Is It Intelligent? A Systematic Review of Intelligence in the Most Cited Papers in IoT

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Abstract. Artificial intelligence is a buzz word and even more when its accomplishments have challenged our intelligence. However, what is intelligence? Is there a consensus in its meaning for researchers and professionals? Is it just a sales word? What does it mean in practical terms? To answer these questions, we followed a systemic review of literature in most cited papers about intelligent systems in the Internet of Things (IoT) and discovered that only 58% were intelligent as we defined: "Intelligent Systems are systems conformed by algorithms that are programmed using some machine learning techniques and that can learn from data and perform tasks with a superior performance". The rest 42% were just traditional systems with hardware or software enhancements.

Keywords: Artificial intelligence · Intelligent systems · IoT · Machine learning

1 Introduction

Nowadays, we are witnesses of the breakthroughs of artificial intelligence that is not anymore only in science-fiction books or films. In 2020, Brown et al. [11] demonstrated the accomplishments in several tasks like translation, reading comprehension, completion, simple arithmetic operations, news article generation, poem generation, and other tasks using Generative Pre-trained Transformer (GPT-3). In 1997, IBM Deep Blue computer program beat the world chess champion Garry Kasparov [32]. In 2016, AlphaGo won against the legendary Go player Mr. Lee Sedol [18]. In 2012, AlexNet Convolutional Neural Network (CNN) significantly outperformed previous methods on the ImageNet Large-Scale Visual Recognition Challenge (ILSVRC) [39] achieving human-level performance when classifying objects in images of natural scenes [28]. Waymo, formerly called Google self-driving car project, has led the autonomous driving

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progress for the automobile industry since 2009 [82]. Aside from these impressive examples, we can see its ubiquity and its contribution in other examples: route-finders that display maps and offer navigation advice to drivers; recommender systems that suggest products, movies, books, and music albums based on a user's previous purchases and ratings; medical decision support systems that help doctors diagnose breast cancer [9].

In all these previous cases, we can ask: What is intelligence? Is it similar to our intelligence? What makes a machine intelligent? "Can machines think?" (from A. Turing [77]) Is our intelligence a single entity? or Is there multiple intelligence? (adapted from Gardner [26]). And even more, how can we discriminate against a traditional system from an intelligent one? Is there a consensus about these topics in the scientific community or the industries?

Answering these questions does not lead us to only satisfy our curiosity, but more importantly, they help us: 1) to have a common understanding about Artificial Intelligence (AI) as researchers and practitioners, 2) to avoid using the intelligence term as a sales word and the misuse of it, and 3) to push all the efforts in the right direction for the development of intelligent systems, 4) to find the implicit consensus about the technical or practical definition of intelligence, and 5) to define the main elements of intelligent systems. Nevertheless, we haven't found a simple explanation to solve these questions, as it is explained in the chapter "How should we define AI?" [76]: "AI means different things to different people, and AI researchers have no exact definition of AI. The field is rather being constantly redefined when some topics are classified as non-AI, and new topics emerge". We found papers that have tracked the progress of AI research through the number of published papers [22], or that have discussed "problems, challenges and opportunities in AI" [60], or that have made a detailed review of AI applied in the fashion and apparel industry [29], but they do not have an explanation of what is AI or what are the practical implications in a broader scope or other industries. For that reason, we did a systemic review of most cited papers in the topic "Intelligent Systems in the Internet of Things (IoT)" to answer these questions and to fill this gap between the theory and practice of AI in IoT.

The remaining article is organized as follows: Sect. 2 discusses the definitions of artificial intelligence. Section 3 describes the steps involved in the systemic review process. Sections 4, 5, and 6 present the results, discussion, and conclusions of the study respectively.

2 Intelligent Systems

When we talk about the intelligence of systems, we refer to artificial intelligence. Also, "intelligence: the ability to learn or understand or to deal with new or trying situations, the ability to apply knowledge to manipulate one's environment or to think abstractly as measured by objective criteria (such as tests)" [52], "artificial intelligence: the capability of a machine to imitate intelligent human behavior" [51], "the ability of a digital computer or computer-controlled robot to perform tasks commonly associated with intelligent beings" [10], "artificial intelligence: the ability of machines, computers, systems to learn and solve problems" [60]. Even though, these definitions do not help us to discriminate against a traditional system from an intelligent one, or to understand the technical aspect of intelligence. To grasp a better understanding, we condensed the history of artificial intelligence in the following subsection where we can appreciate the progress of the "artificial intelligence" concept, and then, we defined it.

