computer ethics, and professional ethics more generally.

## Ethical Frameworks

It is important firstly to define terms more fully, and in this section, we will discuss a range of ethical theories that predominate. These theories can apply to any aspect of ethics, not only computer science, and overarch how individuals and professional groups may think about ethical dilemmas they are presented with on a day-to-day basis.

From a theoretical perspective, there are several approaches to ethics that a human being or society can adopt, although there are three main branches that most approaches stem from. These can be defined as consequentialist approaches, deontological approaches, or virtue approaches. For an extensive and accessible overview of these ethical theories the work of Michael Sandel is highly recommended [Sandel 2009].

Consequentialist ethics "relates to the potential outcomes of an action and the ethical results of that action" [McMenemy 2016, p. 4]. The focus is therefore on the ends of an activity or actions, not necessarily how that end has been achieved. The most famous consequentialist theory is utilitarianism, where the goal is to maximize utility, or happiness, for the largest number. The end, then, is a happier society by virtue of an activity or action. Taken to its extreme, utilitarianism can support the suffering of an individual or small group of people if the majority of people benefit. For example, a utilitarian might argue that surveillance of individuals is acceptable based on the activity keeping the wider society potentially safer. This potential to ignore human rights in some circumstances makes many people who believe in human rights wary of utilitarianism as a system of ethics and social justice.

Deontological ethics relate to the idea that "there are certain values or actions that are inherently good or bad" [McMenemy 2016, p. 5]. Deontological ethics are often referred to as duty-based, and in this school of thought, the human being as an individual is given a key role. Deontological ethics are often in opposition to consequentialist theories, especially utilitarianism. Arguably, the most famous deontological ethicist was Immanuel Kant, who famously believed that human beings must always be considered as ends in themselves, not as a means to someone else's, or society's, ends. This is a stance in contrast with that of consequentialism, since in that ethical discipline it is the act itself that is of paramount importance, not necessarily the impact it will have on individuals or groups of people. For a deontologist, then, protecting human rights as the starting point of an ethical system is of paramount importance, and any action must always put the human rights of people first.

Virtue ethics relates to the character and dispositions of a person, with the emphasis on maximizing good character and becoming a good person [McMenemy 2016, p. 5]. The main figure in virtue ethics is Aristotle, who believed that all human beings should aim for what he called eudaimonia or happiness. However, in Aristotle's philosophy, happiness relates to living a good life by becoming a virtuous person. For Aristotle, virtues or dispositions were on a mean, with excess at one end of the scale, and deficiency at the other. A virtuous person would be able to know how to react in a given situation with the correct disposition. For example, anger is a vice in some contexts, but a virtue in others. In virtue ethics, knowing how to react at the right time is the hallmark of the virtuous person.

## Professional Ethics and Computer Science

It is of course the application of ethics in a professional context that is of concern for this book. In applying the ethical theories discussed here to professional scenarios, we are in the realm of professional ethics. Each of us may have our own approach to ethics based on one or more of the theories discussed here, however, professional organizations and employers will usually codify their own ethical stance and expect their members or employees to understand and adhere to them. An excellent example of the range of professional concerns computer scientists should be mindful of are codified in the Association for Computing Machinery (ACM) Code of Ethics and Professional Conduct [ACM 2018]. You should consider codes of ethical principles like the ACM's as a blueprint for ethical practice and how you deal with colleagues and clients, and the wider society.

We can divide the kinds of concepts defined in codes like the ACM's into broad categories:

- Respect of the subject matter: this can entail a range of issues such as respect for the client or employer, or the kind of data being measured and processed, or the information and computer systems you are working within, or even social issues that might be affected by your work. For example, when creating a system that records a person's health information, such as a fitness tracker, the designers should take into consideration that person's right to privacy and autonomy. They should ensure that only the data that is vital for the system to operate is stored, and that the data is only shared in ways that protect the person's wider interests, and with their permission.
- Due diligence: ensuring whatever you do is done with care and professionalism at all times. For instance, a software engineer designing a system should ensure that it is designed carefully and is fit for the purpose it is supposed to fulfil. A badly-designed app or device that records health data inaccurately due to sensor or software malfunctions is of little use to a user.

- Precautionary principle: when advancing knowledge in an area, making sure it is done with the kind of carefulness that ensures advances are reflected and reviewed upon before being made mainstream. For example, a commercial pressure may exist to be the first to market for a piece of software or device that it is believed will be extremely lucrative. However, an ethical professional would ensure that the system is safe to use and would not in any way damage the interests of the buyer or the wider society.
- Openness/transparency: ensuring that the work you undertake is as transparently done as possible, notwithstanding any issues of confidentiality that may be necessary for clients/employers. For example, when building a new system for a client, it is important to make them aware of any interactions that system may have with other systems they may already have in place. If a new system makes data on another system vulnerable, this must be openly revealed to the client or employer to ensure appropriate actions can be taken.
- Avoiding conflicts of interest: relates to ensuring that any work undertaken does not bring into conflict any private interests with your professional interests.
- Respect of social norms and conventions: this is a major concern and should ensure that you do not undertake any activity that breaches the law of the land you are working in, or negatively impacts social norms. Laws specifically affecting software engineers include laws related to cybercrime and computer misuse, data protection, and intellectual property, as well as the laws that generally operate within the wider society.
- Respect for the work, expertise, and intellectual creation of others: ensuring that you respect the skills and knowledge of others, both in terms of their contribution to projects you may be involved in, but also in terms of the intellectual efforts of others. it is common for software engineers to work with a range of other professionals, who bring their own expertise to the table, such as designers, clinicians, and the skills and knowledge of these professionals should be respected. In addition, professionals should always respect the intellectual work of others: therefore, it is unethical to claim credit for work that is not your own if you had no part in it.

## Summary

This short summary of ethics and computer science sets the scene for the ethical scenarios discussed later after each chapter. Given the wide range of analytical approaches, that can be taken with issues related to professional ethics, and the differing worldviews these might represent, it is highly recommended that readers familiarize themselves with some further reading on ethics in computing. Recommended texts include Brinkman and Sander's *Ethics in a Computing Culture* (2012) and Quinn's *Ethics for the Information Age*, (7th edition, 2017), as well as the professional context laid out in the aforementioned ACM code cited above.

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# 1 Internet of Everything

**Ioannis Chatzigiannakis and Christos Tselios**

## 1.1 Introduction

The interconnection of digital and physical domains is growing fast as a result of the enormous activity in a number of application and research fields, such as the Internet of Things (IoT), or pervasive and physical computing, merging information, and intelligence hidden in the network in several application domains [Gubbi et al. 2013, Porter and Heppelmann 2015]. We are continuously looking for innovative ways of better monitoring our environment, interfacing ourselves and our activities to the computing infrastructure to realize ambient intelligent environments [Dunlop and Brewster 2002, Robinson et al. 2009, Pfisterer et al. 2016]. Ambient intelligence refers to normal working and living environments being surrounded by embedded devices that can merge unobtrusively and in natural ways using information and intelligence hidden in the network connecting these devices (e.g., IoT). Such devices, each specialized in one or more capabilities, are intended to work together based on an infrastructure of intelligent systems, to provide a variety of services improving safety, security, and the quality of life in ordinary living, traveling, and working environments. The blend of ambient intelligent environments with the Web promises an Internet of everything (IoE) full of new opportunities to deliver new wide-impact services and products [Pfisterer et al. 2011, Christopoulou et al. 2014, Mainetti et al. 2015, Athilingam and Jenkins 2018].

