Double Deep Machine Learning

Moshe BenBassat (moshe.benbassat@plataine.com)
Arison School of Business, Interdisciplinary Center (IDC), Herzliya, Israel

Abstract

Very important breakthroughs in data-centric machine learning algorithms led to impressive performance in ‘transactional’ point applications such as detecting anger in speech, alerts from a Face Recognition system, or EKG interpretation. Non-transactional applications, e.g. medical diagnosis beyond the EKG results, require AI algorithms that integrate deeper and broader knowledge in their problem-solving capabilities, e.g. integrating knowledge about anatomy and physiology of the heart with EKG results and additional patient’s findings. Similarly, for military aerial interpretation, where knowledge about enemy doctrines on force composition and spread helps immensely in situation assessment beyond image recognition of individual objects.

An initiative is proposed to build Wikipedia for Smart Machines, meaning target readers are not human, but rather smart machines. Named ReKopedia, the goal is to develop methodologies, tools, and automatic algorithms to convert humanity knowledge that we all learn in schools, universities and during our professional life into Reusable Knowledge structures that smart machines can use in their inference algorithms. Ideally, ReKopedia would be an open source shared knowledge repository similar to the well-known shared open source software code repositories.

The Double Deep Learning approach advocates integrating data-centric machine self-learning techniques with machine-teaching techniques to leverage the power of both and overcome their corresponding limitations. For illustration, an outline of a $15M project is described to produce ReKo knowledge modules for medical diagnosis of about 1,000 disorders.

AI applications that are based solely on data-centric machine learning algorithms are typically point solutions for transactional tasks that do not lend themselves to automatic generalization beyond the scope of the data sets they are based on. Today’s AI industry is fragmented, and we are not establishing broad and deep enough foundations that will enable us to build higher level ‘generic’, ‘universal’ intelligence, let alone ‘super-intelligence’. We must find ways to create synergies between these fragments and connect them with external knowledge sources, if we wish to scale faster the AI industry.

Examples in the article are based on- or inspired by- real-life non-transactional AI systems I deployed over decades of AI career that benefit hundreds of millions of people around the globe. We are now in the second AI ‘spring’ after a long AI ‘winter’. To avoid sliding again into an AI winter, it is essential that we rebalance the roles of data and knowledge. Data is important but knowledge- deep and commonsense- are equally important.

1. Introduction

In recent years, Deep Learning (DL) algorithms achieved very important breakthroughs and outstanding results [10], [1]; primarily in image, speech and natural language understanding; leading to impressive performance in ‘transactional’ tasks such as bank-check verification, detecting anger, alerts from a Face Recognition system, or EKG interpretation. DL algorithms use data to automatically train neural networks to make intelligent inferences for tasks covered by the training data. They are based on mathematical/statistical models which means that their behavior is predictable. Once trained to a certain level, they are likely to perform consistently- within their statistical error boundaries- for cases within the scope of their training data. Another key advantage of DL algorithms is the ‘no human touch feature engineering’ for pattern recognition tasks, meaning no need for lengthy research projects requiring domain experts, e.g. fingerprints experts, or EKG experts, to find/extract good differentiating features for classification decisions. Again, impressive achievements which are universal and domain-agnostic. During the early part of my AI career, I could have certainly benefited from DL in many pattern recognition projects, including: object recognition for a Ballistic Missile Defense system (cold war time), ultrasound wave recognition for an autonomous machine digging coal on the moon, EKG, EEG/ERP waves, radar signals, and handwritten character recognition. I view DL’s remarkable progress and achievements as key development in the future of AI; and as a mathematician, it is music to my ears.

However, with all due appreciation, DL algorithms have their limitations, as discussed below, specifically with ‘non-transactional’ applications that require broader and deeper reasoning; possibly involving multiple deep knowledge sources, e.g. optimizing manufacturing and service operations, medical diagnosis and equipment troubleshooting, or military situation assessment and mission planning. Early successes with DL led to overstating its applicability, reaching extreme claims such as ‘with DL and a sufficient amount of data you can solve all AI problems’. The examples bellow, inspired by real life AI
This article is NOT against Deep Learning’s algorithms and architecture; their track record speaks for itself. It is in favor of enriching and amplifying DL, and AI in general, by using the wealth of knowledge that mankind developed in many fields over thousands of years.