2.1 History of Artificial Intelligence

In the Brief History of AI [75], under the title "Ancient History", it is mentioned conceptual achievements like the intellectual roots of AI and the appearance of intelligent artifacts in literature. In [63,75], there is an overview of the "Modern History" of artificial intelligence that is compiled in the next paragraphs.

The gestation of AI dates between 1943 and 1955 with Alan Turing's vision and its persuasive agenda in his famous article "Computing Machinery and Intelligence" [77]. A. Turing introduced the Turing Test, machine learning, genetic algorithms, and reinforcement learning. The birth of artificial intelligence was in 1955 where the term artificial intelligence was used the first time by John McCarthy, a math professor at Dartmouth who organized the seminal conference on the topic in 1956 [15,49].

Early enthusiasm and great expectations of AI comprehends from 1952 to 1969 wherein 1958, McCarthy defined the high-level language Lisp, which was to become the dominant AI programming language for the next 30 years. Nevertheless, it was eclipsed with a dose of reality (1966–1973) in the form of limitations, difficulties, and failures such as the attempt to speed up the translation of Russian scientific papers in the wake of the Sputnik launch in 1957, no progress in machine evolution (the belief of an appropriate series of small mutations to a machine-code program can generate a program with good performance for any particular task. Now called genetic algorithms), the end of support for AI research in the United Kingdom, the impossibility to recognize when two inputs were different in a two-input perceptron (a simple form of artificial neural network).

Between 1969 and 1979, we highlighted the importance of expert systems like MYCIN, a program with about 450 rules to diagnose blood infections and was able to perform as well as some experts, and considerably better than junior doctors. Since 1980, AI has become an industry, and in 1986, it was reinvented the back-propagation learning algorithm that is a key element in artificial neural networks. Since 1987, there was progress in speech recognition, machine translation, robotics, computer vision, and knowledge representation due to new techniques like hidden Markov models (HMMs), data mining, and Bayesian networks. In 1995, the intelligent agents as a whole agent have appeared as a topic to develop human-level AI, artificial general intelligence, and friendly AI. Since 2001, the availability of very large data sets and its usage has emerged as an important aspect in the building of AI algorithms. And finally, the examples of Sect. 1 enrich this history.

2.2 Definitions

As explained in the chapters "What is AI?" and "Related Fields" by The University of Helsinki [76], we tend to use suitcase words for terms that carry a whole bunch of different meanings or that encapsulate jumbled ideas or dozens of different mechanisms (Marvin Minsky, one of the greatest pioneers in AI [53]). Its course also suggests that AI is not a countable noun, it is a scientific discipline, like mathematics or biology, it is a collection of concepts, problems, and methods for solving them, and it is related to other fields. Deep Learning is part of Machine Learning (ML), ML is part of AI, AI is part of Computer Science. All these fields and Data Science have concepts and methods in common. Moreover, AI is the field devoted to building artifacts that are intelligent (operationalized through intelligence tests) [70]. AI is the ability of machines to make decisions, learn similarly as humans, and complete tasks that normally require the intelligence of humans, including speech recognition, visual perception, decision making, and language translations [48]. AI corresponds to a system, machine, or computer that thinks humanly, thinks rationally (the ideal performance), acts humanly, or acts rationally [63,70].

