Eager to Take Part in the Global AI Race? Better, Look for Traps Waiting There for You

Emanuel Diamant
VIDIA-mant
Kiriat Ono, Israel 5510801
e-mail: emanl.245@gmail.com

***Abstract*—The concept of Artificial Intelligence (AI) was introduced about 60 years ago. At the same time, Artificial Neural Networks (ANNs) were devised as a means for AI implementation. They were conceived as a collection of small interconnected computational units (called artificial neurons), which are supposed to imitate the biological neurons of the human brain. Essentially, ANNs were devised as data processing units – 60 years ago, all things in the world were considered computational. But today, the brain is thought as an information processing system. Therefore, biological neurons (and their artificial analogs) should be considered as information-processing units. This shift in the underlying assumptions is overlooked by almost all AI designers. I hope that a clarification of this issue will help AI designers to avoid dead ended trails and harmful pitfalls on their way to a successful and trustworthy AI realization.**

Keywords- Artificial Intelligence; Artificial Neural Network; information; information processing

I. INTRODUCTION

It is generally agreed and accepted that the human race is on the eve of a great and unknown time – the time of the AI era advent and victory. What once was considered a futuristic technology today begins to penetrate almost every aspect of our life.

The unprecedently rapid pace of AI infiltration is usually attributed to the latest Deep Learning Neural Nets (DLNN) explosion. Although Neural Nets have their roots a lot of years ago, DLNNs have rapidly became the best known technique in AI, yielding numerous state of the art results in a wide variety of domains such as speech recognition, image processing , language translation and as such tough and difficult tasks.

Wikipedia defines Deep learning as a set of machine learning algorithms that attempt to model high-level abstractions in data by using model architectures composed of multiple non-linear transformations. Deep learning software works by filtering data through a hierarchical, multilayered network of simulated neurons that are individually simple but can exhibit complex behavior when linked together, [1]. The might of Deep learning is now servicing AI research and development (R&D) supremacy.

Although in its long history AI's R&D has seen several ups and downs, the current surge of interest in AI is unmatched in its extent and enormity. The reason for this is the advent of the Big data era: Advances in sensor technologies, explosive growth of computing power, proliferation of broadband internet equipment, have led to an unprecedented flood of data inundating our surrounding. In such circumstances traditional practice of human-centered management of data volumes does not hold anymore and has to be delegated to a machine (a computer as we usually call it today). It is self-evident that such a computer has to possess many human-like cognitive abilities, which underpin understanding, analysis, and interpretation of the incoming data streams. In short, has to possess AI abilities.

The urgent need for AI solutions apt to meet the growing flood of Big data has led to an unprecedented rise in AI R&D efforts undertaken today around the world.

II. THE AI RACE

As the opportunities of AI technology become more recognized and appreciated, more and more nation states begin to consider their own AI strategies. Tim Dutton, in [2], has summarized a package of such national programs announced in the past two years.

In 2018, 25 European countries have joined up to make sure that the AI revolution doesn't leave them aside. The EU Commission has adopted a document that includes a commitment to increase the EU's investment in AI from €500 million in 2017 to €1.5 billion by the end of 2020, and the creation of the European AI Alliance, [2]. President Emmanuel Macron unveiled France's €1.5 billion plan to turn his country into a world leader for AI research and innovation. The U.K. Parliament has urged its government to draw up a policy to help the country become one of the world's AI leaders. Germany, too, has its grand ambitions in AI, [3], [4].

All these announcements are inspired by the idea that Europe must catch up with the United States and China in an AI arms race. Although the leadership of the United States and China is worldwide acknowledged and appreciated, the real state of affairs in AI R&D in US and China remains blurred and ambiguous.

The accepted (in the USA) free-market-oriented approach results in an entangled combination of classified research, public contracts from development organizations (like DARPA), and partnerships with the private sector, [4]. The extent of government funding in each of the sectors is blurred and unclear: In its unclassified 2017 budget, Pentagon reported on spending approximately $7.4 billion on

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AI and the supporting fields, [3]. Billions more are invested in classified R&D, but how large are the figures is unknown. DARPA alone pledged to invest $2 billion in AI over the next five years through its AI Next initiative [5].

Similarly blurred and fuzzy are China's intentions in the AI. Only the budget figures are much more higher: The Chinese government pledges to build a US$150 billion AI industry by 2030, [4].

It is worth to be mentioned that human brain research, which is closely related and associated with AI's R&D, exhibits remarkably lower levels of government support and funding: The USA BRAIN Initiative is provided with $1 billion budget for ten years of project duration. European Human Brain Project is funded with 1.3 billion euro for the same 10 years long research span.

III. UNEXPECTED HURDLES

Despite the hype and the fascination that naturally surrounds AI undertakings, the real state of affairs is far from being satisfactory – despite of a long history of use and exploration, the operational principles of the DLNNs remain unclear and ambiguous. There is still little insight into their internal operations, and a lack of knowledge on why and how they achieve their impressive performances. From a scientific point of view, this is entirely unsatisfactory. Without a clear understanding of how and why the NNs work, the development of better models inevitably reduces to trial-and-error experimentation [6].

