

1                   **Machine Learning and Applications in Ultrafast Photonics**  
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14                   **Abstract**

15                  Recent years have seen the rapid growth and development of the field of smart photonics,  
16                  where machine learning algorithms are being matched to optical systems to add new  
17                  functionalities and to enhance performance. An area where machine learning shows particular  
18                  potential to accelerate technology is the field of ultrafast photonics – the generation and  
19                  characterization of light pulses, the study of light-matter interactions on short timescales, and  
20                  high-speed optical measurements. Our aim here is to highlight a number of specific areas  
21                  where the promise of machine learning in ultrafast photonics has already been realized,  
22                  including the design and operation of pulsed lasers, and the characterization and control of  
23                  ultrafast propagation dynamics. We also consider challenges and future areas of research.  
24

25 Machine learning is an umbrella term describing the use of statistical techniques and numerical  
26 algorithms to carry out tasks without explicit programmed and procedural instructions.  
27 Machine learning algorithms are widely used in many areas of engineering and science, with  
28 particular strengths in classification, pattern recognition, prediction, system parameter  
29 optimization, and the construction of models of complex dynamics from observed data.  
30 Machine learning tools have been widely applied in fields such as control systems, speech  
31 processing, neuroscience and computer vision [1].

32 In optics and photonics, early applications of machine learning have mostly been in the  
33 form of genetic algorithms for pattern recognition [2], image reconstruction [3], aberration  
34 corrections [4], or the design of optical components [5, 6]. More recent work has focused on  
35 the analysis of large data sets [7, 8] and on inverse problems where the superior ability of  
36 machine learning to classify data, to identify hidden structures and to deal with a large number  
37 of degrees of freedom have led to a many results. Particular areas of success include in the  
38 design of nanomaterials and structures with specific target properties [9–11], label-free cell  
39 classification [12], super resolution microscopy [13, 14], quantum optics [15], and optical  
40 communications [16–18].

41 In addition to applications in the general area of data processing, there is particular  
42 potential for machine learning methods to drive the next generation of ultrafast photonic  
43 technologies. This is not only because there is increasing demand for adaptive control and self-  
44 tuning of ultrafast lasers, but also because many ultrafast phenomena in photonics are  
45 nonlinear and multi-dimensional with noise-sensitive dynamics that are extremely challenging  
46 to model using conventional methods. While advances in measurement techniques have led to  
47 significant progress in experimental studies of such complex dynamics, recent research has  
48 shown how machine learning algorithms are providing new ways to identify coherent  
49 structures within large sets of noisy data, and can even potentially be applied to determining  
50 underlying physical models and governing equations based only on the analysis of complex  
51 time series.

52 Our aim here is to review a number of specific areas where the promise of machine learning  
53 in ultrafast photonics has already been realized, and to also consider challenges and future  
54 directions of study as well as application where significant impact is expected in the coming

55 years. Before presenting specific details, we first illustrate in Fig. 1 an overview of different  
56 machine learning strategies and associated architectures, listing the core concepts,  
57 implementation methodologies, and applications where these have been applied in ultrafast  
58 photonics.

## 59 **LASER DESIGN AND SELF-OPTIMIZATION**

60

### 61 **Self-tuning of ultrafast fibre lasers**

62

63 Ultrafast lasers are essential tools in many areas of photonics including telecommunications,  
64 material processing, and biological imaging [19–23]. They have also played a central role in  
65 several Nobel prizes awarded for femtosecond coherent control (1999); the development of the  
66 precision frequency comb (2005); and more recently the generation of high-power  
67 femtosecond pulses via chirped pulse amplification (2018). Although some ultrafast sources  
68 are based on relatively simple designs, the operation of many important laser systems is in fact  
69 very complex with dynamic pulse shaping determined by the interplay between a range of  
70 nonlinear, dispersive, and dissipative effects [24]. Although this complexity certainly creates  
71 challenges in controlling and optimizing the laser emission, it also offers considerable  
72 performance advantage not available with simpler systems. A key challenge is then to harness  
73 this complexity.

74 The difficulty in optimizing a particular ultrafast laser arises from the number of degrees of  
75 freedom (or control parameters) that need to be balanced to achieve stable operation or reach a  
76 specific dynamical regime. Of course, efforts to develop self-optimized or auto-tuned lasers  
77 have been made for many years, with the dominant approach being to linearly sweep through a  
78 subset of the available parameter space while monitoring the laser output and using a feedback  
79 loop to obtain and maintain a desired operating state. While this is a straightforward approach  
80 for simpler laser designs with limited parameters, it becomes intractable when the laser  
81 operation depends on many degrees of freedom, or when multiple output characteristics need  
82 to be optimized simultaneously. Moreover, there is an increasing demand in both research and  
83 industrial applications for fully autonomous operation and active realignment in the presence  
84 of external perturbations, as well as for the ability to make dynamic changes in pulse  
85 characteristics adapted to the target environment (e.g. propagation medium or material). It is

86 for such systems with greatly added complexity that approaches based on machine learning are  
87 especially promising and desirable.

88 An important example here is the widespread fibre laser, where polarization control, pump  
89 power, spectral filtering and loss combine to create a wide range of possible operating regimes  
90 governed by a rich landscape of nonlinear dynamics [25, 26]. Depending on the exact choice  
91 of parameters, the same laser can exhibit very different behaviour: continuous-wave lasing,  
92 noise-like pulse generation, Q-switching, mode-locking, multiple pulsing and bound states. It  
93 is for this multi-variable optimisation problem that machine learning has recently led to a  
94 number of dramatic improvements. The general approach has been to combine an algorithmic  
95 feedback loop together with the electronic control of intra-cavity elements varying  
96 polarization, pump power, and spectral filtering. Figure 3 shows a generic illustration of  
97 machine learning strategies, control elements, and output parameters for optimization of  
98 ultrafast fibre lasers. Specifically, Figure 3A illustrates the training phase where control  
99 electronics and advanced measurement devices are used to probe the parameter space and map  
100 the corresponding operation states, respectively. Collected data are then fed to machine  
101 learning algorithms for training. Figure 3B shows the self-tuning regime where the operation  
102 state of the laser is characterized in real-time with a simplified measurement system fed into  
103 the machine learning algorithm controlling the electronics to lock the system to a desired  
104 regime. This is where machine learning is particularly powerful as, once trained, the algorithm  
105 allows systematic scanning of the parameter space for optimum operation. Examples of  
106 machine learning algorithms that can be used are highlighted in Fig. 2, and general guidelines  
107 in applying them are provided in Box 1.