In this study, when we say artificial intelligence, we mostly mean machine learning [15] because machine learning is a more appropriate concept to answer our research questions than AI. In the same manner, in "Artificial intelligence, revealed" [23], Yann LeCun, one of the fathers of Deep Learning and a winner of the 2018 ACM A.M. Turing Award [1] that is known as the "Nobel Prize of Computing" [3], explained that a machine learning algorithm "supervised learning" is a technique for adjusting parameters in a program to recognize things that are similar to what a machine has been trained on but has never seen. Additionally, another useful explanation comes from Yoshua Bengio, another winner of the same award. He said that machine learning allows computers to learn from examples, to learn from data. Bengio's mission is to discover and understand the principles of intelligence through learning [8]. His start-up Element AI [20] considers that the function of AI is defined by its ability to find patterns in enormous data sets, and to solve problems faster and more accurately than humans can [21]. Likewise, in Deep learning review, Geoffrey E. Hinton, the godfather of Deep Learning [78] and a winner of the same award, in collaboration with the two aforementioned authors, presented: the key aspect of deep learning is that the representations needed for detection or classification are learned from data using a general-purpose learning procedure, and not designed by human engineers [42]. They also noticed that the key advantage of deep learning above other techniques like linear classifiers or kernel methods is that the good representation can be learned automatically using a general-purpose learning procedure.

To summarize all the presented information and to elaborate our working definition, we consider that algorithms are the basic operational aspect of AI and its key elements are 1) Autonomy: the ability to perform tasks in complex environments without constant guidance by a user, and 2) Adaptivity: the ability to improve performance by learning from experience [76].

Definition 1. *Intelligent Systems are systems conformed by algorithms that are programmed using some machine learning techniques and that have the ability to learn from data and perform tasks with a superior performance*

This definition has the following implications: 1) the intelligence can be found on the used algorithms, 2) the definition discriminates some machine learning techniques from others, e.g. deep learning over linear classifiers, 3) the algorithms need to learn from data using a general-purpose learning procedure, and not a hand-crafted one, 4) the tasks involve input data and output results, 5) they have superior performance than traditional programming methods and sometimes better than human level, 6) examples of the tasks are speech recognition, natural language processing, image recognition (computer vision or machine vision), recommendation, anomaly detection [25,33,48].

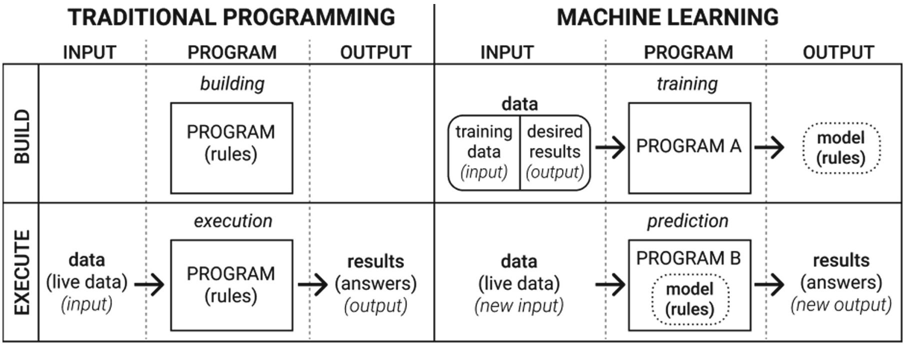

Fig. 1. Traditional programming vs. Machine learning

The Fig. 1 helps us to understand the difference between a traditional program and a machine learning program [4,6,17,30,38,56,66,74]. Programming a system, machine or computer consists of building a program to execute it and output results from input data. Every program on its basis is an algorithm that establishes the steps or rules to generate the output given the input. A didactic example in traditional programming is the sum operation of two numbers where the program has a rule explicitly written by a human. This program $y = x_1 + x_2$ is able to execute the sum operation resulting in the output y = 2 with the inputs $x_1 = 1$ and $x_2 = 1$. On the other hand, in machine learning, the rules are the output of the training program A. These rules were not explicitly programmed by a human, and they serve to the predicting program B. Continuing the previous case, the input data in the training process is conformed by the training data $x_1 = 1$ and $x_2 = 1$, and the desired result $y = 2$ wherein the traditional programming, x_1 and x_2 are the inputs and y is the output. Then, this input data obtains the output rule $y = x_1 + x_2$, and this model serves to the program B that has a similar execution as traditional programming but with new inputs $x_1 = 2$ and $x_2 = 2$, and new output $y = 4$.

This working definition and its implications is used to classify intelligent systems from traditional systems.

3 Materials and Methods

To discover what is the true meaning of intelligent systems in practical terms, we followed a systemic review of literature about intelligent systems in the Internet of Things (IoT).

