Prescription for Profit

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Letter from Academia

AI is being marketed as a panacea solution or a complex "black box" by the PR spin doctors. How to profit from AI in business applications is still unclear. The lack of understanding of knowledge representation, data structures and feature engineering, are a few of the core underlying problems, devoid of easy solutions. This short guide is a note on strategy with respect to the use of AI tool kits. What is necessary for rational use and integration of AI tools with business are humans.

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1 Pragmatic use of Artificial Intelligence

Pragmatic use of Artificial Intelligence (AI), which can catalyze corporations to profit from applications of AI, is the ultimate goal for business and industry. Academia could help industry achieve this goal, albeit in part, the rational part.

The probability of bursting the public relations bubble, and the hype about the promises made on behalf of AI, are increasing. It may be reduced if industry and management better understood why the world must opt to lower its expectations of "intelligence" as an outcome from AI tools.

The suggestions in this letter does not distract from the rational possibilities of using the principles of AI in data analytics, decision support, and even, in automation.

During 1955-56, the term "AI" rather than "computational rationality" was used to describe a "new" and "emerging" field. The difference between the terms is a matter of states because "intelligence" is continuous (core attribute of many biological processes) while "computational rationality" is a discrete process. The latter is explained by the boundaries of limited rationality which systems generate, based on computable models.

The cognitive glue, necessary to bond discrete events to form the continuum, may be a cherished objective, but remains an illusion for science, and delusion for engineers, at this time. This brings to mind the pithy words of John Searle "brains cause minds" as if to say that a mere collection of cells (neurons, glia) will lead to thought, action and consciousness. It is true, the brain is a collection of these cells, but does that suffice to serve as a platform, to extrapolate the brain to the scope of the human mind?

To illustrate the issue on page 7 (see https://dspace.mit.edu/handle/1721.1/108000), I refer to (https://link.springer.com/content/pdf/10.1007%2Fs11633-017-1093-8.pdf) a recent paper. It starts with states (each binary bit has two states, 0 and 1) and memory storage capacity. A human brain has $1x10^{14}$ neural cells (100 trillion synapses) with approximately $2x10^{15}$ states, equivalent to a storage capacity of 500 terabytes (assume 4.6 bits of information stored by each synapse). Hence, $2x10^{15}$ is the number of synaptic connections in a human brain. Is this, then, the capacity of the human mind?

In our mind, cognition allows us to read, write, create, and understand language, simple and complex. Our vision can distinguish topology of objects, colors, size, depth, shades. Our five senses, in combination, can respond to an array of input, to produce a vast (unknown) number, and variety, of output. If artificial neural nets claim to "capture" the brain and if we can scientifically describe this *capture* as "brain in a box" then, this network, if etched on a "neuromorphic chip" is the sum total of "intelligence" that we may rely on, for all our activities. By this rationale, "intelligence" is governed by the maximum number of states of our synapses. That number is about $2x10^{15}$ and that is, by this account, the total number of instances or the magnitude of combinations of our thoughts. Is this a true statement?

As Danko Nikolic points out, an English speaker's vocabulary has about 15,000 words which consists of 5% adverbs, 20% adjectives, 20% verbs and 55% nouns (750, 3000, 3000, 8250 words in each of the four categories, respectively). From those numbers, we can calculate the number of all combinations, of sentences, of different lengths. For four word sentences, consisting of a noun, followed by a verb and ending with a noun plus an adjective, we obtain 8250×3000×8250×3000 or about $2x10^{18}$ combinations. We have not even pondered about the semantic boundaries of the syntax in the four-word sentences. This number ($2x10^{18}$) is already bigger than the limit that is posed by the total number of synapses in the brain ($2x10^{15}$). By this reasoning, there isn't enough memory in our brains to generate a different response even for sentences with 4 words!

At this stage, we have only considered "speech" and limited our expression to 4-word sentences. Limited by the storage capacity of the total number of synapses in our brain ($2x10^{15}$) we will not be able to see, hear, taste or touch, among other things. Do we still wish to continue, and support marketing campaigns, suggesting that deep neural nets are equivalent to biological intelligence, which powers AI? Hence, is there intelligence in AI?

The fact that humans possess at least five senses, and do much more than what $2x10^{15}$ synapses may allow, is due to the fact that this number is an anatomical representation of the number of discrete connections. This is the ***structure*** of the organizational aspect of the anatomy and topology of the human brain. Structure is ***not*** the same as ***function*** in the same manner that anatomy (human skeleton) is not equivalent to physiology and physiological function (human organism), even though the skeleton (structure) is quintessential for physiology (function).