108 Ultrafast fibre lasers mode-locked by nonlinear polarization evolution (NPE) are  
109 particularly complex, because a change in the polarization state affects both spectral and  
110 temporal pulse shaping, as well as the gain to loss balance in the cavity due to the intrinsic  
111 saturable absorber role played by the polarization-dependent losses. The first studies  
112 combining an algorithmic feedback loop with some cavity control parameter were in fact  
113 proof-of-concept numerical simulations of an NPE fibre laser, where it was shown that multi-  
114 pulsing instability could be reduced via filters optimized with a genetic algorithm [27], and  
115 that stochastic changes in environmentally-induced birefringence could be mitigated by

116 applying a singular value decomposition method [28] or using variational autoencoders on the  
117 birefringence state map [29, 30]. This modelling was rapidly followed by an experimental  
118 implementation using a singular fitness function to identify self-starting regimes in an NPE  
119 laser [31]. A number of subsequent experiments for various laser configurations (NPE, ring-  
120 cavity, figure-of-eight) have used genetic algorithms to achieve self-tuning and auto-setting in  
121 different regimes such as Q-switching, mode-locking, Q-switched mode-locking, or the  
122 generation of on-demand pulses with different duration and energies [32–36].

123 Table I summarizes a selection of results that have been obtained to date (extended from  
124 [37]), also providing the characteristics of the particular algorithms used in each case. In most  
125 of these studies, the feedback loop typically uses an advanced search or genetic algorithm  
126 targeting a desired optimal state based on some particular fitness or objective function as the  
127 reference criterion. Although these results are highly promising, genetic algorithms have to be  
128 carefully designed due to their sensitivity to the initial choice of population which can lead the  
129 fitness function to converge toward a local optimum and be detrimental to multistable  
130 dynamics often seen in ultrafast lasers. They also cannot accommodate for long-term  
131 dependencies, and the fitness function typically monitors a single parameter limiting the  
132 operating regime that can be achieved. Another important drawback of genetic algorithms is  
133 their relatively slow convergence time on the scale of minutes or even hours (see Table 1).  
134 However, recent developments have shown that one can reduce this time considerably using  
135 algorithmic modifications that can mimic human logic, with the possibility to lock the laser to  
136 a desired operating state and to recover to this state from perturbation in less than one second  
137 [38, 39]. Further improvement in self-tuning speed is likely to require algorithms that also  
138 include models of the pulse generating mechanism in order to provide more targeted control.  
139 Unfortunately, whilst models based on nonlinear Schrödinger-like equations (NLSE) are  
140 generally able to reproduce experimental characteristics qualitatively, quantitative comparison  
141 with experiments remains challenging. This is because accurate modelling necessitates the  
142 knowledge of a wide range of parameters which are not readily accessible in practice (for  
143 example, the random birefringence in the fibre). Ultrafast lasers are also stochastic systems  
144 and the impact of noise can generally be only reproduced via computationally intensive  
145 Monte-Carlo simulations that require the analysis of a very large amount of data. One can

146 anticipate that the use of machine learning techniques for pattern recognition combined with  
147 the latest advances in real-time measurement techniques [40, 41] could lead to better  
148 understanding of ultrafast laser dynamics, allowing for the construction of laser systems with  
149 improved robustness.

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## 152 **Control of coherent dynamics**

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154 In addition to directly controlling laser emission as described above, there is widespread use of  
155 extra-cavity shaping technology to modify the characteristics of ultrashort pulses and other  
156 light sources used in particular applications. Because such optimization can involve multiple  
157 parameters that are interconnected in complex ways, this is an area where machine learning  
158 can clearly surpass other forms of manual or partially-automatised control.

159 For example, pulse compression to a transform-limited duration is essential to femtosecond  
160 spectroscopy that uses few-cycle laser pulses to probe physical or chemical interactions.  
161 Recently, it was shown how an adaptive neural-network algorithm can control a pulse-shaper  
162 and accelerate significantly the compression implementation with a convergence speed 100  
163 times faster than that obtained using more conventional evolutionary algorithms (see Fig. 4A)  
164 [42]. Similarly, a neural network was used to determine and optimize the parameters of a pulse  
165 shaping system composed of a series of dispersive and nonlinear fibre elements in order to  
166 generate arbitrary pulse waveforms (parabolic, triangular or rectangular) of desired duration  
167 and chirp [43].

168 Genetic algorithms can also be used for these purposes, and their application to solve highly  
169 nonlinear optimisation problems such as fibre supercontinuum generation has also been very  
170 successful [44–47]. Using custom pulse train preparation via an integrated pulse-splitter, a  
171 genetic algorithm was used to optimize supercontinuum dynamics to maximize spectral  
172 intensity in specific wavelength bands [47] (Fig. 4B). In another study, it was shown how  
173 Gaussian-like peaks could be generated at desired wavelengths in a supercontinuum spectrum  
174 using a genetic algorithm to tailor the spectral phase of the incident ultrashort pulses [46].  
175 Genetic algorithms have also been applied to the design of fibres with optimized dispersion  
176 and nonlinearity coefficient to maximise the bandwidth of coherent supercontinuum in the

177 mid-infrared [44].

178

### 179 **Ultrafast characterisation**

180

181 A central element in the application of machine learning to tune an ultrafast laser is the  
182 feedback loop coupling the emitted pulses with the laser cavity parameters. Although some  
183 success has been obtained through optimization based on measurements of pulse spectra or  
184 temporal autocorrelation functions, ideally a feedback signal based on more complete pulse  
185 measurements would be desirable. However, such complete pulse characterization on  
186 femtosecond and picosecond timescales generally requires complex optical systems, and the  
187 retrieval of the field parameters is an inverse problem which can be particularly time-  
188 consuming to solve [48].

189 Recently, deep neural networks have found applications in solving such inverse problems in  
190 areas such as coherent imaging [49, 50], imaging through scattering media [51, 52] or super-  
191 resolution [53], and they are now also showing great promise in pulse reconstruction. The first  
192 attempt to apply a neural network to reconstruct a short pulse actually dates back to the mid-  
193 1990's and the first development of frequency-resolved optical gating (FROG) [54], although  
194 this was limited in making strong assumptions about the functional form of the pulse being  
195 retrieved. In other work, genetic algorithms have also been successfully applied to FROG trace  
196 retrieval [55, 56] but pulse retrieval times still took several minutes. More recently, a  
197 convolutional network trained on simulated data was used to reconstruct pulses from  
198 experimental FROG traces and was shown to be superior to conventional methods even in the  
199 presence of high noise (Fig. 4C) [57]. Additional studies have employed convolutional  
200 networks to reconstruct pulses from dispersion scan traces [58], or from multimode fibre  
201 nonlinear speckle measurements [59]. Phase recovery for image reconstruction [60–63], X-ray  
202 pulse characterisation [64, 65] are also among important emerging and growing areas of  
203 applications of machine learning techniques.

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## 205 **COMPLEX DYNAMICS AND TRANSIENT INSTABILITIES**

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### 207 **Hidden physics models**

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210 The application of machine learning to derive predictive models from sparse or noisy  
211 measurements has now penetrated research into the study of the basic properties of physical  
212 systems. In particular, a new field of “hidden physics models” has arisen where closed-form  
213 mathematical models or nonlinear differential equations governing a physical system [66] are  
214 identified automatically by analyzing samples of the dynamical data using “physics-informed  
215 neural networks”. In some cases, the form of the governing equation(s) may be known or  
216 assumed in advance, and the goal is to extract only the unknown coefficients [67].  
217 Alternatively, one can combine a neural network with a compressed sensing-like method to  
218 only identify the active terms of the equation(s) from a basis of candidate nonlinear functions  
219 [68].

