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ADOPTING COGNITIVE COMPUTING SOLUTIONS IN HEALTHCARE

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This paper discusses possible motivations to adopt cognitive computing-based solutions in the field of healthcare and surveys some recent experiences. From a very practical point of view, the use of cognitive computing techniques can provide machines with human-like reasoning capabilities, thus allowing them to face heavy uncertainties and to cope with problems whose solution may require computing intensive tasks. Moreover, empowered by reliable networking infrastructures and cloud environments, cognitive computing enables effective machine-learning techniques, resulting in the ability to find solutions on the basis of past experience, taking advantage from both errors and successful findings. Owing to these special features, it is perceptible that healthcare can greatly benefit from such a powerful technology. In fact, clinical diagnoses are frequently based on statistics and significant research advancements were accomplished through the recursive analysis of huge quantity of unstructured data such as in the

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case of X-ray images or computerized axial tomography scans. As another example, let us consider the problem of DNA sequence classification with the uncountable combinations that derive from such a complex structure.

1 Introduction

Pushed by the fast and unstoppable innovation in Information and Communication Technology (ICT), we are experiencing daily evolutions in applications and services that we commonly use. This is due to both the wide availability of computational resources, and the large amount of data exchanged at high speed between a variety of heterogeneous devices and systems. Such an overwhelming progress impacts on a vast class of applications and gives way to the raise of a new wave of advanced services. In particular, the technological framework enabling this new wave can be depicted by the following keywords: Cloud, Semantic Web, Big Data, and Cognitive Computing. In this paper, we focus on cognitive computing that, in turn, relies on the cloud infrastructure and profitably implements semantic Web techniques to analyse big data, making them meaningful and transforming them in valuable information. In fact, cognitive computing systems owe their success to the capability of fast-processing huge amounts of data through the novel and sophisticated machine learning algorithms they are based on. In the present situation, healthcare is one of the pioneer fields in which cognitive computing is being applied extensively. We will present an overview of challenging research topics and we will showcase some of the results already achieved.

The remainder of the paper is organized as follows. In Section 2 a general introduction to cognitive computing is presented. Section 3 covers issues on programming such systems, while Section 4 takes into account recent cognitive computing applications in the specific field of healthcare. Conclusions follow in Section 5.

2 Cognitive Computing

From a practical point of view, we regard cognitive computing as the revamp of precedent well-funded theories that hardly found practical applications at the time of their formulation, due to the lack of computing power. This is the case, for example, of Artificial Intelligence (AI) and neural networks, which are characterized by high complexity and by the need of executing huge numbers of parallel operations in strict time frames. Traditional AI techniques rely on the model of expert systems and exploit statistics and complex mathematical model, thus require that a significant amount of operations per second is executed on large dimension data sets for their training. In this respect, cognitive computing can be considered as the revenge of AI since, nowadays, we have computing architectures suited to face large dimensional problems on large data sets. This continuous number crunching allows performing analytics and deriving new knowledge, which results in the ability to anticipate solutions in a heterogeneous class of problems. As an example, let us consider the Internet search engines. They employ such a kind of AI, to the aim of giving back information that is relevant to the users, based both on individuals' data and on the application of patterns. This involves issues such as, e.g., language contextualization, classification, clustering, entity extraction, and more. As another example, let us consider the popular sites of electronic commerce and the recommendation systems they adopt. When one is seeking an item, or immediately after a purchase, the algorithm driving the recommendation system exploits cognitive computing techniques to provide focused shopping advices related to the products one is browsing, has marked as favourite, has added to his/her wish list, also relying on users' preferences and on their purchase history (Pazzani & Billsus, 2007).

To conclude, we observe that cognitive computing systems should be regarded as a "more human" AI. In fact, they mimic human reasoning methodologies, showing special abilities in dealing with uncertainties and in solving problems that typically entail computationally heavy processes. Moreover, they expose learning capabilities, thus their knowledge base is continuously-growing and, accordingly, their reasoning ability is continuously-enhancing. Besides, cognitive computing plays an important role in improving both man-to-machine and machine-to-machine communications, and in fostering the development of new human-computer interactions models, based on the Natural User Interface (NUI) paradigm such as, e.g., conversional systems (Nishida *et al.*, 2014). Moreover, through the effective and reliable simulation of the reasoning processes, machines can be trained to learn from experts' behavior in approaching problems and from their problem-solving techniques, to become, in turn, able to train newbies and to teach humans new concepts and/or new procedures. Such intelligent systems could be used, e.g., in training and customization, or other activities that requires data analysis in order to improve both processes and products (Earley, 2015).

