Artificial Intelligence Yesterday, Today and Tomorrow

H. Jaakkola[*], J. Henno [**], J. Mäkelä ***and B. Thalheim[****]
[*] Tampere University, Finland
[**] Tallinn University of Technology, Estonia
[***] University of Lapland, Finland
[****] Christian Albrechts University at Kiel, Germany
hannu.jaakkola@tuni.fi; jaak.henno@taltech.ee; jukka.makela@ulapland.fi; thalheim@is.informatik.uni-kiel.de

***Abstract* - Artificial Intelligence (AI) is one of the current emerging technologies. In the history of computing AI has been in the similar role earlier - almost every decade since the 1950s, when the programming language Lisp was invented and used to implement self-modifying applications. The second time that AI was described as one of the frontier technologies was in the 1970s, when Expert Systems (ES) were developed. A decade later AI was again at the forefront when the Japanese government initiated its research and development effort to develop an AI-based computer architecture called the Fifth Generation Computer System (FGCS). Currently in the 2010s, AI is again on the frontier in the form of (self-)learning systems manifesting in robot applications, smart hubs, intelligent data analytics, etc. What is the reason for the cyclic reincarnation of AI? This paper gives a brief description of the history of AI and also answers the question above. The current AI "cycle" has the capability to change the world in many ways. In the context of the CE conference, it is important to understand the changes it will cause in education, the skills expected in different professions, and in society at large.**

Keywords - Artificial Intelligence, Learning, Deep learning, Lisp, Prolog, Expert Systems, Fifth Generation Computer, Emerging technology, Frontier technology, Computer-supported decision-making, Computer and education.

I. Introduction

Technology analysis is an important field of applied research. It gives an understanding of technological changes and their consequences in daily life and society. Every educator at all levels should be familiar with this topic, because they are educating people for the future and for future professions. Some technologies affect work life dramatically – some professions are disappearing, some are being born and almost all are changing, many of them becoming enriched. New technologies – *innovations* - are triggers that, when adopted by the users, cause changes in society. The changes may be *incremental* (improvements in a current trend) or *radical* (step up to a new level and continuing the existing trend there). In some cases innovations may cause *changes in technological systems* (combining several innovations provides new opportunities to adopt the innovation) or in *paradigms*, creating the foundation for changes in society [1]. The authors have discussed the principles of technology analysis in some of their earlier papers [2; 3]. We will not repeat the topic in this paper, but encourage the reader to study them to get a good understanding of the principles of technological forecasting and analysis.

Several market research companies analyze technology trends and publish their findings in annual reports. The best known and most followed are Gartner Group, IDC, Forbes, Forrester, Fjord, and Cisco. Their reports are both general and focused on certain areas. Quite useful studies are also available in a variety of national sources, which focus on country level expectations and changes. A good example of this in the Finnish context is a report [4] which lists the expected effects and opportunities provided by more than a hundred radical technologies in Finnish society. Again, these changes must be taken into account in education.

Emerging technologies are technologies whose development, practical applications, or both are still largely unrealized or have just reached the breakthrough phase. The time span related to their significant adoption in practice is often set at five years. The essential point is that the emerging technology includes innovation potential – competitive edge – in practical applications (modified definition by the authors). In our paper [5], we collected data from sixteen technology analysis sources in 2017. The findings were classified into seven main sectors: AI was one and maybe the most important of these. The analysis included more than 100 emerging technologies causing significant changes in the time span of 10-20 years. To continue our story, in this paper we will focus on discussing aspects related to Artificial Intelligence (AI).

Artificial Intelligence (AI) is the theory and development of computer systems able to perform tasks normally requiring human intelligence, such as visual perception, speech recognition, decision-making, and translation between languages. It is often connected to the features of a computer system that have elements of human behavior (modified definition by the authors). The overall *research problem* handled in this paper is "*The role of Artificial Intelligence in the current and future society*". We have divided the topic into the following research questions: 1. What are the essential elements of AI now and in the past? 2. Why does AI reappear in cycles and have renewed innovation power almost once a decade? 3. What kind of opportunities AI does offer current society?

To answer RQ1, we will give a short analysis of the evolution of AI since the mid-1950s (Section 2). Section 3 provides (at least partially) an answer to RQ2. Section 4 focuses on the opportunities provided by the current AI-related technologies and answers RQ3. Section 5 concludes the paper.

II. Evolution of Artificial Intelligence – The Four Cycles

A. Motivation

Some technologies appear repeatedly in cycles at the top of the list of emerging technologies – they appear, the effects of their innovative role are remarkable for a while, then they disappear only to reappear again. In our paper [6] we called this phenomenon the "*reincarnation cycles of technologies*". The paper briefly introduced two such technologies – *AI* and *Data Management*. It also included a similar phenomenon that is based on the *evolution of concepts* in the course of time; *software quality* was handled as an example of this.

We consider the importance of AI in current society to be so high that we wish to return to the reincarnation issue in this paper in more detail. The *fourth cycle of AI*, which is ongoing, will have a dramatic effect on jobs, employment, data handling, and many other things, *education* included. In the following, we start with a brief, simplified *history of AI*. After that the reasons behind its cyclic reappearance are explained: the main elements are a *constant demand* for such applications and the *renewed possibilities* to implement intelligence in a new way and in new contexts. The first reason (*demand*) should be clear: people want to have more intelligent, easy-to-use systems and applications helping their life both in private and in business. They want to automate boring, repetitive routine work. They would like to have intelligent assistance and augmented support in their daily routines. We will return to this issue in the discussion part at the end of this paper (Section 4). The second reason (possibilities) is explained by the progress in technology. We will deal with this issue briefly as a separate topic (Section 3).