220 Using these approaches, a number of applications in ultrafast photonics have been  
221 demonstrated to analyse pulse propagation dynamics in optical fibre or in fibre lasers  
222 associated with the generation of localised and dissipative soliton structures (Fig. 4D) [67].  
223 Model-free approaches in the form of reservoir computing (unlike physics-informed neural  
224 networks) have also been implemented to predict coherent dynamics in particular cases of  
225 soliton-like propagation (Fig. 4D) [69]. At present, however, such work has been based on  
226 numerical data only - the next step in this field is clearly to uncover the governing models  
227 from experimental data sets.

228 Another important area of work involves the study of temporal dependencies observed in  
229 nonlinear pulse propagation dynamics, where the temporal and spectral intensity profiles at a  
230 specific time instant or propagation length depend on the intensity profiles at earlier times or  
231 distance. Recurrent neural networks with internal memory (that are traditionally used for  
232 processing and predictions of time-series) are particularly well suited to modelling this type of  
233 dynamic behaviour. Indeed very recent results exploiting the memory-capacity of recurrent  
234 neural networks show how a recurrent neural network with long short-term memory cell  
235 architecture can accurately predict the nonlinear propagation dynamics of short pulses for a  
236 wide range of scenarios from higher-order soliton compression (where comparison was made  
237 with experiment) to octave-spanning supercontinuum generation [70]. In addition to these  
238 studies of single-pass nonlinear propagation dynamics, there is clear potential to use recurrent  
239 neural networks in predictions of the complex multi-scale intermittence dynamics also seen in



240 optical fibre lasers [71].

241

### 242 **Chaotic systems and instabilities**

243

244 Chaotic modulation instability in NLSE-like systems is one of the most fundamental examples  
245 of instability in optics, with analogs in many other physical systems. Indeed, the study of how  
246 incoherent noise can “self-organize” within the NLSE to yield coherent breather structures has  
247 attracted wide interest, specifically because of possible links with rogue waves and extreme  
248 events [72]. However, the complexity of the measurement techniques needed to directly  
249 capture such chaotic breathers on ultrafast timescales has imposed severe constraints on the  
250 dynamical regimes that can be explored in experiments [73, 74].

251 Machine learning has been used to address this problem directly by training a neural  
252 network to determine the temporal characteristics of a chaotic field based only on the spectral  
253 intensity characteristics (which are easier to measure). Using numerical data generated from  
254 NLSE simulations, a neural network was used to construct a nonlinear transfer function that  
255 maps noisy broadband spectra to the local intensity maximum of the chaotic temporal field  
256 (see Fig. 4E). This function was then applied to experimental data measured using a high  
257 dynamic range real-time spectrometer [75]. A similar approach was recently used to determine  
258 the peak power, duration, and temporal delay of extreme rogue solitons in noisy  
259 supercontinuum generation [76]. Also analyzing chaotic data from modulation instability,  
260 unsupervised clustering analysis using the k-mean algorithm was shown to successfully sort  
261 intensity spectra into sub-classes associated in the time-domain with specific solutions of the  
262 NLSE related to analytic soliton structures [75].

263 The application of machine learning techniques has been extended to even more complex  
264 systems such as those observed in transient laser behaviour and extreme events [77].  
265 Specifically, using the knowledge of previous pulses in a chaotic time series from an optically  
266 injected semiconductor laser operating, machine learning methods (nearest neighbors, support  
267 vector machine, feed-forward neural networks, reservoir computing) were analyzed for their  
268 ability to predict the intensity of upcoming pulses emitted from the laser [77, 78]. Although  
269 this work was numerical, it clearly shows the potential of such prediction in experiment.  
270 Attempts have also been made to model highly incoherent system evolution including

271 multidimensional spatiotemporal systems [79] but the predictions in this case tend to diverge  
272 over longer distances [80].

273

### 274 **Multidimensional systems**

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276 A major benefit of neural networks is their ability to efficiently analyze the properties of multi-  
277 dimensional systems. This can be particularly useful in multimode fibre systems where spatio-  
278 temporal coupling increases dramatically the parameter space and complexity of nonlinear  
279 propagation dynamics. The potential of machine learning in this case was recently  
280 demonstrated with experiments tailoring supercontinuum generation in a graded index fibre  
281 through control of the injected spatial beam profile via a neural-network driven spatial light  
282 modulator [81].

283 Extension to spatial control for enhanced near-field interactions was also shown by  
284 combining a neural network with a genetic algorithm to optimise spectral-phase shaping of an  
285 incident field to achieve second harmonic generation hotspot switching in plasmonic  
286 nanoantennas [82]. In this latter work, the genetic algorithm was added to generate a wide  
287 range of nanoantenna designs to be fed into the neural network.

288

### 289 **OUTLOOK AND CHALLENGES**

290

291 Ultrafast photonics systems are generally very complex, often nonlinear, and with dynamics  
292 extremely sensitive to both their internal parameters and external perturbations. The design  
293 and optimization of these systems have been typically based on physical models, numerical  
294 simulations, and trial-and-error approaches. With the increased complexity of these systems,  
295 driven by the demand for high stability, robustness against disturbances, tunability and  
296 adaptive control, these approaches are now starting to reach their limits such that future major  
297 advances will require new methodologies that can analyse the systems characteristics at a  
298 global level. One may therefore anticipate that machine learning techniques able to discover  
299 hidden features and independently adapt as they are exposed to new data, are likely to play a  
300 central role in the next generation of ultrafast systems and applications. There are of course  
301 many ways machine learning techniques can be exploited, and we discuss below some  
302 possible future direction of research and challenges to overcome.

303 Ultrafast fibre lasers are dynamical systems operating in regimes determined by dispersion,  
304 nonlinearity, gain, losses, and saturation effects. Optimization, breakthrough performance,  
305 high stability against perturbations, and automatic-tuning requires in-depth understanding of  
306 the full system parameter space, which can be achieved by combining accurate real-time  
307 characterization and advanced data analysis. Machine learning-based approaches have the  
308 potential to reduce the complexity and number of measurement devices typically required.  
309 They could further allow for converting results of measurements into a higher-dimensional  
310 space where the separation of the role played by the different cavity elements is more apparent,  
311 aiding the construction of universal models. Machine learning may also yield significant  
312 developments in full and high-speed characterization of short pulses or complex fields arising  
313 from highly nonlinear dynamics. Adaptive optics and coherent control typically rely on  
314 ultrafast laser systems where the spatial, temporal and spectral properties of the laser beam are  
315 central to optimum performance in e.g. metrology [83], spectroscopy [84, 85], energy  
316 harvesting [86] or astronomy [87]. By enabling more systematic strategies rather than heuristic  
317 approaches (e.g. in the optimization of multidimensional systems including beam shaping and  
318 space-time focusing in multimode fibers [88–90]), machine learning could enable  
319 unprecedented level of control in those applications. Another important area where we expect  
320 machine learning to lead to significant progress is the discovery of models using data-driven  
321 strategy, allowing for finding governing mathematical equations of complex optical  
322 phenomena or photonics systems. It is even conceivable that in the future ultrafast fibre lasers  
323 could become testbeds for the physics discovered from machine learning.