Furthermore, cognitive computing is thought to be the corner-stone for the future enlargement of the Internet of Things (IoT) scope (Zhang *et al.*, 2012) and, consequently, on the relevant interconnect technologies (Orii *et al.*, 2016). In fact, the expected near-future scenario is forecasting people and things to interact naturally (Coccoli & Torre, 2014), striving spoken language, while producing and consuming data performing their actions. Therefore, we need advanced analytics to gather information and extract data and vice versa, to the aim of realizing novel somehow-intelligent systems that are able to react in real time to unpredictable external stimuli with unknown origins. In this respect, we observe that the more important benefits that can derive from cognitive computing will not reside in the cognitive systems themselves, but in the coupling of cognitive systems with the surrounding environment. Then a novel era for engineering will rise, in which design will be driven by desired behaviours rather than by design constraints: *what* will make the machines rather than *how* they will be made (Holtel, 2014).

In conclusion, owing to the prospect resources and capabilities available within a working environment based on the use of cognitive computing, we can envisage the inception of a new generation of semi-autonomous systems committed to improve the quality of life, addressing critical societal issues (Mohideen & Evans, 2015), helping people in facing a variety of small complications as well as awkward jobs. Such new systems will be mainly based on the imitation of human attitudes and reasoning (Mohda *et al.*, 2011). Systems based on cognitive computing can successfully accomplish difficult tasks such as, e.g., classification, natural language processing, and data mining, thus are able to perform advanced activities such as, e.g., sentiment analysis, relationships extraction from unstructured corpus, image recognition, speech-to-text and text-to-speech conversions. Another prospected advantage is the growing confidence in humans that machines can provide reliable answers, i.e., within an acceptable range of trust, in delicate areas, such as, e.g., medicine, education or economics (Coccoli *et al.*, 2016).

3 Programming Cognitive Computing Systems

As already mentioned, cognitive computing systems owe their powerful characteristics to the recent enhancement of traditional AI pushed by the availability of new technologies, to the rapid development of new machine learning techniques, and to the large availability of data coming from a heterogeneous set of sources and devices. These reflect in the possibility of implementing effective model-based reasoning capabilities, which make cognitive systems able to perform complex tasks such as, e.g., discovery, reasoning, and multimodal understanding in a variety of domains (Banavar, 2015) such as, e.g., healthcare, insurance, and education (Coccoli *et al.*, 2017). As a consequence, cognitive computing and the relevant technology are going to play a key role in engineering systems of the future (Noor, 2015).

3.1 The Cognitive Computing Consortium

Given such premises and the forecast on the future cognitive computing development and achievements, it is necessary to set up an open working environment where researchers and IT professionals can find non-proprietary definitions that can be used as benchmark. To this aim, a cross-disciplinary group of experts from industry, academia and the analysts' community, founded the Cognitive Computing Consortium[1]. Constituents come from a mix of research centres, companies and institutions such as Synthesis and NextEra Research (founders) with Pivotal, Basis Technology, HP, IBM, BA Insight, CustomerMatrix, SAS, Interactions, Bebaio, Microsoft, and universities such as, UCSF and the Babson College. It is worthwhile noticing that most of the sponsors are companies involved in big data analysis.

