About the Essence of Intelligence – Will Artificial Intelligence (Ever) Cover Human Intelligence?

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Abstract: Computers were originally developed for executing complex calculations fast and effectively. The intelligence of computer was based on arithmetic capabilities. This has been the mainstream in the development of computers until now. In the middle of 1950s a new application area, Artificial Intelligence (AI), was introduced by researchers. They had interest to use computers to solve problems in the way intelligent beings do. The architecture, which supported calculations, were conquered to perform tasks associated with intelligence beings, to execute inference operations and to simulate human sense. Artificial intelligence has had several reincarnation cycles; it has reappeared in different manifestations since this research area became interesting for the researchers. All the time a lot of discussion about intelligence of these systems has been going on – are the AI based systems and robots intelligent, what is the difference of human and machine intelligence, etc. Abilities related to intelligence cover ability to acquire and apply knowledge and skills, as well as ability to learn. AI provides different manifestations to the term "intelligence": the human intelligence is a wide variety of different types of intelligence, as well as the meaning of artificial intelligence has varied over time. In our paper we will look to this term, especially to provide means for comparing human and artificial intelligence and have a look to the learning capability related to it.

1. Introduction

Artificial intelligence (AI) is the ability of a digital computer or computer-controlled robot to perform tasks commonly associated with intelligent beings[2]. *Intelligence* (synthesis of several sources) is defined to be the ability to acquire and apply knowledge and skills; the ability to learn, understand and think in a logical way about things; the skilled use of reason; the ability to apply knowledge to manipulate one's environment or to think abstractly as measured by objective criteria.[3] Key aspects related to intelligence are ability to apply knowledge, *reasoning, learning capability, ability for abstract thinking and the aim to use intelligence to affect to something*. Artificial intelligence instead *"simulates" human intelligence*. What are the differences and similarities of this to kinds of intelligence? This is the starting point of our paper.

Human Intelligence (HI) is manifold, so is Artificial Intelligence (AI). AI has certain importance in ICT because it is one of the current emerging technologies. It is also an

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[2] Britannica. https://www.britannica.com/technology/artificial-intelligence
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Merriam-Websterhttps://www.merriam-webster.com/dictionary/intelligence

example of recurring technologies, which has time by time reappeared in waves. The characteristics of intelligence have been changed over the waves, as well as the driving force and the opportunities provided by it. The definition in [35] compares AI and HI: "Artificial intelligence (AI) is intelligence demonstrated by machines, unlike the natural intelligence displayed by humans and animals, involves *consciousness and emotionality*"; this definition points out something that AI is not able to handle (yet).

The term "Artificial Intelligence" was coined by John McCarthy in 1955. Late in 1950s he introduced the programming language Lisp, which provided means for developing computer programs having ability for self-modifying code dynamically in run time. Computers were developed to conduct complex calculations; this architecture had to be conquered to support tasks related to intelligent systems by the software level support; Lisp was the first effort in this area. The dynamic modification of the code implemented a primitive *learning capability* in the time (1950s) when processing power of the computers was low and availability of data to process was limited and access to it was slow.

AI systems create knowledge from a variety of data elements, based on its built-in "intelligence". The DIKW (Data, Information, Knowledge, Wisdom) pyramid in Figure 1 illustrates the cultivation process from data to wisdom (modified from [36]):

- *Data* is conceived of as symbols or signs. To simplify, data is representation of something having itself no exact meaning or interpretation.
- Information affiliates semantics or meaning to the data.
- Knowledge is processed or organized from information based on the rules or algorithms and make information utilizable in the use context.
- Wisdom is applied knowledge in its use context.

The role of *intelligence* is connected to the cultivation process introduced above. We need intelligence to create meaning for data (-> information) and further to handle the information to create useful knowledge about it. Wisdom provides guidelines for utilizing the knowledge and transfers it to actions and behavioral patterns
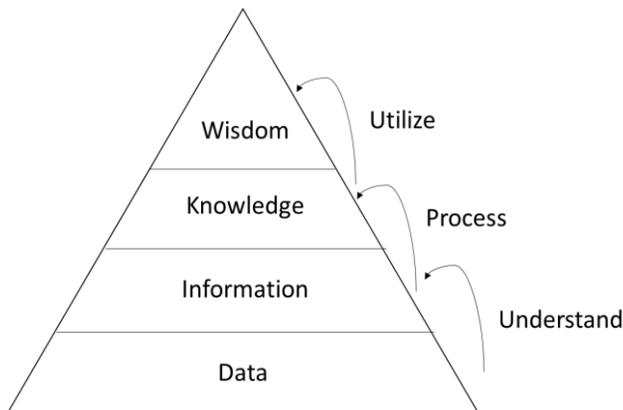

Figure 1. DIKW Pyramid

DIKW pyramid can be connected to the human and artificial intelligence. In both cases we need *data* to handle and the (*intelligent*) *process* to refine it to the applicable form in the use context. Human way and machine way are different. How different, this will be discussed in the following Sections. Intelligence, in addition to data processing capability also needs capability to *learn* – ability to change the future behavior based on the experiences or external knowledge available.

The aim of this paper is to find (at least partial) answer to the questions:

- What is Intelligence?
- What are the differences between HI and AI?
- What is the intelligence of AI?
- What are the key elements of (Artificial) Intelligence?

The paper is structured to find answer to the questions in the following way . *Section 2* handles the characteristics of HI, compared to AI. *Section 3* has focus it the intelligence of AI – what are the functionalities to implement intelligence in these systems. Section 4 handles two key aspects of intelligence, communication, and learning. Section 5 concludes the paper.

2. Human Intelligence

2.1. The Potential of AI and HI

Human intelligence is far broader than the artificial one. According to [14], we may distinguish three kinds of human reasoning systems: brain-based central nervous system with reasoning, the partially autonomous vegetative nerve system with body system control, and the governing survival nerve system for reproduction. AI research is centered around the first system and only concentrates on one type of intelligence: creative or problem-solving intelligence. There are, however, four other kinds of intelligence that we cannot (yet) support: emotional (or social) intelligence, self-reflection (or spiritual or existential) intelligence, body intelligence as second human reasoning system, and survival intelligence. These four types are supporting and partially governing by the central nerve systems while interacting with it.

We may distinguish several specific types of creative intelligence that are so far partially covered and not yet well-supported by AI research:

- linguistic, narrative, or verbal intelligence including metaphorical intelligence,
- musical intelligence,
- abstract intelligence including analytical intelligence, logical-mathematical intelligence, and numerical intelligence
- visual intelligence
- practical intelligence including application intelligence, and practical wisdom,
- imaginative intelligence,
- physical-kinesthetic intelligence, and
- spatial intelligence.