Why examine and explain history? To understand the opportunities for tomorrow, it is important to understand the path to today. The same factors have been driving progress for decades. The development tends to be continuous (trend-based) and history largely determines the future. Sometimes something unforeseen happens; this means discontinuity in the trend in the form of *radical changes*, or even in the form of *changes in technological systems*, or as a transfer to a *new paradigm* in social systems (these innovation steps are explained in [1] and also handled in [3].) All of this provides us with the means to analyze the continuation of the cyclic progress of AI. If the cyclic progress continues, we may ask: What are the future cycles? When are they coming? What are the driving forces behind them? The final question might be whether there is any reason to believe that there will not be any more new cycles? Our historical overview points out two additional aspects. The first is "*What is the reason for the delay between the theoretical foundations and the appearance of certain technologies?*" Our answer is that the enabling technologies needed are not yet mature enough. The second aspect is "*What happens to an innovative technology at the end of its life cycle?*" Every technology has a life cycle with four phases: *embryonic, growing, mature, aging and decline*. The technology is mainly adopted for normal use in the growing and mature phases (benefit to use it is highest, uncertainty about its usefulness is low). After that (aging, decline), innovative technology becomes embedded in the daily infrastructure and no longer has any meaningful competitive edge.

B. Historical Overview

AI has its roots in antiquity in the form of myths, stories and rumors of artificial beings endowed with intelligence or consciousness by master craftsmen [7].

Where the "ancient" AI left these ideas at a theoretical (story) level, the invention of the digital computer *enabled* these ideas to be put into practice. However, a lot of ancient philosophical foundations (theories about the human mind and human way of thinking) have been useful as a theoretical foundation in AI research.

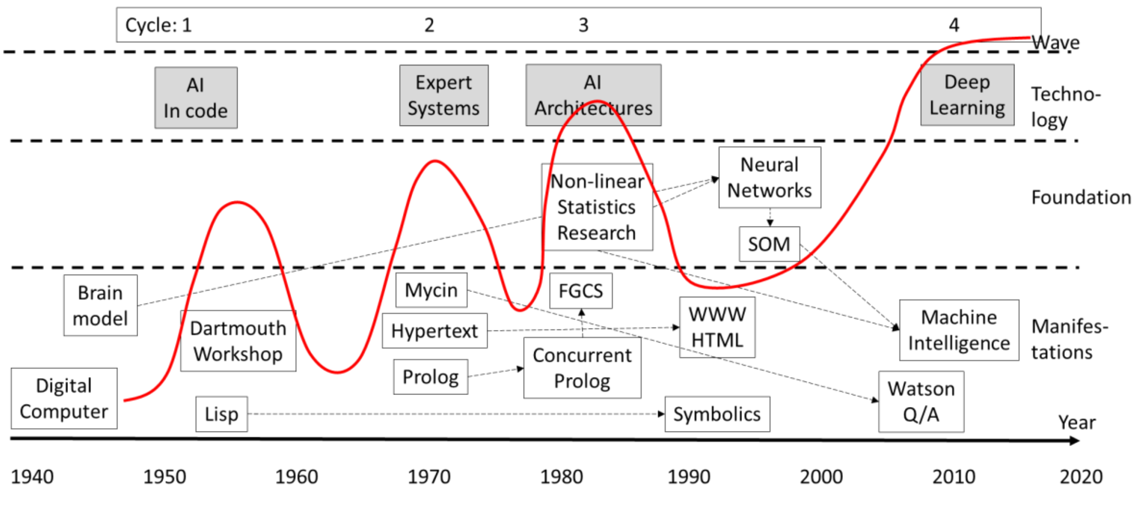

Figure 1. A short, simplified history of artificial intelligence focusing on the viewpoints of this paper.

The milestones of the "brief " history of AI are collected in Figure 1 and explained in the rest of this section. We have also added a "wave line" to describe the cycles – rises, falls, and transfers to a new cycle. The term "AI" was coined by *John McCarthy* in 1955; he is the inventor of the *Lisp programming language* and also a key person in organizing the workshop held on the campus of *Dartmouth College* during the summer of 1956. This workshop was the starting point of current *AI research*.

In analyzing the progress of AI it is worth keeping in mind that the traditional electronic programmable computer was and still is developed for *fast complex calculations* on algorithmic bases, not for modeling the *inference/reasoning* type operations of the human brain. There is still the same mismatch (with the exception of the third wave discussed below) between the computing logics and inference/reasoning based operations needed in AI. These operations are still transferred to normal algorithmic operations and conducted by "*brute force*" bases that have advanced *algorithms* as the key factors.

C. The first wave - 1950s

The *first wave of AI* in the role of emerging technology focused on *programming languages* like Lisp (in the 1950s) and later Prolog (early 1970s; Alain Colmerauer and Philippe Roussel.)[1]. In Lisp the novelty was *modifiable code* – the program (application) was able to modify itself in runtime. This can be seen as a simple *learning capability* of the computer program – the opportunity to react to the state of the computer. *Prolog* is a "*logic programming language*" in which the expressions are rules to be executed, able to create new rules and to modify the behavior of the old ones. Typical of this wave is the fact that the *knowledge needed to solve the problem is in the program's algorithms and known only by the programmer* and used to cast the solution method in terms of algebraic formulas.