Following a discussion of Deep Learning’s current limitations for certain AI needs, I proceed to presenting the Double Deep Learning approach and the idea of Wikipedia for Smart Machines as directions to overcome these limitations. The double use of the word ‘deep’ refers to: first, data-centric deep learning as we all know it, and second, teaching computers deep knowledge, like the difference between teaching physicians versus paramedics, or teaching engineers versus technicians. The computer teaching process could potentially involve some automatic or semi-automatic learning from publications and other documented sources.

“Soon We Won't Program Computers. We'll Train Them Like Dogs” (https://www.wired.com/2016/05/the-end-of-code/) was the title of a June 2016 WIRED Magazine’s article focusing on the key difference between classic software programming that provides explicit step by step instructions how to solve a problem, and Machine Learning software by which you provide sample cases and a generic training algorithm that keeps iterating until the software learns how to solve the problem at a desired performance level. The “dog” analogy was inspired by classic behaviorism studies: “…Pavlov triggered his dog's salivation not through a deep understanding of hunger but simply by repeating a sequence of events over and over. He provided data, again and again, until the code rewrote itself”. Paraphrasing on this title to describe the Double Deep approach, I would say: Soon We Won't Program Computers. We'll Train Them Like We Train Human University Students with Universal Deep Knowledge and with Sample Cases, e.g. medical students. Let us teach computers fundamental knowledge and equip them with generic inference algorithms that will leverage these knowledge modules as they solve a specific case. In medical schools we teach students (a) anatomy and physiology, (b) characteristics of specific diseases/disorders by means of signs/symptoms/test results, along with sample cases, (c) how to execute a good diagnostic process, generically. Note that (a) and (b) are knowledge modules, that are independent of (c) which is a generic inference process. In practice, when a patient arrives he/she does not announce “I have Appendicitis”. He presents initial complaints/signs, and then a physician uses a generic inference engine (c), while accessing knowledge modules (a) and (b) to drive a cost-effective diagnostic process. That’s how I built with my team medical diagnostic systems for endocrinology, for emergency and critical care, for arthritis, for space medicine and for toxicology [2], [3]. The same inference engine- based on Bayesian Inference Networks- was applied to knowledge modules of different medical fields. (The anatomy and physiology part did not exist in the way I would do it today). See more in the last sections of this article.

The Double Deep Learning approach could serve to build DL’s next generation solutions that integrate knowledge modules from the wealth of humanity’s knowledge repository, and thus amplify and expand the applicability of DL. It is likely to improve DL on both sides of the spectrum: increase quality and scope (breadth) of “good” decisions, and, not less important, reduce the amount of glaring mistakes, such as those we see by contemporary personal assistants like Siri, Cortana, and Alexa. (It is OK for an algorithm to make a mistake in a ‘twilight zone’ where a human professional may also err. It is totally unacceptable for an algorithm to make glaring mistakes that even a human beginner would not make. More research effort should be devoted to eliminating glaring mistakes by DL-based solutions as they raise very fundamental questions about the intelligence of the algorithm and risk its credibility). Also, a lot has been said about the risks of DL machines taking over the world. One way to start dealing with that, is to integrate at the output points of DL algorithms- (or within their neural net?)-sanity checks that are based on external knowledge, to monitor DL’s output and, when needed, interfere with the ensuing actions before they are executed, e.g. mistakenly shutting down a nuclear station, or a production line. Several examples are given in the next two sections.

The article is based on lessons I learned over decades of AI-focused career. All examples are based on- or inspired by- real-life non-transactional AI systems I deployed with my teams that benefit hundreds of millions of people around the globe. For example, as of mid-2017, ClickSoftware’s products schedule daily close to 750,000 Field Engineers (FE) for many of the world’s largest service providers. Assuming that each engineer delivers on average 3 to 3.5 jobs per day, and works roughly 210 field days per year, this means that, over a year period, these products touch the life of about 500 Million people, which are roughly 6% to 7% of the 7 Billion+ world population.
2. DL Limitations: Application-Oriented Overview

(a) **When Sufficient Volume of Data does not Exist.** DL requires data, massive amounts of data, e.g. thousands of speech recording hours are needed to build a speech understanding system. For many business scenarios such volumes of data simply do not exist (notwithstanding Big Data, see below).

**Example 1: Troubleshooting New Equipment:** Consider building an AI solution to support field service technicians of a new complex medical imaging equipment that just came out. It will take several years before large and rich enough fault data become available for training a DL-based solution that can guide service technicians with efficient fault isolation and subsequent repair actions. **Do we do nothing until sufficient data is available for a DL-based solution?** In fact, by the time sufficient data is accumulated, the current equipment model is about to be replaced by a newer model. How would a DL algorithm know which data is only partially applicable, or no longer applicable?