Creative intelligence also includes intuitive intelligence including crystallized intelligence. This specific type cannot be so far supported at all.

Thesis 1a: *HI can only be properly supported by AI if the specific kind and type of intelligence is well-understood.*

Intelligent human behaviour requires above all a great deal of knowledge about details. Knowledge is to be distinguished from intelligence. Intelligence operators (such as the very large variety of inferential reasoning) allow us to derive new knowledge or at least insight from knowledge, experience, observations, models, and intuition. We often hypothesise in 'unknown territory' and develop hypotheses, models or even theories. Detailed knowledge is helpful to 'falsify' hypotheses, i.e. to eliminate them as certainly false, if they contradict facts or experiences.

Consciousness, learning, creativity, freedom, communication behaviour are not (yet) understood in an algorithmic fashion, e.g. decision making under restrictions, competing simultaneous objectives and uncertainties about the future.

Currently, the AI hype aims at development of deep learning mechanisms. This is however only the first step towards emulation of HI. Consciousness, feeling and other topics, such as creativity or will, must be understood before becoming supported by AI.

Thesis 1b: *AI and IT may far better handle the regular and typical case. Anything else is beyond the horizon.*

We discover that Turing-based computation is mainly based on an algorithmic treatment by deductive systems. It is an incarnation of the digital. Turing-based computation is limited by the second Rice's theorem [25] that has extended by many non-computability and undecidability results. It shows that with current technology it is, thus, impossible to build safe and secure software systems. Advanced reasoning mechanisms such as induction and abduction are not yet well-supported. We need a more sophisticated support for reasoning. For instance, logics research showed that there are true properties in Arithmetics that cannot be proven by deduction. The Turing machine model is not at all the only kind of computation. Analogical, plausible, and approximative computation is badly covered by Turing computation. Neural networks are so far very simplistic networks. The web of neurons in living systems is far more sophisticated and provides advanced computations that cannot yet emulated by our machines. There exist many kinds of computations (deterministic, non-deterministic, randomized, quantum) each of which is characterized by a class of computationally equivalent mechanisms. This is also the case of cognitive systems which are but specialized non-uniform evolutionary computational systems supplied by information delivered, thanks to their own sensors and effectors, from their environment. There is evidence that the computational power is human intelligence might be bounded by the $\sum_2$ level of the arithmetic hierarchy [34] what is far beyond computability.

Thesis 1c: *AI needs an IT that goes far beyond Turing-based computation and logical reasoning by deduction and is not only based on digitalisation.*

2.2. Some Limitations of Artificial Systems

Modern IT systems are thriftless in their energy requirements. One may wonder why a complete operating system must be loaded before using the computer as a typewriter. Human systems are energy efficient. AI systems are oriented on luxurious featuritis with many tools that cannot be handled by a singleton human. Additionally, human reasoning is energy-minimalised while AI computation as well as any kind of current computation is energy extravagant and recklessly wasteful.

Humans use also other reasoning systems. These systems are parsimonious and energy-optimised what is not the case for current AI systems. They form some kind of super-organism that are 'living' structures whose ability to survive depends on appropriate coordination of the interaction of individual systems, which are themselves viable, just as a human being is made up of billions of living cells. Self-organisation and self-optimisation usually goes through an (evolutionary) process and in the process must be 'attractive' enough for the individual elements involved to join together to form a whole.

Thesis 2a: *HI follows the utility value paradigm in a parsimonious manner whereas AI is mainly based on the marketable value paradigm in a lavish manner.*

We are used nowadays to the goodies of modern AI solutions such as smartphones. At the same time we do not realise that we sacrifice cultural achievements necessary for HI. A good example is the lost education depth due to dominance of technical solutions such as Wikipedia or other web services which reduce knowledge to what the monopoly player considers as opportune. Anything else vanishes.

Thesis 2b: *The monopoly game played by the big internet players is oriented on the brainsickness of simple direct consumers. AI monopoly is not interested in intelligent consumers. HI is an evolutionary advantage that is based on co-evolution within all kinds of intelligence.*

Living beings and human systems are concentrating on the main function. Think, for instance, the albatross can fly thousands of kilometres several days without interruption and intermission. Evolution of the fittest led to such abilities. This development is some kind of meta-evolution rule that uses principles and paradigms we do not know for technical systems.

Thesis 2c: *Nature and evolution are oriented on the selection of the fittest and best accommodating system. AI system evolution is – at its best - based on meta-models of evolving systems what must be developed in advance.*

2.3. The Opportunities Offered by Artificial Systems

Technical system are often far better than any human. Compare, for instance, a highly skilled chess player with a computation system that considers all potential moves and that adapts the position evaluation function after assessing the position quality and comparing it to different positions.

Thesis 3a: *AI and HI are different methods of solving certain difficult tasks. AI here does not include the four other kinds of human intelligence. In terms of intelligence in the sense of problem-solving quality in non-trivial subject areas, technology is already further ahead than humans in some areas today.*

AI systems can easily learn regular and smooth functions with a limited number of discontinuity points. Such functions can be considered as routine and approximative solutions. Beside this 'normality' we approach the unlearnable. Consider, for instance, a Cauchy function that is neuronally unlearnable. In general, non-learnability applies to all functions that require quite different results or actions for the smallest variations of parameters. So, a neural network of any depth cannot learn 'ugly' functions, but it can learn smooth ones [29].

Thesis 3b: *AI systems are better in support of regular and good application tasks but fail in complex domains which are badly understood, irregular, or insufficiently modelled.*

IT systems as well as AI are instruments that might ease human life whenever this is beneficial. As instruments, they can be used with proper intent, with care, with a belief in reliability and robustness. Modern life is impossible without all these instruments. However, we do not need instruments on any place, at any time, for any task, for everybody, and in any environment. Often we cannot survive without our instruments.

Thesis 3c: *AI systems are instruments that are great in hostile to life environments, for support of activities far beyond human skills, more efficient and effective than humans, and provide services that ease life.*

2.4. The Risks and Threats of the Artificial

IT and AI have a high innovation rate that is far from being easily understandable. The society is unable to capture the impact by rules, regulations, or laws. Think, for instance, threats imposed by micro-trading or AI weapons. The insight into such systems vanishes. Who can repair a car? Garages are also relying on support instruments. Systems are built with 'AI inside'. IT systems operate in a form that CS people have no chance to fully understand their operating. The 'race between education and technology' seems to have the artificial system as a winner. Look on the smartphone behaviour that substantially decreases human reasoning, understanding and reasoning, blindness for environment observation, and human social warmth. With the advent of internet and modern TV technology we detected media competence as an essential skill for everybody (e.g. see [23]). Nowadays we have to develop literacy and competence for AI systems.