3.2 Programming Cognitive Computing Systems

To the aim of spreading the adoption of cognitive computing, specific platforms and tools exist, enabling programmers to develop suited, effective and reliable systems tailored to solve their problems. In recent years, many big players in the IT scenario delivered their own cognitive computing kit and this is driving both market and technology in the direction of making such systems affordable and widely available. Among these, in the following we mention the most significant examples that are, in alphabetical order:

(i) Enterprise Cognitive Systems by Enterra. Formerly known as Cognitive Reasoning Platform (CRP), the enterprise cognitive systems framework is defined by its developers as "an artificial intelligence platform that allows organizations to capitalize on the power and potential of big data through advanced analytics and actionable insights that fundamentally inform organizations about the business, customers, and value chains in which they operate". They also claim it can easily combine "[..] the efficiency and accuracy of computational computing with the analytic and predictive abilities of human reasoning. [..] can receive extraordinary volumes of data from any source, structured and unstructured, understand the nature of the data, learn from the relationships and connections it discovers, make decisions, and take actions to achieve defined outcomes";

(ii) Deep Learning Technology Center. It is the structure owned by Microsoft where to work with the Cognitive Toolkit, which was formerly known as the Computational Networks Toolkit (CNTK), made available in open source for anyone to use in their own work on GitHub. It is depicted by its developers as "A [..] commercial-grade toolkit that trains deep learning algorithms to learn like the human brain". This tool allows creating deep learning networks for different activities and "[..] empowers you to harness the intelligence within

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[1] http://cognitivecomputingconsortium.com

massive datasets through deep learning by providing uncompromised scaling, speed and accuracy with commercial-grade quality and compatibility with the programming languages and algorithms you already use";

(iii) DeepMind. It is the platform offered by Google that, in 2014, acquired the namesake UK-based AI company aimed to solving artificial intelligence problems. Their claim is "Solve intelligence. Use it to make the world a better place". Then, to show the effectiveness of their work, in 2015, Google announced the creation of a specific AI that learns by itself and is able to win video games. Indeed, they "were able to create a single program that taught itself how to play and win at 49 completely different Atari titles, with just raw pixels as input. And in a global first, the AlphaGo program took on the world's best player at Go - one of the most complex and intuitive games ever devised, with more positions than there are atoms in the universe - and won";

(iv) IDOL (Intelligent Data Operating Layer). It is the software layer offered by Hewlett-Packard, whose tagline is "Unified machine learning platform for enterprise search and big data analytics - text analytics, speech analytics, image analytics and video analytics". Delivered by HP, which acquired Autonomy in 2011, within their big data software platform, IDOL is offering many services and solutions for, e.g., data analysis and IoT. They claim that the "IDOL Natural Language Question Answering empowers organizations to tap into the full potential of big data by breaking down the barriers between machines and humans. It effectively unleashes the power of machine learning by enabling natural language based human-centric exchanges in delivering the contextually relevant information";

(v) Watson, by IBM. It promises to "go beyond artificial intelligence". It is a technology platform using natural language processing and machine learning to reveal insights from large amounts of unstructured data. IBM claims that Watson "can understand all form of data, interact naturally with people, and learn and reason, at scale. [..] you can analyse and interpret all of your data, including unstructured text, images, audio and video [..] you can utilize machine learning to grow the subject matter expertise in your apps and systems [..] you can provide personalized recommendations by understanding a user's personality, tone, and emotion [..] you can create chat bots that can engage in dialog".

4 Cognitive Computing Applications in Healthcare

Following the digitization process of medical records occurred in the recent years, we notice that, as other application fields, healthcare too is suffering from an explosion of information. On one hand, a huge amount of data reveals new opportunities for the advancement of research and for the effective treatment of diseases. On the other hand, such an information overload is hard to manage for both physicians and care providers. The unique reasoning ability of cognitive systems can perform detailed analysis and comparisons exploiting all the data available, thus becoming an effective companion.