**Big Data.** Internet of Things (IoT), connected vehicles, and other intense IT technologies are all around us producing vast amounts of data serving as an excellent source for building AI solutions, e.g. context-aware real-time factory floor optimization, or traffic capacity management; two AI-based solutions I am actively involved with. DL and other machine learning technologies are perfect fit for many cases. While recognizing this potential, we should also be aware though that ‘big data’ is sometimes not big enough for DL, as the following story illustrates:

In a recent business plan presentation of a young entrepreneur, he proposed using DL to recognize patterns of certain business situations while referencing the recent successes in face recognition and animal classification as evidence to the power of DL. When asked about the data he plans to use, he replied proudly and confidently “5 years of good quality, comprehensive daily data (75 variables)”, which indeed is quite nice in a business environment. But this is just under 2,000 cases (365*5); a small number of cases for a DL algorithm to produce useful results.

(b) **Explainable AI.** Today’s DL solutions operate like a “black-box” and even their developers **cannot fully explain their reasoning.** For non-transactional applications in business, medicine, or military, explaining the reasoning is mandatory, or at least very highly desirable. DARPA’s recent initiative into ‘explainable AI’ is very important [7],[9].

(c) **Transactional vs non-Transactional Tasks.** I used earlier the terms ‘transactional, and ‘non-transactional’ tasks. Rather than going into formal definitions, let me use EKG interpretation to clarify the difference.

**Example 2: EKG Classification vs Medical Diagnosis.** With thousands of EKG training data signals, a DL algorithm can do an excellent job classifying an EKG signal shape, e.g. producing as output: Class = "ST Elevation", see [12] based on 64,000 EKG records. If the user now asks the DL algorithm to elaborate on the meaning of its output for patient diagnosis, he/she is unlikely to receive a meaningful answer. A physician, on the other hand, will explain that ST Elevation represents ventricular contraction and may indicate an artery clog that may damage the heart muscle (Myocardial Infarction). The difference between the DL algorithm and the Physician is the level of understanding of EKG findings. The physician’s answer is based on layers on top of layers of anatomy and physiology knowledge, including the electrical impulses and their relationship to EKG findings. For an AI-based medical decision-making system, just EKG classification is a narrow point solution (‘transactional’) to a small part of the problem. Such system should go beyond signal analysis and also connect a given EKG shape to the way the heart functions and fails, and integrate these with other patient findings.

Can a DL algorithm learn from patient data ONLY the anatomy and physiology of the human heart? That is: learn the four chambers structure, the arteries, the valves, the conduction system and the pacemaker, the walls, …, the function of each module and the overall blood flow. I doubt it simply because **patient data does not contain the information to enable such learning.** (To appreciate the complexity, check https://www.youtube.com/watch?v=RYZ4daFwMa8 for an excellent heart simulation that connects the human heart and EKG). Even with man-made fully documented equipment, e.g. Semiconductor equipment, or Medical Imaging, the challenge for machine self-learning of equipment’s structure, function and process flow is enormous. For medical diagnosis the challenge is higher because we are still looking for the engineering design documentation of the human body, ….

As a scientist, I am all in favor of research to push further the spectrum of what data-only approaches can learn, while also understanding its boundaries. As a business executive and AI practitioner, I believe that producing today a working AI system for non-transactional tasks like diagnosis in cardiology and emergency medicine, a more promising approach is to teach computers explicitly the anatomy/physiology knowledge like we teach human medical students, rather than wait until, **and if,** a data-only DL algorithm will learn it from zero at a comparable level.

Several articles report that DL has been successful in medical diagnosis, e.g. for cancer. A fairer description of
the situation would be: DL algorithms support narrow aspects of the medical diagnosis process by providing point solutions such as classifying an EKG signal or detecting tumors in a medical image, or searching for past patients that are most similar to a given patient.