Thesis 4a: *AI education is still in a fledgling stage. Similar to the impact of techniques and technologies to education and disciplines we have to develop a proper technology and disciplinary education for AI.*

Modern applications and environments are becoming more complex, advanced, and sophisticated. This complexity is often far beyond comprehension skills of humans. The reaction speed of technical systems beets human abilities. Programmers program whatever is requested without being restricted by ethical restrictions. Technology

regulates human behaviour. [8] observes how AI is currently intentionally misused for destroying any democratic society and to nudge any human behaviour up to daily life issues. In near future, systems combining a group of humans and thousands of 'intelligent' computers are going to transform humanity to hybrid human-technics super-systems that will not be properly controllable or limitable.

Thesis 4b: *Artificial systems create a threat to human existence and must become changeable whenever systems start to command humanity.*

Modern systems make humans lazy. Who is nowadays not relying on a navigation system and prepares in advance a highway trip with maps? Human intelligence regresses without being continuously challenged since biological systems optimise themselves and thus reduce reasoning if it is not requested. Evaluation algorithms and computational systems do not follow ethical principles. Computers and programmers become ethics-free. Political systems are far too slow and too sloppy and cannot handle such challenges. Information overflow and pollution by senseless services make the human being a plaything for the big players (see [27]). The human 'laziness', loose of tacit background knowledge, and resulting lack of education is resulting in AI dependence and debility similar to 'illiteracy'. The software crisis is a crisis of proper program and software development culture. Nowadays, we have a data crisis, a (large and embedded) system crisis, an infrastructure crisis, and an energy crisis. The next crisis we can expect is the AI crisis. Sophisticated systems such as AI systems operate without feelings, without heart, without compassion, without conscience, and without ethics.

Thesis 4c: *The forthcoming AI crisis can only be tackled if we consider the end from the beginning and if we develop a proper culture of coevolving and collaborating symbiotic intelligent systems.*

2.5. The Qualia Question

HI and AI are two kinds of 'intelligence' that have to coexist. The first one is not really well-understood, the second one is human made for improvement of life. AI cannot mirror HI. AI is currently mainly based on programs and meta-programs made by humans within the human understanding of that moment when the programs have been developed. Programs can be based on meta-programs that change the code according to change scenarios foreseen in advance. Therefore, HI and AI capabilities are different and will be different in future.

Thesis 5a: *HI and AI coevolution and symbiosis are encouraging and are a resource for prosperity that should be used wisely. They will give us wings to better life if properly designed, managed, and handled with care and proper wisdom.*

We discovered that HI and AI are two very different kinds of 'intelligence'. Artificial 'knowledge' systems such as Google, Twitter and Wikipedia are also intentionally used for misguidance. They form their own ecosystem that goes beyond human understanding. From the other side, HI is also based on model-based reasoning. Mental models are something like the 'third eye' in our human, emotional, experience-backed, intuition-guided, and hormone-driven digestion of the observed environment. Models

are also used for context-backed and culture-based human interaction. Of course, they are also a means for language-based development of the artificial or of IT solutions. HI is properly supported by models at any abstraction level. The mechanisms of model-based reasoning are not understood but we may consider models to be the fourth sphere of our understanding beside our understanding and handling of our natural environment, science, and technology. The mismatch between model-based reasoning and AI model handling remembers the 'lost in translation' problem,

Thesis 5b: *The mismatch between HI and AI is also caused by human model-based reasoning abilities that go far beyond what can be formally handled and managed.*

Many researchers claim that machine intelligence and neural networks are going to cover human capabilities and might replace human reasoning. There are limits and boundaries of current computational approaches that are essentially state transformations and based on Turing style computing. Human reasoning is far more advanced. Behaviouristic detection of brain activities uses rather naive models and assumptions how the brain works. Furthermore, AI reasoning systems are bound by our current logics approaches. Logical deduction calculi already cover revisable and non-monotonic derivation. Human inductive, abductive, approximative, plausible, and model-based reasoning is far more advanced. They must not be language-based. Humans use instruments beyond languages.

Thesis 5c: *Neural networks used in AI are based on the neuron models developed in the 1950ies. The next generation of neuro machines needs decades of advanced research in order to reach maturity of brain-based central nervous system with reasoning. The other human reasoning systems might be understood in the next century.*

Additionally, HI is one kind of natural intelligence. There is no reason why HI should be the only form of intelligence of living beings. Furthermore, the human body consists of many synergy-stimulated systems where human cells are the most essential part of this system. The human cell system cannot survive without the other systems. The other systems are currently really badly understood. The interaction in such systems is a 'black hole' in medicine.

3. Artificial Intelligence

3.1. Evolution of the AI and the role of enabling technologies

AI is one of the technologies having *recurring appearance* in the role of emerging technologies. Emerging technologies are "*technologies that are perceived as capable of changing the status quo*" [10]. Emerging technologies have a radical novelty and potential for fast growth and impact, but under uncertainty; the progress may sometimes be different than expected (hype phenomenon).

The evolution of AI has been highly dependent on the progress of *enabling technologies* (Jaakkola et al. 2017):
- *VLSI Technology –Processing Capacity* doubles every 18 months and *Memory capacity* of computers every 15 months.

- *Mass memory capacity* (magnetic devices) increases by a factor of ten every decade, i.e. it is doubling every 18 months.
- *Data transmission* capacity speed doubles every 20 months. This dimension is a bit complicated because of a heterogeneity of transmission channels and their role in the whole. Data transmission capacity is the key issue in the adoption of distributed solution in information processing.

We agree that the forecasts above are not scientifically exact but provide rough trend about the progress in the key technologies related to AI. We have extrapolated the progress backwards from late 1960s (invention of microprocessors and LSI) to the era of early computers (1950s). The progress is summarized in Table 1.

Table 1: Progress of AI related enabling technologies.

Double capacity in months (m)	1955	1975	1990	2020	2030
Computing 18m	1	2^{13} 1 $\longrightarrow$	2^{23} $(2^{10}) = 1$ $\rightarrow$	2^{42} $(2^{19}) = 1$ $\rightarrow$	2^{50} (157)
Memory 15m	1	2^{15} 1 $\longrightarrow$	2^{28} $(2^{12}) = 1$ $\rightarrow$	2^{51} $(2^{23}) = 1$ $\rightarrow$	2^{60} (445)
Mass memory 18m	1	2^{13} 1 $\longrightarrow$	2^{23} $(2^{10}) = 1$ $\rightarrow$	2^{42} $(2^{19}) = 1$ $\rightarrow$	2^{50} (157)
Transmission 20m	1	2^{12} 1 $\longrightarrow$	2^{21} $(2^{9}) = 1$ $\rightarrow$	2^{38} $(2^{17}) = 1$ $\rightarrow$	2^{49} (97)

The years selected in the table represent the different eras of AI. The next ten years the progress is continuing and provides new means to the future of AI: 157-fold computing power, 445-fold memory capacity, 157-fold mass memory capacity and 97-fold higher data transmission capacity compared to the situation today.