D. The Second Wave - 1970-1980s

The second wave relates to expert systems (1970s – 1980s). An *expert system* is a computer application that reasons using knowledge to solve complex (dedicated) problems. Three principal approaches were used in implementing expert systems. In *rule-based expert systems* the problem solving was based on a predefined (modifiable) rule base, which was used to solve the problem given to the system. In *frame-based expert systems*, the problems were solved by matching the problem to the frames in the system's frame base. We have taken the freedom to categorize *hypertext* in the category of expert systems. This technology was born at the same time as expert systems and has radical consequences in the way we use computers today. *Hypertext systems* are intelligent text systems in which the text (and other type of) "documents" are connected to each other with flexible references (hyperlinks). These hyperlinks in a way provide the means for building "intelligent" document systems – paths to move in the document set in a way to solve the problem. Hypertext is one of the key concepts of the *World Wide Web (WWW)* and its implementation technologies. Whereas in first-wave technology the knowledge needed to solve the problem lay in the program's algorithms, in expert systems the *problem solving logic is known by its users*.

The first expert systems were launched by Stanford University. The research group led by *Edward Feigenbaum*[2] – known as the father of expert systems – developed systems that were able to handle the expertise of highly valued and complex application areas. This work resulted in the first known expert systems in the 1970s: *Mycin* for diagnoses of infectious diseases and *Dendral* for identifying unknown organic molecules. The best known expert system – or actually computer system and application platform - is *Watson*3, which is a question-answering system capable of answering questions posed in natural language and used in a variety of application areas. Its knowledge resources are also available via APIs to third parties to develop their intelligent applications. Watson connects another important component to the system intelligence – the *user interface*, which in this case is *natural language*. Progress in natural language interpretation and its use as a system interface also has a decades-long history; we have excluded it from this paper, but wish to point out that in most cases an easy-to-use interface is connected to the success of intelligent systems.

In the area of hypertext, three names are worth mentioning. In the middle of the 1960s, *Ted Nelson*[4] coined the terms *'hypertext'* and *'hypermedia'*. These were a part of his model for creating and using linked content. He started implementing a hypertext system called *Xanadu*; its first public release was completed thirty years later in 1998. *Douglas Engelbart*[5] worked at the Stanford Research Institute in the project developing the NLS *collaboration system* in the early 1960s. The preliminary version of the system, demonstrating a 'hypertext' (meaning editing) interface was launched to the public in 1968. The revolutionary breakthrough in hypertext happened in the 1980s, when *Tim Berners-Lee*[6] created his hypertext database system (ENQUIRE) for CERN in 1980. This was the foundation for the hypertext-based worldwide web concept. At the turn of the 80s/90s, he specified the HTML language, implemented web browser and server software, and developed the first operative version of the HTML protocol over the Internet. The rest of this progress is well-known everywhere.

E. The Third Wave - 1990s

The mismatch between the logical structures demanded by AI operations (inference/reasoning) and computer architectures was disturbing for some quarters?? – and breaking this mismatch was seen as a remarkable

[1] About Lisp: https://en.wikipedia.org/wiki/John_McCarthy_(computer_scientist); About Prolog: https://en.wikipedia.org/wiki/Prolog.

[2] Feigenbaum: https://en.wikipedia.org/wiki/Edward_Feigenbaum; Mycin: https://en.wikipedia.org/wiki/Mycin; Dendral: https://en.wikipedia.org/wiki/Dendral

[3] About Watson: https://en.wikipedia.org/wiki/Watson_(computer)

[4] About Ted Nelson: https://en.wikipedia.org/wiki/Ted_Nelson

[5] About Engelbart: https://en.wikipedia.org/wiki/Douglas_Engelbart; NLS: https://en.wikipedia.org/wiki/NLS_(computer_system). Engelbart is also known as a developer of the first computer mouse and window-based user interface, among many other remarkable innovations..

[6] About Tim Berners-Lee: https://en.wikipedia.org/wiki/Tim_Berners-Lee

opportunity for innovation. In the 1980s, efforts to remedy this mismatch were undertaken by developing *specialized computer architectures* – and thus the third wave started. The two programming languages mentioned above – Lisp and Prolog – were used in developing intelligent software. If these could be implemented in computer architecture, processing of such software would become much more effective.

The biggest initiative came from Japan, where an enormous national project called "*New (Fifth) Generation Computer System*" (FGCS)[7] started in 1982. The *Institute for New Generation Computer Technology (ICOT)*[8] had a revolutionary ten-year plan to develop large computer systems, which were applicable for knowledge information processing; it was open (exceptionally) even for foreign partners and covered activities in the area of computer architecture, software, and (intelligent) applications. The computer architecture was based on the derivative of Prolog – *Concurrent Prolog* – developed by Ehud Shapiro[9], who was invited to ICOT in the role of visiting research fellow. The execution of Concurrent Prolog allowed *parallel processing* following the idea of *dataflow architectures*. The plan was for a PSI (Personal Sequential Inference machine) to act as a work station and a PIM (Parallel Inference Machine) to act in the role of central "super computer"; it was based on massively parallel architecture (thousands of processors). The processing power of these was calculated in LIPS (Logical Inferences Per Second) instead of traditional MIPS (Million Instructions Per Second).