(d) Thinking versus Calculating, Newton’s Physics and DL. With data about billions of “things”, and thousands of apples, that fall down every day, DL algorithms, with no human touch, can certainly come up with a model to calculate the time at which any given falling object will touch the ground. But can DL today come up with Newton’s laws? I mean produce models that represent deeper understanding of Earth forces along with “compact” formula such as Time to hit the ground=SQRT(2*Hight)/g, where g=gravity=9.8 (as opposed to a gigantic black box neural net)? If you are only interested in building calculators for smart machines, you probably would ask back: “Why do I need a compact formula if I get the right result with a DL-generated neural network (possibly even more accurate if the data also includes air resistance?” My answer is that the importance of deep understanding/grasping of Newton’s laws (mid 1600’s) goes way beyond a calculating tool for falling objects. For example, the beautiful law of inertia is not at all about calculation: ‘An object at rest (or in motion) remains at rest (or in motion), unless acted upon by an external force...’ The abstraction, generalization, and analytic formula of Newton’s laws were the basis for future physicists to refine and expand them and discover new ones on Earth forces. Similar processes in the 1800’s led to deeper understanding of heat and energy and the discovery of Thermodynamics laws, then Electricity, continuing all the way to Plank and Einstein (1900-1905) with quantum physics and relativity theory, and on to the Apollo project (1960’s), up until today, a time in which we also have fairly good understanding on gravity forces in Space far away from Earth. In most cases, science discoveries were (a) based on sparks of brilliant human theoretical thinking with very little data to learn from, as Sir Isaac Newton put it: “No great discovery was ever made without a bold guess”, and (b) relied on what was already known; quoting Newton again: “If I have seen further, it is by standing on the shoulders of giants”. As opposed to learning from zero, which is what a typical DL algorithm does.

Why is this relevant to AI? Because physics is one of the cornerstones of engineering, which, in turn, is the basis of all equipment around us that enable life in the modern world, e.g. agriculture equipment, food production equipment, medical equipment, cars, airplanes, and of course, computers and mobile phones. AI systems to support equipment maintenance and troubleshooting can improve substantially equipment’s uptime thereby offering great value. Having led the development of the AITEST troubleshooting AI software and deployed it for dozens of complex equipment around the globe [4], [5], I am confident that equipment-specific design knowledge, as well as universal engineering knowledge, can greatly improve the performance of any ‘data-only’ smart machines. That’s because data can tell you how equipment fails, equipment-specific design knowledge and universal engineering knowledge can tell you how it works. Both types of knowledge are required to reach high performance for diagnostic and repair decisions. The AITEST system illustrates the first steps in this direction, i.e. automatic conversion of engineering diagrams (topology and test paths) into a Bayesian Inference network (on a massive scale).

In summary, it is one thing to learn from data how to recognize visual objects or acoustic signals. It is a totally different challenge to derive from data full understanding of Newton’s laws, how to build a bridge, or how equipment or human organs operate with their dynamic process flows.

(e) Glaring Mistakes: Every other day we hear jokes about glaring mistakes by AI personal assistants, e.g. Siri, Cortana, Alexa, that quickly lead you to recognize the very limited understanding, scope and depth that the software has. DL developers typically focus on maximizing overall percentage accuracy. How do you protect a DL-based smart machine against glaring mistakes that even human beginners would not make? The more you push a DL algorithm for an overall higher percentage accuracy, the higher the likelihood that glaring mistakes will sneak in (one manifestation of overfitting).
While in some applications glaring mistakes may be something to joke about, in others, e.g. military air-defense, they could be catastrophic. Just imagine shooting down a passenger airplane mistakenly classified as a threatening object. Similarly, for potential misclassification mistakes by autonomous land vehicles or drones. It only takes one or a few glaring mistakes to make users question the ‘true’ intelligence of the software to a point that the solution loses credibility and is soon rejected/shelved (before a costly or catastrophic event makes it too late). Arguing that the overall accuracy performance is within the, say 90%, promised error boundaries, does not help much. Business software providers should specifically note that recovering from ‘unforgivable’ glaring-mistake events could take a long time and be very costly for the business. The client may activate liability clauses in the contract, and worse,
the competition may run a whole marketing campaign around it to destroy your product’s reputation. That’s why I always guide my teams with the following principle:

**Glaring Mistake Protection Principle:** In addition to working towards high overall accuracy, you should also always include sanity checks to protect against glaring mistakes with individual cases. Before displaying the output of your ‘ultra-intelligent’ algorithm to a human user, or take automatic action, run sanity checks for extra protection.