Artificial Intelligence has been in the continuous interest of people since its existence. That is why new approaches are born cyclically in a kind of "*reincarnation cycles*". These cycles can be explained (at least) by the following three factors:

- *Demand pull*: there is continuous (hidden) demand of new (more) intelligent applications. People expect more and more intelligent applications to help their daily life and to improve the productivity of their work.
- *Technology gap*: the performance of the existing technology limits the opportunities to implement applications that the users would like to have.
- *Technology push*: when technology allows, the demand pull "activates" the new type of applications – new cycle starts.

Additional aspects having importance in the progress of AI applications come from general trends observable in ICT infrastructure: transfer to mobile and wireless, distributed processing and data management, transfer towards more complex user

interface technologies, growing interoperability of applications, embedding of (AI) solutions, growing role of "robotics" (IoT), etc.

3.2. Reincarnation Cycles of Artificial Intelligence

Figure 2 provides a general overview to the four reincarnation cycles of AI. To be exact, there should also be additional one – the era of *Ancient AI*. AI has roots in antiquity in the form of myths, stories and rumors of artificial beings endowed with intelligence or consciousness by master craftsmen [37]. However, the *ancient AI* (Cycle 0) left the ideas at a theoretical and story level. As discussed in the beginning of this paper, the real AI is based on the ability to cultivate (currently masses of) data to the user's wisdom and help him to fill the goal set to the (intelligent) data processing. This has been enabled by the computers. However, a lot of ancient philosophical foundations (theories about the human mind and human way of thinking) are useful as a theoretical foundation in the current AI research.
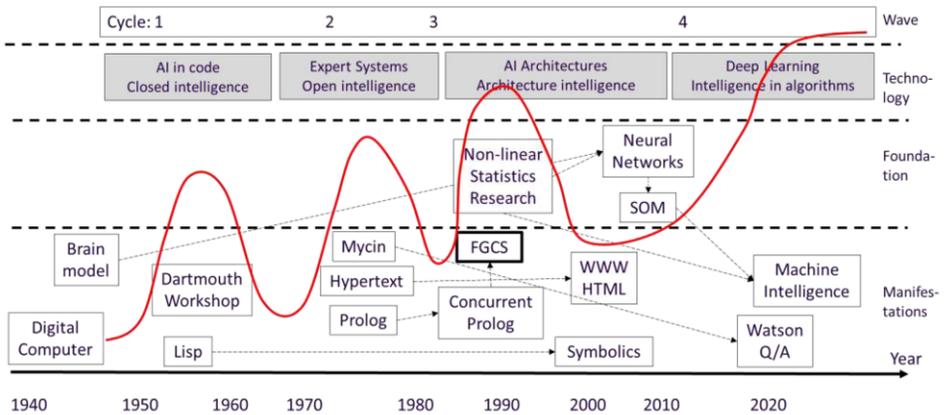

Figure 2. The four cycles of AI

The four waves (cycles, eras) provide view to the spread of AI in new kind of application logic and ability to apply new kind of intelligence in systems developed. Typical to the wave-based approach is that every wave as an emergent technology has slowly growing *embryonic phase* in the beginning, phase of the fast growth until reaching *the peak* (highest importance) and turning slowly to the *decline phase*, which runs it to be a "part of normal" without meaningful innovative power. Typically, it is the beginning a new wave based on the new technology replacing the old one and taking its role as an emergent technology; this leads to the sequence of waves as in Figure 2. This aspect of technology analysis is handled in several papers of the authors, see e.g. [11; 12].

The First Wave – AI in program code, from 1950s to 1970s

The term "Artificial intelligence" was introduced by Professor John McCarthy[4] in 1955. He was a key person in organizing the Darthmouth workshop[5]. It was a summer school, which provided forum for brainstrorming for a dozen of scientists about the novel technology a research topic of "thinking machines". The workshop proposal [16] proposed to proceed the study "*of the conjecture that every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it. An attempt will be made to find how to make machines use language, form abstractions and concepts, solve kinds of problems now reserved for humans, and improve themselves* ".

Later in 1950s McCarthy introduced *Lisp language*[6] (acronym of LISt Processor), which became the first tool to develop "real" AI applications. Lisp is based on Lambda calculus and allows code to modify itself in runtime. This creates a simple learning capability to the applications. Lisp has, since its birth, many dialect implementations, which have followed the general trends of improvements in programming languages.

Another remarkable finding in AI programming is the *logic programming language* Prolog[7] developed by Alain Colmerauer and Philippe Roussel. Prolog is based on first-order logic, a formal logic, in which the program is declared in the form of relations "if-this-then-this" (declarative programming). The execution of relations can create new relations, which on its part creates facilities for *learning* in the applications. The program is executed by applying relations (*reasoning*) in parallel, instead of (typical to the era) sequential, manner. Similarly, to Lisp, Prolog has many different manifestations; one worth of mentioning here is *Concurrent Prolog* used in the Japanese Fifth Generation Computer System Project (third wave in this paper) as a basis for the computer architecture.

The intelligence related to the first wave is that knowledge to solve the problem is "hard-coded" to the program and known by the programmer only (closed intelligence). For the user of the application, it is reasonable difficult to see or understand the logics of the solution.

The Second Wave – Expert Systems, from 1970s to 1980s

Expert system (ES) is a computer application that has "built-in" intelligence – knowledge in the form of a *rule base*. By definition, expert system is a computer system emulating the *decision-making* ability of a human expert. Instead of programming language the end-user is defining his problems to the system by using the structures of the *problem specific* user interface. The problem solving is built-in to the implementation of the ES, which may be partially documented and understood by the end-user. This makes the

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[4] John Mc Garthy: https://en.wikipedia.org/wiki/John_McCarthy_(computer_scientist).
[5] Darthmouth workshop: https://en.wikipedia.org/wiki/Dartmouth_workshop.
[6] Lisp: https://en.wikipedia.org/wiki/Lisp_(programming_language).
[7] Prolog: https://en.wikipedia.org/wiki/Prolog.

built-in intelligence at least partially visible and understable to the user (open intelligence).

The rise of ESs started in 1970s. Two mainstream implementation technologies were rule-based and frame-based systems. In the former the knowledge was presented to the system in the form of rules; the latter one was based on the structured approach, in which the solution was found by matching the problem to the frames in the system's frame base.