However, the project did not succeed in commercializing these advanced computers. The *Mitsubishi Melcom* computer is the only one we managed to find from the material. In the scope of advances in technology knowledge, the project was *a huge success*. Japan became one of the leading countries in computer systems development (parallel architectures especially), skills in software development rose dramatically, and Japanese research in the area of advanced applications (image processing, speech recognition, natural language processing, online language translation, etc.) gained a significant fillip. Even the Web Ontology Language (OWL), which is a family of knowledge representation languages for authoring ontologies, has its roots in this project and is widely used as a formal way to describe taxonomies and classification networks, essentially defining the structure of knowledge for various domains[10]. The lesson learned in this case is that the *secondary results* may be of high importance, even though the main goal (new computer architecture) was not so successful.

The effort required to commercialize the results came from the USA. In Symbolics[11], Lisp was implemented in the processor. Symbolics Inc. had its roots in MIT (Cambridge, Massachusetts). Symbolics computers were produced in the 1980s; however, they never became a commercial success and finally disappeared from the market.

To conclude, AI support on the architecture level only remained potential, in spite of enormous investments in Japan and marketing efforts in the case of Symbolics. Why was this? One reason is that ultimately there was not the demand which would have provided a push for these advanced architectures. The growth of the processing power in traditional computers was a strong competitor to these "one matter"/"single issue" architectures. The 30 years since these efforts are good evidence of this. Will these solutions come back some day? Such activities are again in the air.

F. The Fourth Wave

Intelligence is based on learning – first in the taught subject matter and then in self-learning. The human way? In the *fourth wave of AI* today the key element is the system's ability to learn: The system is first taught to understand certain basic facts of the target problem and after that it learns about mistakes, wrong decisions, and the reactions of its environment. Very human like? The key elements in this are the ability for the fast processing of massive amounts of data and the availability of such data. Two *technologies* in these applications play a central role – *neural networks* and *deep learning*. We will not go into detail about these technologies, but a short review of the history concerning the topic is necessary so that it will be possible to understand the message of our paper.

The idea of a *neural network*[12] is to build a model that resembles the structure of a human brain – both the structure and "calculation." The roots of this theory date from the 1940s, when Warren McCulloch and Walter Pitts introduced their model of the human brain combined with a mathematical logics based computation model. Neural networks use "what-if" based rules and the network is taught (supervised learning) by means of examples. In this way, the network learns the non-linear dependencies between variables. Otherwise, the neural calculation resembles statistical linear models. The Self-Organizing Map (SOM)[13] is a type of neural network that is based on *unsupervised learning.* It was developed by Finnish academician Teuvo Kohonen in the 1980s. A multidimensional input (learning) data set is organized into low-dimensional geometric relationships (layers) that can be represented as a two-dimensional (low-dimensional) map. It can be used as an abstraction of the real data space. The advantage of SOM over a traditional neural network is its self-learning capability, including the capability of error correction. *Deep learning*[14] theory has its roots in the 1980s in the work of Geoffrey Hinton. It is based on the independent learning of masses of data. The learning algorithms are based on the use of nonlinear statistics and the learned data is organized in a multi-layered neural network.

7 About FGCS: https://en.wikipedia.org/wiki/Fifth_generation_computer

8 The key persons in ICOT were Hideo Aiso, Tohru Moto-oka, Koichi Furukawa and Kazuhiro Fuchi.

9 About Ehud Shapiro: https://en.wikipedia.org/wiki/Ehud_Shapiro

10 About OWL: https://en.wikipedia.org/wiki/Web_Ontology_Language

11 About Symbolics: https://en.wikipedia.org/wiki/Symbolics

12 About Neural networks: https://en.wikipedia.org/wiki/Artificial_neural_network; https://fi.wikipedia.org/wiki/Neuroverkot

13 About SOM: https://en.wikipedia.org/wiki/Self-organizing_map; https://fi.wikipedia.org/wiki/Itseorganisoituva_kartta

14 About deep learning: https://en.wikipedia.org/wiki/Deep_learning; https://fi.wikipedia.org/wiki/Syv%C3%A4oppiminen

G. The Waves Concluded

It took more than thirty years to make the theories work in practice as part of current AI applications. *Parallel computing* and *big data technologies* have made this possible; earlier, data was the bottleneck (to quote Professor Aapo Hyvärinen's seminar presentation, Helsinki, August 31st, 2017). AI today provides revolutionary opportunities in a wide variety of applications that replace human work, or support humans in their work, in the form of robotics, as part of a variety of intelligent devices, in the transfer toward *human computing* (coming independently of our will), etc.

The four cycles of AI can be synthesized in the following way:

- *first cycle* **-** *programming*: the implementation tool was the programming language; the intelligence built into the system was in the algorithms and only programmers had a profound understanding of their details; programming languages provided an application-independent tool to be used in developing different applications;
- *second cycle – expert systems*: intelligence was built into the tool (knowledge engineering application) and knowledge about its operations was openly available in the system specifications; expert systems were built for specific purposes only;
- *third cycle – AI architectures*: intelligence was in a way built into the platform, which provided its services to the applications in an effective way; the platform did not limit its usage from the applications' point of view;
- *fourth cycle – self-learning applications*: deep learning and machine intelligence provide the means for the use of AI in a wide variety of contexts; the key (value) components are *algorithms and data*. Still these applications are dedicated to certain (narrow) application areas.

