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Perspective paper: Can machine learning become a universal method of laser photonics?

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ABSTRACT

Machine learning methods are being successfully applied in various domains of human activity, including optics. Can they become a universal instrument capable of improving user aspect of photonic devices? Is their application a necessary element of such improvement? Answers to fundamental questions arising from application of machine learning methods in ultrashort-pulsed lasers are discussed. Future prospects and current fundamental limitations of such methods are analysed.

1. Introduction

The present work focuses on conceptual problems of application of machine learning (ML) methods in photonics, practical questions arising upon familiarising oneself with numerous books [1–12], specialised journals [13–17], courses, webinars, forums and articles [18–53] that mushroomed within recent years around the topic of which new possibilities can be developed from intellectual analysis of data in our life generally and in photonics particularly. It is stated that we are approaching the threshold of a new scientific revolution (or at least the threshold of total automation) and that the coming technological paradigm will be actively based on algorithms of artificial intelligence (AI). The current wide-spread excitement around ML/AI leads one to think about the applicability of ML methods in those fields where their advantage is not immediately obvious, even though overall, ML methods are at the centre of the new technological revolution and their further development is quite certain.

Massive development of ML methods (including the recent adoption of deep learning [6–8,10] relying on a vast number of adjustment parameters) began with rapid pace of computer technologies, technical possibilities of big data manipulation, and understanding of complexity limits related to constraints of the human brain (Fig. 1). Owing to the advent of computers, a certain part of algorithms was successfully transferred from man's mind into an artificial digital medium where they may be executed much faster, retained more reliably, etc. On the basis or with significant reliance on ML algorithms, more and more advanced robots are being created, unmanned vehicle technologies are developed, progress is being made in data recognition technologies (including speech recognition and machine translation), inverse problem solving (molecular design, etc), epidemic process modelling, and so forth (a few recent examples of successful application of ML methods are given in [54–64]). Introduction of ML/AI into certain technologies has substantially accelerated their advancement. Success in these technologies was construed to warrant wider application of ML methods in drivers fields and gave grounds to conclusions as to universal nature of these methods, a claim, no doubt, exaggerated. It is often assumed that ML/AI alone is able to fully develop the true potential of such complicated equipment as lasers, solving problems better, faster, and cheaper than man (or at least on the level of human achievement). Let us find out whether or not this may be so. First of all, we would like to understand if a laser system is one capable of learning. Would AI be capable of extracting knowledge from data streams in laser systems and of further modifications to the initial algorithms according to the new knowledge? Would it be thus possible to improve the operation of a laser system in some sense?

Photonics, as well as optics, constitute vast and diverse fields. Successful application of some approaches in one department of photonics does not necessarily mean that similar approaches will be as successful in its other departments.

It is necessary to recall that the methods in question pertain to AI and are conceived to search for solutions by learning in the process of solving analogous problems. What kind of analogous problems may exist, for example, in short-pulsed fibre lasers? Arguably, this is generation of pulses with different parameters and/or structure. What can be facilitated by applications of ML methods that generally produce results in proportion to the digested data volume? Conceivably, the laser could, as a result, be operated better, while generating the desired output parameters. Conceptually, this is all valid and a positive effect of ML

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application should be obvious. However, the devil is in the detail, and hypothetical possibilities may be as far from reality as mathematics is from physics.

2. Discussion

We can start by asking how big data could be generated in short-pulsed lasers. Even the presence of various generation regimes producing different pulses does not automatically prove big data in the laser. At a minimum, these data must be registered and transmitted for processing and analysis. It is implied that the laser should be buried under a pile of measurement equipment (auto-correlator, spectrum analyser, and so on) and sensors for collection of data required for implementation of ML methods (Fig. 2). The more a machine knows, the more intelligent it is. Therefore, the more complex and 'smart' its behaviour may be. Data collection equipment may be used at the laser fabrication facility or directly on user's premises. It is obviously unprofitable to use such equipment as an 'appurtenance' to each laser, because its cost may exceed that of the laser itself. Additionally, the learning time and the data set required for such learning are often overlooked in discussion, even though these parameters are practically important and not infrequently, it is taking into consideration of these parameters that determines applicability of ML methods.