324 To date, the majority of machine learning applications to ultrafast photonics have been  
325 based on genetic algorithms or feed forward architectures. While these implementations have  
326 undoubtedly led to remarkable and pioneering results, there are still important approaches that  
327 have yet to be fully exploited. Indeed, it is likely that realising the full potential of machine  
328 learning will necessitate the combination of several strategies that have so far been used only  
329 separately. For example, recurrent networks based on long short-term memory cells, gated  
330 recurrent units, or reservoir computing that possess internal memory can be used to model  
331 dynamical systems consisting of time series of different states. These approaches could enable  
332 significant progress in understanding and optimizing nonlinear systems, allowing

333 identification of long-term dependencies and internal dynamics in ultrafast lasers, or the  
334 prediction of complex evolution maps associated with the propagation of short pulses in  
335 nonlinear media and related instabilities. Also, the capabilities of unsupervised learning to  
336 draw inferences and reveal hidden internal structures from data sets without labelled responses  
337 could be of significant interest in problems where dimensionality reduction is key. These  
338 include e.g. multimodal systems or noise-sensitive dynamics where specific regimes can be  
339 divided into a number of different clusters associated with measurable parameter(s). Moreover,  
340 approaches employed for the design of nanophotonic components in the form of machine  
341 learning combined with the adjoint method [91] could be a powerful tool for the inverse design  
342 of ultrafast photonics systems. The concept of generative adversarial networks [92] where two  
343 distinct networks are optimized in the backpropagation operation [93] is another promising  
344 avenue to explore in ultrafast photonics.

345 There are of course important challenges ahead. When using recurrent network to analyze  
346 and predict dynamics, proper sampling along the evolution dimension (time or distance) is  
347 essential to extract and reproduce the long-term evolution structure. Memory limitations can  
348 then become an issue especially in the context of lasers where it takes usually many cavity  
349 round trips for a regime to stabilize. Unsupervised learning analysis divides the data into  
350 subsets with similarities, but crucial information on the criterion used to perform the division,  
351 or on what the similarities actually are within the clusters is lacking. This means that in order  
352 to fully exploit the power of unsupervised learning, further human investigation is generally  
353 needed to establish the link between the clusters and specific parameters of the system  
354 analysed. This can be a limiting factor, especially for the case of noise-sensitive systems where  
355 tiny variations can result in dramatically different evolution patterns.

356 The use of machine learning algorithms for real-time processing of photonic systems that  
357 can produce data in excess of billions of bits per second requires the ability to manage high  
358 data volumes, as well as a hardware framework capable of dealing with ultrafast processing  
359 rates. In order to reduce the large volume of data, one could use the approach of spike-based  
360 neural networks that can reconstruct features of spatio-temporal states based on a fraction of  
361 that regime information. Inspired by the human brain that strongly compresses the information  
362 received from the eye [94], spike-based neural networks use a specific set of rules such as

363 spike time-dependent plasticity leading to self-organization of the network's topology and  
364 allowing to identify possible correlations in the input data. When combined with lateral  
365 inhibition (a spike-based form of a winner take all topology), spiking-based neural networks  
366 can self-configure to perform a cluster analysis with performance similar to that achieved with  
367 a k-mean algorithm [95]. Efforts to develop a hardware framework allowing for high-speed  
368 processing and optimization on short time scales have already been made, and several all-  
369 optical network architectures have been proposed based e.g. on multiple layers of diffractive  
370 surfaces where each point on a given layer acts as a node [96], or based on optical matrix  
371 multiplication using a cascaded array of Mach–Zehnder interferometers integrated into a  
372 silicon photonic circuit [97]. Another promising approach could be to combine all-optical  
373 field-programmable gate arrays and fully parallel photonic neural network hardware. Of  
374 course, one important constraint to the development of all-optical neural net- works that needs  
375 to be carefully studied is the tolerance to photonic component fabrication imperfections [98].

376 In the past few years, there have been remarkable developments enabled by the use of  
377 machine learning techniques, and an active field of machine-learning ultrafast photonics has  
378 now been established. As research continues to progress both in the development of machine  
379 learning algorithms and ultrafast photonics technologies, we can expect even more fruitful  
380 interactions with increased influence of the former in the physical understanding, design,  
381 optimization, and operation of the latter.

382

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398 **References**

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- 400 [1] Jordan, M.I. & Mitchell, T.M. Machine learning: trends, perspectives, and prospects.  
401 *Science* **349**, 255–260 (2015).
- 402 [2] Mahlab, U., Shamir, J. & Caulfield, H.J. Genetic algorithm for optical pattern recognition.  
403 *Opt. Lett.* **16**, 648–650 (1991).
- 404 [3] Kihm, K.D. & Lyons, D.P. Optical tomography using a genetic algorithm. *Opt. Lett.* **21**,  
405 1327–1329 (1996).
- 406 [4] Albert, O., Sherman, L., Mourou, G., Norris, T.B. & Vdovin, G. Smart microscope: an  
407 adaptive optics learning system for aberration correction in multiphoton confocal  
408 microscopy. *Opt. Lett.* **25**, 52–54 (2000).
- 409 [5] Eisenhammer, T., Lazarov, M., Leutbecher, M., Schöffel, U. & Sizmann, R. Optimization  
410 of interference filters with genetic algorithms applied to silver-based heat mirrors. *Appl.*  
411 *Optics* **32**, 6310–6315 (1993).
- 412 [6] Martin, S., Rivory, J. & Schoenauer, M. Synthesis of optical multilayer systems using  
413 genetic algorithms. *Appl. Optics* **34**, 2247–2254 (1995).
- 414 [7] Zibar, D., Wymeersch, H. & Lyubomirsky, I. Machine learning under the spotlight. *Nat.*  
415 *Photonics* **11**, 749–751 (2017).
- 416 [8] Zhou, J., Huang, B., Yan, Z. & Bünzli, J.-C.G. Emerging role of machine learning in light-  
417 matter interaction. *Light Sci. Appl.* **8**, 84 (2019).
- 418 [9] Nadell, C.C., Huang, B., Malof, J.M. & Padilla, W.J. Deep learning for accelerated all-  
419 dielectric metasurface design. *Opt. Express* **27**, 27523–27535 (2019).
- 420 [10] Malkiel, I. *et al.* Plasmonic nanostructure design and characterization via deep learning.  
421 *Light Sci. Appl.* **7**, 60 (2018).
- 422 [11] Hegde, R.S. Deep learning: a new tool for photonic nanostructure design. *Nanoscale Adv.*  
423 **2**, 1007–1023 (2020).
- 424 [12] Chen, C.L. *et al.* Deep learning in label-free cell classification. *Sci. Rep.* **6**, 21471 (2016).
- 425 [13] Ouyang, W., Aristov, A., Lelek, M., Hao, X. & Zimmer, C. Deep learning massively accel-  
426 erates super-resolution localization microscopy. *Nat. Biotechnol.* **36**, 460–468 (2018).
- 427 [14] Durand, A. *et al.* A machine learning approach for online automated optimization of super-  
428 resolution optical microscopy. *Nat. Commun.* **9**, 5247 (2018).
- 429 [15] Palmieri, A.M. *et al.* Experimental neural network enhanced quantum tomography. *npj*