As researchers, we can envisage a variety of applications in which cognitive computing can contribute to evolve healthcare but, in the current situation, its most promising feature appears to be the ability in managing huge quantity of information. In fact, cognitive system can easily overtake present solutions for big data management and decision support and these class of problems is very common in medicine, especially for prevention and diagnosis based on statistics analysis and visual pattern recognition. Most impressive and eye-catching results have been achieved in cancer diagnosis and results in this field have been proudly announced by the technology provider of the above-presented Deep Mind, Google, and Watson. As already stated, recognizing and classifying images is another peculiar ability of cognitive systems (Teo *et al.*, 2012) and this feature is a strategic asset in the prevention of cancer pathologies, especially for what concerns breast cancer, lung cancer and prostate cancer (Strickland, 2013). In fact, a cognitive system that "sees" is a valuable support, relieving the doctor from the task of analysing many hundreds of thousands of documents about the same pathology in a little time-frame as well as for providing the semantic interpretation of diagnostic images (Ogiela *et al.*, 2006). However, it is worth pointing out at this point how the application of the cognitive system in the medical field in particular finds a series of barriers and resistances by physicians and nurses, mainly due to the lack of basic computer skills. Nevertheless, there is evidence that where cognitive systems are used for healing, a 50% improvement in results is observed, while hospitalization costs are reduced by half (Gatenbein, 2014). In addition, there is also a reduction in diagnostic errors, especially in carcinogenic pathologies. This last observation is changing the focus of operators, because in the United States the first cause of death is due to diagnostic errors.

To clarify the situation, we propose a literature review of cognitive computing solutions and related technologies applied to the healthcare. We will not enter in details of specific solutions and methodologies adopted, yet we will remain at an abstraction level where the benefits are highlighted and foreseen for the future development of novel decision support systems and autonomous services as well, to the aim of improving individuals' quality of life and health. In the following, with no ambition to be exhaustive, we report some recent works that illustrate the above-cited ability. It is worthwhile noticing that many articles in the clinical literature refer to systems based on IBM Watson and we reserved a specific section for those.

4.1 Decision Support

Decision making and decision support can benefit from cognitive computing capabilities. One example of this is reported in the paper "Temporal Modeling in Clinical Artificial Intelligence, Decision-Making, and Cognitive Computing: Empirical Exploration of Practical Challenges", Bennett and Doub (2014) describe a decision system based on Markov Decision Processes and the use of neural networks, implementing the so-called temporal modelling approach, that allows capturing certain aspects of human cognition. In this respect, the computing system should resemble the same process, hence cognitive computing solution re expected to improve performances of the above-cited approach. Other methods, such as, e.g., Interactive Metric Learning (IML) are described in the paper "IBM's Health Analytics and Clinical Decision Support", by Kohn *et al.* (2014). Another core aspect in healthcare involving decision support systems is related to the management of patient records. In their paper "Cognitive computing for electronic medical records", Devarakonda and Mehta (2016) describe the problems due to the overload of information in Electronic Medical Record (EMR) systems and the inability to make sense of this information to provide the best care for their patients. They identify the solution in the use of cognitive systems designed to perform advanced analysis on the patient record data. These may also require the understanding of natural language questions about the patient record content, helping physicians to automatically identify urgent abnormalities, and provide precise causes for such abnormalities. In such a cognitive computing view, the EMR is transformed in an active entity that helps making decisions, leveraging the large amount of knowledge within the medical sciences, drug information, and medical ontologies.

4.2 Big Data and Analytics

In the editorial "Big Data and Analytics", by Tan *et al.*, the authors put in evidence how the digitization process occurred in health and in the management of patient data, as well as the rapid adoption of health information systems have led to the generation of huge volumes of primary and secondary data within the health care industry, that cannot be processed and managed by traditional data processing tools and that have to be duly managed, in order to make them a valuable asset for both improving the therapy effectiveness and advancing research to enhance prevention and health outcomes, also for reducing costs (Tan *et al.*, 2015). In this respect, they introduce health analytics as "the systematic use of health data and related business insights developed through applied analytical disciplines (e.g. statistical, contextual, quantitative, predictive, cognitive, other models) to drive fact-based decision making for planning, management, measurement and learning" (Cortada *et al.*, 2012). Consequently, health analytics require a variety of statistical techniques borrowed from modelling, machine learning, data mining, to analyse current and historical facts to make predictions about unknown events. Then, Chen *et al.*, in their paper "IBM Watson: how cognitive computing can be applied to big data challenges," extend the scope of cognitive computing to the entire life sciences field (Chen *et al.*, 2016), pondering on issues that life sciences researchers have to cope, detailing how cognitive technologies can help finding new solutions to aggregate big data for a better understanding of the latent information they may contain.