It is ***function*** that generates the amorphous quality of intelligence and makes humans intelligent. The numbers in the structure are discrete. The numbers matter, of course.

With 302 neurons, potential structural relationships in *Caenorhabditis elegans* (worms) may not qualify to provide intelligent functions or even pattern recognition.

The function of intelligence is best perceived as a *continuous* fabric, inextricably linked with data, rules, patterns, experiences, knowledge and learnings to inform or support decisions.

The almost unlimited number of connected continuity, the underpinning of intelligent human action, is a result of $2x10^{15}$ synapses which are being formed, and re-formed, connected and disconnected, re-connected and re-configured, in an asynchronous, dynamic manner, in response to signals, perceived, received, in processing or being transmitted. Signals may originate from diverse sources (internal, external, autocrine, endocrine) or may be presented to sensory interfaces in a multitude of shapes or forms.

Continuity is not an attribute of a computable model. The term AI was less appropriate than "computational rationality" in 1956 and it is even less appropriate, today. But, we may use the term AI, for the sake of posterity, its magnetic image and public imprint.

The term intelligence is supposed to present a mental image relating evolution of words, objects, ideas, in terms of meaning and context. It is not a discrete, structural, one to one syntax, which can be translated. It is an *interpretation*, based on semantics, and by extension, logic, and ontology. The fact that intelligence may not be amenable to simple syntactic translation was demonstrated by the almost abject failure of the Russian to English translation during 1960s (prior to use of convolutional or recursive neural nets).

The "artificial" architecture of intelligence may have literary roots. Perhaps, a reference to *Leviathan* by Thomas Hobbes (1651) or similar, from that school of thought. Hobbes argued for "artificial animal" based on observation that the heart is a spring, nerves are strings and joints are wheels. Attempts to mimic birds and develop "artificial flight" did not lead to aviation. The right approach by the Wright Brothers was to view flight as a function of aerodynamics, which gave birth to the airline industry. Reality of flying, for human use, was not a reproduction of the fantasy of viewing birds in flight.

2 From Taylorisms to Terabytes

The movement from Taylorisms to terabytes needs AI, and its tools. Hence, AI, despite its limitations and a handicapped terminology, presents opportunities for companies to automate business processes. But, fantasy driven scenarios, about winning at GO or poker, may not suffice for integrating AI or ML applications, in the real world. While ERP implementations enhanced competitiveness, several companies also uncovered nightmares. The promised opportunity from ERP never came to fruition, for some. Do we have a sense of *déjà vu* with AI? The rain on the AI parade falls mostly on input data and the output/outcome. Unless reliably automated, the outcome requires people to do something with the information. Is it actionable? AI analytics cannot help if input data is noisy or corrupt. How do you know the data or the outcome is of poor quality?

AI and ML can augment performance. In case of AI (more than ERP) those changes create highly skilled tasks which require education, prudence and domain expertise, *from humans*. Businesses are forever in an elusive quest for "low hanging fruit" without gaining the wisdom from repeated failures. The pursuit of "low hanging fruits" require only low level skills. That *modus operandi* may not help, at all, to profit from AI.

Generating value from AI by recruiting more data scientists is an amorphous escape clause. Several domains converge under the umbrella of data science, which makes it impossible to ascribe the term data scientist, to any one individual. Data science is a team sport. Bringing the talent together, and synthesizing the unpacked problems, are tasks that few companies can execute because companies do not have, or rarely employ, strategic *cube-on-cube* thinkers.

Companies do not even know, that they do not know, that they lack trans-disciplinary cross-pollinators. Companies and HR are unable to comprehend that they need people with broad spectrum of knowledge "cubes" and a matrix of experiences, unlike those that can fit in a box. "Thinking different" is not a principle that HR departments can practice. Hence, the clamor for data scientists but lack of jobs describing the need for out-of-the-box thinkers, followed by an absence of zeal, to pursue the road not taken.

Thinkers are pivotal to assist teams to dissect problems into components, to identify the confluence of domains, and underpinnings of potential solutions. Creative thinkers are key to assist the leaders to move the fulcrum and mentor the rank and file to frame the correct questions. Hiring and allowing *cube-on-cube* thinkers to form agile, case-dependent teams, staffed with vertical experts, across silos (network of business units), may be the first step to profitability, from advanced applications, which are fueled by convergence, such as, AI, analytics, robotics and nanotechnology.