Developers of autonomous vehicles are investing in multiple sensors, e.g. cameras, Lidar (Light and Radar), and ultrasound, to overcome the limitations of each individual sensor technology. One more direction to overcome these limitations is to add intelligent algorithms based on humanity knowledge, including common sense knowledge, as well as deeper universal “world” knowledge, e.g. environmental, physics and engineering, and human/animal behavior. Beyond ordinary glaring mistakes, such algorithms could also contribute to overcoming mistakes due to intentional adversarial images designed to fool DL-based systems, see [https://www.theverge.com/2017/11/2/16597276/google-ai-image-attacks-adversarial-turtle-rifle-3d-printed-in-the-context-of confusing a turtle for a rifle](https://www.theverge.com/2017/11/2/16597276/google-ai-image-attacks-adversarial-turtle-rifle-3d-printed-in-the-context-of confusing a turtle for a rifle).

External knowledge is a good way to equip DL-based solutions with ‘sanity checks’/‘second opinion’ to fight glaring mistakes. The example in the next paragraph also illustrates this point.

**(f) External Knowledge which is not in DL’s Data Set Could be Very Helpful:** When a DL model does not produce good enough results, those who are radically religious about ‘data-only’ ‘no human touch’ philosophy adopt a closed garden DL doctrine and limit their options to improve performance to those within the DL world, such as: add data, change neural net architecture, or augment the data with pre-processing operators, and then run again DL. Using external knowledge or alternative inference algorithms are taboo. The following example provide good reasons when and why to avoid the data-only doctrine:

**Example 3: Aerial Image Interpretation; a Twilight Zone Case.**

David and Abi- top notch experienced aerial image interpretation analysts at an Air-Force base- are faced with one of those challenging cases where they cannot decide whether an object O in an image is equipment type A (agriculture) or B (military). They have tried all options to enhance the image, but uncertainty is still very high. Sam, a security specialist who stops by just to say hello, arrives at the peak of their heated debate on A or B. As he is waiting, he looks at the picture and calmly says: “guys, coming from a farmer’s family, and judging by the terrain and vegetation, I strongly doubt it is equipment A, because no farmer would use A in this situation”. After a short pause, Abi says “if this is B, we have a major development”, and David replies: “Absolutely, I am going to wake up Jim (their boss)”.

Sam was using knowledge which is not in the picture data. Adopting the ‘data only’ doctrine of some contemporary DL practitioners is like David and Abi ignoring Sam’s input. It limits the progress of DL. Well, a DL fan would now suggest collecting more data that cover Sam’s farming knowledge and then re-run DL. That’s a good theoretical exercise, but it does not go far, because equipment B only shows up about twice a week for a short while, and every time with a slightly different silhouette, meaning about 100 pictures of B over a full year. Will this be sufficient for DL? Indeed, data augmentation can also be used to fight the low volume of data, and, yes, separate DL networks can be built to learn contexts where objects appear by terrain, vegetation, time of the year, etc., but **why learn from data what humanity already know?**

Table 1 summarizes some of the above key messages and DL’s limitations. All rows in Table 1 are based on- or inspired by-real life ‘non-transactional’ AI systems I deployed and provide further evidence that knowledge plus data are likely to yield higher AI performance than data only. See also Shoham [13]

**Table 1: Data Tells you… Knowledge tells you**

| Object                      | Data tells you… | Knowledge tells you… |
|-----------------------------|-----------------|----------------------|
| MRI (Medical equipment)     | How it fails    | How it works         |
| Frigate ZX8                  | What it looks like | Its capabilities    |
| EKG signal                  | Arrhythmia type C | Relationship to heart’s anatomy, physiology |
| Apples falling to the ground | How to calculate time to hit ground | Deeper understanding of Earth forces |

**Where do we go from here?**

**3. Double Deep Learning**

The maximum knowledge a Deep Learning (DL) algorithm can learn is encapsulated in its data set for the given task, which, typically, is **substantially less than the full humanity’s knowledge for the same task**. The **Double Deep Learning** approach
advocates integrating data-centric machine self-learning techniques with machine-teaching techniques to leverage the power of both, and overcome their corresponding limitations. While the first ‘deep’ is for data-centric Deep Learning, the second ‘deep’ is for ‘machine teachers’ of knowledge and it stands for extra focus on teaching deep ‘foundations’ and ‘first principles’ for reasoning in the task domain; in addition to shallow prescriptive knowledge or just facts whenever needed. By ‘deep’ teaching I mean going beyond teaching just ‘shallow’ ‘experiential’ knowledge which DL self-learning algorithm can also achieve if data is available. This was the main drawback of early days rule-based expert systems of the 1970-80’s. By analogy it is like the difference between teaching physicians versus teaching paramedics, or teaching engineers versus teaching technicians. Or quoting Aristotle: “Knowledge of the fact differs from knowledge of the reason for the fact”. Or, as I discussed above in Example 2, knowing that EKG signal has ST changes, is different than understanding the reasons for this finding, and what actions to take. In 2015, Dietterich and Horvitz [6] also called to attention that:”...we have made surprisingly little progress to date on building the kinds of general intelligence that experts and lay public envision when they think about ‘artificial Intelligence’”. DARPA’s important initiative into ‘explainable AI’ [7] is also likely to contribute to the Double Deep Learning approach.