- 430 *Quantum Inf.* **6**, 20 (2020).
- 431 [16] Zibar, D., Piels, M., Jones, R. & Schaeffer, C.G. Machine learning techniques in optical  
432 communication. *J. Lightwave Technol.* **34**, 1442–1452 (2016).
- 433 [17] Musumeci, F. *et al.* An overview on application of machine learning techniques in optical  
434 networks. *IEEE Commun. Surv. Tut.* **21**, 1383–1408 (2019).
- 435 [18] Lugnan, A. *et al.* Photonic neuromorphic information processing and reservoir computing.  
436 *APL Photonics* **5**, 020901 (2020).
- 437 [19] Knox, W.H. Ultrafast technology in telecommunications. *IEEE J. Sel. Top. in Quant.* **6**,  
438 1273–1278 (2000).
- 439 [20] Sibbett, W., Lagatsky, A.A. & Brown, C.T.A. The development and application of  
440 femtosecond laser systems. *Opt. Express* **20**, 6989–7001 (2012).
- 441 [21] Sugioka, K. & Cheng, Y. Ultrafast lasers—reliable tools for advanced materials processing.  
442 *Light Sci. Appl.* **3**, e149 (2014).
- 443 [22] Fermann, M.E., Galvanauskas, A. & Sucha, G. *Ultrafast lasers: technology and applications*,  
444 vol. 80 (CRC Press, 2002).
- 445 [23] Xu, C. & Wise, F.W. Recent advances in fibre lasers for nonlinear microscopy. *Nat.*  
446 *Photonics* **7**, 875–882 (2013).
- 447 [24] Grelu, P. & Akhmediev, N. Dissipative solitons for mode-locked lasers. *Nat. Photonics* **6**,  
448 84–92 (2012).
- 449 [25] Richardson, D.J., Nilsson, J. & Clarkson, W.A. High power fiber lasers: current status and  
450 future perspectives. *J. Opt. Soc. Am. B* **27**, B63–B92 (2010).
- 451 [26] Fermann, M.E. & Hartl, I. Ultrafast fibre lasers. *Nat. Photonics* **7**, 868–874 (2013).
- 452 [27] Fu, X. & Kutz, N.J. High-energy mode-locked fiber lasers using multiple transmission  
453 filters and a genetic algorithm. *Opt. Express* **21**, 6526–6537 (2013).
- 454 [28] Fu, X., Brunton, S.L. & Kutz, J.N. Classification of birefringence in mode-locked fiber  
455 lasers using machine learning and sparse representation. *Opt. Express* **22**, 8585–8597  
456 (2014).
- 457 [29] Kutz, J.N. & Brunton, S.L. Intelligent systems for stabilizing mode-locked lasers and  
458 frequency combs: machine learning and equation-free control paradigms for self-tuning  
459 optics. *Nanophotonics* **4**, 459–471 (2015).
- 460 [30] Baumeister, T., Brunton, S.L. & Kutz, J.N. Deep learning and model predictive control for



461 self-tuning mode-locked lasers. *J. Opt. Soc. Am. B* **35**, 617–626 (2018).

462 [31] Andral, U. *et al.* Fiber laser mode locked through an evolutionary algorithm. *Optica* **2**,  
463 275–278 (2015).

464 [32] Andral, U. *et al.* Toward an autosetting mode-locked fiber laser cavity. *J. Opt. Soc. Am. B*  
465 **33**, 825–833 (2016).

466 [33] Woodward, R. & Kelleher, E. Towards smart lasers: self-optimisation of an ultrafast pulse  
467 source using a genetic algorithm. *Sci. Rep.* **6**, 37616 (2016).

468 [34] Woodward, R. & Kelleher, E. Genetic algorithm-based control of birefringent filtering for  
469 self-tuning, self-pulsing fiber lasers. *Opt. Lett.* **42**, 2952–2955 (2017).

470 [35] Winters, D.G., Kirchner, M.S., Backus, S.J. & Kapteyn, H.C. Electronic initiation and  
471 optimization of nonlinear polarization evolution mode-locking in a fiber laser. *Opt.*  
472 *Express* **25**, 33216–33225 (2017).

473 [36] Kokhanovskiy, A., Ivanenko, A., Kobtsev, S., Smirnov, S. & Turitsyn, S. Machine learning  
474 methods for control of fibre lasers with double gain nonlinear loop mirror. *Sci. Rep.* **9**,  
475 2916 (2019).

476 [37] Meng, F. & Dudley, J.M. Towards a self-driving ultrafast fiber laser. *Light Sci. Appl.*  
477 *(News & Views)* **9**, 26 (2020).

478 [38] Pu, G., Yi, L., Zhang, L. & Hu, W. Intelligent programmable mode-locked fiber laser with  
479 a human-like algorithm. *Optica* **6**, 362–369 (2019).

480 [39] Pu, G., Yi, L., Zhang, L. & Hu, W. Genetic algorithm-based fast real-time automatic  
481 mode-locked fiber laser. *IEEE Photonics Technol. Lett.* **32**, 7–10 (2020).

482 [40] Kokhanovskiy, A. *et al.* Machine learning-based pulse characterization in figure-eight  
483 mode-locked lasers. *Opt. Lett.* **44**, 3410–3413 (2019).

484 [41] Pu, G. *et al.* Intelligent control of mode-locked femtosecond pulses by time-stretch-assisted  
485 real-time spectral analysis. *Light Sci. Appl.* **9**, 13 (2020).

486 [42] Farfan, C.A., Epstein, J. & Turner, D.B. Femtosecond pulse compression using a neural-  
487 network algorithm. *Opt. Lett.* **43**, 5166–5169 (2018).

488 [43] Finot, C., Gukov, I., Hammani, K. & Boscolo, S. Nonlinear sculpturing of optical pulses  
489 with normally dispersive fiber-based devices. *Opt. Fiber Technol.* **45**, 306–312 (2018).

