Guidelines for designing AGI

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***Abstract*— ML as the technical implementation of AI is not fully exploited as it could and should be. "Learning" in ML is actually an identification process based on sophistical memorizing, without involving any thinking or imagination. Although comparing to a lot of control methods, this modeling is highly dynamic as it changes by each input, but in the big picture, when looking at the full potential of intelligence, this is a passive model, since it has a fixed structure (such as DNN or any other network) and there're no higher brain features/capabilities involved in it, as thinking, imagination, etc.**

We suggest in this paper, a general methodology how to tackle this issue, in order to develop further the AI field, to a more meaningful phase in the history.

Most guidelines are situated in a continuum between mandatory to suggestion, but it is hard to define which is which.

I. Introduction

Not only that "Learning" as defined in ML is simply an identification process based on sophistical but limited memorizing, without involving any thinking or imagination. But reinforcement learning is also type of a low/narrow intelligence, which exists also in animals, such as in Pablo's dog experiment, where learning were taught by positive (reward) and negative (punishment) feedbacks.

ML is still a part of AI for a good reason - it replaces the need for the user to know and be familiar with the problem extensively [1], and gives a general method that can find good solutions from example training. Also, this is kind of a higher type of programming - where no explicit coding is done.

However one must remember that studies showed that for a successful ML we need to know the system, also ML is a very task-specific strategy. Also ML is a static structure/model imitation of the brain, while there is the effect of dynamical processes, such as construction/destruction of neurons. Moreover, it is not fair to compare performances of ML to a regular control-based method designed by a human [1] or to the use of statistical methods [2], after studying the system. The reason is that ML know the problem only from a limited set of examples, that frequently do not represent all situations, but it also lack the comprehensive vision as a human has. Hence, this is another reason for the necessity with conclusion-generating AI.

Also the curse of dimensionality (COD) says that as the input vector of information is larger, then we require exponentially more examples to keep the same performance level. That's whyBut downsizing dimensions methods because of a small number of available examples result also in poorer performance.

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But this is because of the wrong attitude towards AI. If we'd relax the performance or replace it totally with other criteria to judge AI, then we'll exchange the desire to fit some NN model to the data (by enormous amount of examples) and thus fixing this model to represent this specific data and nothing else, with enabling freedom for the AI to generalize and process (by less amount of examples).

....(taken from proposal) There are such NNs which use back-propagation for their weight adaptation, e.g. for traffic congestion prediction [**?**], or to replace traffic simulator [**?**] by training on simulation parameters (as input) and their outcomes (as outputs). [**?**] also demonstrates that NN is best for performance if its structure is appropriate to the data it is trained upon. Not too much neurons nor too little.

Remark: This optimal number of neurons and layers might be because there are the most appropriate features to describe the trained data. Any other structure may result in some kind of a spreading over some features that are not really representative, of the data.

... Many DNN's are developed for a very specific tasks in relation to visual information. Such features for example as a change in light, different angles, recognition of boundaries of objects in an image. And all that only on static photos, before we consider to add movement and video type of change in time. The amount of work and theory developed around computer vision area is huge, but I don't consider this as an effective method to use real intelligence. Since we doing it all again as we did with simple model algorithms: programming very big code to handle for example a task of computer recognizing space or a robotic arm movement task, to take into account all possible scenarios.

Or the fact that most of the thinking and planning occurs in the human part taking, and in the machine end all is left is an execution.

But this is not a progress. We should learn the basic real intelligent learning as it occurs in human, without these complex programming, the way we distinguish and recognize objects in a changing environment. And we have to build an AI such that it isn't expected to be stable or perfect right away, immediately at first execution. This is a wrong attitude towards actual intelligence.

On the contrary, we have to give it the time to develop, just as an infant baby and a child do, and not demand from it to give always "correct" answers, but instead - as a human does

- allow it to make a mistakes based on partial understanding and learn from it not as a new input in DNN, but as another step in a more general and mature step of development. As a more general point of view on the data he encountered during its lifetime.

In other words, as the comparison between serial thinking verse parallel one [3] show, that in serial one we prefer judgment and quick selection or fast results with emphasis on certainty, in parallel however it is fluent and non-judgmental in favor of fluency and multiple solutions and options together with their probabilities, i.e. allowing and welcoming uncertainty instead of fighting it. The same is here, model-based methods and control are mostly designed for fast good results, to prove effectiveness. But human intelligence shows, that it takes years for an infant to gather linguistic capabilities and fine motor sensing. It takes a many months, in which the baby is mumbles or pronounce poorly and have a gross motor skills (i.e. in movement and drawing). This observation support the idea that the more AGI is general, to deal with as variant knowledge as possible, the more efforts it take to adapt and learn this knowledge. And the opposite is true also - the more the AGI is specific, like current control methods, than the more it fits to be effective in special data and faster in results.

This is actually the difference between efficiency and effectiveness [4], where efficiency concentrates on the best exploitation of available resources, while effectiveness is about performance measure of how well the goal is achieved. Consequently, the AI must be efficient more than effective, since we're less interested in some specific desired outcomes, but rather a good thinking machine which can be validated only on the long run. Same idea expressed within the comparison between serial and parallel thinking [5], where using parallel thinking means a more general, comprehensive and planning, including the freedom and the space to explore, taking intelligent risks and long trial-and-error. In contrast, we have demand for perfection and immediate success in serial thinking. In other words, a broader view to see how one can be more effective in the bigger picture rather than in some specific and narrow tasks.

We shouldn't forget that we mimic the next best thing. Just like we imitated many processes in nature such as GA, flying, and many more - what a man engineered frequently had a poorer quality. Because usually these versions were only a simplified copies of the real thing. So how can we expect so much more from an imitation of human brain activity? With so little knowledge about it yet, and yet expect it to perform better than the real thing? Better than human.

REFERENCES

[1] B. Abdulhai, R. Pringle, and G. J. Karakoulas, "Reinforcement learning for true adaptive traffic signal control," *Journal of Transportation Engineering*, vol. 129, no. 3, pp. 278–285, 2003.

[2] M. G. Karlaftis and E. I. Vlahogianni, "Statistical methods versus neural networks in transportation research: Differences, similarities and some insights," *Transportation Research Part C: Emerging Technologies*, vol. 19, no. 3, pp. 387–399, 2011.

[3] E. De Bono, *Parallel thinking*. Random House, 2016.

[4] [Online]. Available: https://simania.co.il/bookdetails.php?item$_id = 145306$

[5] E. De, *Parallel thinking: From Socratic thinking to de Bono thinking*. Penguin Books, 1995.