The progress described above covers the period from the 1950s to 2019 – approximately 70 years. The time between cycles 1->2 was 20 years, 2->3 15 years, and 3->4 20 years. We have already earlier stated that two conditions must come true in order to make a new cycle operative: continuous demand (*demand pull*) and technology supporting the implementation (*technology push*). In our examples, we have stated that specific theories were available decades before they were utilized. The *continuous demand* seems to be true: people expect more and more intelligent applications to help their daily life or to improve the productivity of their work. We believe that this demand will remain permanent in AI applications.

So what is left? The key trigger in the progress must be technology. This is also *our hypothesis*. A consequence of this is that *by following the progress in technology we are able to forecast future changes in the AI sector* – even the existence of the fifth cycle, its appearance, time, and form. To make our forecast, we have to understand the major changes in the *enabling technologies*, look for the *gaps* in the existing intelligent services, analyze the reasons for the gaps, and find technology that is able to fill them.

Enabling technologies are the triggers that provide an opportunity to make the desired changes come true (fill the gap) or prevent it (the gap still exists). The analysis of the cycles introduced the three key elements of enabling technologies: *computing power and memory capacity (= VLSI, circuit technologies), data storing capacity,* and *data transmission speed*. These technologies also largely explain the cyclic behavior in the context of continuous demand (for new applications). Every cycle starts when it is triggered by an innovation (in practice, handling capacity) in an enabling technology. Every innovation has a limited capability to maintain changes and finally it is embedded in the "normal" (as noted earlier in this paper). The gap between invention and its utilization follows the same formula. Non-applicable theoretical foundations remain potential as an application gap that will finally be filled when the triggering technologies become available.

III. The Cycles Explained – Enabling Technologies

Our hypothesis above covers three enabling technologies. Additional ones can be listed, but ultimately they are in some way derivatives of and connected to the progress in the three key technologies discussed below. All these technologies seem to have continuous exponential growth, allowing the use of computers in new applications.

The book [8] handles a wide variety of laws that are based mostly on empirical observation. In our particular case the following laws are relevant:

- *processing capacity* **-** Moore's law: the price/performance of processors is halved every 18 months (transistor density);
- *data storage* **-** Hoagland's law: the capacity of magnetic devices increases by a factor of ten every decade; and
- *data transmission* **-** Cooper's law: wireless bandwidth doubles every 2.5 years.

These and some additional laws are discussed below to build a scenario explaining the cyclic reappearance of AI.

Moore's law [8, pp. 244-247; 9] – the original article [10] – refers to the co-founder and chair of Intel in the 1960s, Gordon Moore. The law deals with the packing density of transistors, which is predicted to double every 18 months. Its practical consequences are *doubling processor capacity in 18 months* and *memory capacity in 15* months for the same price. Although the law was based on Moore's observations in the late 1950s, it is still valid and the physical limits of chip materials have not yet slowed down the progress.

Hoagland's law [8, pp. 247-249; 9] deals with the capacity of the data storage devices in current use – magnetic disks. It predicts the capacity of magnetic devices to *increase by a factor of ten every decade* (i.e., *doubling every 18 months*). The law is attributed to *Albert Hoagland*, who was one of the developers of the first magnetic disks. Let us take a look at the periods introduced in Figure 1. The first cycle was the time of punch cards, the second was mainly magnetic tapes and small capacity disks, and from the third cycle on, magnetic disks have practically superseded all other devices. Its new competitor is SSD-based mass memory, which is not yet (and maybe will never become) competitive in storing big masses of data.

There are several laws indicating the growth of data transmission. *Cooper's law* [8, pp. 249-250] (Martin Cooper, Motorola) reports the growth of data transmission in *wireless networks*, which is predicted to *double every 2.5 years*. Gerry Butter (Bell Lab's / Lucent Optical Networking Division) predicted that the amount of data one can transmit using *optical fibers doubles every nine months*, which means that the cost of transmission by optical fiber is halving every nine months (*Butter's law*) [9]. Nielsen's law [11] summarizes the transmission speed from the users' point of view; according to Nielsen's law, *users' bandwidth grows by 50% per year* (i.e., doubling every 20 months, which is 10% less than Moore's law for computer speed). The new (version of the) law incorporates the data from 1983 to 2018. The report by Cisco [12] summarizes the progress in practice. It provides evidence on the fast growth of *mobile traffic*: the Compound Annual Growth Rate (CAGR) in 2016-2021 is forecast to be 47% (total in the period from 7 to 49 Exabytes). The traffic has grown 4000-fold over the past 10 years and almost 400-million-fold over the past 15 years. It also indicates the transfer towards applications having high bandwidth consumption (streaming, VR (CAGR 60%), AR (46%), MR).

VLSI technology is the kernel of all the enabling technologies. The progress in VLSI technology indicates fast growth in processing power (doubling every 18 months) and memory capacity (more? available for the same price in 15 months). These capabilities indirectly also drive the progress in data transmission (switches and network devices) and data storage (controllers) in addition to their basic technologies. Table I represents the changes in essential computing capabilities in the period from the 1950s to today (divided into cycle steps in Figure 1; includes some rounding errors to simplify the presentation).