Increasingly simple systems are being equipped with computing and networking capabilities [Leutheuser et al. 2017, Athilingam and Jenkins 2018]. Common electronic devices, including household appliances, automotive components, building automation systems, or community facilities, enrich our environment with huge amounts of sensors and actuators that can communicate with each other and with the Internet [Chatzigiannakis et al. 2011b, 2012]. In the end, this will eradicate the separation between the physical and the virtual world and will enable people to interact with each other, and with everyday objects, through invisible systems embedded into these objects [Akribopoulos et al. 2009, 2010].

New systems emerge that orchestrate myriad devices, Web services, business processes, people, companies, and institutions that are continuously integrated and connected with individual properties, objectives, and actions [Gavalas et al. 2017]. The coexistence and cooperation of embedded systems with our social life is unveiling a brand new era of exciting possibilities [Ringas et al. 2011a, 2011b, Atzori et al. 2012]. With an ever-increasing amount of data available, it is simply infeasible to expect individuals to be aware of the full range of potentially relevant possibilities and be able to pull them together manually. In this new era, everyday objects will automatically process unprecedented amounts of diverse data and deliver actionable insights into affiliated networking interfaces [Rodríguez-Rodríguez et al. 2018, 2019a, 2019b]. We shift from passive machines that wait for user commands to a highly interconnected multi-purpose ambient intelligence [Chatzigiannakis et al. 2011b, Dunlop et al. 2016]. We expect ambient intelligence to anticipate the volume, the variety, and the velocity of real-world data, according to user needs, preferences, and actions and suitably process and extract knowledge so that it can be used by a multitude of human and societal interests.

The chapter continues with the presentation of two application domains, one related to healthcare and assisted living and the other on awareness and behavioral change, that allow us to highlight the importance of digital signal processing (DSP) and machine learning (ML) techniques in IoE applications. Section 1.3 provides an overview of the basic enabling technologies for the realization of the IoE: the computational elements of individual devices for local processing and analysis of data; the networking elements for bringing together the devices and Web services; the components available for energy storage and micro-generation; and the sensing and actuation elements for interacting with the environment and humans. In the past, several different computing paradigms were proposed for analyzing data generated by the devices and services participating in the IoE; Section 1.4 provides an overview of the dominant approaches. Section 1.5 looks into the critical issue of cybersecurity and how ensuring end-to-end security in the IoE is fundamentally different from typical, conventional information and communication technology (ICT) infrastructure. The section looks into the privacy of confidential data, the role of trust, and how data protection regulations extend in the IoE. Finally, the chapter concludes with Section 1.6, which provides four technical challenges and future research directions.

## 1.2 The Importance of DSP and ML in IoE Applications

Several application domains will be affected by the IoE either by enabling new services or by improving the efficiency of existing ones [Perera et al. 2014]. There is a diverse range of such applications presented in this book: Chapter 5 case study (CS) 1 discusses how to combine data arriving from sensor deployments, social networks, and government/organizational sources to deliver services for smart tourism; Chapter 11 CS7 looks into intelligent vehicle technologies that track drivers' physical state, combine data related to the state of the driving environment and deliver smart services that improve road safety. Among all the possibilities, this section provides some insights into two categories and highlights the importance of DSP and ML algorithms.

### 1.2.1 Healthcare and Assisted Living

The design of advanced health monitoring systems has always been a topic of active research [Mulder et al. 2009]. Recently, it has been reinvigorated by the numerous advances in sensing technologies [Wang et al. 2017] and smart textiles [Qi et al. 2017, Schneegass and Amft 2017], the miniaturization of embedded systems and energy generators [Kang et al. 2015], communication protocols [Amaxilatis and Chatzigiannakis 2018], and access technologies [Centenaro et al. 2015, Raza et al. 2017, Sanchez-Iborra et al. 2018]. In the IoE, wearable and remote monitoring devices enable the real-time monitoring of physiological and clinical parameters (e.g., the heart rate, respiration rate, temperature, etc.), and the data streams generated are used by ML applications and decision support systems to predict critical clinical states.

Consider the use of ambient intelligence for the realization of assisted living technologies to address the needs of a rapidly aging society [Calvaresi et al. 2017, Nousias et al. 2018a]. The aging population, the increasing cost of formal healthcare, the caregiver burden, and the importance that individuals place on living independently, all motivate the development of innovative ambient-assisted living technologies for safe and independent aging [Stavrotheodoros et al. 2018]. Smart home technologies assist older adults to continue living with safety and independence [Lithoxoidou et al. 2017, Amaxilatis et al. 2017b]. An example of an ambient intelligence environment is depicted in Figure 1.1 where devices located in a smart home as well as smart wearable devices create an assisted living environment. The ambient intelligence parameterizes the operation of the environment, continuously adjusts the offered services to the needs of each individual user, and interacts with the physician to allow remote fine-tuning [Martínez et al. 2017]. The intelligent environment delivers personalized feedback to the user, suitably

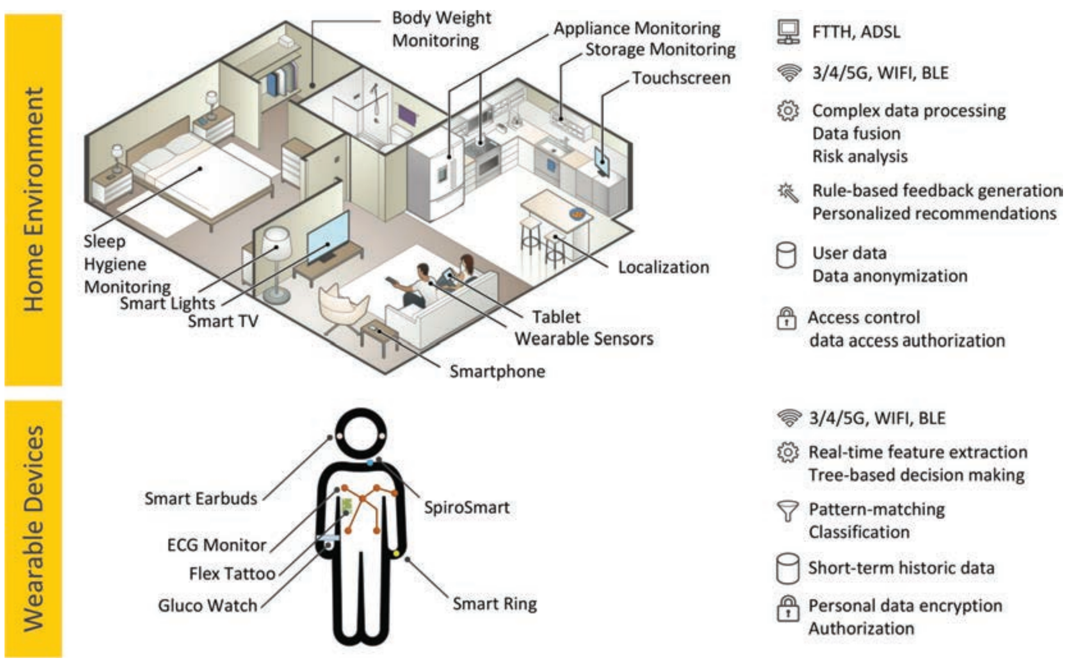


**Figure 1.1** The Internet of everything encompasses everyday objects that process sensor data and interact with Web services to deliver ambient intelligent environments.

adjusting the interaction to better assist the user needs [Loitsch et al. 2017, Nousias et al. 2018a].