490 [44] Zhang, W.Q., Afshar, S. & Monroe, T.M. A genetic algorithm based approach to fiber  
491 design for high coherence and large bandwidth supercontinuum generation. *Opt. Express*

- 492       **17**, 19311–19327 (2009).
- 493 [45] Arteaga-Sierra, F.R. *et al.* Supercontinuum optimization for dual-soliton based light  
494 sources using genetic algorithms in a grid platform. *Opt. Express* **22**, 23686–23693 (2014).
- 495 [46] Michaeli, L. & Bahabad, A. Genetic algorithm driven spectral shaping of supercontinuum  
496 radiation in a photonic crystal fiber. *J. Opt.* **20**, 055501 (2018).
- 497 [47] Wetzel, B. *et al.* Customizing supercontinuum generation via on-chip adaptive temporal  
498 pulse-splitting. *Nat. Commun.* **9**, 4884 (2018).
- 499 [48] Ryczkowski, P. *et al.* Real-time full-field characterization of transient dissipative soliton  
500 dynamics in a mode-locked laser. *Nat. Photonics* **12**, 221–227 (2018).
- 501 [49] Kamilov, U.S. *et al.* Learning approach to optical tomography. *Optica* **2**, 517–522 (2015).
- 502 [50] Rivenson, Y., Wu, Y. & Ozcan, A. Deep learning in holography and coherent imaging.  
503 *Light Sci. Appl.* **8**, 85 (2019).
- 504 [51] Borhani, N., Kakkava, E., Moser, C. & Psaltis, D. Learning to see through multimode  
505 fibers. *Optica* **5**, 960–966 (2018).
- 506 [52] Li, Y., Xue, Y. & Tian, L. Deep speckle correlation: a deep learning approach toward  
507 scalable imaging through scattering media. *Optica* **5**, 1181–1190 (2018).
- 508 [53] Liu, T. *et al.* Deep learning-based super-resolution in coherent imaging systems. *Sci. Rep.*  
509 **9**, 3926 (2019).
- 510 [54] Krumbügel, M.A. *et al.* Direct ultrashort-pulse intensity and phase retrieval by frequency-  
511 resolved optical gating and a computational neural network. *Opt. Lett.* **21**, 143–145 (1996).
- 512 [55] Nicholson, J., Omenetto, F., Funk, D.J. & Taylor, A. Evolving FROGS: phase retrieval  
513 from frequency-resolved optical gating measurements by use of genetic algorithms. *Opt.*  
514 *Lett.* **24**, 490–492 (1999).
- 515 [56] Shu, S.F. Evolving ultrafast laser information by a learning genetic algorithm combined  
516 with a knowledge base. *IEEE Photonics Technol. Lett.* **18**, 379–381 (2006).
- 517 [57] Zahavy, T. *et al.* Deep learning reconstruction of ultrashort pulses. *Optica* **5**, 666–673  
518 (2018).
- 519 [58] Kleinert, S., Tajalli, A., Nagy, T. & Morgner, U. Rapid phase retrieval of ultrashort pulses  
520 from dispersion scan traces using deep neural networks. *Opt. Lett.* **44**, 979–982 (2019).
- 521 [59] Xiong, W. *et al.* Deep learning of ultrafast pulses with a multimode fiber. *arXiv preprint*  
522 *arXiv:1911.00649* (2019).

- 523 [60] Rivenson, Y., Zhang, Y., Günaydın, H., Teng, D. & Ozcan, A. Phase recovery and  
524 holographic image reconstruction using deep learning in neural networks. *Light Sci. Appl.*  
525 **7**, 17141 (2018).
- 526 [61] Sinha, A., Lee, J., Li, S. & Barbastathis, G. Lensless computational imaging through deep  
527 learning. *Optica* **4**, 1117–1125 (2017).
- 528 [62] Wu, Y. *et al.* Extended depth-of-field in holographic imaging using deep-learning-based  
529 autofocusing and phase recovery. *Optica* **5**, 704–710 (2018).
- 530 [63] Goy, A., Arthur, K., Li, S. & Barbastathis, G. Low photon count phase retrieval using deep  
531 learning. *Phys. Rev. Lett.* **121**, 243902 (2018).
- 532 [64] Sanchez-Gonzalez, A. *et al.* Accurate prediction of x-ray pulse properties from a free-  
533 electron laser using machine learning. *Nat. Commun.* **8**, 15461 (2017).
- 534 [65] White, J. & Chang, Z. Attosecond streaking phase retrieval with neural network. *Opt.*  
535 *Express* **27**, 4799–4807 (2019).
- 536 [66] Raissi, M. Deep hidden physics models: deep learning of nonlinear partial differential  
537 equations. *J. Mach. Learn. Res.* **19**, 932–955 (2018).
- 538 [67] Raissi, M., Perdikaris, P. & Karniadakis, G.E. Physics-informed neural networks: a deep  
539 learning framework for solving forward and inverse problems involving nonlinear partial  
540 differential equations. *J. Comput. Phys.* **378**, 686–707 (2019).
- 541 [68] Brunton, S.L., Proctor, J.L. & Kutz, J.N. Discovering governing equations from data by  
542 sparse identification of nonlinear dynamical systems. *P. Natl. Acad. Sci.* **113**, 3932–3937  
543 (2016).
- 544 [69] Jiang, J. & Lai, Y.-C. Model-free prediction of spatiotemporal dynamical systems with  
545 recurrent neural networks: role of network spectral radius. *Phys. Rev. Res.* **1**, 033056  
546 (2019).
- 547 [70] Salmela, L. *et al.* Predicting ultrafast nonlinear dynamics in fibre optics with a recurrent  
548 neural network. *arXiv preprint arXiv:2004.14126* (2020).
- 549 [71] Lapre, C. *et al.* Real-time characterization of spectral instabilities in a mode-locked fibre  
550 laser exhibiting soliton-similariton dynamics. *Sci. Rep.* **9**, 13950 (2019).
- 551 [72] Dudley, J.M., Genty, G., Mussot, A., Chabchoub, A. & Dias, F. Rogue waves and  
552 analogies in optics and oceanography. *Nat. Rev. Phys.* **1**, 675–689 (2019).
- 553 [73] Närhi, M. *et al.* Real-time measurements of spontaneous breathers and rogue wave events