4. Wikipedia for Smart Machines
ReKopedia: An Open-Source Shared Knowledge Repository

ReKopedia Concept

Think about a repository that contains software representation structures of humanity’s science & technology knowledge in various disciplines; call it the ReKopedia repository. ReKo stands for reusable knowledge. The representation structures could be whatever we agree on, e.g. state transition graphs, neural nets, Bayesian nets, logic, fuzzy logic, frames, or rules, as long as they are reusable by smart machines. I am proposing a community-wide initiative to establish an open-source shared knowledge repository under which people contribute knowledge structures that are compatible with some protocols and enable others to use them. Ideas from Service Oriented Architecture (SOA) and other software initiatives can serve as a basis to learn from, e.g. self-contained modules, no need to know the inside technical details, and, of course, the concept of Web Services e.g. SOAP, CORBA or REST. Modularity is key, together with mechanisms to combine modules into higher level knowledge modules, which, when applied iteratively, create layers on top of layers of humanity knowledge. In today’s shared economy spirit, where almost every AI algorithm can be found in open-source libraries like Python or R, the ReKo repository can be a significant complement and energize the AI industry. The same way we agreed to share open source software code, we will agree to share ReKo knowledge structures. Note that knowledge sharing via textbooks and school teaching has already been a hallmark of mankind for generations. Let us do the same for smart machines.

In the early 2000’s, Google set a goal to scan all humanity’s published books. Now, in the AI era, let us embark on a similar audacious goal to create a Wikipedia for Smart Machines (target readers are not human, but rather smart machines):

Goal - Humanity Knowledge in Software Structures: develop methodologies, tools, and automatic algorithms to convert humanity’s documented knowledge into software structures that smart machines can use in their inference algorithms.

I am not talking about a monolithic centrally managed initiative, but rather a distributed self-organized initiative managed by a mutually agreed upon governance.

ReKopedia Content

Content contribution to the ReKopedia repository can be made in any order and can come from everywhere, subject to some covenant rules. As people build smart machines for a variety of applications, they will contribute knowledge modules to the repository.
I can also envision work-groups in different disciplines, e.g. Medicine, Agriculture, Environment, Military, Engineering, Manufacturing, Field Service, Finance, Insurance, Marketing, and Sales, each coming up with a long-term plan and priorities for the content to populate their domain in the ReKopedia knowledge repository. Reviewing the syllabuses of schools and universities in different areas will teach us the content we teach humans, and can be a good starting point for the content we should teach machines. The CYC project [11], initiated by D. Lenat in the 1980’s with initial focus on commonsense knowledge, led to a commercial product that offers extensive set of reusable knowledge modules and is available through his company.

ReKo Representations and Algorithms

We do not have today all the answers to build ReKopedia for smart machines, in terms of knowledge and problem representations and their corresponding algorithms, but we have very good foundations in Mathematics, Computer Science,
classic AI, Simulation theory, Management Science, Operations Research and related fields. The key principle, in my opinion, is to maximize separation between the knowledge modules and the inference algorithms that will operate on them, as Example 4 illustrates for medical diagnosis.

**Example 4: ReKopedia Modules for Medical Diagnosis: Representation and Practice**

As an indication, the Bayesian Network structures (Figure 1) we developed for knowledge representation in the MEDAS [2]; an AI system for emergency and critical care disorders and their inference algorithms (Figure 2), were also used for Space medicine, for Arthritis, for Toxicology, and for other situation assessment applications beyond medicine. From years of experience, I learned that, on average, about 50 human expert hours are needed to put into Bayesian Network templates the knowledge for diagnosing a single medical disorder. This means that with 50,000 hours we can complete 1,000 disorders which are likely to involve tens of thousands of symptoms, signs, syndromes, test results, and other findings. Assuming 50 to 100 MD’s working part time with support staff over 1 to 2 years, a $15M budget would take care of the expenses to build ReKo modules for a non-marginal part of medicine. In fact, the MEDAS approach advocates hierarchical structures of disorders, which means that after completing a base set, the average time per disorder will come down from 50 hours per disorder.