Assisted living can also extend to working environments and support the aging workforce. As the population is aging, new strategies are developed to effectively increase the labor force participation of older workers and reduce the rates of early retirement and labor market exit. At the same time, industries appear increasingly dependent on the knowledge, skills, and experience of their older workers. Ambient intelligence can support companies to meet the challenges posed by an aging workforce and keep older workers employed for a longer period of time and also to support older workers maintain their ability to work and adapt to the rapidly changing work conditions [Lithoxoidou et al. 2017]. The worker-centric environment continuously and unobtrusively monitors the health, behavior, cognitive, and emotional status of the worker and helps counteract for crucial issues hindering the aging workers' work ability and well-being. A context-aware selection of the suitable feedback mechanism and the appropriate time is critical to help older workers be less stressed and more productive members of the organizations they work for [Tams and Hill 2017].

Like the two cases presented already, several mobile health (mHealth) applications, related to the self-management of chronic diseases, for example, asthma [Votis et al. 2015, Kocsis et al. 2017] and frailty [Pippa et al. 2016], require the use of sensing devices for real-time monitoring of several vital parameters, such as heart rate and activity monitoring. These assisted living environments generate a massive dataset of vital information that hides rich structures that could be analyzed for several reasons ranging from the prediction of potentially upcoming dangerous events or motivation of individuals to monitor their health status on a continuous basis. The integration of low-power signal processing algorithms and ML techniques within the sensing device can ensure communication, storage, and energy scalability, as the number of sensors increases, while providing diagnosis-grade accuracy. Multi-functional feature extraction mechanisms executed within the embedded processors will enable the interpretation of a wide variety of sensor signals and provide person-centric analysis addressing the needs of each individual user.

### 1.2.2 Awareness and Behavioral Change

The utilization of the IoE in the educational domain so far has trailed other more commercial application domains. Today, a plethora of hardware and software initially deployed as part of vertical single-purpose solutions (e.g., for monitoring electricity consumption, environmental conditions, both indoor and outdoor) are reorganized toward multi-purpose collaborative applications interacting across industry verticals, organizations, and people. Data arriving from unimodal closed systems can deliver a superset of high-value proposition applications, producing real-world data that could be directly used in educational activities [Pfisterer et al. 2011].

Consider climate change and our response as a society by pursuing environmental awareness and broad dissemination of green technologies within educational environments. Raising awareness among young people and changing their habits concerning energy usage are considered key in achieving a sustainable energy behavior. The educational community could have a sizeable impact on the reduction of energy consumption, granted that we succeed in teaching sustainability principles and responsible consumption behaviors [Heggen 2013]. Ambient intelligence can support such initiatives with immediate and individualized feedback to students regarding the impact of their actions. School lab activities planned specifically for students as part of science classes can promote behavioral change by informing them regarding mitigation actions and sustainable behaviors.

Road transport is another area where ambient intelligence can assist in the education of drivers toward safer driving behaviors, thus reducing road accidents,

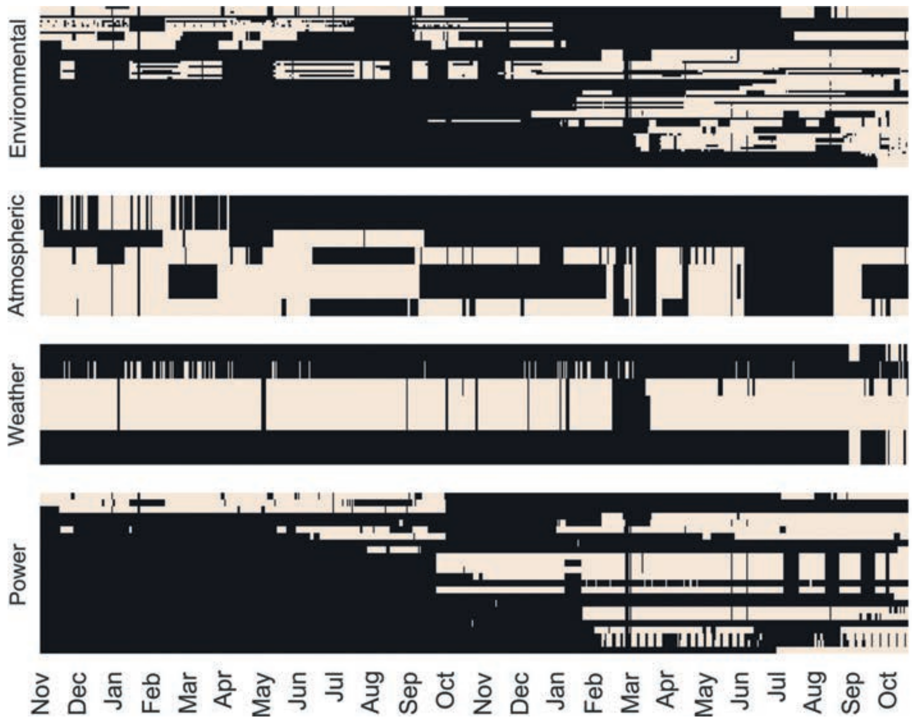


**Figure 1.2** Data availability of a real-world IoE deployment of 880 sensing elements over 19 school buildings across Europe promoting green awareness and sustainability lectures from November 2016 to October 2017. Missing data are represented with black color.

as well as a more efficient utilization of the engine operation, saving fuel and thus reducing emissions of $CO_2$ into the atmosphere [Santos 2017]. Modern cars are already equipped with a plethora of sensors that collect in real time several parameters related to the operation of the engine and the car in general. Ambient intelligence can extract such information (e.g., engine rounds per minute, position of the gear box), fuse it with the physiological data of the driver (e.g., via wearable devices), and convey educational messages. Certain driving behaviors are encouraged in a way such that drivers are motivated to adopt an eco-friendly driving style without distracting them from safe driving [Lalos et al. 2017].

A common problem in all these cases is that the acquired measurements are often corrupted with varying density, non-uniformities, and missing values [Zhu et al. 2018, Nousias et al. 2018b]. As an example, consider Figure 1.2 that depicts the availability of data collected by an IoE deployment over 18 school buildings across Europe from November 2016 to October 2017 [Amaxilatis et al. 2017a, Zhu et al. 2018]. Dealing with these challenges becomes more demanding if we wish to minimize the storage and communication requirements in order to increase the energy efficiency of the aforementioned devices and as a result their battery lifetime, such as schemes that take advantage of sparsity for the efficient compression of an electrocardiogram (ECG) in mobile computing platforms [Lalos et al. 2014, 2015]. Those imperfections do not allow analysis and exploitation at the full potential of the time series datasets by approaches that require complete data frames, thus undermining the robustness and accuracy of remote clinical services. Smart watches, in particular, have already demonstrated their capability to unobtrusively support healthcare in the everyday living of patients with chronic conditions, but rigorous assessment of their accuracy and use in clinical settings is mandatory [Lu et al. 2016, Reeder and David 2016, Stahl et al. 2016]. However, it is important to mention that the rich temporal structure hidden in the massive dataset can also be efficiently exploited for dealing with the aforementioned challenges using fast and effective approaches.

# 1.3 Elements and Enabling Technologies for DSP and ML in IoE Applications

## 1.3.1 Devices

Since the initial visions proposed in the Smart Dust Project 15 years ago [Hill and Culler 2002], wireless sensor networks (WSN) have seen a tremendous development, leading to the realization of the IoE. Today, there is a large variety of hardware that is easy to set up and use.