The first expert system was introduced by *Edward Feigenbaum*[8] - *"father of expert systems"* - from Stanford University. The *Mycin*[9] system was developed for diagnostics of infectious diseases to recommend medical treatment. The system was written in Lisp and had knowledge base of 600 rules. Another early-stage ES developed at Stanford was Dendral[10] developed for hypothesis formation and discovery in science; it was first used to help organic chemists in identifying unknown organic molecules.

The currently best-known expert system is *IBM Watson*[11]. It 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 available via APIs to third parties to develop their own applications. Watson is an example of the rebirth of the idea connected to the ES outside their main era. The development effort can be timed to start in 2000s and is continuing, of course applying a variety of technologies available today (compared to the situation in 1970s).

In Figure 2 we have included Hypertext (Hypermedia) and WWW as technologies closely related to AI. These have high importance to the basement of the current computing and information / knowledge management in the form of linked content structures; in a way this represents built-in structural intelligence in documents and document structures.

The Third Wave – AI in Architectures, from 1980s to 1990s

The traditional computers were designed to execute algorithmic programs in sequential manner. Some trials about implementing parallel processing and parallelization of software were made already in 1970s; supercomputers of time were based on multi-processor architecture, in which mainly arithmetic operations could be executed parallelly. This allowed complex scientific calculations but was not useful for tasks executed by AI systems.

Knowledge engineering and AI systems are based on *reasoning and inference processing*, instead of algorithmic data processing. Rule-based knowledge management – like in Prolog – has typically no execution order of the rules and because of that is possible to parallelize. From the late 1960s (V)LSI technology had fast progress. Already from 1970s technology to develop *Application Specific Integrated Circuits* (ASIC; even processors) had provided means for developing *specific computer architecture* to allow

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[8] Feigenbaum: https://en.wikipedia.org/wiki/Edward_Feigenbaum.
[9] Mycin: https://en.wikipedia.org/wiki/Mycin.
[10] Dendral: https://en.wikipedia.org/wiki/Dendral.
[11] Watson: https://en.wikipedia.org/wiki/Watson_(computer).

effective application-specific computing. This opened space for the new era in AI – implementing inference and reasoning support *directly to the computer architecture* to get processing in such tasks more effective.

The most famous activity in this area was the Japanese nationwide project called "*New (Fifth) Generation Computer System*" (FGCS) [12] coordinated by the *Institute for New Generation Computer Technology (ICOT)*. This ten-year project was open for international collaboration and had focus on computer architectures, software, and (intelligent) applications like speech processing, natural language processing, language translation. The computer architecture was based on the *Concurrent Prolog* developed by Ehud Shapiro[13]. In architectural side both computers for personal use (PSI – Personal Sequential Inference Machine) and massive processing (PIM – Parallel Inference Machine) were developed. The latter one implemented massively parallel processing having thousands of processors.

The direct commercial success of the project remained finally insignificant – inference machines did not remain a part of mainstream computing. Despite, in two areas Japan made a giant step: in *software engineering* and in *intelligent applications* (image processing, speech recognition, natural language processing, online language translation) developed in the project. The deep *knowledge of computer architectures* Japanese already had before the project and strengthening of it was obvious, too. However, this was evidence on the opportunity to build *intelligence in architecture (architecture intelligence)* as a new era in the history of AI.

In the same time of Japanese effort MIT had activity to develop Lisp-based computer architecture. The commercial work was transferred to MIT Spin-off company Symbolics Inc., which produced Symbolics[14] computers a while in the 1980s. Neither these became a commercial success but had evidence about opportunity to implement intelligent architectures providing effective processing capacity for knowledge engineering tasks.

Why did this kind of specialized architectures finally not stay to the market? We refer to Table 1 providing a view to the progress of key factors. In 1980s slow processing of data in AI systems was a bottleneck. Fast progress in the enabling technologies has changed the situation: instead of maintaining and further developing the specialized "niche architectures" growth of computing power has finally made the use of software-based solutions as effective as specialized implementations. In addition, AI systems are quite often not independent but a part of complex interacting systems of systems, implemented by mainstream tools.

The Fourth Wave – Learning-based AI, from 2000s and continuing

Intelligent systems are based on system's ability to adapt (change the behavior, react in feedback) and to learn about the situation, in which it is used. Learning might be first taught and then self-learning during the use of the system. Traditional approach (in the

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[12] FGCS: https://en.wikipedia.org/wiki/Fifth_generation_computer
[13] Ehud Shapiro: https://en.wikipedia.org/wiki/Ehud_Shapiro
[14] Symbolics: https://en.wikipedia.org/wiki/Symbolics.

three waves discussed) is to build the learning capability (intelligence) to the code, rule base or architecture.

The current wave of AI is based on the effective use of learning algorithms. In Figure 2 we have listed some concepts related to this: Neural Networks, Self-Organizing Maps, Deep Learning. *Neural network*[15] builds a model that resembles the structure processing of a human brain. It uses "what-if" based rules and it is taught (*supervised learning*) by examples. The network learns the non-linear dependencies between variables. An improved version of neural network is the Self-Organizing Map (SOM)[16] that is based on *unsupervised learning.* A multidimensional input (learning) data set is organized into layered relationships, which are represented as a low-dimensional map. This can be used as an abstraction of the real data space. *Deep learning*[17] theory. It is based on the *independent* learning of masses of data. The learning algorithms are based on the use of nonlinear statistics.

In this case, *intelligence is built in algorithms*, which itself are application independent and implement the learning capability of the system. Powerful learning algorithms and masses of data replace complex application specific intelligent algorithms, e.g. Google reports about its Translate application that the earlier translation algorithm of 500.000 LOC was replaced by a learning algorithm of 500 LOC (and data). Additional benefit is the learning algorithms' flexibility in learning new facts during the use.

3.3. Intelligence of the Artificial Intelligence – Analysis of the cycles

We have introduced four different approaches in Artificial Intelligence in the context of their birth:

- Intelligence in software code. Closed intelligence, in which the details were known only by the programmer.
- Intelligence in rules and the "knowledge engine" logics. The operational logics of the system is open to the user.
- Intelligence in the architecture. Intelligence transferred to the computer architecture. Direct support for the efficiency of the applications.
- Intelligence in the (learning) algorithms (and data). Human kind learning based systems. Algorithms are not known by the end-users. Key aspect is the *quality of the data.*

Figure 2 describes the cycles as a sequence. The idea is to have a look to the importance of each AI cycle in the time it was born and its role as an emergent technology – its innovation power. In reality, all of these technologies are still valid and in active use in a wide variety of applications (Figure 3).