3.1 Article Retrieval

We considered computer science-related databases for article retrieval: IEEE Xplore with more than five-million documents [34], ACM [2] with 2,888,831 publications, ArXiv with 1,790,396 scholarly articles [7]. We decided to use just one large database to accelerate this process. We accessed the IEEE Xplore on March, 5th, 2020, used the query string "Intelligent systems in IoT" (the spaces were considered as OR), and filtered by IEEE as the publisher. We chose the more recent articles.

3.2 Article Selection

To select papers, we followed this strategy. We explored intelligence concepts in the titles. We used the words smart, intelligent, intelligence, machine learning, supervised learning, automation, autonomous, and other related words to tag the titles. Then, we grouped the titles by area to have sample papers in different scopes or industries. We had two ways to determine the area. One way was extracting the word that modifies that area or component in the tags with the word "intelligent", e.g. in an "intelligent transportation systems", the area was "transportation systems". The other way was writing the whole tag in the tags with the word "intelligence", e.g. in an "artificial intelligence", the area was "artificial intelligence". Finally, we selected the most cited papers. We considered 80% of the sum of the maximum article citation count per area. For example, in the vehicle area, we selected the article with 32 article citation count which is the maximum value of three papers with article citation counts of 32, 4, and 1 each, and then, we summed it with the maximum values of all other areas.

3.3 Information Extraction

The data collection process included the reading of all selected papers to determine what enables intelligence in the systems. We read the abstract, all the figures, tables, or charts, the conclusions, discussions, introductions, material and methods, and results, in that order. We collected the information in a table with these variables: Author, Year, Title, Pages, Citations, Abstract, Purpose, Scope/product/process, Explicit definition, Implicit definition, Other concepts.

Scope/product/process was the key element where the intelligence lies. The definitions were about the intelligence concept in that scope/product/process on an empirical basis. Other useful information was put on Other concepts. The analysis had two measures: type of intelligence and the detail or specification considered by the papers understudy.

All the information was collected and summarized in a Google Sheet spreadsheet [68]. The papers were downloaded in PDF format and were stored in the reference management application Mendeley [50]. We read the papers in that desktop application and we highlighted the texts that we considered relevant for the variables in the systemic review. Our database sheet had the following basic columns: Title, Authors, Publication Year, Abstract, DOI (Digital Object Identifier), Article Citation Count. We added the columns Tag, and Group Area to facilitate the selection process. Also, we used the same spreadsheet to analyze and evaluate the results classifying the documents in intelligent systems or traditional ones.

If our classification determines similar percentages, it means that there is no consensus in practical terms about traditional systems using intelligence in a different way than our definition determined from the literature.

Other used tools were Overleaf [57] to write the document, Figma [24] to elaborate diagrams, and Word Art [83] to generate a word cloud.

4 Results

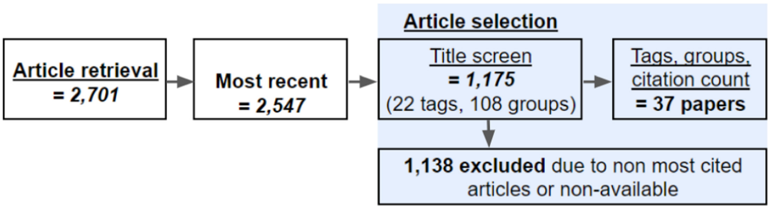

Fig. 2. Screening process

The result of the selection process is depicted in Fig. 2. First, we found *2,701* papers since 2010. Then, we included the more recent papers that were *2,547* papers representing 94% and comprehends the year range from 2017 to 2020. We found *2,547* papers using our selection criteria: 609 in 2017, 926 in 2018, 925 in 2019, and 87 in 2020.

Second, we tagged *1,175* paper titles (46% of 2,547) with 22 tags related to intelligence. Ordered by frequency in papers: smart, intelligent, intelligence, machine learning, automated, automation, cognitive, deep learning, autonomous, neural network, automatic, reinforcement learning, supervised learning, autonomic, unsupervised learning, machine intelligence, q learning, automata, automating, deep network, incremental learning, self-learnable. The top 3 tags were "smart" (627 titles = 53% of 1,175), "intelligent" (377 titles = 32%) and "intelligence" (63 titles = 5%) whose accumulated title count was 1,067 representing 91% of 1,175. There were 1,036 titles with just one tag and 139 with more than one tag: 130 with two tags and 9 with 3 tags. Examples, for two tags: "intelligent, smart"; for three tags: "deep learning, intelligent, smart".