Some experimental processors have been introduced in an attempt to provide multiple heterogeneous cores that can accommodate both generic tasks such as networking and other input/output (I/O) operations as well as dedicated DSP and ML tasks. One such example is the Intel® Curie™ module (Intel, Santa Clara, CA, USA). The module provides a generic x86 core suitable for carrying out all tasks while a second core, the so-called pattern-matching engine (PME), provides a dedicated core for conducting classification based on the K-nearest neighbor (KKN) algorithm and the radial basis function (RBF) algorithm. The PME offers 128 neurons which can contain up to 128 8-bit feature values (dimensions). The ML techniques implemented at the hardware level are described in detail in Chapter 4.

Another notable example relates to the combination of field-programmable gate arrays (FPGAs) with embedded processors in order to carry out DSP tasks. For example, in Fakhari and Fathy [2010], a new high-throughput architecture is introduced for decreasing the computational complexity in discrete cosine transform (DCT) tasks by combining parallelism and pipelining of a Xilinx Virtex-5 FPGA (Xilinx, San Jose, CA, USA). Such a heterogeneous processor allows the offloading of image-processing tasks to the FPGA that can be executed at much higher speed, and with reduced memory costs. In Gomes et al. [2015], an FPGA-based embedded processor is proposed, which uses the system-on-chip (SoC) FPGA technology to offload critical features of the communication stack to dedicated hardware, aiming to increase a system's performance. For example, various ranges of the application of the blowfish algorithm can be implemented for data encryption. Chapter 3 introduces some fundamental DSP tasks that are indispensable tools in IoE applications.

In fact, I/O has become the limiting factor in scaling down size and power toward the goal of IoE [Pannuto et al. 2016]. Reducing the size of embedded processors requires composing optimized and specialized—yet reusable—components with an interconnect that permits tiny, ultra-low-power systems. In contrast to today's interconnects, facilitating ultra-low-power system operation is a very challenging task especially when heterogeneous cores can be selectively active or inactive. A chip-to-chip interconnect named Management Bus (MBus) was introduced recently [Pannuto et al. 2015], a new 4-pin, 22.6 pJ/bit/chip chip-to-chip interconnect made of two "shoot-through" rings. MBus facilitates ultra-low-power system operation by implementing automatic powergating of each chip in the system, easing the integration of active, inactive, and activating circuits on a single die. In addition, MBus introduces a new bus primitive: power oblivious communication, which guarantees message reception regardless of the recipient's power state when a message is sent [Communication Systems for Meters 2020]. This disentangles power management from communication, greatly simplifying the creation of viable, modular, and heterogeneous systems that operate on the order of nanowatts.

### 1.3.2 Networking

One fundamental aspect of the IoE is the networking technologies that allow the communication between the embedded devices and the Web services. For this reason, all the efforts up until now have focused predominantly on general purpose wireless low-power transmission technologies such as Institute of Electrical and Electronics Engineers (IEEE) 802.15.4 (ZigBee, Z-Wave) and IEEE 802.15.11 [Bluetooth, Bluetooth low energy (BLE)] [Gubbi et al. 2013]. In certain application domains, specific wireless networking protocols have been proposed; for example, in smart grids the open meter standard (OMS) wireless meter-bus (WM-B) protocol is specifically designed for smart metering devices and can operate at the 169 and 868MHz industrial, scientific, and medical (ISM) frequencies (WM-B). These technologies provide reasonably high bit rate exchanges over a short range. Due to this low-power and short-range mode of operation, deploying a large-sized network requires the use of communication protocols that deliver messages based on a multi-path approach [Chatzigiannakis et al. 2006a]. Such a multi-path approach provides certain benefits, such as the capability to overcome communication obstacles [Chatzigiannakis et al. 2005, 2006b], and the overall improvement of security of the network [Chatzigiannakis et al. 2007]. Experimentation over real-world WSN has highlighted the difficulties and limitations of the multi-hop short-range paradigm [Baumgartner et al. 2011]. In order to overcome these technical difficulties, several alternative solutions have been proposed, for example, by varying the transmission range of the nodes [Chatzigiannakis et al. 2005], providing hierarchical network structures [Amaxilatis et al. 2011], or even employing mobile nodes to facilitate network management [Chatzigiannakis et al. 2008]. Despite all these efforts, the reduced transmission range creates several difficulties that are hard to overcome. As a result, real-world deployments need to use a combination of networking technologies in order to deliver urban-scale coverage in the context of smart city services [Sanchez et al. 2014, Chatzigiannakis et al. 2016].

Recently, a new approach has been proposed that exploits sub-GHz communication that allows transmission over longer distances, and very low data transmission rates that allow power consumption to be significantly reduced [Centenaro et al. 2015]. This approach of network has been titled low-power wide area networks (LPWANs) as opposed to short-range high-frequency communication. Low-frequency signals are not as attenuated by thick walls or multi-path propagation as high-frequency signals, thus contributing to the robustness and reliability of the signal [Boulogeorgos et al. 2016]. In an LPWAN, the embedded devices are connected to concentrators (also called a *collector* or a *concentrator*) that are located several kilometers away. Evidently, LPWANs provide multiple benefits for IoE deployments, providing *higher autonomy* due to the reduced energy consumption, and *decreased deployment costs* as a small number of concentrators is required [Boulogeorgos et al. 2016].

An LPWAN uses proprietary modulation techniques that are derivatives of the chirp spread spectrum (CSS) and operate in the sub-GHz bands. It allows end-nodes to communicate independently and asynchronously, similar to an ALOHA-protocol. As a result, an LPWAN concentrator can receive data on the same channel from multiple IoE devices at the same time if the bit rates are different. This increases the capacity of nodes in an LPWAN. However, due to restrictions of the low-duty cycle regulations in the unlicensed sub-GHz bands, an LPWAN creates asymmetric situations where concentrators that are connected to a large number of IoE devices will be able to send downstream messages (i.e., messages arriving from the network servers to the IoE devices) less frequently to each node than a concentrator handling fewer IoE devices. Existing designs foresee both IoE devices and concentrators transmitting only 1% of the time to achieve low power consumption and high deployment numbers. In addition, since IoE devices are operating in a low-power mode, listening to the communication channel for down-link messages is sometimes done, also severely limiting downstream message exchanges. Keeping in mind that many of the proposed applications require the deployment of a *very large number of devices*, it is critical to propose certain extensions to existing LPWAN structures so that they can eventually accommodate very dense deployments of IoE devices without exceeding the capacity of the LPWAN [Mikhaylov et al. 2016, Varsier and Schwoerer 2017].

### 1.3.3 Energy

In terms of energy requirements, existing IoE deployments try to maximize the number of embedded processors that are connected to continuous and non-volatile power supplies. However, there are still many applications where some devices need to rely on finite power sources. In such deployments, the high power consumption of processing and/or transmission of large volumes of data generated puts constraints on long-term operability and forces developers to sacrifice accuracy for an increase in battery life [Khan et al. 2016]. Many attempts have been made in the past to deliver energy-efficient data processing and data transmission protocols in an attempt to reduce power consumption and prolong the lifetime of a network.

A very promising technology is the magnetic capture of vibration. The principle is simple. A magnet is hung from a spring or similar structure and placed inside a coil. When the magnet vibrates due to outside forces, it creates alternating current in the coil surrounding it. An example installation produced from a 0.85mm movement over 180μW of power [Beeby et al. 2006].

A promising alternative energy source is ambient sunlight that can be used while in outdoor as well as indoor environments. Typically, a small solar cell (1.5V, 50mA) installed outdoors can easily produce 150mW, while an indoor cell can produce, for example, in an unfavorable angle to an incandescent lamp, up to 51μW. Very recently, attempts were made to implant solar cells under the human skin in order to provide sufficient power for wearable devices implanted in humans [Bereuter et al. 2017]. The obtained overall mean power is $67 \pm 108$μW measured from the summer to the winter solstice, which is enough to completely power, for example, a pacemaker or at least extend the lifespan of any other active implant.