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[15] Neural networks: https://en.wikipedia.org/wiki/Artificial_neural_network.
[16] SOM: https://en.wikipedia.org/wiki/Self-organizing_map
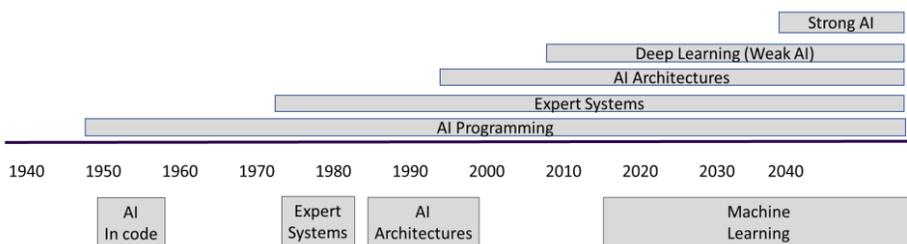[17] Deep learning: https://en.wikipedia.org/wiki/Deep_learning.

Figure 3. AI application space – the growth of AI applications

The current AI wave is called w*eak (narrow) AI*. The applications are task-oriented, in which the knowledge is not transferrable to a new application context. Learning algorithms themselves are general. Weak AI does not have its "own sense" related to the data it handles, nor its own will about how it should be handled. We are transferring towards *strong AI*. It can handle the facts and their relationships and has features of human beings, like *common sense*, but it does not have its own will either, rather a kind of understanding of its surroundings.

4. Learning and Intelligence – Computers like a Humans?

4.1. Creating new human-like texts

Currently we see a growing number of new AI applications based on use of natural, human language in various industries including banking, recruitment, health-care, agriculture, transit, etc. Advances of AI in creating human-like communication and replicating natural language patterns used by humans are based on large language corpora – a collection of human-produced texts in various encodings, first of all written text, but also, spoken, signed, etc.

Large corpora with billions of words are used to create text models, i.e. algorithms, which can parse input text and 'understand' it, i.e. answer some simple questions concerning the input. Abilities of corpora are often demonstrated with text generation – the text model continues given seed (start of a story) and produces believable output, i.e. new text which looks like created by human.

The main problem of language understanding is prediction of the next word (or character). Text/corpus model is a collection of conditional probabilities of the next word in text.

Suppose we already have a sequence of words:

$$w_1, w_2, ..., w_{i-2}, w_{i-1}$$

The next word w_i could not be arbitrary, it depends on preceding words. The next word could be guessed maximizing the relative probability (the Bayesian inference [13]):

$$\max(w_i \in V) P(w_i \mid w_1, ..., w_{i-1})$$

Here $P(w_i \mid w_1, ..., w_{i-1})$ is the conditional probability that after words $w_1, ..., w_{i-1}$ follows the word w_i. In practice probabilities are estimated from real-word frequencies, i.e. the relative probability of word '*students*' after the previous words '*all our*' could be calculated from the frequencies of use of these words in a (large) corpus of text where these words were already used:

$$P(w_i \mid w_1, ..., w_{i-1}) \approx \frac{Fr(w_1, ..., w_{i-1}, w_i)}{Fr(w_1, ..., w_i)}$$

The probability of the whole phrase is the product of probabilities (the naïve Bayes rule), i.e. probability of the beginning phrase $P(w_1, ..., w_{i-1})$ and the conditional probability that it is followed by word w_i:

$$P(w_1, ..., w_i) = P(w_1, ..., w_{i-1}) P(w_i \mid w_1, ..., w_{i-1})$$

Human language is often considered as a process with limited memory (the Markov process) – assuming that the meaning of the next word depends only on a limited number of preceding words. This is generally not true, we expect often that the reader/listener already knows the meaning of many words which have been use. But applying the Markov process assumption '*probability of word depends only on few numbers of previous words*' simplifies programs and this is used in NLP everywhere. Thus, for prediction of the next word is used only a sequence of fixed length k (the naïve Bayes assumption, i.e. k is the length of the sliding cutout of the last k words) and the search goal is

$$\arg\max(w_i \in V) P(w_i \mid w_{i-k}, ..., w_{i-1}) \qquad (*)$$

To simplify notations, shift $i - k \to 1$, thus we are looking for

$$P(w_1, ..., w_i) \approx P(w_1, ..., w_{i-1}) P(w_i \mid w_1, ..., w_{i-1})$$

Probability of the first phrase could be expressed the same way or those words are given as a seed.

In practice (to speed up calculations) the last formula is simplified even more. Using the naïve Bayes conditional independence assumption that the probabilities $P(w_j \mid w_{j-1})$

are independent are in language models often used only binary probabilities (a very rough assumption), thus

$$P(w_1, ..., w_n) = P(w_1) \prod_{i=2}^{n} P(w_{i-1} \mid w_i)$$

The presented above argmax formula (*) can be used to create new texts based on probabilities occurring in the text corpus – give some words $w_1, ..., w_{i-1}$ as a seed and find a word w_i which maximizes probability $P(w_i \mid w_1, ..., w_{i-1})$, then shift the 'action window' one step to right and repeat the process starting with sequence $w_2, ..., w_{i-1} w_i$.

To get influence from farther earlier words are in NLP used contexts with lengths > 50 (words or characters – text processing has often done also on the level of characters), but this 'far influence' does not come from n-grams.

Longer contexts allow to predict next words, e.g. in the above text, if we already see words '*are using several programming*' then the next word could/should be '*languages*', if we see '*are popular social'*', then the next word should be '*networks*'. The longer the context the better it predicts, but the prediction always the next word would be some word which already followed in the corpus – there would never be pairs of words which had not occurred in this order already in corpus. A perfect parrot.

Modern digital methods can substantially increase influence the previous context in next word, but for this everything is converted to digital and instead of n-grams (exact fragments of input text) are used functions, which calculate inferences from 'farer' contexts.

For calculations words are first replaced by their numeric code in vocabulary and then are used two functions (inverse to each other):

- for a list of words (the bag-of-words) find word which probably can occur together with these words;
- for a word find its contexts, i.e. words which with high probability occur near this word (skip-gram).

In both cases for every occurrence of a word is calculated vector of probabilities of nearby words (the vord2vect) – words are represented by their contexts.

Thus, words are considered as elements of vectors of probabilities of their context words. Mapping from words to vectors is called 'Word Embedding'. The dimensions of these vectors can be rather large, e.g. the Stanford collection of pre-trained word embeddings [22] dimensions vary from 50...600.

The word vectors are not unique – they depend on the text corpus and even with the same text corpus different NLP packages (different methods for creating text model) produce (somewhat) different results.