- 554 in optical fibre modulation instability. *Nat. Commun.* **7**, 13675 (2016).
- 555 [74] Tikan, A., Bielawski, S., Sz waj, C., Randoux, S. & Suret, P. Single-shot measurement of  
556 phase and amplitude by using a heterodyne time-lens system and ultrafast digital time-  
557 holography. *Nat. Photonics* **12**, 228–234 (2018).
- 558 [75] Närhi, M. *et al.* Machine learning analysis of extreme events in optical fibre modulation  
559 instability. *Nat. Commun.* **9**, 4923 (2018).
- 560 [76] Salmela, L., Lapre, C., Dudley, J.M. & Genty, G. Machine learning analysis of rogue  
561 solitons in supercontinuum generation. *Sci. Rep.* **10**, 9596 (2020).
- 562 [77] Amil, P., Soriano, M.C. & Masoller, C. Machine learning algorithms for predicting the  
563 amplitude of chaotic laser pulses. *Chaos* **29**, 113111 (2019).
- 564 [78] Cunillera, A., Soriano, M.C. & Fischer, I. Cross-predicting the dynamics of an optically  
565 injected single-mode semiconductor laser using reservoir computing. *Chaos* **29**, 113113  
566 (2019).
- 567 [79] Vlachas, P. *et al.* Backpropagation algorithms and reservoir computing in recurrent neural  
568 networks for the forecasting of complex spatiotemporal dynamics. *Neural Networks* **126**,  
569 191–217 (2020).
- 570 [80] Pathak, J., Hunt, B., Girvan, M., Lu, Z. & Ott, E. Model-free prediction of large  
571 spatiotemporally chaotic systems from data: a reservoir computing approach. *Phys. Rev.*  
572 *Lett.* **120**, 024102 (2018).
- 573 [81] Teğ in, U. *et al.* Controlling spatiotemporal nonlinearities in multimode fibers with deep  
574 neural networks. *APL Photonics* **5**, 030804 (2020).
- 575 [82] Comin, A. & Hartschuh, A. Efficient optimization of SHG hotspot switching in plasmonic  
576 nanoantennas using phase-shaped laser pulses controlled by neural networks. *Opt. Express*  
577 **26**, 33678–33686 (2018).
- 578 [83] Diddams, S.A. The evolving optical frequency comb. *J. Opt. Soc. Am. B* **27**, B51–B62  
579 (2010).
- 580 [84] Assion, A. *et al.* Control of chemical reactions by feedback-optimized phase-shaped  
581 femtosecond laser pulses. *Science* **282**, 919–922 (1998).
- 582 [85] Bartels, R. *et al.* Shaped-pulse optimization of coherent emission of high-harmonic soft X-  
583 rays. *Nature* **406**, 164–166 (2000).
- 584 [86] Herek, J.L., Wohlleben, W., Cogdell, R.J., Zeidler, D. & Motzkus, M. Quantum control of

- 585 energy flow in light harvesting. *Nature* **417**, 533–535 (2002).
- 586 [87] Davies, R. & Kasper, M. Adaptive optics for astronomy. *Annu. Rev. Astron. Astrophys.* **50**,  
587 305–351 (2012).
- 588 [88] Florentin, R. *et al.* Shaping the light amplified in a multimode fiber. *Light Sci. Appl.* **6**,  
589 e16208 (2017).
- 590 [89] Florentin, R., Kermene, V., Desfarges-Berthelemot, A. & Barthelemy, A. Space-time  
591 adaptive control of femtosecond pulses amplified in a multimode fiber. *Opt. Express* **26**,  
592 10682–10690 (2018).
- 593 [90] Liu, B. & Weiner, A.M. Space–time focusing in a highly multimode fiber via optical pulse  
594 shaping. *Opt. Lett.* **43**, 4675–4678 (2018).
- 595 [91] Hughes, T.W., Minkov, M., Williamson, I.A.D. & Fan, S. Adjoint method and inverse  
596 design for nonlinear nanophotonic devices. *ACS Photonics* **5**, 4781–4787 (2018).
- 597 [92] Goodfellow, I. J. *et al.* Generative adversarial nets. *Adv. Neural Inf. Process. Syst.* **3**, 2672–  
598 2680 (2014).
- 599 [93] Subramaniam, A., Wong, M.L., Borker, R.D., Nimmagadda, S. & Lele, S.K. Turbulence  
600 enrichment using physics-informed generative adversarial networks. *arXiv preprint*  
601 *arXiv:2003.01907* (2020).
- 602 [94] Van Rullen, R. & Thorpe, S.J. Rate coding versus temporal order coding: what the retinal  
603 ganglion cells tell the visual cortex. *Neural Comput.* **13**, 1255–1283 (2001).
- 604 [95] Diamond, A., Schmuker, M. & Nowotny, T. An unsupervised neuromorphic clustering  
605 algorithm. *Biol. Cybern.* **113**, 423–437 (2019).
- 606 [96] Lin, X. *et al.* All-optical machine learning using diffractive deep neural networks. *Science*  
607 **361**, 1004–1008 (2018).
- 608 [97] Shen, Y. *et al.* Deep learning with coherent nanophotonic circuits. *Nat. Photonics* **11**, 441–  
609 446 (2017).
- 610 [98] Fang, M.Y.-S., Manipatruni, S., Wierzynski, C., Khosrowshahi, A. & DeWeese, M.R.  
611 Design of optical neural networks with component imprecisions. *Opt. Express* **27**, 14009–  
612 14029 (2019).
- 613 [99] Young, S.R., Rose, D.C., Karnowski, T.P., Lim, S.-H. & Patton, R.M. Optimizing deep  
614 learning hyper-parameters through an evolutionary algorithm. In *Proceedings of the*  
615 *Workshop on Machine Learning in High-Performance Computing Environments*, 1–5

616 (2015).

617 [100] Penkovsky, B., Larger, L. & Brunner, D. Efficient design of hardware-enabled reservoir  
618 computing in FPGAs. *J. Appl. Phys.* **124**, 162101 (2018).

619 [101] Klein, A., Falkner, S., Bartels, S., Hennig, P. & Hutter, F. Fast Bayesian hyperparameter  
620 optimization on large datasets. *Electron. J. Stat.* **11**, 4945–4968 (2017).

621 [102] Antonik, P., Marsal, N., Brunner, D. & Rontani, D. Bayesian optimisation of large-scale  
622 photonic reservoir computers. *arXiv preprint arXiv:2004.02535* (2020).

623 [103] Meng, F., Lapre, C., Billet, C., Genty, G. & Dudley, J.M. Instabilities in a dissipative  
624 soliton-similariton laser using a scalar iterative map. *Opt. Lett.* **45**, 1232–1235 (2020).

625

626 **BOX 1. General considerations when applying machine learning models**

627

628 **Choosing an architecture and associated parameters** Neural networks are universal function  
629 approximators whose performance significantly depends on their hyperparameters (variables that  
630 determines the network structure and training). Selecting the optimum architecture (Figs. 1-2) and tuning  
631 the hyperparameters often involves significant heuristics, exhaustive scans, trial and error, and leveraged  
632 optimization tools (genetic algorithms or Bayesian methods). Nevertheless, one may consider the  
633 following guidelines to select an appropriate architecture and hyperparameters: a feedforward neural  
634 network is a good choice if the map from input to output lacks temporal context. This is typically the case  
635 when one considers input-output mappings of “single-pass” systems such as pulses undergoing nonlinear  
636 propagation, where fluctuations are expected to be independent and uncorrelated, and also for particular  
637 classes of similarly (partially) uncorrelated instabilities in Q-switched lasers. If data contains structure  
638 along a particular input dimension (e.g. space, time or wavelength), architectures including filters such as  
639 convolutional neural networks are better candidates; one may employ fully connected topologies for input  
640 data apparently lacking such features. If the output is expected to depend on current and past input data,  
641 recurrent topologies (long short-term memory, gated recurrent units, or reservoir computing) should be  
642 used.