A key technology to provide power and enhance the lifetime of devices is through energy harvesting from human-generated power [Bayramol et al. 2017]. Energy harvesting technologies can enable the long-term deployment of wearable devices and allow more reliable operation, higher sampling rates, and the incorporation of additional features in practical devices. In fact, it has been shown that body heat and movement generate more than 60W [Starner 1996] that, if harvested efficiently, can be used to power the operation of cardiac pacemakers, hearing aids, or even smartphones [Zheng et al. 2014].

### 1.3.4 Sensing and Actuation

The way humans interact with material objects around them has evolved exponentially over the ages: starting from basic interaction mechanisms such as buttons and mouse devices, new flexible materials allow the development of flexible electronics that introduce completely new interaction mechanisms [Aditya et al. 2018]. From visual-based guidance systems to recognition based on retinal scans, fingerprints, or gesture recognition, the possibilities are virtually endless. With the advent of augmented reality (AR) and virtual reality (VR) technologies, new areas with endless possibilities have come into existence [Kasprzak et al. 2013, He et al. 2017].

Activities that, until recently, were conducted "passively" between people or between people and their environment are now technologically invisibly augmented in order to offer new kinds of experiences [Harries et al. 2016]. The introduction of new interaction methods allows us to move beyond systems that rely on a visual display as the basis of the interaction process [Eslambolchilar and Murray-Smith 2008, Robinson et al. 2009]. The location of the users as well as the environmental conditions of their locations introduce innovative alternatives for the implementation of human–computer interfaces [Robinson et al. 2008]. We see classrooms enhanced with visual equipment and small, portable computers (tablets, netbooks, etc.) for the students, near-field communication (NFC) technologies emerging and personalized advertisements, or even mixed-reality games and virtual worlds [Barrie et al. 2009]. The potential of combining sensors and mobile devices in order to produce new exciting entertainment applications is huge [Akribopoulos et al. 2009, Chatzigiannakis et al. 2011a, Kasapakis and Gavalas 2015].

Miniature vibrating motors are used to provide feedback to the user without the need for a visual display [Dunlop and Taylor 2009]. Small-factor vibrating motors can be used to develop IoE systems for training for physical activities, such as sports [Spelmezan et al. 2009]. Moving beyond simple vibrations, providing tactile feedback through wearable devices that combine arrays of nanovibrators enables more intuitive interactions with the end-users [Bloomfield and Badler 2008, Spelmezan 2012]. Tactile feedback has been shown to be beneficial when learning motor skills, and can help to instruct a user on both how and when to perform a movement, as well as providing the user with feedback when a movement is incorrect [O'Neil et al. 2015]. Haptic feedback can give blind people the opportunity to navigate through the Internet by touch [Kaklanis et al. 2009].

In these new interaction approaches, different DSP mechanisms and ML techniques play a dominant role, being incorporated into design algorithms, which result in the accurate translation of the user inputs based on the data collected from the various sensors [Juan 2012, Nousias et al. 2016]. Chapter 6 CS2 examines the use of brain signals for the realization of brain–computer interfaces (BCIs), while Chapter 7 CS3 looks into the implicit noise that is captured by the imperfect sensing technologies such as capacitive touchscreens, depth cameras, or microphones and how it can be overcome to deliver human–computer interaction (HCI). Chapter 10 CS6 studies how to combine information on the physical state of the user as well as the ambience to allow the human–computer interface to adapt to the current context of use and in this way improve the efficiency and effectiveness of interaction.

## 1.4 Computing Paradigms for IoE Data Analysis

### 1.4.1 Cloud-based Computing

The dominant approach followed by large industries focused small-to-medium enterprises (SME) and startups is the development of cloud-based IoE platforms that simplify the interconnection of smart devices, the collection of data generated to the cloud, and the central processing of the information utilizing other cloud-based services (see Figure 1.3). Existing commercial platforms provide a cloud-based back end that helps developers focus on how to accelerate the creation of compelling solutions that integrate with existing business processes and information technology (IT) enterprise infrastructure. With existing IoE deployments being sparse and incorporating a limited number of sensors, this approach performs adequately.

As big data has been introduced, several approaches have been introduced using the MapReduce paradigm [Dean and Ghemawat 2008] (e.g., Apache Spark[1]) that essentially split the analysis into batches. More recently, new tools have been developed that allow the analysis of the time series in a streaming way, hence the name stream processing frameworks (among the most well known are Apache Storm[2] and Flink[3]). For a survey of possible stream processing optimizations and variations, see Hirzel et al. [2014].

1. http://spark.apache.org/.
2. http://storm.apache.org/.
3. https://flink.apache.org/.

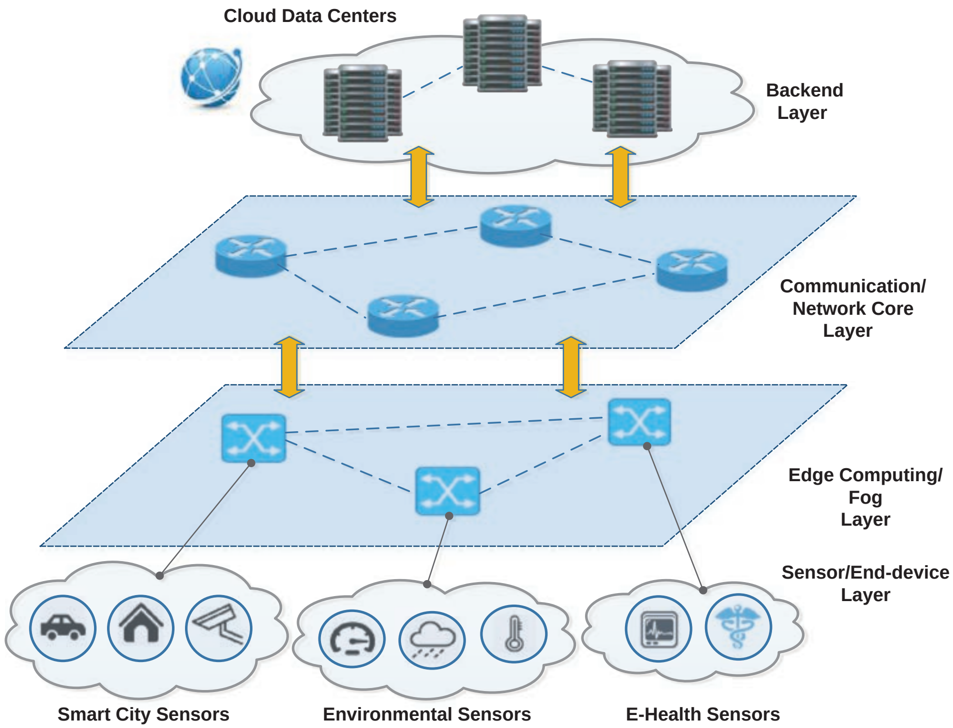


**Figure 1.3** Fog computing layer: an efficient intermediary between end user equipment and cloud infrastructure.

## 1.4.2 Edge Computing

As IoE deployments become more common, the total number of interconnected devices sharply increases. Following this newly introduced paradigm, everyday objects will obtain specialized interfaces allowing them to connect to affiliated networking infrastructure and to upload an unprecedented amount of highly diverse datasets. The dominant functional requirements of contemporary IoE services which shape the actual deployment framework include: (i) demand for increased bandwidth, since lots of barren datasets are collected by the end nodes and are submitted to the cloud to be processed; (ii) the need for decreased latency, especially for industrial or safety-critical systems such as patient monitoring platforms, automated production lines, and traffic optimization applications, which often require end-to-end latency of just milliseconds; (iii) autonomous operation, independent of networking connectivity, where data accumulation must proceed seamlessly even in cases of outage and once connectivity is re-established, newly obtained datasets should be uploaded to the corresponding repository;

(iv) increased reliability and security, which will ensure trustworthy access to services and nullify chances of data leakage or compromised content.