TABLE I. CAPACITY CHANGES 1955-2019, PROJECTED TO 2030

Double capacity in months (m)	1955	1975	1990	2019	2030
Computing 18m	1	2^{13}	2^{23} (2^{10})	2^{42} (2^{19})	(157)
Memory 15m	1	2^{15}	2^{28} (2^{12})	2^{51} (2^{23})	(445)
Mass memory 18m	1	2^{13}	2^{23} (2^{10})	2^{42} (2^{19})	(157)
Transmission 20m	1	2^{12}	2^{21} (2^{9})	2^{38} (2^{17})	(97)

The figures in Table 1 represent changes in capacity from the base year 1955 (first cycle) over the three other cycles; the base year value is 1. The numbers in parentheses are changes from the earlier cycle (changes between columns). The last column provides a scenario ten years *from now*: computing power is 157-fold, memory capacity 445-fold, mass memory 157-fold, and data transmission speed 97-fold compared to the *capacity of today*. In data transmission we used Nielsen's prediction, which may be somewhat pessimistic. If something is not possible today, maybe it will be in ten years' time (based on continuous demand). In 10 years from now, we will be able to run more complex software and handle greater amounts of data (in primary memory) for fast processing, we will have access to bigger data repositories and faster data transmission will allow the use of distributed data and also distributed parallel processing (to increase the processing capacity). Today, when applications are mostly based on the cloud-type of services and most of the user terminals (smart phones, laptops, PCs, tablets) also have significant (local) processing capacity, the processing needed for problem solving is distributed between terminal and "cloud". What kind of problems will we be able to solve at the terminal level (locally) in ten years' time that are not yet possible? What about taking the whole computing infrastructure into account on a general level?

IV. ARTIFICIAL INTELLIGENCE IN PRACTICE – DISCUSSION ON THE SITUATION IN 2019 AND BEYOND

The present wave in AI is focused on *learning*. As introduced in Section 3, the key technologies are *deep learning* and *artificial multilayered neural networks*. It is justifiable to say that currently a lot of business value is bound to data and the algorithms handling it in an intelligent way. Yuval Noah Harari addresses the role of algorithms in current society in his book "Homo Deus," with reference to Facebook (FB) and Google: "The algorithms of FB and Google follow all our activities (on the Internet). Algorithms compare our behavior to the behavior of others and based on that are able to predict our behavior" (freely interpreted by the authors of this paper). We are profiled by intelligent algorithms, which have an enormous amount of data organized in the form of "learned knowledge" of human behavior.

However, the current AI boom is mostly based on w*eak (narrow) AI*, which is focused on one specific task and does not understand the data it handles – data is just data. *Weak AI* does not have its "own sense" related to the data it handles, nor its own will about how it should be handled. The next step will be *strong AI*, which understands facts and their relationships; it also has features of human beings, like *common sense*. It does not have its own will either; rather a kind of understanding of its surroundings.

The path towards this "general AI" is unknown but is generally accepted by scientists. [15]. The first alternative is to continue the current trend (deep learning) with more data processing power. The second alternative is to follow the proposal of Andrej Karpathy (Tesla). He has introduced the concept of *Software 2.0*. Current algorithmic programming produces an exact algorithm that a computer follows instruction by instruction. In Software 2.0, the programmer produces only a skeleton program that specifies a goal the program should reach and the software platform produces the full solution to the task. Idealistic? – time will tell! /we do not know as yet! The third path would be a merging of

[15] This discussion is a free interpretation of the column of Professor Heikki Ailisto in the Finnish ICT journal Tivi, February 2019. ISSN 2342-4001.

deep learning, semantic methods, and common knowledge about the application context

Two Finnish reports [13; 14] list ten *core competences* in the area of AI: (1) Refined *Data analytics*; (2) *Sensing and situation awareness* (of autonomous systems); (3) *Natural language understanding and cognition*; (4) *Interaction with humans* (advanced interaction tools and methods); (5) *Digital skills* (work life, education, training); (6) Machine learning; (7) System level and systemic impact (AI technologies on the whole); (8) Computing equipment, platforms, services, and ecosystems; (9) Robotics and machine automation (the multidisciplinary physical dimension of AI); and (10) Ethics, morals, regulation, and legislation.

As can be seen, AI is not just a single technology but a collection of technologies, methods, applications, and schools of research and thought. It must also be seen as a part of the larger trend of digitalization.

The report [4] deals with the opportunities provided by new technologies for Finnish society in the time frame from the present to 2037 (at the time the report was written, a 20-year time span). In spite of having the focus on one economy its findings are very appropriate for a global context. The report lists the following high importance application areas of AI: (1) Speech recognition, speech synthesis, and interpretation; (2) Neural networks and deep learning; (3) AI platforms; (4) Face and emotion recognition; (5) Verbot/chatpot – interacting robots; (6) Real-time 3D sketching of the environment; (7) 3D imaging; and (8) Teaching materials for AI applications.

AI applications are processing-intensive and need a lot of computing capacity. Most of the AI applications are still run by conventional computers. Some manufacturers have started to develop special architectures to speed up the processing capability. This has become reasonably easy thanks to advances in VLSI technology (compared to the situation in the third wave of AI). Although applications are able to learn even with a relatively small learning data set – especially if they know the conceptual model of the application, the exactness of results would improve with larger amounts of learning data. A new method is to use one AI application to generate learning material or to give feedback to another one. In any case, AI learns from every experience.