4.3 Watson in Healthcare

In the paper "Paging Dr. Watson: IBM's Watson Supercomputer Now Being Used in Healthcare", Lee (2014) outlines how the supercomputer has moved on to practical applications and why it was "taught" to understand the complexities of healthcare, putting emphasis on using the term *taught* rather than *programmed*. After a brief history of cognitive computing in history, practical uses for Watson in are duly listed, such as, cancer research, supply chain management, and consumer empowerment to help create better outcomes in healthcare. Significant case studies are presented, including the work done with the Memorial Sloan-Kettering Cancer Center (MSKCC) and with the MD Anderson Cancer Center (University of Texas), which both experienced that the large amount of data collected from their patients and stored in heterogeneous systems were essentially useless due to the inability of merging the results achieved by the oncology team with the clinical trial data. Another application of Watson in oncology is reported in the paper "Envisioning Watson as a Rapid-Learning System for oncology" (Malin, 2013), which also, emphasizes on the unprecedented reasoning ability of the cognitive computing system, using machine learning to determine how to weigh clinical factors in patients, to the aim of identifying the more suited treatment options and give a decision support to physicians. In practice, Watson was trained to do this, similar to a medical school student, which learns by observing more experienced physicians.

Besides, we observe that these successful applications are leading to future developments involving the same technology. In fact, we highlight that the New York Genome Centre (NYGC) and IBM are collaborating (Ratner, 2015) to analyse genetic data to speed up the process of treatment for patients with brain cancer (Douglass & Kearns, 2017). The IBM Watson cognitive computing system will be trained to analyse genomic data from a small group of patients with glioblastoma diagnosis, one of the most aggressive and malignant brain tumours. Its cognitive abilities will be used to analyse gene sequence variations between normal brain tumour biopsies, medical information, and clinical records to help physicians locate a variety of treatments and tailor the type of cure for specific cancer. Then, applying cognitive computing power accelerates the ability to address personalized cure for fatal diseases such as cancer. Another interesting development filed is enhancing medicine in developing countries where 70% of new cases of brain cancer occur. In India, there is only one oncologist for about 1,600 patients. A cognitive system such specifically designed for Oncology (Manipal, 2017) can help with large numbers of patients. The Manipal Hospital in India is one of the private hospital chains that treat 200,000 patients a year. A physician with Watson's help takes only 20 seconds to collect information about a patient. This is a big difference because it allows very fast to give patients a cure. In addition to the speed we have much more precision: mistakes in formulating a diagnosis are reduced. Currently, IBM Watson for Oncology is used also in China, Thailand, Finland. Important results in a different field are reported in Barrow (2017). Barrow Neurological analysed 1,500 genes by discovering that five of them had never been connected to SLA. Moreover, IBM actively collaborates with the New York Collaborative Care Centre to develop a health management platform (Douglas & Adigun, 2017, CNYCC, 2017). UNC Lineberger is another comprehensive cancer centre, which adopted cognitive solutions to accelerate DNA analysis and inform personalized treatment options for patients (UNC, 2017).

Conclusions

From this overview, we can argue that cognitive computing in healthcare is a hot and promising topic. Both academics and industry are making big efforts to improve the performances of current systems and to propose novel solutions based on the profitable exploitation of big data. However, we put in evidence that most of the reported experiences are from United States where the healthcare system is organized in a peculiar manner, which is quite different from the majority of other Countries.

Furthermore, unfortunately, there is still a lack in infrastructural settings, the availability of open big data, and in general the minimum requirements for the hardware to effectively run such systems are still high, despite they can rely on modern and sophisticated cloud-based architectures. Nevertheless, cloud computing is expected to uphold its rapid growth in the very next future so that we can forecast the wide availability of affordable services for many applications. This will be one of the main pillars to base the diffusion of cognitive systems on, and will ease the penetration of such a novel variety of systems that will foster new services and will bring disruption in many settled paradigms. The cognitive healthcare will have a strong impact on cloud evolution. In fact, there will be a need to create an optimized cloud for all cognitive data - a hybrid and secure cloud. It is worth considering that in addition to the cloud, we also need to redesign the data architecture due to the heterogeneity of medical data. This is because in medicine 90% of data is image and 80% of medical data is not available on the Web, also due to security and privacy issues. Finally, cognitive health care will have a very strong impact on industry.

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