Unfortunately, cloud infrastructure appears to be incapable of handling the volume, the variety, and the velocity of IoE data due to inherent limitations derived from increased network latency as well as excessive bandwidth consumption when trying to transfer massive datasets to distant servers. It is therefore necessary to establish a contemporary computing model, encompassing a specific breed of upgraded features derived from the actual requirements the IoE introduces to frameworks intending to capitalize on the new characteristics of the specific ecosystem.

One of the dominant generic concepts for tackling increased latency and delay was none other than "edge computing," originally proposed in Garcia Lopez et al. [2015]. The fundamental idea of edge computing is to eliminate distance between the source of the data and the corresponding computational resources responsible for handling it. More precisely, as stated in Varghese et al. [2016], edge computing enables data processing at the network edge; therefore, it basically consists of components equipped with all the necessary resources for supporting edge computation, categorized as end user equipment (e.g., smartphones), edge networking devices (e.g., border routers, bridges, base stations, wireless access points), and edge servers. Following the localized computing paradigm, edge computing provides faster responses to the computational service requests and most often eliminates the need for bulk raw data transfer to the core network. Yet, it is not pertinent to the common deployment paradigms of infrastructure as a service (IaaS), platform as a service (PaaS), and software as a service (SaaS), but is somehow directly associated to the end device ecosystem [Shi et al. 2016].

In an attempt to combine the prime aspects of both edge and cloud computing, certain deployment paradigms have been introduced, namely mobile cloud computing (MCC), fog computing, and multi-access edge computing (MEC). These paradigms are presented in the following paragraphs.

#### 1.4.2.1 Mobile Cloud Computing

MCC gained significant momentum due to the proliferation of smart mobile devices and the constrains they have in terms of energy, storage, and computational resources [Mahmud et al. 2018]. Even though new mobile devices are now more powerful than ever before in sheer processing capacity and speed, sometimes they fail to meet application requirements, in order to allow users achieve the highest possible quality of experience, when on the move. Moreover, high battery consumption is considered a diminishing factor of any mobile device's operational ability, which is often limited to less than a full day. It is therefore preferable to execute certain demanding applications outside the mobile device instead of locally, having the user equipment (UE) utilize computing and storage resources available on distant centralized clouds accessible through the Internet. According to Barbarossa et al. [2014], MCC extends battery life by offloading energy-consuming applications to the cloud and enables sophisticated applications and higher data storage capabilities to mobile users; however, it fails to efficiently address the issue of additional load both on radio and backhaul of mobile networks.

#### 1.4.2.2 Fog Computing

Fog computing is a distributed computational paradigm strategically placed between IoE sensors/devices and Web services. It efficiently distributes computational, communication, control, and storage resources closer to the end users, in compliance with the cloud-to-things continuum [Chiang and Zhang 2016], rendering both edge and core networking components (e.g., core routers, regional servers, switches, etc.) able to be used as computational infrastructure. In particular, as shown in Figure 1.3, fog computing layer nodes have dedicated interfaces for communicating with the network core layer, the actual gateway of any cloud data center to the outside world. In modern networking deployments, the network core layer consists of software-defined networking (SDN) nodes which facilitate extensive governance and precise supervision [Kreutz et al. 2015]. This scheme allows multi-tier application deployment and service demand mitigation for large numbers of interconnected devices, enhances the overall framework robustness, and therefore makes it much more suitable for IoE use cases. As IoE devices/sensors are densely distributed and require real-time responses to service requests, fog enables IoE data to be stored and processed within the origins' vicinity, leading to latency minimization. Such an approach also eliminates the possibility of cloud infrastructure to be compromised due to malicious activity, since packets originating from end devices do not directly reach the cloud entry point but undergo a second inspection process that discards all potentially harmful or problematic content. However, as stated in Akrivopoulos et al. [2017], fog computing lacks certain security features such as authenticated access to services due to its highly distributed architecture, as well as a unified monitoring entity that ensures optimal resource management. From an architectural perspective, it is impossible to ensure predefined levels of quality of experience (QoE) for end users by design, since the actual computing is not integrated into the core network or any of its newly introduced distributed network stack layers [Kliazovich and Granelli 2008]. Finally, there are no specific standardization bodies for fog computing with significant momentum or vision; therefore, the overall architecture is arbitrarily developed and unoptimally deployed.

### 1.4.2.3 Multi-access Edge Computing

MEC is an architectural model for providing cloud computing capabilities paired with an IT service environment at the edge of the mobile network, within the radio access network (RAN) and in proximity to the service subscribers. The networking environment that is created based on this model is characterized by ultra-low latency, high bandwidth, real-time access to radio network and context information, location awareness, efficient network operation, and service delivery, thus ensuring high QoE for all interconnected users. It is therefore almost certain that the specific model enables innovation and value creation through application leveraging, bringing many advantages to all stakeholders, from mobile operators to service providers and end users.

Heavily dependent on a virtualized platform, MEC is evolving in parallel with the latest developments of mobile base stations where the concept of cloud radio access network (C-RAN) gains significant momentum [Checko et al. 2015]. C-RAN exploits the notion of a distributed protocol stack described in Kliazovich and Granelli [2008], with some of its layers now moved from distributed radio remote heads (RRHs) to centralized baseband units (BBUs). The BBUs' computational resources are then pooled together in virtualized clusters, commonly referred to as vBBUs or "whiteboxes," able to support large numbers of RRHs. Even though the available resources of vBBUs are primarily exploited for centralized control and baseband processing, certain computational offloading in the network edge can also be supported. Due to the underlying virtualization platform, MEC is regarded as one of the three fundamental technologies for the upcoming 5G networking era, together with network functions virtualization (NFV) and SDN by the European 5G Public Private Partnership (5G-PPP), since it facilitates the actual transformation of the mobile broadband network into a programmable ecosystem and paves the way toward meeting the original standards of 5G in terms of expected throughput, latency, scalability, and automation.

The design philosophy behind MEC follows an approach complementary to NFV. While NFV is focused on network functions, the MEC framework enables applications running at the edge of the network, using similar infrastructure such as commodity servers and intelligent networking appliances. To allow operators benefit as much as possible from their investment, it will be beneficial to reuse the infrastructure and infrastructure management of NFV to the largest possible extent, by hosting both virtual network functions (VNFs) and MEC applications on the same platform. This approach renders MEC capable of opening services to consumers and enterprise customers alike, allowing adjacent industries to deliver mission-critical applications over a mobile network. It introduces a new value chain, fresh business opportunities, and a myriad of new use cases across multiple sectors.