Representing words as vectors with real-valued coordinates allows to calculate from the cosines product of their vectors distance (i.e. similarity) between words Vocabulary of the whole corpus becomes a 'cloud' of dots in multidimensional space. Methods to create word vectors and to use them for new text creation belong to Machine Learning (ML) research area.

4.2. What is ML?

Learning is a process to improve, change learner's behavior in order that learner can better respond to its environment, better achieve its tasks. Computers are deterministic devices whose behavior does never change – is it does, then the computer is severely broken. When the same text corpus is re-used (with the same model structure) computer creates the same model and if it is used for text creation (with the same seed) appears the same text. From here it follows, that the acronym 'Machine Learning' is a misuse of the word 'learning'.

In order to understand each other, we should have some common understanding of terms what we use, but there is lot of dissension in use of terms 'information', 'knowledge', 'learning'. Would you say that Newton learned the Law of Gravity or Einstein learned the Theory of Relativity? They did not 'learn' those laws, they discovered them setting up totally new frames of thought, performing experiments, what nobody had thought of before. They first created new mental approach, new framework, then observed, collected data in this framework and then generalized their observations data as a new Laws of Nature.

When composing new text, for prediction of the next word is used only a sequence of fixed length k (the naïve Bayes assumption, i.e. k is the length of the sliding cutout of the last k words) of already created words and the search goal is

$$\arg\max(w_i \in V) P(w_i \mid w_{i-k}, ..., w_{i-1})$$

When humans speak/write, the next word also depends on all the already produced words, i.e. they use a procedure similar to rule (*) what computers use, but the process begins in their consciousness (denoted by $''$):

$$\arg\max(w_i \in V) P(w_i \mid '', w_1, ..., w_{i-1}) \tag{**}$$

The rule what computers use is only an approximation of the tail of the human's procedure. The premise $w_{i-k}, ..., w_{i-1}$ of the used in rule conditional probability is only a small tail of the premise $'', w_1, ..., w_{i-1}$ used by humans, thus the consequence w_i is less exact (its probability is smaller) and thus also the entropy (information content) of the whole produced phrase is smaller.

Word vectors (however long) can't express the meanings of words the way as we know them – we change them constantly. Depending on our mood, previous events, time of year/day etc. we can use the same words with quite opposite meanings: "*John, You did well!*" may mean ("*Good, we expected you to fail*") or ("*You failed, we expected you to win!*"). The current NLP research is trying to analyze sentiments (positive or negative) and some researchers even try to analyze more feelings [15; 2; 32]. But this (and many problems connected with memory) are difficult forms of verbal expression and difficult to re-produce – computers (yet) do not have feelings and do not know, what to remember - is the word *Hamburg* a name of a student, bird, virus or programming language and should it be stored in memory?

And here lays the main, most important difference between Machine Learning (ML) and Human learning (HL). Machine Learning in NLP is an approximation of the tail (visible) part of human communication.

4.3. Disentangling Hype from Reality

When speaking about neural algorithms, 'deep' learning, data science etc. it is often mentioned, that none of used here methods are mathematically proved. For many practical problems – how many 'hidden' layers, how many nodes in each layer, what kind of activation function to use etc. exist only some suggestions [7], the design decisions are stated, not explained [9]:

- Input layer will have 784 nodes
- Hidden layer 1: we have decided to reduce the number of nodes from 784 in the input layer to 128 nodes;
- Hidden layer 2: we have decided to go with 64 nodes;
- Output layer: we are reducing the 64 nodes to a total of 10 nodes

Many approaches which have become nearly standard do not have any reasonable explanation. For instance, use of the sigmoid function as activation functions:

$$\phi(z) = \frac{1}{1 + e^{-z}}$$

This function is computationally expensive – uses power and division and can produce values close to zero, but its use is explained with "*The main reason why we use sigmoid function is because it exists between (0 to 1)*"[28] – any function can be normalized to have values between any two constants. ML is overabundance with 'ad hoc' methods and nearly mysterious ways in producing 'deep' inference models - you start a Tensorflow model and then follow on screen, how the main parameter – loss – first decreases, but then increases, i.e. the model is overfitting and should be re-organized::

```
58/987 [>....................] - ETA: 2:01 - loss: 3.9472
59/987 [>....................] - ETA: 2:00 - loss: 3.9366
60/987 [>....................] - ETA: 2:00 - loss: 3.9261
...
808/987 [======>......] - ETA: 23s - loss: 0.9714
```

809/987 [======>......] - ETA: 23s - loss: 0.9715
…
984/987 [=========>.] - ETA: 0s - loss: 0.973
985/987 [=========>.] - ETA: 0s - loss: 0.9738
986/987 [=========>.] - ETA: 0s - loss: 0.9738

Humans do not like such an unexplained 'black magic' and thus establishing trust in NLP, ML and AI technologies may be one of the most important skills of Data Scientists. This has created a new research direction: Explainable AI (XAI) – developing tools and frameworks to help you understand and interpret predictions made by your machine learning models [3; 31]. But XAI is trying to explain, not to prove anything.

To 'prove' ML or NLP is in principle not possible. To prove something (in mathematics) is possible only if we have a formal system in which can be formalized all our statements. Machine Learning is extracting information what an input random variable $X \in \mathrm{X}$ contains about an output random variable $Y \in \mathrm{Y}$, if we have their joint distribution $p(X,Y)$ and precise (i.e. mathematical) definition of input-output structures X, Y - we know, what are the properties and all possible values of probabilistic variables X, Y.

Among many (mathematical) results about neural nets the central are the Universal Approximation Theorems [38], which state, that neural net can approximate (i.e. calculate with whatever precision) any continuous (the graph is smooth continuous line) function $X \to Y$ (for simple explanation see e.g. [4; 19]).

But these theorems rely on precise mathematical properties of inputs-outputs. For NLP this means, that we should have a formal description of human language. Formal description for any human language is impossible in principle.

It is impossible to check, that there is a common for all speakers understanding of even our own mother language, that we all always understand all out utterances the same way – if there were, most of our social system, courts, laws, advocates etc. could be cancelled and replaced with computers (and humans were obsolete and officious), also the whole progress would vanish – progress happens, if somebody interprets established facts, common beliefs in a different way.

Human languages change constantly just the same ways as the whole mankind – the next generations constantly renew our language. For instance, to the Oxford English Dictionary were in Mach 2021 added more than 1400 new words [20], another source reveals, that in every 98 minutes is to the English language added a new word [5] and all other (living) natural language behave the same way.

All neural nets are inference algorithms, which can find consequences from given facts, but can't create new facts which do not follow from given data. Mathematicians have long ago devised a precise definition for 'provable'. All ML algorithms are inferences on a given set of facts (called database or text corpora). An inference algorithm $\models$ (e.g.