Data science must start with data. Data must be acquired, processed and curated to serve the business needs. Hence, the critical demand for domain experts, and field knowledge providers, who must help identify the obvious, common, and uncommon "features" that businesses are seeking. Then, add non-obvious relationship analyses, and garnish with unconventional wisdom. To harvest the latter, perhaps crowd sourcing may be useful.

Organized data, using the principles of knowledge representation and application of logic and ontology, is a starting point, to construct computable models/structures of the domains of interest (agnostic of industry, vertical or horizontal). In the computational phase, we can use algorithms and tools from AI including ML, DL, ANN, CNN, RNN.

The trinity of out-of-the-box thinkers, who can connect the cubes, with field knowledge providers, and computational experts, is the "secret sauce" which must be continuously stirred, shaken, configured and re-configured, to blend the correct team, case by case, to profit from AI, and use the ability of AI, in problem solving. This approach and grasp of the extended fabric, is lacking in businesses and absent within corporate leadership.

The marketing hype, which is furiously polishing the chrome, on the AI engine, may help to explode the bubble and trigger a second AI winter. Global warming will be essential to thaw the AI ice age. But, before we boil the ocean, let us try to warm up to what may be necessary, the prerequisites, what is missing, how deep is the abyss and how education may bridge the chasm. Let us imagine, we have managed to fast forward to the spring of AI. Assume, AI in the tool kit is generating probabilistic output.

As pointed out by Jeanne Ross, an AI application indicates that a lead has a 95% chance of converting into a sale, while another has a 60% chance. Should we assume the salesperson knows what to do with that information?

ML applications may help lawyers identify appropriate legal precedents, help vendor management teams ensure compliance with contracts, assist financial institutions to gauge risk. These systems use ML to perform mundane tasks. Systems can learn to develop spreadsheets and search databases for relevant information. But, in order to generate competitive advantage from ML (AI), we may need skilled humans to process the outcome. Hence, companies must redesign accountabilities, motivate employees to deploy ML tools, when they believe it may enhance outcomes. The educated workforce of the future must possess higher order skills, capable of consuming intelligence, and trigger actions to benefit, and hopefully, profit, from the deployment of AI tool kits.

Hence, these AI tools must be capable of use by general employees. The tools may be drag and drop interfaces representing abstractions. The employee may not need to deal with the computational complexities, programming principles and Boolean operators. To use these abstracted tools and intuitive interfaces, the educated workforce, in future, must possess skills which catalyzes the *consumption of intelligence, the outcome*. The educated consumer is the best customer for the future of AI and to profit from AI tools.

This raises a critical issue concerning K-12 education and how learning must be adapted to deal with the imminent socio-economic disequilibrium. Education must address the changing face of the supply chain of talent as well as the ingredients which are necessary to future-proof workforce preparation and make the workforce future-ready.

The future is not about apocalyptic reduction of employment. It is about a refresh of skills, which must be updated and upgraded, for the humans in the loop, to play relevant roles. We need the AI tool kit to help reduce uncertainty, and better manage, volatility.

To achieve that goal, executives need to appreciate the principles of data analytics and AI. Leaders must support education, inculcate insight and remain eager to learn, before they leap to manage. Leaders must institute internal education and external learning liaisons, where thinkers are viewed as assets and not as cost centers. Leaders must stress on understanding how AI works rather than blindly purchasing “black box” solutions.

The digital world will still need to serve analog communities. AI may lead to profit, if allowed to offer reliable computational assistance to the workforce, customers, and the global ecosystem of consumers, seeking credible, rational, near real-time, and perhaps predictive, decision support.

All things considered, the path to profitability rests with the imagination and the vision of the executive management and their counterparts in academia, and government.

Corporate leaders must evolve in their leadership roles. Leaders must assume the risk of leadership. Leaders must engage to provide broader guidance, bring parties to the table (competitors) and advocate for interoperability of architectures, to enable digital connectivity. Without security, digital transformation could be annihilated. Without connectivity, without data from different systems and ecosystems, without knowledge of what is *beyond the boundary*, the ability of AI, analytics and tools such as blockchain applications, will be curtailed. The outcome will be less valuable, less actionable, less profitable.

Hence, leaders must champion digital transformation by leading, and inspiring global teams, and navigating businesses to lift many boats, not just their personal yachts.

Acknowledgments. 1) This “letter” also appears as APPENDIX 6 in the essay “03.AI” available from the MIT Library – see folder “CHAPTERS” https://dspace.mit.edu/handle/1721.1/106496. 2) *The Fatal Flaw of AI Implementation* by Jeanne Ross, MIT SMR (14 July 2017) served as a source of a few examples and the reference to enterprise resource planning.