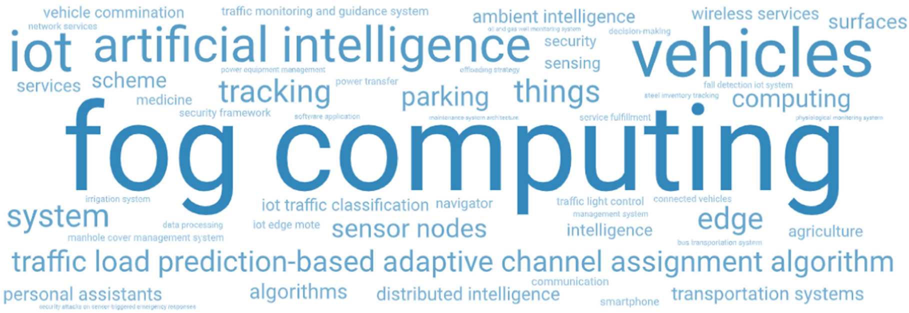

Fig. 3. Word cloud of groups

Third, we grouped the papers by area or component and we detected *108* groups. We showed the most cited groups in Fig. 3 with the sum of article citation count represented as its word size.

Then, we obtained *37* papers choosing the ones with the maximum article citation count in its group and if they were available for us. Their sum of article citation counts was 512 representing 80% of 640 article citation counts. "fog computing" was the area with the maximum of 62 article citation count representing 9.7% of the 640. Reading these papers took us about one hour per paper.

As we show in Fig. 4, our research discovered that in practical means, there are 42% of systems that claim they are intelligent but they are traditional ones: 38% of them are hardware enhancements like adding sensors to a traditional system and 62% are software enhancements to a traditional algorithm.

In detail, we summarize the papers through a brief description of the technical aspects of systems in the following paragraphs. And, we use the word 'enhanced' to describe the improvements to a traditional system that we do not consider 'intelligent' according to our definition.

4.1 Hardware Enhanced Systems

When the authors of these papers considered intelligence, they referred to a hardware enhancement like giving sensing capabilities to a system or component. In [87], "Intelligent Things" means elements that have been optimized with sensors and were used in an infusion monitoring system (droplet count, remaining medicine). In [36], the "Intelligent Manhole Cover Management System" involves

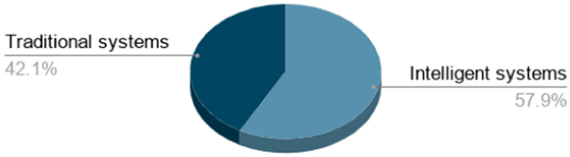

Fig. 4. Result of intelligence in most cited papers on intelligent systems in IoT

an efficient, enhanced, and connected system that uses sensors (tilt, vibration, and location sensors) for self-perception and a traditional algorithm to perform efficient actions. "Intelligent Connected Vehicles" [88] and "Intelligent Vehicles" [71] are described as vehicles with advanced capabilities like sensing (GPS, RFID, headlight range sensor, mirror sensor, transmission sensor, and fuel level sensor) and diagnostics. In [79], "Intelligent steel inventory tracking" denotes an automatized process with the sensing ability that reads codes in RFID and performs efficiently. This ability could be used in an intelligent system that takes decisions on its own. Perhaps, in [46], the "Intelligent Agriculture Service Platform" refers to a platform that collects, monitors, senses, and makes decisions; in practice, the paper only shows the platform as a sensor-enabled one.