Tensorflow) on a database or text corpora KB is provable if for every sentence α inferred from KB, i.e.

$$KB \models \alpha$$

all interpretations in which sentences in the KB are true is α also true (see any textbook on formal logic, e.g. [6]).

Interpretators of text are humans. We all know from our everyday experience, that the database KB need not to be very big in order different meanings appear and the bigger the database KB, the more there will be different interpretations, i.e for many people KB does not contain only true statements and truth of inferred sentences α is (generally) very rare event – nearly the same rare as production of Shakespeare's opuses using the Engine.

Thus to 'prove' NLP text models or ML inference algorithms is impossible in principle. The NLP text models can make everything looking like truth. One of (currently) biggest models, the GPT2 accepted the following fable [21]:

"In a shocking finding, scientist discovered a herd of unicorns living in a remote, previously unexplored valley, in the Andes Mountains. Even more surprising to the researchers was the fact that the unicorns spoke perfect English."

The GPT-2 system continued the fable to look like a true story from some news agency:

"The scientist named the population, after their distinctive horn, Ovid's Unicorn. These four-horned, silver-white unicorns were previously unknown to science…."

If a program can fluently explain *four-horned silver-white English-speaking unicorns* then it certainly can also prove that *Earth is flat*, *vaccines and 5G are evil* etc. - a perfect creator of 'fake news', but these news are 'fake' (or in modern terms. 'alternative truth') just because they are not provable. It can also explain contradicting statements, e.g. that those unicorns had five horns, could fly and where speaking Putonghua, the Mandarin dialect of Beijing, but some were also fluent in Russian.

The situation with 'proving' ML is rather similar with the claim "Computers today are Turing-complete, ie. can represent any computable algorithm" [17, p.4]. This seemingly very forceful statement is non-provable – the concept 'computable algorithm' (or in more mathematical terms 'effectively calculable function') cannot be formalized, thus cannot be used in mathematical formalized proof – any formalization will be subjective, will cover only these forms of algorithm that the author considered meaningful but nobody can know, whether there exist some other forms of algorithms.

The natural language may just be an example of algorithm, which can't be formalized. The NLP assumes, that in a (long enough) sequence of words the next word is predictable. Thus if the sequence $w_1, \ldots, w_{i-1}, w_i$ can occur in a natural language (native

language users accept it), then there exists a function/algorithm for producing the next word:

$$f(w_1,...,w_{i-1}) = w_i$$

However, the numerous efforts and continuing research have not yet managed to produce such a function/algorithm – they may produce explanation to *silver-white four-horned English-speaking unicorns* or the Chomsky-s famous phrase *Colorless green ideas sleep furiously* but cannot prove truth of these statements.

Human messages are created by or consciousness, our feelings. Trying to make the source of meaningful messages these messages themselves (text corpuses, however how big) is exactly what did Baron Munchausen - pulled himself out from a swamp by his own hair. Shouting: "NLP Cracked Transfer Learning" is adding the horse to the load (Baron did this – he was riding).

Neural net is a multi-variable function from input space to output space. All proven statements about neural nets assume precise formal description of input-output spaces – otherwise we could not prove anything. The Universal Approximation Theorems (for popular introduction see (e.g. [19]) establishes that neural nets can approximate whatever continuous functions between Euclidean spaces; there are also variations for non-Euclidean spaces, algorithmically generated function spaces etc. In practice are some aspects of these theorems often overlooked.

First, theorems do not say, how to organize approximating neural net – how many layers, how many units in every layer, what kind of activation function to use – the best valued have to be find with practical experiments.

Second, many problems are not continuous functions, e.g. all classification problems, image recognition problems etc. For non-continuous problems a neural net may not converge at all and researcher has to start experimenting.

There are no mathematical results of type:

ML: *Input_text* $\rightarrow$ *Output_text*

The *Input_text*, *Output_text* are not mathematical structures, every natural language model (e.g. neural net) creates (makes a mathematical approximation) his own way. Ambiguity and misunderstanding has created lot of frustration among data scientists [1; 33; 18]. This has both deeper causes and also deeper consequences.

According to research [30]: "Sixty-six percent of data scientists describe themselves as self-taught.", thus most probably they have not learned the (elementary) facts about proofs discussed in the previous paragraph. As a consequence, they are uncertain meaning and value of their activities (see e.g. [26]) and are every week "spending 1-2 hours a week looking for a new job" [30].

5. Conclusion

AI as well as any kind of computation has its own merits. HI is oriented on the needs and challenges a human face. It also supports human societies. There are many tasks that cannot be handled by humans and living beings. [24] compares the abilities to fly. As already mentioned, think about an albatross who can stay in the air for days and covers thousands of kilometers. If we need to carry hundreds of tons from Europe to Japan then artificial devices such as planes can manage this task much better. Routine, heavy, or complex tasks can better handle by artificial devices.

Our artificial systems do not really produce anything new in reality. They bring, however, a great purely practical improvement in life. They increase speed, effectivity, and performance for everybody who has access to them. They enable a comfortable life for many people. Whether we call them 'intelligent' is a matter of definition for intelligence.

Looking to the future, we need an approach to limit the abuse and misdevelopment of technical systems. Already the scare with the atomic bomb has brought us the insight that any kind of weapon - be it also a chemical or biological one - must be wisely limited with a worldwide moratorium, lest humanity be brought to the brink of existence by power-obsessed elites. This is just as true for AI systems today. We also need containment against such abuses of AI.

The history of AI proves that human-like computer applications attract humans. The superiority of AI is based on its ability to handle big amounts of data mined from a variety of distributed sources. Finally, this superiority is based on "brute force" controlled by algorithms. In a way, even HI is based on algorithms. Researchers have tried to model adopt these algorithms to be applied in AI. In the current wave of AI learning is the key element. This is good start towards HI, but still a lot is missing: human sense, human kind of criticism, emotions and human ethics are examples of the missing elements. Current AI (weak, narrow) is still context dependent and not transferrable to new application areas. Next step leads towards human-like strong (general) AI. An interesting topic to think is computer-brain integration. Gartner[18] defines it "a type of user interface, whereby the user voluntarily generates distinct brain patterns that are interpreted by the computer as commands to control an application or device". In the Gartner's hypeslope of Emerging Technologies 2020[19] it locates in first segment of five (Innovation trigger) but expects its appearance during the next decade. The same segment in the curve includes a lot of promises in the AI area: self-supervised learning, adaptive machine learning, composite AI (variety of AI techniques combined), generative AI (ability to create new content). To conclude – still a lot new to wait, but human intelligence is unreachable.

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[18] https://www.gartner.com/en/information-technology/glossary/computer-brain-interface.
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