MEDAS reached convincing performance in its early stages [2], and by 1990 it reached “90% agreement with gold standard” [8], long after I moved on to other areas. As for probability values on the links and nodes of the Bayesian Nets, we can start with known values from medical publications and data bases, or expert’s subjective values, and then, as more patient data is accumulated, apply machine learning algorithms to update them. The Bayesian Nets should be complemented and connected with ReKo modules that capture knowledge about anatomy, bio-engineering, DNA, and other knowledge sources that can improve the inferences made by the Bayesian inference algorithms.

Looking not too far in the future, where in large parts of the world patient data is automated starting at birth date, including genome map data for every individual, ReKopedia-based AI systems can take intelligent healthcare automation to new heights in terms of early warning, prevention, diagnosis and treatment, reducing cost while improving quality.

**Automatic Learning of ReKo Structures from Humanity Documented Knowledge**

Developing tools to automate the conversion process of natural language material; including diagrams and pictures, into ReKo structures, can accelerate it considerably, but it requires taking Natural Language Understanding (NLU) to a higher level. We are not there yet. To get an appreciation of the challenge, consider the task of automatic summary generation of documents. The state of the art of this field tells us that AI NLU software is still far away from “truly understanding” what it reads, let alone extracting knowledge from it, as compared with a college student reading a chapter in an Economy 101 textbook and being able to solve homework exercises. This should not stop us, however, from starting to manually build the ReKo repository for whichever field of science and technology we desire.
Hierarchical Structure of Medical Disorders (BenBassat 1977)

Figure 2: Cycle of Diagnostic Assessment, BenBassat 1980’s [2], [3]

The Cycle of Diagnostic Assessment
5. Summary

Today’s DL-based AI applications are typically point solutions for transactional tasks that do not lend themselves to automatic generalization beyond the scope of the data sets they are based on. The AI industry is fragmented, and we are not establishing broad and deep enough foundations that will enable us to build higher level ‘generic’, ‘universal’ intelligence, let alone ‘super-intelligence’. We must find ways to create synergies between these fragments and connect them with external knowledge sources, if we wish to scale faster the AI industry.

We are now in the second AI ‘spring’ after a long ‘winter’. To avoid sliding again into an AI winter, it is essential that we rebalance the roles of data and knowledge. Data is important but knowledge- deep and commonsense- are equally important.

If indeed AI is the driver of our next economic and social revolution (like electricity was), we’d better establish solid foundations and infrastructure to develop and disseminate it; preferably with standards and fair economics.

Personal Note & Acknowledgments

This article is based on decades of my AI-focused career that are a blend of being a mathematician/statistician/computer scientist (USC, Tel-Aviv University, UCLA), and being a business entrepreneur and 15 years CEO of ClickSoftware, a NASDAQ (CKSW) public company. I have been researching, practicing and educating Artificial Intelligence from the first AI “Spring” of the 1980’s, during the AI “Winter” of the 1990th and early 2000 years, and now in the AI renaissance of the 21th century. My academic research was supported by NIH, NSF, DARPA, NASA, BMD (Ballistic Missile Defense Agency), ARI (U.S. Army Research Institute), Israel Defense Forces, and others.

As the founder and CEO of ClickSoftware (inventor of service chain optimization- patent awarded, acquired in 2015 by a private equity firm), and Plataine (a leader in AI and IoT-based solutions for manufacturing optimization), we leverage AI technologies to solve large scale real-life business problems. We developed innovative AI products that benefit hundreds of millions of people around the globe.

For more details and Publication List see http://www.moshebenbassat.com/

I am very grateful to Israel Beniaminy, my son Avner Ben-Bassat, and other colleagues for deep and useful discussions, as well as comments on early drafts of this article.