We conclude this part of our paper by referring to our earlier paper [5], which lists a variety of findings related to emergent technologies based on our review of leading technology analysts, and to Gartner group's report "Gartner Top 10 Strategic Technology Trends for 2019" [15]. Gartner lists the following emerging technologies: (1) *Autonomous things*: Robotics, Vehicles, Drones, Appliances, and Agents; (2) *Augmented Analytics*: By 2020, more than 40% of data science tasks will be automated; (3) *AI-driven development*: AI is embedded into applications and AI is used to create AI-powered tools for the development process; (4) *Digital twins*: digital twins mirror a real-life object, process or system; (5) *Immersive technologies*: technologies such as augmented reality (AR), mixed reality (MR), and virtual reality (VR) create added value even to AI applications in the form of a user interface to the real application; (6) *Smart spaces*: A smart space is a physical or digital environment in which humans and technology-enabled systems interact in increasingly open, connected, coordinated, and intelligent ecosystems; and (7) *Digital ethics and privacy*: Even Gartner lists this topic at the top. This is because data has become an important resource and people are aware of its usage. Three items (out of ten) in Gartner's list are beyond the scope of the topic discussed in this paper.

V. CONCLUSION

Is AI a science or not? An interesting critical debate is available in three "discussions"[16] we found when preparing this paper. The first reference (Maurizio Matteuzzi) discusses the topic "Why AI is not a science." An interesting perspective (different to ours) to the history of AI is given by Güven Güzeldere and Stefano Franchi in the second reference. The third reference lists interesting quotes about AI. All three of these sources represent criticism of AI. We will leave these to the reader to prove that the topic encompasses many dimensions.

The paper described the progress of AI from a historical and contemporary perspective. The motivation to write this paper was the observation that some technologies tend to reappear in the role of emerging technologies from time to time – mostly irregularly. We have analyzed its "reincarnation" cycles and found two factors in the background: *continuous demand* and *progress in enabling technologies*. Continuous demand includes such problems that cannot be tackled using existing technology; as a result, they remain to be solved in the future. Eventually, when improvements in enabling technologies allow, the new cycle will start to satisfy the "*unsatisfied need*." In 2030 (Table I), we will be able to satisfy needs that demand 157-fold computing power, 445-fold main memory size, 157-fold mass memory capacity, and 97 times faster data transmission compared to the situation today.

What happens to the applications that appeared in older cycles? Nothing – they just remain and are *embedded into the "normal"* without any significant innovation power. What is the next cycle and when will it occur? The current AI can be characterized by systems capable of "mechanical learning". The system learns and can use the learned facts to create new knowledge; however, without understanding their relationships or use context. In our paper we listed three scenarios. According to our understanding, the most probable future step is the transition to *strong AI*, in which the learning capability enables understanding of facts and their relationships and has human features like *common sense*, including a kind of awareness of its surroundings. A human-computer "mental connection" will become (and already is partially) possible, when the human brain and

16
(1) Maurizio Matteuzzi: https://web.stanford.edu/group/SHR/4-2/text/matteuzzi.html
(2) Güven Güzeldere and Stefano Franchi: ttps://web.stanford.edu/group/SHR/4-2/text/introduction.html (see the pictures in the article)
(3) Quotes: https://en.wikiquote.org/wiki/Artificial_intelligence

computer can be connected in such a way that human neural signals can be utilized by computer applications.

Why have we submitted this paper to the CE conference?. AI changes society and affects future work: professions will appear, some will disappear, and many of them will undergo significant changes. Such changes are AI-supported citizen development, software robots in the production of routine newspaper articles, intelligent chatbots in customer service, service robots, expert systems in routine decision making, and a robot analyzing complex contracts on behalf of a lawyer for instance.

What about *AI in the field of education*? First of all, there is an international journal " International Journal of Artificial Intelligence in Education" published by Springer. This point out the importance of the topic also in the field of education. We made a rough article search in Scobus – it resulted close to 3.000 peer-reviewed papers in the period of 2017-2019. Similar search in Google Scholar resulted over 37.000 references. The analysis of publication forums listed by Scobus search indicates that the papers are mostly published in the journals having clear topic related context – medicine, agriculture, engineering, computing, chemistry, human behavior, manufacturing, nursing, etc. For further readings we collected some material related to the role of AI in education – please see [17; 18; 19; 20; 21; 22]. To go in detail in these we need another conference paper. In general, the papers cover a wide variety of ideas and some frameworks about using AI as a part of teaching process. An interesting view of the future is published by Fast Future Research [16]. It creates a vision to jobs of the future – if some jobs are lost because of intelligent applications, some new are needed.

REFERENCES

[1] C. Freeman and C. Perez," Structural Crises of Adjustment, Business Cycles and Investment Behavior," In Technical Change and Economic Theory, G. Dodi, C. Freeman, R. Nelson, G. , Silverberg and L. Soete, Eds. London: Pinter Publishers, 1988.

[2] H. Jaakkola, B. Brumen, J. Henno and J. Mäkelä, J., "Are We Trendy?", In the Proceedings of the 36th International Convention MIPRO 2013 (Opatia, May 20-24, 2013), Petar Biljanovic et al., Eds, Opatia, Croatia: Mipro and IEEE, 2013, pp. 649-657.

[3] H. Jaakkola, J. Henno, B. Thalheim and J. Mäkelä, "The educators' telescope to the future of technology," In the Proceedings of the 40th Jubilee International Convention MIPRO 2017 (Opatia May 22-26, 2017), P. Biljanović, Ed., Opatija, Croatia: Mipro and IEEE, pp. 766-771.

[4] R. Linturi and O. Kuusi, Suomen sata mahdollisuutta 2018-2037 – Yhteiskunnan toimintamallit uudistava radikaali teknologia, Eduskunnan tulevaisuusvaliokunnan julkaisu 1/2018 (In Finnish.), Helsinki: 2018, Retrieved February 15th, 2019 from https://www.eduskunta.fi/FI/tietoaeduskunnasta/julkaisut/Documents/tuvj_1+2018.pdf.