## 1.5 Security, Privacy, and Data Confidentiality

Regardless of the technology used to connect the smart devices with Web services, as individuals interact directly with the IoE ecosystem, huge amounts of data are being recorded and then shared, aggregated, annotated, stored, processed, and finally consumed. Whenever a modern ICT application is used, several digital traces are being left behind [Bergström 2015, Angeletti et al. 2017b]. These traces are collected, assembled, and used in uncountable ways that nonetheless are often difficult to imagine. There are various reports of concerns regarding the violation of privacy, with particular emphasis on information privacy [Preibusch 2013]. It is clear that collected data may be used to extract or infer sensitive information about users' private lives, habits, activities, and relations, all of which refer to individuals' privacy [Price et al. 2005, Pavlou 2011]. Chapter 9 CS5 provides two concrete cases that illustrate different aspects of the process of inferring personal and social contexts from data arriving from the IoE.

It is not possible to avoid all data collectors and in particular those services that can only be accessed by giving up some personal information [Woo 2006]. On most websites, applications, or services, the disclosure of personal information allows access to premium features, gifts, and enhancements in the online experience and much more [Angeletti et al. 2018]. Paradoxically, the benefits in terms of services offered have such a big value that a significant number of people are willing to give up their privacy for convenience [Woo 2006, Preibusch 2013, Trepte et al. 2013]. For example, online users show privacy concerns about the usage, the disclosure, and the protection of their personal health information [Bansal et al. 2010]. They are also sensible to the fact that it is possible that undesirable social and economic consequences can happen following a misuse of such data [Luck et al. 2006].

IoE systems must guarantee the confidentiality and integrity of the information and the privacy and anonymity of users. Moreover, it is important to guarantee the confidentiality of the end nodes data, especially when the end node devices operate in uncontrolled environments [Angeletti et al. 2017a]. Multiple definitions of privacy exist [Steinfeld and Archuleta 2006], each one focused on different declinations of the same principle: "the ones right to manage valuable personal information." Certain studies account some critical points regarding privacy: improper access, unauthorized use (both direct or secondary), errors, and collection of personal information [Okazaki et al. 2009, Lavagnino 2013]. Information privacy raises issues of access control (user authentication and authorization) and the need for data authentication. In a digital health system, all information is converted into a digital form. Therefore, data protection and privacy protection are very closely connected. In this sense, the goal of security is the application of cryptographic protocols for data transmission and storage. A comprehensive top-down survey of the most recently proposed security and privacy solutions in the IoE is provided in Kouicem et al. [2018].

An IoE system should be designed to guarantee the following:

1. The privacy of users and the confidentiality of personal data (prevention of unauthorized disclosure of information).
2. The integrity of personal data (prevention of unauthorized modification of information).
3. The availability of personal data for authorized persons (prevention of unauthorized or unintended withholding of information or resources).

### 1.5.1 IoE Security versus Conventional Security

Even though there is an increasing number of real-world applications that employ large deployments of IoE devices, the wireless nature of communication in combination with the low-end capabilities of the devices raises security and privacy issues that have not been properly addressed [Mpitziopoulos et al. 2009, Sadeghi et al. 2015].

The resource limitations of the embedded devices, both in terms of computational power and energy capacity, make it difficult to support computationally evolved encryption mechanisms since they introduce delays in data delivery and increase the energy consumption. Several approaches have been proposed in order to address these issues by, for example, implementing the operations of cryptosystems, such as the Rivest–Shamir–Adleman (RSA) cryptosystems, at dedicated hardware components to optimize computational speed and energy consumption, or by introducing alternative implementations based on new mechanisms, such as the elliptic curve cryptography (ECC) [Chatzigiannakis et al. 2011c]. However, it is important to also consider that sensor node brands are very different in their capabilities; thus, providing a single solution is very challenging.

Until now, security for embedded systems was not often built directly into inexpensive sensor devices but considered as an afterthought [Maletsky 2015]. There is an urgent need to deliver cost-effective solutions to enable robust security and also to retain the flexibility to deliver real benefits in the face of expected threats. This requires well-architected and interoperable frameworks across vendors and technologies, integrated at both the software and silicon levels to enable the evolution of security services the whole industry can leverage.

Providing end-to-end security in an IoE needs to consider that the embedded devices are more vulnerable to various attacks as their location is not known at the time of design and protection against tampering is very difficult due to their low cost. Therefore, it is easy to assume that the adversary can easily capture the devices, and easily read the content of their memory, thus learning the cryptographic secrets and possibly modifying their behavior [Chatzigiannakis and Strikos 2007]. In addition, the high device-to-human ratio makes it infeasible to even consider the presence of an online trusted server that monitors and maintains individual devices constantly. Thus, techniques of pre-distribution of keys are much less effective than in traditional networks.

### 1.5.2 The Role of Trust

The research is well aware of the concern of privacy about the confidential information of individuals. For the case of an IoE for healthcare, several studies indicate that the lack of *trust* in ICTs and digital healthcare affects very seriously any effort to migrate from the conventional healthcare procedures to electronic systems [Bodenheimer and Grumbach 2003, Shortliffe 2005]. The term "trust" implies the agreement to depend on a third party (another person, institution, company, or other) based only on the belief of its integrity and/or benevolence [McKnight et al. 2002]. The trustness has been the fundamental prerequisite for the progress of commerce and prosperity in human societies [Fukuyama 1995] and determines to which extent an individual wants to depend on others.

The central role of trust as a major type of social capital in online activities is well established [Fukuyama 1995, Schlichter and Rose 2013]. According to the above, any successful IoE system should target at increasing users' trust. It is clear that both *trust* and *security* play central and fundamental roles: "The more people trust others, the less concern they have for misuse of personal information" [Bergström 2015]. As privacy is connected to security, a similar relationship is also observed between trust and security [Jøsang 1996]. Trust, however, is difficult to establish in an IoE system since it requires interactions between computers, between humans, and between humans and computers.

### 1.5.3 Data Protection Regulations

The need for protecting individuals' privacy has been recognized by law enforcement agencies leading to the creation of laws for data protection. The American Civil Liberties Union (ACLU) believes that a privacy policy for confidential information should be based on the following principles [American Civil Liberties (ACLU) 1994, Barrows and Clayton 1996].

1. Strict limits on access and disclosure must apply to all personally identifiable data, regardless of the form in which the information is maintained.
2. All personally identifiable personal records must be under an individual's control. No personal information may be disclosed without an individual's uncoerced, informed consent.
3. Personal information systems must be required to build in security measures to protect personal information against both unauthorized access and misuse by authorized users.
4. Employers must be denied access to personally identifiable information on their employees and prospective employees.
5. Individuals must be given notice of all uses of their personal information.
6. Individuals must have a right of access to their own personal records, including rights to copy and correct any and all information contained in those records.
7. Both a private right of action and a governmental enforcement mechanism must be established to prevent or remedy wrongful disclosures or other misuses of information.
8. A federal oversight system must be established to ensure compliance with privacy laws and regulations.

The European Union-wide framework known as the General Data Protection Regulation[4] (GDPR) was introduced in 2018 that provides a more uniform interpretation and application of data protection standards across the European Union (EU) and was adopted in some other countries (e.g., the UK). Essentially, it constitutes a fundamental change in the management of data privacy designed to protect and empower all EU citizens' data privacy and with severe implications in the way organizations across EU approach data privacy. The purpose of GDPR is to protect personal data at large, namely "any information relating to an identified or identifiable natural person."

The regulatory framework defines three main roles: *the subject*, namely the resident or individual providing his/her data to the IoE system; *the data controller*, which determines the purpose and meaning of the processing of personal data

4. https://ec.europa.eu/commission/priorities/justice-and-fundamental-rights/data-protection/2018-reform-eu-data-protection-rules_en.

provided by the users; and *the data processor*, which processes the personal data on behalf of the data controller. Note that in many cases the *data controller* has the double role of a data controller and data processor. The following is a short summary of the main requirements defined in the law enforcement directive.