In order to avoid supplementing each laser with a set of measurement equipment, an idea naturally arises that the laser parameters should be characterised 'for all occasions' at the factory (creation of generation regime maps, etc). This approach does not, however, succeed all the time. Real life is richer than any engineer's imagination, therefore it is impossible to circumscribe all the situations related to the laser operation. Supposedly, it is these situations that call for application of ML methods. It should be remembered, nevertheless, that so far these methods have been designed by humans and not always can be used without human intervention. No allusion is made here to occasional use of deterministic algorithms (such as the gradient descent method, for instance) under the guise of ML methods. Instead, it is pointed out that until now, AI is incapable of adequately and efficiently responding 'for all occasions'. There are many reasons for this, beginning with insufficient processing power and ending with poorly developed ML methods.

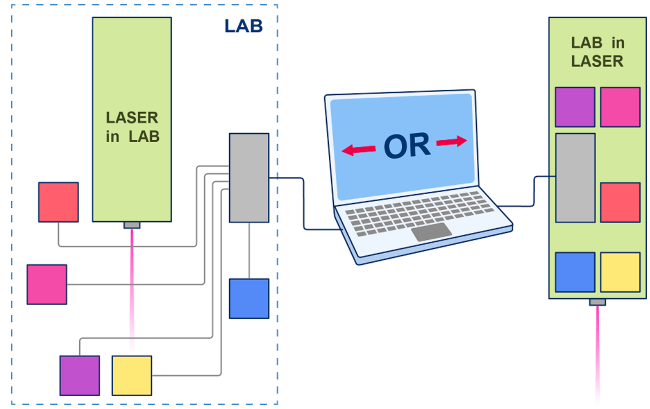

Fig. 2. Possible ways of data collection in a laser: with a set of laboratory measurement equipment (left) and with built-in sensors (right).

Neither should it be forgotten that ML methods may be only efficacious when either the human intellect is insufficient (lacking computational power and memory) or ML algorithms offer a significantly cheaper solution. It must be borne in mind that from the practical point of view, ML is aimed at development of system capable of adaptation to solving various problems without explicit algorithm coding, that is systems capable of learning. The question arises: what is it they are supposed to be learning? Could this be selection of the best (optimal, pre-determined, etc.) solutions from the modest number of solutions possible in a typical laser?

Secondly, even the laser field itself is quite broad (leaving alone the entire photonics domain), there are as many different lasers as, for instance motor vehicles. There exist lasers that do not need any AI, they operate perfectly without it. A simple mnemonical rule may be here suggested: a well-operating laser can dispense with AI algorithms altogether, it is a poorly operating laser that needs ML methods, optimisation, and so forth.

It should also be pointed out that AI algorithms must be profitable: something should become better, faster, cheaper. So far, application of such algorithms often ends up solving a given problem slower and more

