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Random Thoughts: “Comprehensible & Sustainable” Computational Intelligence



My journey as the President of the IEEE Computational Intelligence Society (CIS) began on January 1, 2018 quite smoothly because of enormous help by my predecessor, Pablo (Estevez) and other friends at CIS including Jo-Ellen (Snyder) and Tom (Compton). So far it has been an enjoyable ride, but I have realized that there are challenges and it is fun to deal with them.

In my last message I discussed some of the important issues related to the present day “intelligent systems”. Here I express my personal views on two other important issues: comprehensibility and sustainability. I think time has come for us to emphasize more on “comprehensible and sustainable” Computational Intelligence (CI)/Artificial intelligence (AI).

Good performance is definitely a requirement for any intelligent system. But if the system is not comprehensible/understandable at all, sometimes the system may fail with catastrophic consequences and we may not have any clue of that ahead of time. For example, a deep neural network, known for its unmatched performance, as of now, is a “black box” and we all know of some very simple situations where it miserably failed [1], [2].

Comprehensibility is a fuzzy concept with grades of membership beginning from zero for a black box system to one for a completely transparent system. For example, decision trees or crisp rules are highly comprehensible as long as the number of conditions involved is small. But with an increase in the depth of the tree or the length of the rules the level of comprehensibility reduces, yet they are comprehensible to some degree compared to, for example, a multilayer perceptron. In this context, a fuzzy rule-based system is highly comprehensible when the number of antecedent clauses in a rule is limited. Even when the number of antecedent clauses is high, because of the very nature of fuzzy reasoning, it is easy to visualize how fuzzy rules work and why it is unlikely to make an unexpected decision/generalization. But these systems, although can provide understandability, are usually poor performers compared to support vector machines, deep neural networks, or even multilayer perceptron networks. Thus, it would be good, if we could inject some level of comprehensibility into such systems to realize both comprehensibility and good performance. Fuzzy sets could be a possible vehicle for this. In fact, incorporation of fuzzy concepts may even help to deal with uncertainty. Some attempts have been made in this direction, but it deserves more attention – we need more emphasis on comprehensible CI.

Now I turn to the other issue, sustainable CI/AI: According to the Oxford Dictionary, the word sustainability means “The ability to be maintained at a certain rate or level”. Sustainability demands efficient use of energy, use of renewable energy, and preservation of natural resources and our environment. To design an intelligent system for a given problem almost always we focus on maximizing/minimizing something that will help to satisfy our needs. Usually, these needs are our immediate needs. While

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designing a system, primarily we focus on achieving the best accuracy for the assigned task. It is more often than not, we forget or ignore the long term environmental impacts of what we do. But why should we, who primarily develop learning algorithms for problem solving, care about it? The answer lies here. The carbon footprint of using just a common server is much more than what we can imagine. The total carbon footprint of a Typical Dell PowerEdge R710 rack server is 6360kg CO₂eq assuming a four year life which is comparable to driving 21,500 km in an SUV [3]! The specific configuration of the machine used to arrive at the estimate of carbon footprint is: 2 processors (Intel Xeon); 12 GB of RAM; 4 × 146 GB hard drives (HDD); 2 high output power supplies; 1 DVD drive; and 4 fans. This is just an illustration, newer servers with similar computing power may have lower carbon overhead while others may have more. Computer hardware companies are trying to address this issue. We also have a role to play. Often our learning algorithms run for days/weeks on a much more powerful platform on a big data set. One can easily imagine how much impact computers, in particular data centers, can have on our environment in terms of carbon footprint. So when we design our next algorithm, we should take this factor into account.

The other important facet of sustainability is related to the solutions that we provide. To emphasize this issue I take the help of smart agriculture systems. On September 25 2015, United Nations set 17 goals to transform our world [4]. The

second goal is: End hunger, achieve food security and improved nutrition and promote *sustainable agriculture* (the first goal is: End poverty in all its forms everywhere). It emphasizes that the goal of a smart agriculture system should be not just maximizing the yield but also to ensure the sustainability. Sustainable technologies should cater to the needs of the present generation without compromising the needs of the future generation. Just to clarify, suppose we want to develop an integrated smart system for crop management. Our goal should be to *Maximize the yield using Minimum resources (human effort/cost - not necessarily money) with Minimal impact on the environment for serving the Maximum (inclusiveness, catering social needs) (M^4).* Such systems should be able to guide farmers on the following: What to grow? What would be the optimal distribution of different crops (farmer level, state level, country level)? When and how much to irrigate? When, which and how much fertilizers to use? When, which and how much pesticides to use? And when to harvest? To realize sustainability, the system should assist farmers on all these issues imposing constraint, for example, on the use of nitrogen, pesticides, and water. Why? Nitrate may lead to better yield, but has serious environmental impacts. It pollutes water, kills plants that need low level of nitrogen, promotes growth of non-native grasses and kills lichens, and causes a decline in native species. It has also been linked with causes of many diseases including methemoglobinemia, cancer, birth defects, and hyperthyroidism [5], [6]. So, we need

to ensure the use of the Right nutrient at the Right rate in the Right place, and at the Right time (R^4). Similarly, a smart system should help to minimize the usage of water and pesticides. All these demand complex modeling and optimization to develop systems for prediction of weather, prediction of nutrients' need (at the level of small units of land), control of drone-assisted delivery of precise dose of pesticides and so on. Just in the area of agriculture, there are many other environment-sensitive challenging problems. CI provides a set of very useful tools for these. As examples, for some of the problems, the objective functions to be optimized may not be differentiable and in that case evolutionary algorithms could be handy tools. Like anyone else, farmers will not like black-box type systems. Here use of fuzzy modeling, wherever possible and useful, could be attractive.

To conclude, I would like to emphasize that while designing intelligent/smart systems, we need to take the comprehensibility and the sustainability of the algorithms as well as the sustainability of the solutions they provide much more seriously than we have been doing. These are certainly very difficult and challenging tasks and we need to make an effort to address them.

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