- **Explicit consent.** Clear and definite conditions for acquiring consent from data subjects (citizens) to process data.
- **Data protection officer.** A person is appointed to handle the necessary internal recordkeeping requirements.
- **Sanctions.** Non-compliance can result in serious penalties.
- **Territorial scope.** The directive applies to all organizations processing data from data subjects (citizens) residing in the EU, not only EU-based organizations.
- **Right to access.** The data subject shall have the right to obtain from the controller confirmation as to whether or not personal data concerning him or her are being processed, and, where that is the case, access to the personal data and some other information.
- **Right to rectification.** Incorrect data has to be rectified.
- **Right to be forgotten.** Data subjects have the right to request data controllers to erase their data.
- **Data portability.** Data subjects have the right to request their data in a portable format, which allows one to transfer its data to another data controller.
- **Data protection by design and by default.** Develop default privacy protection mechanisms and implement monitoring processes.
- **Notification requirements.** Data breaches must be reported without undue delay.

IoE service providers must identify the data that is being processed, where it is transferred to, who processes the data, what it is used for, any risks and processes, and ensure all employees are trained. Furthermore, they have to provide all these information to potential users and keep records to show what individuals have consented to, what they were told, and when and how they consented. Note that, an IoE service provider is a processor from a customer perspective but also a controller of data in terms of personnel, sales, and subcontractors. As a consequence, IoE service providers have obligations to make sure that rules are in place and followed.

Particular interest is article 32 of the directive that states that "the controller and the processor shall implement appropriate technical and organisational measures to ensure a level of security appropriate to the risk." To this purpose, a crucial component of data collection in IoE ecosystems is the distinction between pseudonymization and anonymization. Any pseudonymized data that can still be tied to an individual user with the help of other information will still be considered personally identifiable information (PII). Only fully anonymized data will lose the PII label, so IoE services must make the distinction between these two data types.

## 1.6 Challenges and Future Directions

The necessity for data collection, storage, and availability across large areas, the demand for uninterrupted services even with intermittent cloud connectivity and resource-constrained devices, along with the necessity of sometimes near-real-time data processing in an optimal manner, create a set of challenges where only holistic solutions apply.

**Challenge 1** **Resource-constrained devices**

The basis of an IoE is the ability to integrate sensing, computation, and wireless communication in small, low-power devices that can be seamlessly embedded in complex physical environments. Such low-sized embedded devices have limited sensing, signal processing, and communication capabilities and are usually battery operated. Due to this resource-constrained environment of operation, the energy requirements of the electronics are supported by the available battery resources. Even if the overall energy consumption of the computational and networking activities of the device is optimized, the battery is still the most critical resource that hinders the longevity of the device. In addition, the battery is usually a bulky component that reduces the flexibility of the device and thus also the ease of use in the case of wearables. It is therefore critical to develop novel energy scavenging techniques for producing energy within the device by exploiting the natural energy (movement, heat) of the user. Such technologies will prolong the lifetime of the IoE solution significantly also allowing to further reduce the battery size, thus becoming more autonomous.

**Challenge 2** **On-device sensor data processing**

The major challenge in the evolving landscape of IoE devices is to increase the accuracy of the signals collected and broaden the capabilities for interpretation of data while at the same improving the long-term operativity and guaranteeing the privacy of the users. Existing IoE solutions rely on nearby smartphones that act as a gateway for transmitting the recorded sensor signals to Web services, where advanced DSP and ML algorithms are executed. Depending on the number of sensors used, even a trace corresponding to a short period of time may require a large amount of data to be stored on a local memory and be transmitted over the wireless network, affecting the battery duration of the devices as well as that of the accompanying smartphone. It is important to improve existing state-of-the-art IoE solutions by providing the capability of analyzing and interpreting a wide number of sensor data traces within the devices and provide actionable alerts in an energy-optimized way. It is crucial to evolve the current paradigm for developing IoE solutions from a totally Web-centric one to a more distributed one by (i) increasing the available power-efficient computational power of the devices and (ii) introducing energy-efficient sophisticated software executed on the devices, rendering them capable of locally processing the sensor data recordings and detecting abnormal behavior, thus increasing the solutions' reliability. The objective is to increase longevity of IoE deployments by reducing energy requirements due to reduced transmissions of large sensor data and therefore also to reduce the overall size of the electronics and the supporting battery. Moreover, migrating data processing closer to the production site accelerates system responsiveness to events along with its overall awareness, by eliminating the data round-trip to the cloud, consequently leading to improved resource utilization and QoE.

**Challenge 3** **Reliable, privacy-preserving operation**

Data collected by IoE solutions are extremely sensitive and need to be secured since they are directly related to the privacy of the users. Unfortunately, the uncontrolled growth of Internet-centered services has led us to accept many compromises about how data are shared. Existing IoE solutions are totally Web-centric: all personal data collected are stored on the Web and in most cases users no longer own the data they produce. This approach severely limits the ability of the user to maintain control of their personal data. Now, more than ever, there is a need for privacy-preserving applications where users are always in control of their sensitive data. These arguments have been recently further supported in the My Data is Mine declaration that declares that: "Consumers must have control over their data and should get a fair part of the value created by the companies using their data." The ability to combine resource-bound IoE sensors with computational capabilities is equally important for data security and privacy. Since the data collected from the IoE devices is not forwarded to the cloud, it considerably increases the level of data control by allowing the user to maintain control of all the collected data. In this sense, it is beneficial to take advantage of the increased computational capabilities of the new wave of IoE devices and reinforce the privacy of confidential data conforming to all existing regulations relevant to data protection.

**Challenge 4** **Establishment of common standards**

The vision of the IoE has led to substantial standardization progress across different bodies of the IEEE and the European Telecommunications Standards Institute (ETSI), providing technical solutions tailored to the resource-constrained embedded nodes, ranging from the lower to the upper Open Systems Interconnection (OSI) layers. Yet, until now, no standard has managed to attract the vast majority of the stakeholders and dominate the domain. Current IoE deployments are, more often than not, privately run to serve a specific application, enforcing a tight association between the application, the network used by the application, and the sensors that constitute that network [Karkazis et al. 2015]. Clearly, developing common standards for application-specific and mission-oriented systems where no single protocol stack is used is extremely challenging. Most attempts are inherently non-scalable, exhibit low cost-efficiency, are non-adaptive, and usually require tremendous efforts to integrate them with existing and well-established services.

## 1.7 Follow-up Questions

The development of innovative products and services that depend on and extend the IoE is certainly challenging. In the previous section, certain research challenges were identified. Nevertheless, technologies today have reached a certain maturity to allow us to develop new and exiting products and services. Here are some practical questions to keep in mind while thinking of a new product:

- What is the minimum variety of sensor data required to build your model?
- What is the minimum volume of sensor data required to provide reliable decision-making?
- What is the expected variability of the sensor data? What is the maximum variability that data analysis can tolerate?
- Do the sensor data require a certain amount of pre-processing to remove noise, fix corrupted readings, or fill in missing values? Can the smart device carry out these pre-processing tasks? Can we carry out these pre-processing tasks within the network infrastructure before they reach the cloud?
- How often do you need to keep the user informed regarding data collection, data communication, and data processing tasks?
- Do you need to store raw sensor data?
- Can you identify an open standard relevant to storing the data collected?
- Are sensor data stored and communicated in an encrypted format?

- Are the data generated by your smart product or service potentially useful to other products and services?
- Can you identify an open standard relevant to exchanging the data produced by your product or service with third parties?

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