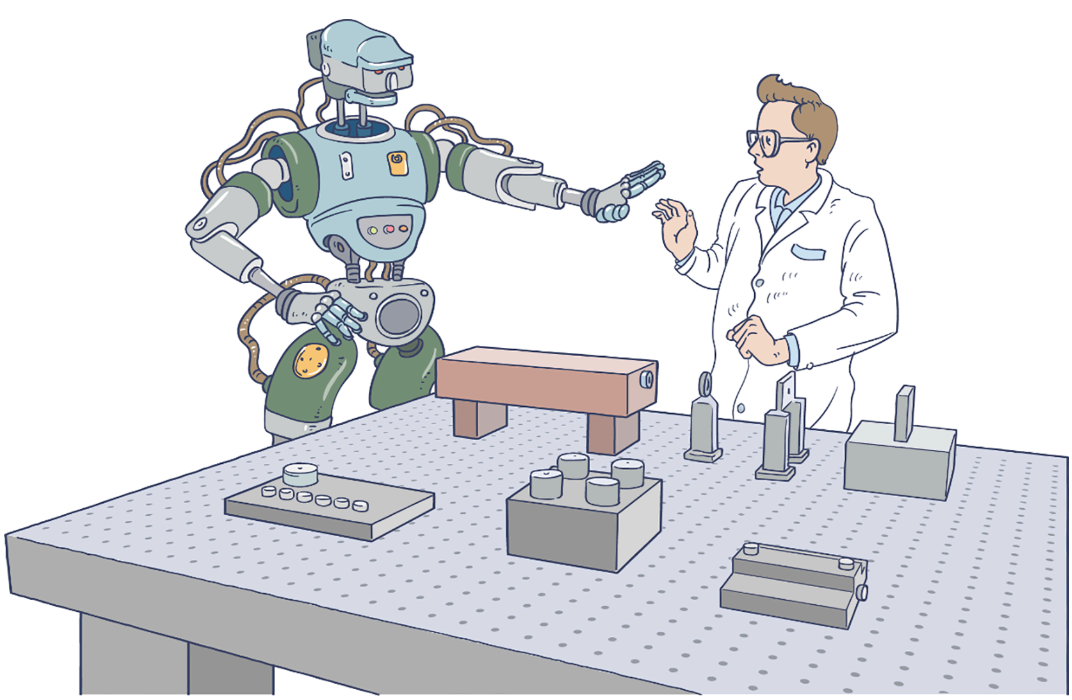

Fig. 1. Artificial intelligence and laser: fad or trend?

expensively, while the quality of the provided solution places it rather in the philosophical realm. Furthermore, analysis of application fields of AI algorithms demonstrates patent lack of universality and obvious specificity of these algorithms. Generally, ML methods rarely enter the design of photonic devices and are not even used as a marketing ploy. This may be caused by the users' distrust of these methods, especially that some of them are in reality backed by conventional explicit branching algorithms for the majority of possible cases.

Machine intellect will undoubtedly become the main technological innovation of the future progress, but today, ML methods find limited application. This is also valid for photonics in general and for lasers in particular (see, for example, [19–26]). We should not think that problems in lasers, which have not been solved by humans (setting of the generation regime, selection of the output radiation parameters, etc.) will necessarily fall within the capabilities of an AI system. So far, attempts to apply AI methods everywhere have been mainly fostered by unreasonable expectations. Machine mind potentially may become much wider applicable, but until today, a 'smart' laser is rather reminiscent of a 'smart' house, and not of an independent intelligent device (when laser works better on the basis of sensor reading). Laser "learning" methods are in reality often those of automatic control that leads to the desired parameters of the output radiation. However, methods of automatic control are not equivalent to those of machine learning. This is not a matter of computerisation of lasers and control over their parameters through deterministic digital algorithms. Such algorithms are also used and often wrongly labelled "AI methods" as a marketing ploy. For a true powerful AI of a human or even super-human level, the problem of tuning for desired (or best) radiation parameters is not a most complicated one. We can expect not only efficient control and management, but also novel solutions (for instance, next-generation ML/AI architectures and so forth).

At present, such an intelligence is more seen as a goal rather than an available result. In answering the question earlier posed on the learning capabilities of a laser system, it should be stated that a specific answer may not be given, because the question is too general. The laser industry is more likely to undergo a technological reset, after which intelligent algorithms will find application alongside new materials and energy efficient approaches. Emergence of 'smart' lasers on the global technology horizon is still much more a tribute paid to new buzz-words than actual development of light generation devices with artificial intelligence capabilities. However, it is already possible to predict that in the foreseeable future (even as soon as within 5–10 years), many devices including lasers will possess a measure of such capabilities. Over a longer period (beyond our predictions) photonic devices, such as laser, passive devices, etc. will be self-learning and this capability will be designed into them, i. e. will be supported by the architecture and implementation of these products. Presently, such (still hypothetical) capabilities are rarely included during the design phase of photonic devices. When such capabilities (at least a USB port for external control to begin with) will be included into the photonic device conception, the behaviour of such devices will certainly become more intelligent.

3. Conclusion

Unreadiness of most modern photonic devices for profitable application of ML methods is only a part of the problem. The key problem still unsolved today is creation of a strong artificial intelligence of the human level that would be able to profitably realise the expected new functionality. This does not, nevertheless, prevent us from developing this field at the level of concepts and new approaches.

CRediT authorship contribution statement

Sergey M. Kobtsev: Conceptualization, Visualization, Project administration, Supervision, Funding acquisition, Writing - original draft, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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