References

[1] Brynjolfsson E. and Mcafee A. The Business of Artificial Intelligence, Harvard Business Review, July 2017
[2] Ben-Bassat M., Carlson R.W., Puri V.K., Davenport M. D., Schriver J. A, Latif M., Smith R., Portigal L. D., Lipnick E. and Weil M. H. Pattern-Based Interactive Diagnosis of Multiple Disorders: The MEDAS System. IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. PAMI-2, No.2:148-160, March 1980
[3] M. Ben-Bassat, Expert Systems for Clinical Diagnosis, In Approximate Reasoning in Expert Systems. M.M. Gupta, A. Kandel, W. Bandler, Y.s. Kiszka (eds.), North Holland, 1985, pp.671- 687.
[4] Ben-Bassat M. Use of Diagnostic Expert Systems in Aircraft Maintenance (9 real life examples), Proceedings of Aircraft Maintenance and Engineering Conference, 1996, Singapore
[5] Ben-Bassat M., I Beniaminy, I., Joseph, D. Combining model-based and case-based expert systems, Research Perspectives and Case Studies in System Test and Diagnosis, 179-205, 1998
[6] Dietterich and Horvitz, E. J. Rise of Concerns about AI: Reflections and Directions, Communications of the ACM, Volume 58, Oct 2015, 38-40
[7] Gunning, D. Explainable Artificial Intelligence (XAI), http://www.cc.gatech.edu/~alanwags/DLAI2016/(Gunning)%20IJCAI-16%20DLAI%20WS.pdf
[8] Georgakis, D. C. Trace, D.A. Naeymi-Rad, F. and Evens. A Statistical Evaluation of the Diagnostic Performance of MEDAS-The Medical Emergency Decision Assistance System Proc Annu Symp Comput Appl Med Care. 1990 Nov 7 : 815–819.
[9] Knight, W. The Dark Secret at the Heart of AI, MIT Technology Review, April 11, 2017
[10] LeCun Y., Bengio Y, & Hinton G. Deep Learning. Nature 521, 436–444, May 2015
[11] Lenat, D.B. CYC: a large-scale investment in knowledge infrastructure, Communications of the ACM, Volume 38, Nov. 1995, 33-38
[12] Rajpurkar, P. Hannun, A. Y. Haghpanahi, M. Bourn, . Ng, A. Y. Cardiologist-Level Arrhythmia Detection with Convolutional Neural Networks, https://arxiv.org/abs/1707.01836, July 2017
[13] Shoahm, Y. Why Knowledge Representation Matters, Comm. ACM, 47-49, Jan 2016

-----------------------------------------------------------------------------------
Appendix: Key Messages

1. Machines can learn many things from data, but data is not the only source machines can learn from.

2. The maximum knowledge a Deep Learning (DL) algorithm can learn is what is encapsulated in its data set for the given task, which, typically, is substantially less than the full humanity’s knowledge for the same task. For instance, using field service data, a DL algorithm can learn how equipment fails, but DL cannot learn from such data how it works.

3. Developing and deploying AI solutions when data is not (yet) available is possible, with substantial business value, by directly embedding explicit humanity knowledge.

4. It is one thing to train a DL-neural-net to calculate the time a falling apple will hit the ground using data about falling apples. It is a totally different challenge to train an algorithm from data only to come up with Newton’s earth gravity laws. If humans can learn from explicit teaching, why can’t machines?

5. Machine learning technologies still have some limitations, e.g. with non-supervised learning. Why wait until- and if- someone trains a DL algorithm to learn from data what humanity already learned and documented in textbooks and other publications? E.g. anatomy, physiology, electrical conduction of human heart. Science-wise it has merit. Business-wise it makes no sense.

6. In today’s AI world, data is over-rated, knowledge is under-rated. By re-balancing the two, AI solutions will benefit considerably. On the other hand, by adopting ‘data-only’ doctrine, you give up many options to improve DL’s performance and expand its applicability.

7. The Double Deep Learning approach advocates integrating ‘machine self-learning’ with ‘machine teachers’. The second ‘deep’ is for ‘machine teachers’ with extra focus on teaching deep ‘foundational’ ‘first principles’ knowledge aiming at higher level intelligence, like the difference between teaching physicians versus paramedics, or teaching engineers versus technicians.

8. Being radically religious about a specific algorithm (e.g. DL) aiming to push its applicability envelope as far as possible, is good, even desirable, from a science perspective. From a business perspective, however, it may not be cost-effective, and may even prevent you from deploying today business solutions that deliver tremendous value.

9. Wikipedia for smart machines. AI can grow faster by establishing an open-source shared repository of reusable knowledge modules (coined ReKopedia here) covering humanity’s science & technology in various disciplines. For illustration, a $15M project is proposed to produce ReKopedia modules for medical diagnosis of 1,000 disorders.