643 Accuracy generally increases with the number of hidden layers or nodes. The number of layers,  
644 nodes and training epochs can be increased until the validation error starts increasing (even if the training  
645 error still decreases). Note that too many nodes can lead to overfitting and reduce generalization (the  
646 ability of a trained model to adapt accurately to data outside the initial training data set). Continuously  
647 reducing the number of nodes for deeper layers is a common strategy to improve generalization, and 2 to  
648 3 hidden layers comprising 50 to 1000 nodes appear sufficient for most tasks in ultrafast photonics. A  
649 neural network’s inference quality is quantified by a cost function such as mean squared or root mean  
650 squared error. The root mean squared error penalizes small divergences more heavily and can be  
651 employed when fast and accurate convergence is essential. Network weights are typically initialized  
652 randomly, and popular activation functions are the rectified linear unit and the sigmoid nonlinearity. The  
653 rectified linear unit is computationally less expensive and avoids vanishing gradients, while the sigmoid’s  
654 upper limit makes blowing-up solutions less likely.

655

656 **Selecting training data** There is generally no one-size-fits-all criterion to determine the volume of  
657 training data needed for a specific network and task. Where possible, one can be guided by available  
658 examples of comparable problems, and more generally, an initial guess can be obtained by considering  
659 the number of classes (output neurons), relevant input features (e.g. optical modes), and parameters of the  
660 underlying model. One can then continuously increase the volume of training data until the validation  
661 error stagnates. The training data should be representative of the system’s possible states, and therefore  
662 sample uniformly the system’s phase space. This can be challenging, especially for ultrafast nonlinear  
663 systems which may rarely visit specific outlier regions (so-called skewed data-set), and can lead to  
664 degraded performance in testing. Feeding representative data sets is also not always possible during  
665 experiments, and data augmentation via simulation is an alternative approach. It is also important to  
666 normalize training data to the ‘useful’ range of the neurons’ nonlinear response (around unity) so as to  
667 prevent the network operating in the linear or saturated regime.

668

669 **Avoiding overfitting** Unlike in genetic algorithms, overfitting can occur in neural networks, typically  
670 when the testing error is large compared to the training error. The risk of overfitting may be reduced using  
671 the following strategies: simplification to reduce the network complexity; data augmentation by  
672 increasing the fraction of noisy data during training; cross-validation where division of data into training  
673 and testing sets is varied during training; early stopping where training is stopped when the testing error  
674 starts increasing; regularization by including penalties in the system’s loss function; drop-out by  
675 randomly removing individual connections during training.

676

677 **Robustness and transfer learning** Ultrafast photonic systems are generally sensitive to their  
678 environment Enabling stable and robust operation is another key objective for machine learning.  
679 Performance degradation upon a change of environmental conditions will mostly depend on the parameter  
680 space and regimes explored during training and testing. It is therefore important to include training data  
681 that incorporates possible environmental variations (see also Selecting Training Data). Using  
682 unsupervised learning to determine the dynamic relation between external conditions and system output is  
683 another approach.

684 A related question is “transfer learning”, or how a neural network architecture optimized for a  
685 particular system can be ‘transferred’ to a different yet related problem. In particular, the output of an  
686 ultrafast system can be divided into different regimes depending on the system parameters. This is  
687 particularly true for mode-locked laser pulses which typically correspond to fundamental solitons,  
688 dissipative solitons, or periodic breathers depending on the laser dispersion, nonlinearity, gain, loss, and  
689 filtering. Transfer learning may then use training data generated with simplified mathematical models or  
690 experiments with reduced complexity. In fact, transfer learning is in itself an important topic of machine  
691 learning research and from that point of view ultrafast photonic devices could be ideal testbeds for  
692 investigating transfer learning problems in general.

693

694



695 **FIGURE CAPTIONS**

696

697 **FIG. 1.** Overview of main machine learning concepts and implementations that can be used in  
698 ultrafast photonics. The figure illustrates the core concepts and corresponding implementation  
699 methodologies as delimited by the coloured arcs, and links these to particular applications where  
700 these have been applied in ultrafast photonics. There are also other concepts including semi-  
701 supervised learning and reinforcement learning which use some of the implementations  
702 mentioned in the figure, but these have yet to be exploited in an ultrafast context. Of course, we  
703 also stress that all these methods have been used in many other fields of science in addition to the  
704 ones shown here.

705

706 **FIG. 2.** Widespread and promising machine learning architectures for ultrafast photonics. **A:**  
707 Genetic algorithm. **B:** Feed-forward neural network. **C:** Convolutional neural network. **D:**  
708 Unsupervised learning. **E:** Recurrent neural network. **F:** Reservoir computing. The different  
709 algorithms can be used as indicated: in pre-training before being applied to a particular  
710 experimental system, for real-time optimization and tuning, or a combination of both where the  
711 algorithm is pre-trained and subsequently updated during system operation.

712

713 **FIG. 3.** Illustration of machine-learning strategies for optimization and self-tuning of ultrafast  
714 fibre lasers using control of intra-cavity elements via a feedback loop and control algorithm. **A.**  
715 Training phase where control electronics acting e.g. on the polarization state (EPC: electronic  
716 polarization controller) sweep the parameter space to map different operating states of the laser  
717 to be used as inputs to the control algorithm (see Fig. 2). Guidelines for algorithm and parameter  
718 selection are given in Box~1. In the case of a search algorithm, the training phase is not  
719 necessary. Output characteristics are measured by diagnostics tools such as optical spectrum  
720 analyser (OSA), fast photodiode (PD) and oscilloscope (OSC), or radio-frequency spectrum  
721 analyser (RFSA) and subsequently used as input to the control algorithm. **B.** Machine learning  
722 assisted operation where the laser operation is measured in real-time and fed into the control  
723 algorithm.

724

725 **FIG. 4.** Machine learning applications in Ultrafast Photonics. **A.** Pulse compression. **Aa.**  
726 Optimization procedure. **Ab.** Convergence comparison between neural network and evolutionary  
727 algorithm. **Ac.** Compressed pulse FROG. **B.** Controlled nonlinear propagation. **Ba.** Schematic.  
728 **Bb** and **Bc.** Examples of customized supercontinuum spectra. **C.** Pulse reconstruction using  
729 convolution neural network. **Ca.** Architecture. **Cb.** Reconstructed FROG. **Cc.** Reconstructed  
730 pulse. **D.** NLSE solution using a neural network. **Da.** Pulse evolution (top) and comparison of  
731 predicted and exact solutions (bottom) at three particular points (dashed lines). **Db.** Kuznetsov-  
732 Ma (left) and Akhmediev breather (right) dynamics showing expected evolution (top), predicted  
733 evolution (middle), and relative difference (bottom). **E.** Modulation instability. **Ea** Simulated  
734 spectra (network input) and **Eb** temporal profiles (network output). **Ec.** Network schematic for  
735 correlation of spectral and temporal characteristics. **Ed.** PDF of predicted temporal intensity  
736 based on experimental spectra (dashed red line) compared with simulated PDF (blue line). Panel  
737 A adapted with permission from REF [42], OSA. Panel B is adapted from REF [47], Springer  
738 Nature Ltd. Panel C adapted with permission from REF [57], OSA, Panel Da adapted with  
739 permission from REF [67], Elsevier. Panel Db adapted with permission from REF [69], APS.  
740 Panel E adapted from REF [75], Springer Nature Ltd.

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