Machine Learning and Statistical Physics: preface

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Contents

This special issue is meant to provide a picture of the state-of-the-art and open challenges of Machine Learning from a Statistical Mechanics (mainly *of Disordered Systems*) perspective.
Indeed, during the last decade, Deep Learning has yielded to a number of astonishing applied results [**?**] yet, admittedly, many of these mainly stem from technological advances in hardware (i.e. a systematic drift from a single CPU to clusters of GPUs) and from the development and the spreading of clouds (namely massive repositories where these machines can be trained). While much of the underlying theory is contained in classical textbooks like those by Nishimori [**?**] or by Coolen, Kühn and Sollich [**?**] or even in the ancient milestone by Amit [**?**], there is still a long way to go before *a theory for Artificial Intelligence* will be available.
Indeed, it emerges quite clearly that in the past few years technology has finally overcome bare-theory and this generated an urgent need for deeper theoretical inspections: as Statistical Mechanics of Disordered Systems has already paved a main route for Machine Learning, it is quite natural to ask it for further progress [**?**].

This special issue is split in two major, and to some extent, complementary aspects:

Theory
Methods from mathematical and theoretical physics, with particular emphasis on glassy physics, are being deployed to analyse theoretically the performance of many machine learning approaches: this can lead to improvements over existing algorithms or a better understanding of the conditions required for good performance.
The present special issue provides valuable contributions to this investigation: within this branch we may include the papers by *Dahmen, Gilson and Helias* (J. Phys. A: Math. Theor. 53 354002), *Howell, Wenping, Marsland and Mehta* (J. Phys. A: Math. Theor. 53 334001), *Decelle and Furtlehner* (J. Phys. A: Math. Theor. 53 184002), *Biroli, Cammarota and Ricci-Tersenghi* (J. Phys. A: Math. Theor. 53 174003), *Harsh, Tubiana, Cocco and Monasson* (J. Phys. A: Math. Theor. 53 174002), *Abbara, Baker, Krzakala and Zdeborová* (J. Phys. A: Math. Theor. 53 164001), *Schmidt and Zdeborová* (J. Phys. A: Math. Theor. 53 124001), *Li and Saad* (J. Phys. A: Math. Theor. 53 104002), *Genovese and Tantari* (J. Phys. A: Math. Theor. 53 094001), *Alemanno, Centonze and Fachechi* (J. Phys. A: Math. Theor. 53 074001), *Spigler, Geiger, d'Ascoli, Sagun, Biroli and Wyart* (J. Phys. A: Math. Theor. 52 474001), *Hou, Wong and Huang* (J. Phys. A: Math. Theor. 52 414001), *Yoshida, Karakida, Okada and Amari* (J. Phys. A: Math. Theor. 52 184002), *Agliari, Albanese, Barra and Ottaviani* (J. Phys. A: Math. Theor. 53, XXXXX).

Inspiration & Application
Methodical approaches developed in statistical physics have inspired, and continue to inspire, machine learning algorithms (for example through the use of mean-field theory and its variants), also, regarding the latter, machine learning techniques have recently come to the fore in solving problems in statistical and more generally theoretical physics (ranging from the automatic detection of phases of matter to learning efficient representations of quantum wave functions).
The present volume provides valuable contributions to these investigations, too: within these branches, we may include the review by *Gabrié* (J. Phys. A: Math. Theor. 53 223002) and

the papers by *Gabrié, Barbier, Krzakala and Zdeborová* (J. Phys. A: Math. Theor. 53 334004), *Çakmak and Opper* (J. Phys. A: Math. Theor. 53 274001), *Yasuda and Obuchi* (J. Phys. A: Math. Theor. 53 014004), *Noguchi and Kabashima* (J. Phys. A: Math. Theor. 52 424004), *Obuchi and Sakata* (J. Phys. A: Math. Theor. 52 414003), *Sheikh and Coolen* (J. Phys. A: Math. Theor. 52 384002), *Goldental and Kanter* (J. Phys. A: Math. Theor. 53 414001), *Kappen* (J. Phys. A: Math. Theor. 53 214001), *Öcal, Grima and Sanguinetti* (J. Phys. A: Math. Theor. 53 034002).

We do hope that this special issue as a whole could be able to cover the main aspects of the prolific intersection between Statistical Physics and Machine Learning, and, likewise, that the Journal of Physics A audience will enjoy reading it as we enjoyed looking at its growth.

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