For that reason, the issue of explainability, interpretability, and transparency of ANNs applications has become a subject of hot public discourse and is repeatedly raised at many AI design related conferences, forums and gatherings, [7], [8], [9], [10].

An interesting turn in this discussion has been inspired by the recent announcement of Ali Rahimi (and his friends) that Machine Learning (ML) and AI "have slipped out of the bounds of science and engineering into alchemy", [11]. At the 2017 NIPS conference, Ali Rahimi declared that AI researchers do not know why some algorithms work and others don't. Relying on a trial and error strategy, AI algorithms have become a form of "alchemy." [12].

IV. OVERLOOKED REASONS

There is a common agreement among the participants of the public discussions about the measures that should to be taken in order to reach more "user friendly" and explainable ML/ANN constructions [13]. However, what is surprising in these recommendations is that, (agreeing with the statement that better theoretical understanding of the ANNs functional principles is compulsory for further successful development of ML/AI applications), no single attempt is undertaken to elaborate such theoretical principles. Therefore, I consider as my duty to try and to develop these overlooked theoretical grounds.

As to me, contemporary ANN designers are ignorant and unaware about the difference and the inconsistency between artificial and natural biologic neurons. While artificial neurons are intentionally designed to be **data processing** computational units, the natural biologic neurons are evolutionary developed to deal with and carry out **information processing**.

60 years ago, the world was at the dawn of a computing era, and the human brain was regarded as a computing device. Intelligence was considered as a human trait and as a product of human brain activity. Therefore, Intelligence was considered to be a computable function, and Computational Intelligence has evolved as a respected field of human-related computer science.

To facilitate human brain functioning studies, Artificial Neural Networks (ANNs) were conceived as a set of tightly interconnected simple computational units resembling the network of biological neurons in human brain. As it was just mentioned, ANNs units' functionality indisputably implies data processing ability. That is, **ANNs were designed and used as data processing (computational) devices**.

However, in recent decades, a significant paradigm shift in brain functionality understanding has occurred. Now, **human brain is considered as an information processing apparatus**. Intelligence, thus, should be seen as an **information processing outcome**. Subsequently, brain neurons should be seen as information processing units (not data processing instruments, as it was before). At the same time, Intelligence is no more an exceptionally human trait – it is a feature common to all living beings, with and without brains or nervous systems. (Another argument in favor of an information processing principle).

Contemporary AI designers are not aware about these revolutionary transforms. The difference between data and information is not seen and not understood properly by the contemporary research community and therefore the subject is overlooked and neglected. Often, the notions of data and information are used interchangeably, most often being mixed and blended. That is the legacy of Shannon's Information Theory or, let us be more accurate, the way of how people understand and use Shannon's Theory. I do not think it would be wise to deepen our understanding of these inconsistencies. Rather, I think, it will be more appropriate to understand what actually information is.

V. LET ME EXPLAIN

There is a widespread conviction that a consensus definition of Information does not exist. I do not agree with this. On several occasions, I have already published my opinion on the subject [14], [15], [16]. This time, with all fitting excuses, I would like to repeat some parts of these earlier publications in order to preserve consistency of this discussion.

Contrary to the widespread use of Shannon's Information Theory, my research relies on Kolmogorov's ideas on information, [17]. According to Kolmogorov, a not random binary string (called a separate finite object) can be represented by a compressed description of it (produced by a computer program in an algorithmic fashion) "in such a way that from the description, the original message can be completely reconstructed" [18]. The compressed description of a binary object has been dubbed as "algorithmic information" and its quantitative measure (the length of the descriptive program) has been dubbed as the description "Complexity".

Taking Kolmogorov's insights as a starting point, I have developed my own definition of information that can be articulated in the following way: "**Information is a linguistic description of structures observable in a given data set**".

To make the scrutiny into this definition more palpable I propose to consider a digital image as a given data set. A digital image is a two-dimensional set of data elements called picture elements or pixels. In an image, pixels are distributed not randomly, but, due to the similarity in their physical properties, they are naturally grouped into some clusters or clumps. I propose to call these clusters **primary or physical data structures**.

In the eyes of an external observer, the primary data structures are further arranged into more larger and complex agglomerations, which I propose to call **secondary data structures**. These secondary structures reflect human observer's view on the grouping of primary data structures, and therefore they could be called **meaningful or semantic data structures**. While formation of primary (physical) data structures is guided by objective (natural, physical) properties of the data, the subsequent formation of secondary (semantic) data structures is a subjective process guided by human conventions and habits.

As it was said, **Description of structures observable in a data set should be called "Information".** In this regard, two types of information must be distinguished – **Physical Information and Semantic Information**. They are both language-based descriptions; however, physical information can be described with a variety of languages (recall that mathematics is also a language), while semantic information can be described only by means of natural human language. (More details on the subject could be find in [19]).