[5] H. Jaakkola, J. Henno, J. Mäkelä and B. Thalheim, "Today is the Future of Yesterday, What is the Future of Today?", Proceedings of the 40th Jubilee International Convention MIPRO 2017, May 22-26, 2017, P. Biljanović, Ed., Opatija, Croatia: Mipro and IEEE, 2017, pp. 741-749.

[6] Jaakkola, Hannu, Henno and J. Mäkelä, "Technology and the Reincarnation Cycles of Software," Proceedings of the Sixth Workshop on Software Quality Analysis, Monitoring, Improvement, and Applications (Belgrade, Serbia, September 11-13, 2017), CEUR Workshop Proceedings Vol-1938, Zoran Budimac, Ed., 2017, pp. 5:1-10.

[7] Wikipedia, History of artificial intelligence, Retrieved February 14th, 2019 from https://en.wikipedia.org/wiki/History_of_artificial_intelligence.

[8] A. Endres and D. Rombach, A Handbook of Software and Systems Engineering - Empirical Observations, Laws and Theories. Pearson and Addison Wesley, 2003.

[9] M. Roser and H.Ritchie, Technological Progress, Retrieved February 15th, 2019 from https://ourworldindata.org/technological-progress

[10] G. E. Moore, "Cramming more components onto integrated circuits", Electronics 38, 8 (April 1965), Retrieved February 12th, 2019 from http://download.intel.com/museum/Moores_Law/Articles-Press _Releases/Gordon_Moore_1965_Article.pdf, 1965.

[11] J. Nielsen, Nielsen's Law of Internet Bandwidth, Retrieved February 15th from https://www.nngroup.com/articles/law-of-bandwidth/.

[12] Cisco, VNI Global Fixed and Mobile Internet Traffic Forecasts - Complete Visual Networking Index (VNI) 2017-2022, Retrieved February 21st, 2019 from https://www.cisco.com/c/en/us/solutions/service-provider/visual-networking-index-vni/index.html#~complete-forecast.

[13] H. Ailisto (Ed), E. Heikkilä, H. Helaakoski, A. Neuvonen and T. Seppälä, Tekoälyn kokonaiskuva ja osaamiskartoitus, Publications of the Government's analysis, assessment and research activities 46/2018, Helsinki: 2018, Retrieved February 18th, 2019 from http://urn.fi/URN:ISBN:978-952-287-549-5

[14] H. Ailisto (Ed.), A. Neuvonen, H. Nyman, M. Halén and T. Seppälä, Tekoälyn kokonaiskuva ja kansallinen osaamiskartoitus – loppuraportti, Publications of the Government's analysis, assessment and research activities 4/2019, Helsinki: 2019, Retrieved February 18th, 2019 from http://julkaisut.valtioneuvosto.fi/bitstream/handle/10024/161282/4-2019-Tekoalyn%20 kokonaiskuva.pdf?sequence=1&isAllowed=y.

[15] Gartner Group, Gartner Top 10 Strategic Technology Trends for 2019, 2018, Retrieved February 18th, 2019 from https://www.gartner.com/smarterwithgartner/gartner-top-10-strategic-technology-trends-for-2019/.

[16] R. Talwar and T. Hancock, The shape of jobs to come - Possible New Careers Emerging from Advances in Science and Technology (2010 – 2030). Final Report (January 2010), Fast Future Research, Downloaded February 18th, 2019 from http://www.fastfuture.com (book store, free download), 2010.

[17] TeachThought, 10 Roles For Artificial Intelligence In Education. 2019, Retrieved March 19th from https://www.teachthought.com/the-future-of-learning/10-roles-for-artificial-intelligence-in-education/.

[18] Forbes, How Is AI Used In Education -- Real World Examples Of Today And A Peek Into The Future, 2019, Rerieved March 19th, 2019 from https://www.forbes.com/sites/bernardmarr/2018/07/25/how-is-ai-used-in-education-real-world-examples-of-today-and-a-peek-into-the-future/amp/.

[19] M.A. Peters, "Deep learning, education and the final stage of automation", 2018, Educational Philosophy and Theory, 50(6-7), 549-553. doi:10.1080/00131857.2017.1348928. Retrieve March 19th, 2019 from https://www.tandfonline.com/doi/full/10.1080/00131857.2017.1348928.

[20] R. Luckin, W. Holmes, M. Griffiths and L.B. Forcier, 2016, Intelligence Unleashed: An argument for AI in Education. Pearson Education, London, Retrived March 19th, 2019 from https://www.pearson.com/corporate/about-pearson/innovation/smarter-digital-tools/intelligence-unleashed.html.

[21] E. Eaton et al., Blue sky ideas in artificial intelligence education from the EAAI 2017 new and future AI educator program. AI Matters, 2018, 3(4), 23-31. doi:10.1145/3175502.3175509, Retreived March 19th, 2019 from https://arxiv.org/abs/1702.00137.

[22] Y. Kim, T. Soyata and R.F. Behnagh, "Towards Emotionally Aware AI Smart Classroom: Current Issues and Directions for Engineering and Education", 2018, IEEE Access, 6, 5308-5331, doi:10.1109/ACCESS.2018.2791861, Retreived March 19th, 2019 from https://ieeexplore.ieee.org/document/8253436

.