4.2 Software Enhanced Systems

In this subsection, intelligence is understood as a software enhancement (e.g. an improved or more efficient traditional algorithm) or enabled computing capabilities. We detail the explicit or implicit definitions in the following sentences. "Intelligent Tracking": an algorithm that is more accurate than others [80]. "Intelligent Edge": efficient, enhanced computation ability [58]. "Intelligent Transportation Systems": efficient platform in resource management [5]. "Intelligent traffic monitoring and guidance system": efficient algorithm to find the shortest path [41]. "Intelligent Parking System": efficient through traditional image processing algorithms [61]. "Intelligent security framework": an algorithm to solve a problem [69]. "Intelligent Bus Transportation System": efficient that shows more useful information and optimizes time for users [27]. "Intelligent Management System": automated, more efficient through thresholds set by a user in agricultural greenhouses [43]. "Intelligent Power Equipment Management": efficient that uses inference for a lot of information [14]. "Intelligent Data Processing": efficient and distributed way to filter data to save costs [86].

4.3 Intelligent Systems

We found intelligence as we defined in the following papers: "Intelligence in Fog Computing" [72], "Intelligent Traffic Load Prediction-Based Adaptive Channel Assignment Algorithm" [73], "Intelligent Sensor Nodes" [35], "Artificial Intelligence" [85], "Distributed Intelligence" [64], "Intelligent Personal Assistants" [65], "Intelligent Edge Computing" [44], "Intelligent IoT Traffic Classification" [19], "Intelligent Algorithms" [81], "Intelligent Wireless Services" [12], "Threat Intelligence Scheme" [54], "Intelligent Fall Detection IoT System" [31], "Intelligent traffic light control" [45], "Intelligent vehicle commination" [67], "Ambient Intelligence Challenge" [16], "Intelligent and secure IoT edge mote" [37], "Intelligent System" [62], "Intelligent Edge Computing" [13], "Intelligent Secure Communication" [84], "Intelligent smartphone" [47], "Intelligent service fulfillment" [55], "Intelligent irrigation system" [59]. They use modern Natural Language Processing (NLP) techniques, algorithms for Self-driving Cars, or Machine Learning (ML) algorithms such as: Neural Networks (NN), Deep Learning (DL), Deep Neural Networks (DNN), Convolutional Neural Network (CNN o ConvNet), Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), Reinforcement Learning (RL), Deep Reinforcement Learning (DRL), Q-Learning, Deep Q-network (DQN), Dyna-Q, Bayes Statistics, Naive Bayes, Non-parametric Bayesian, Genetic Algorithm, K-Means, K-Nearest Neighbor (K-NN), Random Forest, Support Vector Machine (SVM), Adaptive Neuro Fuzzy Inference System (ANFIS), Beta Mixture Model (BMM), Dirichlet Mixture Models (DMM), distributed FrankWolfe (dFW), Expectation–Maximization (EM), FCBFiP (Fast Correlation Based Feature in Pieces), Gaussian Mixture Model (GMM), Hybrid RNN Occupancy Estimation Algorithm, Incremental Aggregated Gradient, Mixture-Hidden Markov Models (MHMM), Multivariate Correlation Analysis, Partial least squares regression (PLSR), Post Decision State (PDS).

5 Discussions

In the most cited papers, we found no consensus about intelligent systems because 42% of traditional systems used the word intelligence in a different way than our working definition.

Machine learning is a clear topic that reveals intelligence in its several algorithms such as Deep Learning, Reinforcement Learning, and others. Artificial intelligence is constantly evolving and some topics are classified as non-AI, and new algorithms emerge.

Our study is similar to [40] that reviewed the field of artificial intelligence and concluded no consensus nor formalism in this field. Its review is more theoretical than practical. [29] reviewed AI but only applied in the fashion and apparel industry and to find gaps in the application of AI techniques. In contrast, we considered other groups like transportation, communication, or agriculture, and to find the practical use of AI based on specific methods or techniques. This study doesn't assume a vague or colloquial definition of intelligence and challenges the technical aspect of the buzz word artificial intelligence.

We just covered one article with the maximum citation count per selected groups for time limitations. We spent about 40 h to only read the chosen papers. We also plan to research the meaning of the term smart to complement this study. Smart was also one of the most frequent tags.

6 Conclusions

It has been always said "not all that glitters is gold". In the same manner, not all that uses the word intelligence is intelligent. As we presented, only 58% of the reviewed papers were about true intelligent systems and the remainder were traditional ones. They are built upon algorithms and those that let machines to learn from data can be called intelligent ones. We consider that this insight is our main contribution and the starting point for a common understanding of artificial intelligence for researchers and professionals in a practical and detailed way.

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