Those, who will go and look in [19], would discover that every information description is a top-down-evolving coarse-to-fine hierarchy of descriptions representing various levels of description complexity (various levels of description details). Physical information hierarchy is located at the lowest level of the semantic hierarchy. The process of sensor data interpretation is reified as a process of physical information extraction from the input data, followed by an attempt to associate this physical information (about the input data) with physical information already retained at the lowest level of the semantic hierarchy.

If such an association is attained, the input physical information becomes related (via the physical information retained in the system) with a relevant linguistic term, with a word that places the physical information in the context of a phrase that provides the semantic interpretation of it (see also the block diagram in [14]). In such a way, the input physical data object becomes named with an appropriate linguistic label and framed into a suitable linguistic phrase (and further – in a story, a tale, a narrative), which provides the desired meaning for the input physical information. (Again, more details can be found on the website [19]).

VI. WHAT FOLLOWS FROM ALL THIS

Equipped with the "In this paper introduced" (ITPI) definition of Information we can now try to analyze what is going on in a typical ANN-based AI installation (it goes without further saying that DLNN, CNN, RNN, and all other NN versions are simply revisions of the same basic NN layout). Usually, as it is always proudly declared, after an act of training the NN transforms autonomously the data at its input into a semantic label or a semantic statement at its output. Terms "physical information" and "semantic information" are not known to the ANN design community. As a result, any information processing goal has not been foreseen and is not fulfilled in the course of ANN data processing activity.

It is unnecessary to remind the readers that according to ITPI theory, direct transition from primary (physical) information description to secondary (semantic) information description is not possible (does not exist). It is unreasonable, from a theoretical point of view. The grouping of primary data structures into secondary data structures is entirely an observer's privilege and prerogative. The rules of secondary structures organization are subjective, that is, they are solely observer's habits and concerns. Intelligence displaying systems (natural or artificial) acquire them as a grant, as a gift, a shared common agreement (a common knowledge base). Afterwards they all are preserved (conserved) in the system's memory. ANN training phase can be seen as a hint of this processing tread. But in ANN practice, which is devoid of any information processing intents, such things are even do not appear.

The term "information" is frequently seen in ANN R&D texts. But it is used in the sense of Shannon's Information Theory. That is, the term information is used as a substitution swap for data. Shannon's theory does not define what information is. It introduces and exploits a notion of "information measure". Which is equivalent to the "entropy" of a data set. Shannon himself has warned not to mix up the terms (information and information measure). But who cares?

An important outcome of the ITPI theory is the referential mode of information processing, which is unknown (to AI systems designers) and therefore is not addressed in any ANN-based AI designs. The long list of missed AI related properties that must be satisfied in an information processing AI system is not even mentioned here because of the limited article space.

VII. CONCLUSIONS

The purpose of this paper is not to reject or deny AI's virtues or to turn down its achievements. The purpose of this paper is to convince interested people that any further success in AI R&D requires immediate rejection of the ANN approach, which today is the main workhorse of AI modeling.

The notions of AI and ANN were introduced about 60 years ago. It was at the down of the computer era, when, according to the spirit of that time, every fact and every

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action were considered as a computational expression. All scientific fields were considered "computational". The brain and its functions were considered computational (recall "Computational Intelligence", which is alive and prosperous even in these days). Brain neurons, accordingly, were regarded as computational units. It is worth to mention that "computational" always implies "busy with data processing".

The beginning of this century was denoted by a rapid paradigm shift in scientific thinking – from data processing predisposition to information processing preference. Almost immediately, Computational Biology has become converted to Cognitive Biology, Computational Neuroscience to Cognitive Neuroscience, Computer Vision to Cognitive Vision. Almost every conventional Computational science was converted to an associated Cognitive science. (Here "Cognitive" implies "Information processing" aptness and ability). Unfortunately, ANN-based approach to AI modeling has not been affected by this general paradigm shifting.

At the same time, the information processing paradigm adopted by the whole spectrum of biological sciences has led to significant advancement in understanding the nature and special virtues of Intelligence. Intelligence is not anymore a uniquely human attribute. It is an evolutionary developed feature present in every living being, from bacteria to humans. Intelligence – as an ability to process information – is present now (evident, observable, discernable) at all levels of living beings spectrum. It does not require Neural Nets complexity, it is ruled by the same principles of information processing at all levels of living beings presence, [20]. Therefore, such things as Narrow Intelligence or General Intelligence for this constellation do not exist. You can guess that Artificial Intelligence and Natural Intelligence (in such a case and with all their diversities) differ only by the level of information complexity that is supposed to be processed or is actually processed in the system.

I hope that clarification of these issues will help AI designers to avoid dead ended trails and harmful pitfalls on their way to a successful and trustworthy AI realization.

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